To watch or not to watch

The influence of Netflix's recommendation algorithm on subscription members' behavioral intentions and recommendation adoption

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ABSTRACT

In this day and age, algorithms have become part of everyday practices. Especially in the growing streaming media industry, algorithmic recommendation systems play an important role in guiding users by suggesting movies and shows to watch. Netflix, the leader in the streaming services industry, has a developed recommender system which challenges viewing practices and is increasingly playing a role in subscription members' watching behavior. This study aims to investigate how people perceive algorithmic recommenders and to what extent these perceptions are associated with intentions to use the recommender system to find something to watch, as well as users' actual adoption of the recommendations presented to them by Netflix's recommender system. Importantly, attitude was examined as a potential mediator in the relationships between perceptions – perceived source credibility and perceived personalization – and intentions to use the recommender system. Recommendation adoption was contextualized by measuring whether people show a higher preference for peer recommendations or recommendations by Netflix. A quantitative survey was distributed among 289 current Netflix users who were 18 years or older. Respondents were mainly found through Instagram, SurveySwap, and Reddit. Mediation analyses using Hayes' (2017) PROCESS macro in IBM SPSS Statistics 26 showed that perceived source credibility and behavioral intentions are significantly and positively associated, with attitude mediating this effect. Similarly, attitude mediated the relationship between perceived personalization and behavioral intentions. Next, a significant and positive relationship was found between behavioral intentions and recommendation adoption. A paired-samples t-test indicated algorithm aversion, as people showed higher levels of recommendation adoption for peers than for Netflix. The results show that personalization and credibility are key drivers for attitudes, and in turn, attitudes affect intentions and behavior. This study contributes to and expands the current and larger understanding of user perceptions and responses, and the further implications and impacts of this artificial intelligence on society.

KEYWORDS: *Netflix, recommendation algorithm, perceived personalization, source credibility, theory of planned behavior*

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1. Introduction

Today, the role of television in the media industry is not what it used to be due to the rise of online streaming services (Jenner, 2018). Compared to cable and broadcast television, where viewers watch what is being offered, audiences now have more choice and control over what they are going to watch (Pittman & Sheehan, 2015). In fact, viewers can now decide what to watch, when to watch it, and which device to watch it on. Streaming services allow for this flexibility, with a broad catalog consisting of thousands of movies and shows that can be watched at any time, on any device. As said by Schwartz (2015), making a decision when there are so many options available is difficult and overwhelming for the consumer, resulting in poor choices or none at all. However, a benefit that comes with streaming services' broad catalogs is that the content appeals to a wide range of tastes and demographics, including specific titles for specific groups of users.

To reduce the negative impact of such overwhelming, big catalogs with many choices, recommender systems have been developed. These recommender systems are software machinery, specifically developed to present appropriate suggestions and recommendations to a particular user (Pazzani & Billsus, 2007). The recommendations are made based on certain filtering techniques, such as similarity in experiences and ratings with other users (the collaborative filtering approach) or users' past behavior and previously liked items (the content-based approach) (Reddy et al., 2019). In essence, the aim of recommender systems is to properly process information on the user and provide satisfactory information and suggestions. These systems are increasingly being developed and becoming popular in various areas.

Since the 1990s, recommender systems have played an important role in particularly the commerce and content markets, such as the e-commerce company Amazon and streaming service and former video-rental company Netflix (Konstan & Rield, 2012). The implementation of such systems can be especially beneficial for organizations that collect data on large groups of consumers and want to provide the best recommendations in the most effective way possible. As mentioned above, one of these organizations is the subscription-based streaming service Netflix. Netflix is considered a dominant player in the reorganization of television, and it plays an active role in challenging viewing practices (Jenner, 2018; Lobato & Lotz, 2020). As a result of the COVID-19 pandemic, Netflix's paid memberships grew to 208 million in the first quarter of 2021 (Netflix, 2021). These subscription members are located in more than 130 countries and have a collective usage of 6 billion hours per month, showing and contributing to Netflix's position as the largest and leading streaming service in the global industry (Cook, 2021; Rataul, Tisch, & Zamborsky, 2018). However, other streaming services, such as Amazon Prime Video and Disney+ have emerged to not only compete against traditional television, but also against Netflix in this growing global industry of streaming media (Budzinski, Gaenssle, & Lindstädt, 2020).

So, considering the industry's dynamics and competition, innovation is crucial to maintain the leading position and grow internally (Gomez-Uribe & Hunt, 2015). Therefore, Netflix has developed a personalized algorithm which helps users to find something to watch by recommending content which fits each individual viewer's personal taste (Jenner, 2018). Many attributes are considered when designing the recommender system, such as users' previously liked genres and even actors and directors (Reddy et al., 2019). In other words, Netflix's recommender system takes into account the user's previously watched movies and shows, to provide similar recommendations and help the user find something to watch.

The effectiveness of recommender systems is visible in previous studies, which found that algorithms play a big role in people's