RECOMMENDER SYSTEMS AND THEIR IMPACT ON ONLINE PURCHASES

Sérgio Luis Ferraz Gominho Alves

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Gabriela Beirão

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Abstract

Recommender Systems (RS) are a powerful and valuable tool spread amongst online sellers, if you ever purchase anything online, you have been exposed to such an important weapon of purchase assistance. Even when you are tired at home and decide to watch a movie on your preferred streaming service, you will be affected by recommender systems and sometimes even without knowing you are being influenced. The RS can help buyers and sellers, providing better options and ensuring the impact of the long tail of the vendor products.

Still, it is unclear how effectively the Recommender Systems influence the buyers' decision-making process at the moment of purchase and how they are affected by these systems. This being stated, this study's objective is to better understand the influence of RS on online consumers and how this is reflected in their purchases.

Qualitative research was conducted with 15 individuals from three countries that make at least one online purchase monthly. Using semi-structured interviews, which were answered openly by the participants, it was possible to gather data and analyze using thematic analysis, coding the patterns that appeared amongst the participants' answers and comparing findings to the literature.

The research findings show that the recommender systems affect the buyers at the moment of the purchase, mainly regarding helping with the product choosing and increasing the average ticket of the buyers, making them spend more than they were planning to do in the first place. It was also possible to relate the effects of the influence of recommender systems mostly to the ones which are social-related, coming directly from a person.

Keywords: Recommender Systems; Online Purchasing.

Resumo

Os Sistemas de Recomendação (SR) são uma ferramenta poderosa e útil que é amplamente difundida entre os vendedores online. Se você já comprou algo online, já foi exposto a essa importante ferramenta de assistência de compra. Mesmo quando você está cansado em casa e decide assistir a um filme no seu serviço de streaming preferido, você será afetado pelos sistemas de recomendação e, às vezes, mesmo sem saber que está sendo influenciado. Os SRs podem ajudar tanto compradores quanto vendedores, fornecendo melhores opções e garantindo o impacto da cauda longa dos produtos do vendedor.

No entanto, ainda não está claro como efetivamente os Sistemas de Recomendação influenciam o processo de tomada de decisão dos compradores no momento da compra e como eles são afetados por esses sistemas. Dito isso, o objetivo deste estudo foi tentar entender quais são os efeitos que eles trazem para os usuários quando compram online e como isso se reflete em sua compra.

Para isso, foi realizada uma pesquisa qualitativa com 15 indivíduos que realizam pelo menos uma compra online por mês, escolhidos por amostragem de conveniência em três países diferentes. Usando entrevistas semiestruturadas que foram respondidas abertamente pelos participantes, foi possível coletar dados e analisá-los usando análise temática, codificando os padrões que apareceram entre as respostas dos participantes e comparando nossas descobertas com a literatura.

Os resultados da pesquisa foram que os sistemas de recomendação afetam os compradores no momento da compra, principalmente no que diz respeito à ajuda na escolha do produto e também no aumento do ticket médio dos compradores, fazendo-os gastar mais do que planejavam fazer inicialmente. Foi ainda possível, notar que os efeitos de influência dos sistemas de recomendação provêm, majoritariamente, de sistemas que envolvam a recomendação advinda diretamente de uma pessoa real.

Palavras-chave: Sistemas de Recomendação; Compras online.

Index

Index of Tables

1. Introduction

Online shoppers now have a dizzying array of options thanks to the explosive rise of e-commerce platforms, streaming services, and social media networks in the age of digital commerce. The decision-making process has become more complicated than ever before as a result of the large number of possibilities available. As effective tools for helping users navigate the digital world, recommender systems now provide customized, pertinent, and timely recommendations tailored to each user's interests and requirements. These technologies are now an essential component of the online user experience, significantly impacting customers' buying and decision-making across a wide variety of platforms and businesses.

Despite the widespread use of recommender systems and their shown ability to increase conversion rates and customer loyalty, there is still much to learn about the specific elements contributing to their ability to persuade consumers to purchase. A greater understanding of these variables is essential to create more efficient, user-centric recommender systems that can meet the many and changing demands of online customers.

This thesis looks at the most important aspects of recommender systems that affect how people decide what to buy when they shop online. The aim is to discover recommender systems critical factors to influence customers during their purchasing process. This thesis will also explore the possible adverse effects of the recommender systems on consumers. This study attempts to give a balanced and thorough knowledge of recommender systems' role in influencing contemporary digital commerce by evaluating both the advantages and disadvantages of these systems.

The study aims to expand extant research on how recommender systems may be tuned to impact purchasing choices, and also provide practical advice to companies wishing to improve the online buying experience for their consumers. This research will contribute to the ongoing development of more useful and user-centric recommender systems by identifying the crucial factors that influence decision-making and investigating the potential opportunities and difficulties associated with recommender systems. This will ultimately promote customer satisfaction, foster long-term relationships between users and online platforms, and shape the future of digital commerce.

That being stated, this study research questions are the following:

1. How recommender systems influence customer online purchasing decision-making?

2. What are the positive and negative impacts of recommender systems on online buying behavior?
3. How the type of recommender systems influences the buying decision?

1.1 Report Outline

This research is organized into seven chapters as shown below:

- Chapter 1 – Includes the topic, the objectives and research questions, and the dissertation structure.
- Chapter 2 – Gives an overview of the previous studies with the literature review concerning the main topics that are addressed in the thesis.
- Chapter 3 – Presents the methodology that was applied to reach the results of the dissertation, and presents the sample and data analysis method.
- Chapter 4 – Presents the results that were reached from the interviews that were performed after the data analysis, showing citations from the interviews and making considerations between them.
- Chapter 5 – Relates the results that were found in the research to the existing literature, looking for filling gaps and to endorse previous hypotheses.
- Chapter 6 – Final Considerations and Conclusions
- Chapter 7 – References used to construct the research.

2. Previous Studies

2.1 Introduction

Recommender systems have become an important part of online shopping and content consumption. They use different technologies and methods to help users find goods, services, or content that match their tastes and habits. As there are more and more digital channels and more and more things to buy online, it is becoming more and more important to study how well these systems affect online purchase decisions. The main goal of this literature review is to look at the different lines of academic and business studies on how recommender systems affect online buying decisions. The review will then look at empirical studies that look at the usefulness of recommender systems. These studies will look at how these systems change how consumers act and make decisions when buying things online. In the last part of this review of the literature, the study will look for gaps in what is known and suggest places for future study.

2.2 Literature review

Recommender systems are a subset of information screening systems that try to guess a user's opinions or reviews for a product or item. (Jannach, Zanker, Felfernig, & Friedrich, 2010) These systems are used in a number of online apps with the goal of giving users unique suggestions based on their past actions, character information, and sometimes specific feedback. Ricci, Rokach, and Shapiro (2011) say that there are three main types of recommender systems: collaborative filtering, content-based filtering, and hybrid recommender systems.

The idea behind collaborative screening is that people who have agreed in the past will agree again. It uses the reviews, click histories, buy histories, etc. of many people to figure out what they like and what they don't like. Content-based screening, on the other hand, suggests things by relating the content of those things to a user's biography. Each item's information is shown as a set of descriptions, like the words in a document, the color of a picture, or the name of the movie's director.

Hybrid recommender systems use both content-based and shared methods to take advantage of the best parts of both while minimizing the bad parts. For example, a hybrid system can use content-based methods to solve the "cold start" problem in collaborative filtering, which means that recommendations can't be made for users without enough rating history. It can also use collaborative methods to include user interactions and improve the performance of content-based recommendations (Burke, 2002).

Friend recommendations are also known as a type of recommender system. Social recommender systems, also called trust-based recommender systems, are a type of recommendation system that uses the social ties between users to make more accurate and specific suggestions.

Guy, Ronen, and Wilcox (2009) say that social recommender systems help solve the sparsity and cold-start problems of other recommender systems, like joint filtering, because trust relationships can give more information for prediction and suggestion. Also, they found that social recommender systems can make users more engaged and happier because people tend to trust tips from their friends more than recommendations made by computers.

Ma, King, and Lyu's study from 2011 also showed how important trust-based recommender systems are. They came up with a model that takes into account both verbal and tacit trust between users to improve the accuracy of recommendations. The results of their study showed that adding details about trust could make suggestions much better.

So, friend recommendations or social recommender systems are a big part of giving people trustworthy choices that are tailored to them.

Product suggestions are based on how closely user preferences and product attributes match using a technique called content-based filtering (Billsus & Pazzani, 2007). The recommender system suggests items with the same features as those a user has previously shown interest in or interacted with (such as genre, director, actors, or keywords). The fundamental tenet is that consumers will be drawn to goods similar to those they have previously consumed or loved. Collaborative filtering, on the other hand, makes recommendations based on the overall user behavior 2009 (Su & Khoshgoftaar). The premise behind this strategy is that consumers will likely continue having similar preferences for or behaviors toward items. User- and item-based Collaborative filtering strategies may be further broken down into these groups.

User-based collaborative filtering identifies users with shared interests or actions (such as viewing history, ratings, and purchases) and proposes products those users have previously eaten or loved. According to Schafer et al., (2007), the central premise is that individuals are more likely to voice their preferences in agreement in the future if they have previously done so. Item-based collaborative filtering emphasizes more on links between items more than it does users. (Karypis, et al., 2001). The method suggests more products often consumed or enjoyed by users who have shown interest in one of the commodities. This marketing tactic is based on the notion that consumers who have consumed or appreciated a particular product are likely interested in related products.

Hybrid recommender systems combine two or more recommendation approaches to enhance performance and overcome the limitations of individual strategies. (Burke, 2002). For instance, a hybrid system may combine content-based filtering with collaborative filtering to provide users recommendations that include their preferences and those of other users with similar interests.

One of the most popular methods in recommender systems, collaborative filtering, has proven successful in several contexts, including social media networks, streaming services, and e-commerce platforms, Konstan & Riedl (2012). It must resolve the scalability problems and the cold-start problem, which is the difficulty in producing suggestions for new users or objects with minimal data, Tuzhilin & Adomavicius (2005). Researchers and practitioners are always improving the performance of recommender systems by exploring new techniques and strategies.

The way individuals engage with audio-visual information has likewise undergone significant changes. The recommender systems used by streaming services such as Netflix, Amazon Prime, and Spotify present users with personalized recommendations to increase user satisfaction. A comprehensive understanding of the factors that play a role in users' decision-making processes is required to successfully design and evaluate effective recommender systems. The appropriateness and customization of suggestions are key elements influencing users' choices (Ricci, Rokach, & Shapira, 2011).

Content that is more likely to be seen by users is that which is relevant to their preferences, interests, and previous actions. Users will be happier and will consume more material if recommender systems can forecast their interests and provide tailored recommendations. The popularity and social influence of the suggested material may also have an impact on users' choices. Users are more inclined to choose movies or videos that are popular, highly rated, or have received the endorsement of their peers or favorite influencers, according to Salganik, Dodds, and Watts' (2006) research. Streaming services may leverage social influence by combining user reviews, ratings, and information from social networks into their recommendation algorithms.

One other important aspect that has the potential to influence consumers' choices is the content's quality and production value (Hennig-Thurau, Houston, & Walsh, 2006). The likelihood that people will notice and watch high-quality films and videos with compelling narratives, talented performers, and stunning images is higher. Streaming services might include quality and production value in their recommendation algorithms to promote high-quality material. On streaming platforms, consumers' decision-making processes are significantly influenced by diversity and chance. According to Zhang and Hurley (2008), users value various suggestions because they may introduce them to new genres, experiences, or information they would not have otherwise come across. Users are introduced to unexpected yet delightful material via serendipitous suggestions, generating a feeling of discovery and enjoyment (Murakami, Mori, & Orihara, 2008).

To provide users with a rewarding and interesting experience, recommender systems must correctly combine variety and relevance. Furthermore, context-aware recommendations use a variety of contextual elements when proposing content, like the time of day, location, or user's mood (Adomavicius & Tuzhilin, 2011). Context-aware recommender systems may provide more relevant recommendations to the user's current position, boosting engagement and happiness.

Understanding the client nowadays is more important than ever. Having data is no longer a problem for the companies, instead, the struggle now is how to manage all this data and how to read the inputs that they provide. There is no use to a super strong recommender system if you can't read the key factors that would influence the decision when purchasing or choosing a movie to watch. This is the most important and valuable data when selling a product or providing a service online. It is the kind of data that will enhance your sales, your customer satisfaction and will improve client loyalty and rate of return.

For online purchasing, Roudposhti, et al. (2018) conducted a Technology Acceptance Model (TAM) to measure the customers' acceptance of recommendations to buy. In that study, Accuracy, Diversity, Ease of use, Familiarity, Recommendation quality, Satisfaction, Trust, and Usefulness were shown to have a substantial effect on a customer's propensity to acquire an item suggested by a recommender system. It is crucial that each segment and market utilize the most suitable kind of recommender system to leverage their businesses.

To understand how diversity plays a part in the recommender systems, Fleder and Hosanagar (2007) conducted research where they compare two different ways of recommending products: one that uses the most popular products and another one that recommends a long tail of not-so-popular products but that match the customers taste. This study is critical since it seeks to better understand how diversity influences recommender systems and how these systems may function to zero in on the most effective strategies used by a wide variety of businesses.

Recommender Systems walk side by side with other components of the purchasing process. Liu, J. et al. (2017) investigated the relationship between RS and customer experience. They concluded that they are substantially connected. It is reasonable to think that when you have a great experience in a physical store and good customer service, it is more likely for you to consider a salesperson's recommendation, which seems to be reflected in online purchases as well.

Due to the number of options on the internet, recommendation systems became needed when people want to purchase. Zhang, Zhao, & Gupta (2018) developed research to understand how these online recommendations could influence buyers' decisions and if or how they affect their loyalty to brands they usually buy to. These authors found that consumer product screening and decision-making quality highly affect customer loyalty. The cost of consumer product screening is positively correlated with deception and information overload and negatively correlated with self-reference. Self-reference, deception, and information overload have a favorable impact on product assessment cost, whereas vividness has a negative impact. Additionally, self-reference is favorably correlated with consumer decision-making quality whereas deception and information overload are adversely correlated.

Deloitte (2020) investigated the influence of recommendations from friends on internet purchases. According to these study findings, an overwhelming majority of customers (83%) are more inclined to buy after obtaining a recommendation for a product from a friend. This lends credence to the conclusions of a survey conducted by Nielsen (2015), which found that most respondents (83%) put more stock in personal recommendations from friends and family than in any other kind of advertising.

In addition, the Local Consumer Review Survey (2019) conducted by BrightLocal highlighted the significance of reading online reviews before purchasing online. According to the poll results, nine in ten customers have used the internet during the last year to search for a nearby company, and 33 percent of those consumers browse online every single day. It was also shown that 82% of customers read internet reviews for local companies, with 93% of those consumers being between the ages of 35 and 54.

To summarize, recommender systems are potent instruments that organizations may use to leverage their customer loyalty, sales, brand recognition, and various other areas of their operations. The elements that may impact the decision-making process of consumers while utilizing an e-commerce platform that uses a recommender system might vary, however many conclusions converge on aspects such as personalization, popularity, trust, utility, and reviews and recommendations from previous purchasers.

Although there are existing studies that identify constructs, it would be adequate use a qualitative approach to fill some gaps that were not approached. However, being in a context of constant and disruptive technological evolution, as well as in the presence of new generations with different lifestyles, and with digital skills, a search or reconceptualization of the constructs is imposed.

3. Methodology

3.1. Introduction

This research has the objective of understanding what are the most relevant constructs that influence the decision-making of clients performing online purchases using recommender systems. To do so, a qualitative study is adequate since it enables one to understand better and in-depth interpret each interviewee's different points of view.

3.2. Research Design

A qualitative approach was chosen for the research since the study aims to understand how certain factors influence the feeling of the customers when purchasing. Qualitative approaches are more human-centered and better to understand in-depth how people think and feel, which is the purpose of the research.

The study focuses on individuals that usually buy online. That is, customers who perform at least one online purchase per month. The sample of interviewees was obtained by using a convenience sampling method. The sample includes fifteen individuals that make at least one online purchase every month from Portugal, Italy, and Brazil.

3.2.1 Sample

The sample for the primary research to be performed was constructed in consideration that a certain profile of interviewees is needed to guarantee that we have adequate and suitable people answering the questions in order to collect relevant data. For this, it was used the non-probability sampling approach, non-probability sampling involves selecting the sample based on criteria that are not chosen at random. As a result, not every person in the population has an equal chance of being included in the sample. It was used then, the convenience sampling method, choosing people that perform at least one online purchase every month, the interviews are spread between Portugal, Italy, and Brazil.

The sample was formed by fifteen individuals which were divided between five women and ten men, with ages between 20 and 43, with an average age of 31.4. Below, we can see Table 1 with the information of the participants.

P#	Country	Age	Gender	Working Field
P1	Portugal	26	Female	Architect
P2	Portugal	29	Male	Management
P3	Brazil	31	Male	Economics
P4	Brazil	30	Male	Management
P5	Brazil	43	Female	Civil Servant
P6	Brazil	20	Female	Student
P7	Italy	39	Male	Priest
P8	Brazil	40	Male	Lawyer
P9	Brazil	33	Female	Economics
P10	Brazil	22	Male	Student
P11	Brazil	28	Male	Entrepreneur
P12	Brazil	42	Male	Civil Servant
P13	Portugal	30	Male	Entrepreneur
P14	Brazil	28	Female	Health
P15	Brazil	30	Male	Entrepreneur

Table 1. Information of the participants.

3.2.2 Data Collection and Analysis

A semi-structured interview was conducted with 15 individuals to collect the data. The interview guide aimed to extract from the interviewees their points of view referring to the purchasing process. The individuals are between 20 and 43 years old and recurrently shop online. With the first question, the goal was to understand the general perceptions, of the purchasing process and the influencing factors on the decision-making. Afterward, the questions pointed toward perceiving the difference in the impact of the various recommender systems and how they influence the purchase process. In addition, it was tried to understand if there was a difference between the human-based recommendations (e.g., client reviews) and recommendations from the company (e.g., similar products picked by the algorithm).

In the first question, "Q1: What kind of products do you usually buy online and do you have a preference where to buy it?" it was tried to segregate the type of products that people with that profile usually purchase online and cross-check the information with the following questions. The second question was designed to understand what is the most important feature that an online retailer should pay attention to attract customers, being "Q2: What is the most important thing in a website where you want to perform a purchase?".

Following this line of thought, it was asked the interviewees if they look for opinions before purchasing and where they do this kind of research, Q3: "Do you look for opinions before buying online? Where do you look for those?”. To add up to the feedback from the second question on the most important website feature, it was wanted to perceive the most important factors regarding the actual purchase, they were dived into what kind of opinions the respondents were looking for, Q4: “What kind of opinions do you seek about the purchase before buying online?”.

After these questions, a different phase of the interview began, where started to emerge in the recommender systems' perceived impacts on the respondents' views. For that, it was asked about how they think they were impacted. Q5: “How do you think these recommendation systems influence your buying process?”. They aimed to understand the impact they perceived when being in touch with the recommender systems. And complementing the previous question, it was asked where the most relevant recommendations come from in their opinion, “Q6: Where comes from the most relevant recommendations? Do you believe and trust the Recommender Systems?”. To end up the interview, it was asked about online reviews and if they usually do this kind of review after purchasing online and where they do that, “Q7: Do you usually give online reviews? Where?”.

The analysis of the interviews was made through thematic analysis, using manual approach. First, the interviews were transcripted in order to read and get familiar with the data. Then, these interviews were coded and clustered under several themes that could be found in the form of patterns, which allowed us to make a deeper analysis of the feelings of the interviewees and how are they affected by the subjects of the questions.

3.3 Synthesis of the Methodology

In conclusion, this research was designed to unearth key triggers that influence consumer decision-making during online purchases with recommender systems. The target was obtaining an accurate outcome, particularly through the lens of qualitative data to better comprehend and interpret the distinct perspectives of each interviewee. The sample for the research was carefully curated, focusing on regular online shoppers from Portugal, Italy, and Brazil. A semi-structured interview approach was used, engaging 15 individuals with diverse demographic profiles, and allowing us to delve deeper into their perceptions of the purchasing process, the impact of recommender systems, and their attitudes toward online reviews. Thematic analysis of the interview responses revealed patterns and offered valid and reliable variables for further investigation. In parallel, secondary research was carried out by reviewing various relevant articles through Scopus and Google Scholar to draw comparisons between the findings and existing literature. The combination of these research methods provided valuable insights into how consumers interact with and are influenced by online recommender systems.

However, the study comes with inherent limitations due to its qualitative nature and small sample size. The convenience sampling method could introduce potential biases, and the findings may not be completely generalizable due to cultural and geographical limitations. As such, while the research provides beneficial initial insights, future studies with more extensive and diverse samples could help enhance the robustness and generalizability of the findings.

4. Results

4.1. Introduction

This chapter shows the results from the qualitative study. Data were analyzed using thematic analysis method to search for relevant themes to answer the research questions. This method of analysis is suitable for exploratory research aiming to find underlying themes and patterns in the data. By finding, analyzing, and reporting themes, the thematic analysis gave researchers a better understanding of the study topic. The results are grouped by themes and each theme going to be detailed.

4.2. Findings

The use of thematic analysis in the interviews uncovered three main themes regarding the impacts of the recommender systems on the online purchasing process: (T1) positive impacts, (T2) negative impacts, and (T3) behavioral impacts. For the first theme, positive impacts, four subthemes emerged: inspiration, awareness, relevance, and informativeness. Considering negative impacts there are three subthemes: privacy concerns, overwhelmedness, and lack of novelty. Finally, the third theme was subdivided into four subthemes, higher spending, purchase changing pattern-fitting, and indifference. Below, all themes and subthemes are shown in Table 2.

Themes	Subthemes	Participants
Positive Impacts	Inspiration	5
	Awareness	3
	Relevance	10
	Informativeness	14
Negative Impacts	Privacy Concerns	6
	Overwhelmedness	5
	Lack of Novelty	6
Behavioral Impacts	Higher Spending	7
	Product Choosing	8
	Pattern-fitting	5
	Indifference	1

Table 2. Themes, subthemes, and number of participants mentioning the subtheme.

T1 – Positive impacts

All the participants mentioned positive impact aspects of the recommender systems, including a wide range of characteristics that were subdivided into subthemes. Some participants had a more effusive opinion on the positive impacts of the recommender systems, pointing out how they use the recommender systems to gain benefits, but most of them answered in a more skeptical way.

Subtheme: Inspiration

Participants pointed out that one of the positive impacts of the recommender systems during the purchasing process is getting inspiration from it. Some interviewees said that during the purchasing process, before buying, the recommendations helped with suggestions and serve as a source of inspiration for purchases.

Respondants were inspired by digital influencers that show their daily life on social media, including new outfits, products, or services. Also, reviews could inspire purchases. It is important to highlight that both reviews and digital influencers are personal-related, and are not recommendations generated directly by an algorithm. This proximity enables people to relate to the ones giving the recommendation, as shown in the following quotes.

> "I think for myself, the most relevant recommendations come from the digital influencers that I follow. Most of the time I get my inspiration to purchase clothes based on what my preferred ones show and based on that, I can choose better what to buy." [F,28]

> "I think I am the most influenced by people that I know giving me recommendations or sometimes digital influencers that I trust. Reviews in the website can be a great help as well, sometimes people give hints on what and how to use those kinds of products." [M,42]

However, the inspiration not always transform into a purchase. Sometimes, as mentioned by other participants, the inspiration can happen with products they already have at home but never happened to think to use in the way that was recommended. For example, mixing different outfits using some pieces of clothes they already have.

Subtheme: Awareness

Some participants mentioned that recommender systems can also create awareness for potential interesting things. They can come up as something that might not be relevant for that exact moment, but they can be used in the future. These participants reported that in some cases, the information will be stored somewhere inside their heads, waiting to be used later. The recommended ads on social media, creates impact, providing individuals with knowledge of some store or product, which may lead to a future purchase. The following quotes illustrates this.

> "Yeah, I do look for opinions, usually from people that I know. And I also see a lot of ads on Instagram, I always click on those kinds of ads. Sometimes I do not buy anything but the I keep the name of the store or the product in mind when I feel interested and might buy afterwards". [M, 30]

> "Yeah, I think the recommendations that come from the website or anything like that make sense. They always recommend products that I have an interest in, maybe products that I already had a look at on their website. So, they know that I have an interest in that or something that has anything to do with the purchase that I am making at the time. Sometimes I don't even buy the recommendation but I will remember them later and will come back to buy it, or maybe something that I like a lot and I just store it somewhere in my mind for afterwards and maybe even recommend those to friends that I know would like them." [M, 31]

The recommender systems not just influence people in the moment of the purchase, but also future purchases when consumers are actually interested in acquiring it. As such, they can also make people come back for new items and increase engagement.

Subtheme: Relevance

A high number of participants mention the relevance of the recommender systems. The relation between the recommendation and the user's preferences was perceived as one of the most important aspects and the most cited, as expressed in the quotes below.

> "They usually give me good recommendations on clothes that I really like. It looks like they really know me and can give me great and relevant recommendations." [F, 43]

> "And also, something like when they recommend something that is based on my profile, things that I like, things that they know I usually consume, so yeah, that's the most relevant for me." [M, 39]
>
> "I think they influence a lot more in the choice of the product. It helps me to choose from so many options. I feel like they know exactly what I think it's relevant and what I like, so when that kind of thing comes up on my screen, it gets my attention of course." [M, 42]
>
> "I think the most relevant for me is when they recommend me products that are on discount. Those are the ones that usually get my attention and it might turn into a purchase because I love those." [M, 29]

The relevance of the recommendations uses users' profile, which triggers emotional drivers. For some of the respondents, this can mean a specific type of recommendation such as profile-based recommendations, which will display items according to the person that is buying, pricing-related recommendations like sales and discounts, or purchasing-related recommendations. The relevance is also related to where the recommendation comes from.

Subtheme: Informativeness

Almost all respondents mentioned that getting information through recommender systems is something that they usually do and that helps in the moment of purchasing. Some of the participants engaged after the purchase by providing informative reviews about the products.
The following respondent mentioned that he likes to dive into reviews websites and Youtube channels rather than sticking with the basic informative data provided by the vendors.

> "Yeah, I usually go after opinions from people that I know and also from those websites where people talk about their purchases. Reviews are made on specific sites like electronic reviews, or even on YouTube channels. I also go there for opinions on the items that I want to purchase." [M, 29]

Again, social-related recommendations are more relevant than automatically generated recommendations. In the following statements, the respondents once again related their preferences to reviews and opinions.

> "Yeah, I do. Sometimes I watch reviews on YouTube, and I also like the websites of reference that talk about technology, electronics, and so on. So that's

> pretty much what I look for, and I'm always looking for the material quality, the durability of the product, things like that." [M, 42]

> "Well, I think they impact a lot positively, and usually, the reviews on the website influence me a lot. So, it helps me with product choices. It's really, really, really useful. I always find some informative insights to help me during my purchase." [M, 30]

> "I follow some influencers, like book influencers. So, they make reviews of books and if I get interested, maybe I will take a look at that book. So yeah, maybe this would be the most relevant kind of recommendation for myself." [M, 40]

The important of the recommendation relevance was evident during the interviews. The quality of the information in the recommendations is an important factor, the more content the recommender system has on the product, the more attractive is going to be to consumers to use that kind of system to help them during the purchasing process.

T2 – Negative impacts

Although, several positive impacts emerged the participants also reported how sometimes the recommender systems can affect them negatively, causing fear, concern, fatigue, and boredom.

Subtheme: Privacy Concerns

During the interviews, participants reported that in some cases, they feel concerned about their data safety and how it is stored and processed, and the amount of information that the systems have on them.

Data safety has become a top priority for individuals, businesses, and governments in a world that is becoming more and more digitalized. The amount of personal and private data that is created, handled, saved, and moved is vast and continues to grow. Cybercriminals want to access this data, which can include banking information, personal identification data, health records, and intellectual property. Cyber attacks like data breaches, hacking, scams, and ransomware threats are becoming more common and more advanced.

Thus, individuals are becoming more aware of potential risks. Almost all participants stated that security is one of the main factors that make them choose amongst a variety of websites to purchase. For some respondents, this means fear of delivery problems, for others privacy concerns, as stated in the following quote.

> "Yes, I think the recommendations make sense. They always recommend products that are similar to the ones I usually buy. Although it is kind of scary how they know so much about my life and have so much of my data in their hands, sometimes I feel like they are listening to me all the time. I wonder if my information can leak to anyone, sometimes." [F, 33]

> "I think the most important thing would be if the website is trustworthy, if it has security. Shopee, for example, only charges the client when they receive the product, and Amazon is a well-known company, so it's more about the trustworthiness. I do not want my personal information in the hands of someone I don't trust, I might get hacked or have my data stolen somehow." [M, 40]

Subtheme: Overwhelmedness

The number of recommendations can have a negative impact on some users. Some respondents mentioned this aspect and argued that this can generate in some cases loss of interest, as expressed by the following sentences.

> "Sometimes I think they are just too frequent, and it can generate the reverse effect, at least on myself, when I am scrolling through Instagram and there are like one thousand recommended ads for me, I just skip them right away, I don't even look at them. I just see that it is a sponsored post that is not from someone that I follow and I skip it." [F, 20]

> "I don't like when I keep getting recommendations on and on, I feel overwhelmed, and seems like they are trying to make me consume something by force. I feel uncomfortable. And whenever I see this kind of thing happening and there is an option available, I click on the "do not show me this anymore" button". [F, 26]

Several participants relate to the negative aspects of the overwhelmedness in recommender systems, such as ads, recommendations, and things that are not asked by users and can have the reverse effect on them. A respondent compared this to a real-life situation:

> "It is like when you are a tourist and you are traveling in the city center. There are going to be dozens of street sellers coming at you and offering stuff you didn't ask for all the time! From a point forward, you won't even look at the products anymore, you will just keep walking and ignore" [F, 43]

Subtheme: Lack of novelty

Although, the recommender systems are appreciated by some consumers due to their ability to recommend products and services inside their interests and preferences, others find it problematic. Respondents said:

> "Yes, they do. They always have good ideas for products that match my style, my profile, and are relevant to my purchases. But with that comes a problem as well because I would like to receive also something different from what I usually consume, this keeps me inside of a bubble you can say, and it works for anything, for products yes but also for world news for example. I would like to know more about what happens outside my bubble." [M, 28]

> "Sometimes I question myself why I receive so many times the same recommendation. It seems like I could only be interested in that item, but clearly, I am not. And it keeps coming, nothing new, always the same item right there. And I never even clicked on it." [M, 30]

Although, other studies showed that recommender systems can suggest products in the long-tail offering, if they are not correctly designed, the concentration of recommendations under a specific subject can make users frustrated and distrustful of recommender systems. The most susceptible type of recommender system are the profile-based recommendations, where people are sometimes looking for getting information outside their general world and they keep always getting fed by the same things.

T3 - Behavioural

The recommender systems can also impact people's behavior in many aspects, such as spending more, and changing their purchases. Some of the users changed their behavior in order to fit into a specific trend or group of people, to be part of a group or an activity.

Subtheme: Higher Spending

The influence of recommender systems on increasing spending was mentioned several times. Respondents said that the recommender systems were a major reason for buying more than they had planned. Namely, product suggestions made by these systems often led consumers to add more things to their carts, as shown in the quotes below.

> "I think the reviews, comments, and ratings on the website influence a lot. They impact my purchases as well. I think I end up spending more at the end of the day because I am always very interested in the recommendations, so I usually buy more than I was planning to. For sure, it makes my total a little bit higher." [M, 30]

> "I think I end up spending a little more because of the recommendations that come, I really like them. And sometimes I add things to my purchase that I wasn't planning beforehand to buy. So, sometimes I end up spending a little bit more but yeah, I think they influence and impact a lot at the moment of the purchase." [M, 30]

> "I think they influence me a lot in my choice. They make the choice easier, help me in choosing the product, and also it makes me spend more because they do recommend things that I really like and I end up adding more things to my cart or picking a more expensive product that was recommended. So that's pretty much about it." [M, 22]

Participants said that when they visit an online store for the first time, they already had a list of things they wanted to buy. But the specific product suggestions that the recommender systems gave them made them change their minds. Because these systems knew a lot about user's tastes and habits, they could offer more things that fit their likes and needs very well. As such, people ended up making purchases they hadn't planned on, which made their total spending go up. This trend shows that recommender systems have a strong ability to persuade customers to buy something, which can lead to them spending more when they shop in physical stores.

Subtheme: Purchase changing

The majority of the respondents mentioned that the recommender systems can make them change their minds about the product that is being purchased. Participants talked about times when the suggestions made by these tools changed the goods they were going to buy. This effect is independent of the recommendation source, like ideas from friends, online reviews, and suggestions from websites. All of these were important parts of the larger recommender system, as illustrated in the quotes below.

> “I think they influence a lot more in the choice of the product. It helps me to choose from so many options. I sometimes change the product that I was going to buy in the first place because I got a recommendation but I don't think I spend more. If I want to buy something and I see the reviews of a similar product with better comments and higher ratings I will definitely change it, even if I really wanted the first product.” [M, 42]

> “I think that they influence me. Usually, when they recommend a product, they say, "Hey, this is for you. This matches your profile," because it usually does. They usually give me good recommendations for clothes that I really like. It looks like they really know me and can give me great recommendations. They help me choose the product. It often happens to me when purchasing to get a recommendation of a product and just change the cart right away.” [F, 43]

Respondents said that when they buy online, they usually already knew what they wanted to buy. But when they got different suggestions, their first choice was often called into question, which made them rethink their options. Recommendations from friends were a big part of this process because they were reliable and easy to understand. In the same way, online reviews gave them important information about the quality and usefulness of the product, which affected their final choice. Lastly, the website, where the purchase was being made, gave ideas that were close to what they liked and how they usually shopped. So, it seemed like the recommender systems were a big part of how people made decisions when shopping online, especially when it came to choosing goods. Again, if the source of the recommendations was from actual people like the reviews and friends, respondents found it more reliable.

Subtheme: Pattern-fitting

Some participants modified their behavior because of the recommendations to fit a pattern. This sometimes has to do with the fashion world, to follow the trends, but also with fitting in a specific group or activity. The fear of missing out sometimes can be stronger than indifference to a product or service:

> "I think for myself, the most relevant recommendations come from the digital influencers that I follow. I'm always looking at what they talk about, their new products, and everything like that, especially for makeup and cosmetics. So yes, I think they would be the most relevant for me. I don't want to miss out on the new trends and what is in the fashion at the moment". [F, 28]

People often talked about times when they changed what they bought to keep up with a trend or to fit in better with a social group. For example, they might buy a trendy piece of clothing or a book that everyone in their book club is reading. These choices were mostly based on suggestions from friends, online influencers, or even the website's own algorithms, which is interesting because it shows how much power recommender systems have in shaping social conformity and trend adoption, as shown below.

> "I usually buy something that I want beforehand. But sometimes when I see a digital influencer using something that I like, I ask for a reference. Also, book influencers influence me a lot. I'm in some channels to buy books for discounts. This kind of stuff also influences me a lot on the things that I want. I participate in book clubs and when they are all reading something, I would buy anyways even if it doesn't match my reader profile because I want to know what is happening and the discussions inside the club" [F, 33]

Subtheme: Indifference

Although, almost every participant mentioning that they are impacted by recommender systems, still, some people say that they are not affected by them, as the following quote shows.

> "Yeah, I think they do recommend things that make sense for me, products that I like. But when I am purchasing, I usually have that thing in mind that I want to buy, and I won't change my decision or buy more because of a recommendation. Usually, I have that thing in my mind that I want to buy, and I go there and buy it. I don't think the recommender systems impact me in any aspect." [M, 40]

This lack of interest can be seen as a sign of a very goal-driven way of buying things. The user is basically a type of customer who sticks to their original shopping goal and ignores any possible distractions that recommender systems might offer. This behavior is interesting because it seems to be an outlier compared to how recommender systems seem to have a big impact on people's buying decisions in general.

Businesses need to be aware of this lack of interest because it shows that there is a group that is still hard to persuade with recommender systems. Understanding why people act this way could be key to coming up with tactics that might appeal to these customers and help recommender systems keep getting better.

5. Discussion

5.1. Introduction

This chapter provides a comparison of the study results with extant literature. Existing research on recommender systems and how people act online provided a starting point for the study. The current study adds to this by contributing with knowledge regarding the complexity of the buying decision-making process, when recommender systems are involved.

The qualitative method provided insightful data about the point of view of online customers. The respondents shared their experiences and points of view sheding light on how recommender systems can have a complex effect on online shopping. The emerging themes showed how recommender systems influence consumers' decision-making processes, and other factors that can also affect online shopping.

5.2 Interpretation

This study showed the influence of recommender systems on inspiring consumers. People often look for or get ideas from the given suggestions, which affects their shopping choices or tastes in some way. The idea that inspiration affects buying choices is in line with earlier research, showing that people often use online shopping sites not just to buy things, but also to get ideas and be inspired (Park, Lee, and Han 2007). Customers could be encouraged to try new goods or groups by well-targeted suggestions (Xu, Forman, Kim, and Van Ittersum 2014). This means that recommender systems can play a big role in broadening people's shopping horizons and pushing them to try new things.

Furthermore, this study also showed that "inspiration" can be used for more than just looking at products. It can also be used to help people decide what to buy. Data showed that recommender systems might not only make them think about a product but also lead them to buy it. This adds to what we already know about how recommender systems work, showing that they can drive not only product research but also sales.

Also, it is important to give suggestions that are complex and tailored to the person. Previous research has shown that recommender systems work (e.g., Xu et al., 2014), but this study shows how important it is for these systems to be relevant and personalized so that they inspire rather than overpower. So, "Inspiration" not only backs up what has been written before but also helps us learn more about how recommender systems can affect how people act online.

Recommender systems also can create awareness about new things, inducing interest in the goods or services that were suggested. Notably, consumers often kept this information in their minds for possible future purchases or to tell others about. This corroborates previous research, showing how successful suggestions can build a mental memory in users, which can affect their future buying decisions (Knijnenburg, Willemsen, Gantner, Soncu, and Newell 2012).

Moreover, the results show that recommender systems have a wider and longer-lasting effect that goes beyond instant sales. Zhang at al. (2018) found that recommender systems are powerful tools for getting people to buy things right away. This new information adds more depth to those results. This study adds to the research by building on the "Interest" theme and pointing out that recommender systems can also plant the seeds for future purchases or tips. This delayed effect, in which the user doesn't buy right away but remembers the advice for later, shows how recommender systems can have an additional effect on how people act.

The relevance of the recommendation, that is the positive effects that happen when users get relevant suggestions that are closely matched to their wants or hobbies, also matters. Relevance can come from advice based on a user's background, a suggestion about price, a suggestion about buying, or even the source of the recommendation itself. Studies have emphasized the value of individual and price-based suggestions (Ricci, Rokach, and Shapira 2011) and He and Oppewal 2013).

Results showed that consumers follow suggestions and buy, confirming previous research. Li and Karahanna (2015) found that offering things linked to a user's purchase past or what they were planning to buy had a big effect on their decision-making. This shows that importance is more than one thing and that recommender systems should look at more than one thing when making suggestions.

A unique contribution of this study, is the emphasis on the relevance linked to the source of the recommendation. To my knowledge, this fact is not mentioned in current literature, however this study showed that the suggestion source is a key factor on the perceived relevance and importance of the recommendation. Most of the participants mentioned that recommendations that come from social-related recommender systems, such as friend recommendations, digital influencers, and online reviews, are more relevant. This may be because they perceive them as coming from real people. It is interesting to note that all respondents said that the source of the suggestion was very important. Thus, future studies should explore in-depth the relevance of the sources of recommender systems figure.

This study confirmed some things already known about how important relevance is in recommender systems. It also brought to light something that was still underexplored, that is how the source of a suggestion affects how relevant it is seen to be. This result opens the door for more study into this topic, which will help us learn more about how good recommender systems work.

The "Informativeness" theme also emerged when respondents talked about their experiences with recommender systems. This theme is about how people get information from recommender systems, which helps them make decisions about what to buy. Also, some of the participants said that after buying the goods, they provided informational content about them.

An interesting result is how customers can not only get information after making a purchase but also add to the pool of information. This sharing of information helps both recommender systems and possible buyers in the future, creating a loop of making and using useful material that can keep going on its own. Li, Wu, and Lai (2013) said that user-generated content makes recommender systems a lot better, which makes shopping for potential buyers a better experience overall.

Also, there is a deep connection between getting information and giving it away in the context of recommender systems. The study adds to the literature by showing that recommender systems are an important source of information for consumers. This new feature gives us important information about how recommender systems could be improved to make it easier for people to share information with each other, which would improve the whole online shopping experience.

"Privacy Concerns" are critical for recommender systems acceptance. This theme included worries about data privacy, how much these systems may know about users, and the possibility of data leaks. This issue is under extensive debate in academia and society. For example, Knijnenburg, Kobsa, and Jin's (2013) study found that privacy worries are a key factor in how users accept and use recommender systems. In the digital age, more and more people worry that recommender systems know "too much" about their users. People in general are becoming more aware of how big their digital trails are and how their personal information could be used without their permission. Malhotra, Kim, and Agarwal (2004), showed that consumers' worries about privacy have a big effect on how they plan to use online services, including recommender systems.

Finally, there were huge concerns about that leakage. Since high-profile data hacks have become more common in recent years, it is not strange that users are worried about the safety of their personal information when they use recommender systems. User's perception of how vulnerable they are and how bad it would be for someone else to use their information can make them less likely to trust online services (Bansal, Zahedi, and Gefen 2016). This study backs up these worries and stresses how important strong data protection methods are for making people trust recommender systems.

In this study, the theme of "overwhelmedness" came up strongly. Respondents said that the sheer number of suggestions made by different recommender systems made them feel bad. This feeling is marked by a sense of being overwhelmed by too many ideas, to the point where subjects said they often skip over these suggestions without even thinking about them. This reminds the idea of "banner blindness" that Benway and Lane (1998) came up with. They noticed that people tend to ignore information that they think could be advertising, especially when there is too much material.

This feeling of being too busy is similar to what several studies have found. Schwartz's 2004 key paper, "The Paradox of Choice," argued that having some choices is good, but having too many choices can cause stress, confusion, and, in the end, a lack of interest. The study confirms this idea by showing that too many tips can make users feel overwhelmed by the number of choices and cause them to stop using the site altogether. This lack of interest could be an example of ad blindness in a different setting, where people have learned to unconsciously avoid suggestions because they find them annoying or unimportant.

Iyengar and Lepper (2000) and Scheibehenne, Greifeneder, and Todd's (2010) studies on "choice overload" show that when users are given too many options, they may have trouble making a choice, which lowers their overall satisfaction. Even though the study's results agree with these observations, they also show that recommender systems need to be used in a balanced way. The systems need to find the right balance between giving users enough useful options to help them make decisions and giving them too many suggestions that might be ignored.

The theme of "lack of novelty" came up as a major factor in the study, some participants were unhappy with how the suggestions they got from different recommender systems are always the same. These users say that the algorithm-based suggestions often circle around the same areas of interest without bringing up anything new or surprising. This fits with Pariser's (2011) idea of a "filter bubble," which says that the personalization algorithms of digital platforms can trap users in a loop of repeated content, limiting their exposure to new and different things.

The results of the study are supported by previous research. Ziegler et al. (2005) looked at the trade-off between applicability and freshness in recommender systems. They said that systems should try to suggest things that match a user's interests, but they should also try to suggest new things to keep things from getting boring and encourage research. In the same way, Vargas and Castells (2011) said that recommender systems tend to be too cautious, sticking to safe predictions based on how users have behaved in the past. This means that recommender systems don't take full advantage of their ability to introduce users to new hobbies. These findings are similar to what the study participants said about not having enough new things to do. This shows that systems need to suggest more new things and different things.

The results on this theme are related to the talk about "serendipity" in suggestions, which is interesting. In their study, Murakami et al. (2008) showed how important "serendipitous" tips are. These are ideas that come out of nowhere but are still interesting and helpful to the users. This element of surprise can make the user experience more interesting and rewarding, which makes the recommender system work better as a whole. Participants' complaints about the lack of surprise seem to come from a lack of chance, which shows how important it is to find a balance between how relevant something is and how new it is.

The idea of "higher spending" also came up in the study. Almost half of the people who took part said that recommender systems can cause them to spend more, often by buying things they hadn't planned to buy. This fits with what the field of behavioral economics has found, which says that decisions can be swayed by things that seem small, which can change how people spend their money (Thaler & Sunstein, 2008). Recommendation systems seem to do the same thing, working as a digital "nudge" that gets people to spend more money.

One important part of this "higher spend" theme has to do with the idea of "upselling," which is a strategy that has been studied a lot in marketing books. Vercellis (2009) said that upselling means that a seller is trying to get a customer to buy a more expensive product or service that has more benefits for the customer and makes more money for the company. In the context of online shopping, this can be done with the help of systems that offer linked items or higher-quality versions of the chosen items. The answers from the people in the study seem to back up this idea, showing that recommender systems can, in fact, lead to upselling and more spending.

This work contributes by giving real-world data from the users' point of view. It shows that recommender systems, while helpful for finding new products and making decisions, can also lead to more spending by accident. In the future, researchers may further explore this topic, looking for ways to find a balance between the benefits of personalized suggestions and the risk that they could lead to overspending or buying things on the spot.

The idea of "purchase changing" also emerged, as more than half of the people said that recommender systems can change what they were going to buy. Consumer behavior research backs up this idea. For example, Simonson and Tversky (1992) found that consumers may go into a shopping situation with a specific product in mind, but their final choice can be changed by a number of factors, including suggestions. This means that recommender systems could play a big part in this process by giving customers options they might not have thought of before.

In consumer decision-making research, the "consideration set model" says that customers usually have a "consideration set" of choices and make their final buying decision based on this set (Roberts & Lattin, 1997). The results match this model. Recommender systems may be able to change or add to this set of things to think about by showing different or extra goods, which could change the planned buy. This shows how convincing recommender systems can be and how they can change the way people act.

The interesting thing about the study is that it looks at the "purchase change" issue from the point of view of real customers. By showing how recommender systems can change what people buy, the results back up ideas that have been put forward in consumer behavior literature. And once again, we could see the pattern of social-related recommender systems taking the lead in the behavioral effects, having online reviews and friend recommendations as the most cited reasons for changing the product. This can lead to more studies in this area, especially about how recommender systems affect buying choices and how they can be improved so that they benefit both customers and companies.

The 'pattern-fitting' theme was evident among a significant number of participants, indicating that recommender systems can steer consumer behavior towards fitting into certain patterns, trends, or groups. This fits with what is known in sociology and market behavior, which says that people often try to fit in with social trends or norms, especially when persuaded to do so (Berger & Heath, 2007). Recommender systems can help guide this "pattern-fitting" behavior by pointing out goods or services that fit with a certain trend or group.

By offering popular or trendy things, recommender systems can quietly get people to follow a certain style or trend. This is what the study calls "pattern-fitting" behavior. This shows how much recommender systems influence market trends and habits.

By looking at the "pattern-fitting" theme in the setting of recommender systems, the work adds to what is known about it. A previous study has shown that outside factors can affect how people act, but the results show how recommender systems, as a form of digital impact, can encourage "pattern-fitting" behavior. This finding not only backs up well-known buyer behavior theories but also throws light on how people buy things online in the digital age.

The theme of "indifference" was much less common in the study. Only one out of the participants said that recommender systems had no effect on their behavior. Consumer behavior literature talks a lot about the idea of "active" customers, which this person seems to be. (Cova and Dalli, 2009) Active customers make decisions on their own, without being influenced by things like ads or suggestions from other people. Most of the time, these people know exactly what they want to buy and don't change their minds. This suggests that recommender systems may have little to no effect on what they buy.

But it's important to remember that the idea of "indifference" is very complicated and can mean very different things to different people. The study centered on a small group of people, which might not be enough to show how different and complicated customer behavior is. Also, the idea of not caring about recommender systems could be affected by things like personal beliefs, how useful people think suggestions are, and past experiences with online shopping. So, future studies should try to dig deeper into this theme, considering a wider range of customer traits and events.

6. Conclusion

Concluding, the work has made important contributions to what is already known about how recommender systems affect people. The analysis of themes like motivation, interest, usefulness, informativeness, privacy concerns, feeling overloaded, lack of novelty, higher spending, picking a product, putting it into a pattern, and not caring showed that online customers have a wide range of reactions to recommender systems.

One of the most important results was that recommender systems had a big impact on the buying choices and spending habits of most of the respondents. This confirmed what was already known about the persuasive power of these systems. Notably, though, the study also gave us some unique insights into what kind of recommender systems can affect people the most regarding their behavior, leading to higher spending or changing their purchases. It was noted that most of the participants were most influenced by social-related recommender systems, which interacted directly person-to-person, such as friend recommendations, digital influencers, blogs, and online reviews. This is an important addition to the literature since there is much being talked about how artificial intelligence is getting stronger every day and being capable of knowing people better and better, but people are still more connected to people, at least so far.

Yet, it was also found that not all users are strongly affected by recommender systems. We found people that said they didn't care about these systems. This result fits with what has already been written about the independence of some busy buyers, but it also shows that more study needs to be done on this less-studied group.

The study outcome provided valuable insights, academically, for better knowledge of the constructs and for the businesses to privilege recommender systems that have the right characteristics. It is needed to take into consideration that there are limitations in the research, all of them inherent in being a qualitative study. It is not possible to reach a definitive conclusion based on a sample of only 15 individuals, future research can try to generalize the findings using wider samples.

In conclusion, recommender systems continue to have a big effect on how people act, but it's important to remember that their effects can be both good and bad. Online stores need to find a way to meet customers' needs for personalized, relevant suggestions while also respecting their privacy and independence. This will require not only making these systems better and better over time but also being more open about how they work and paying close attention to what customers say.

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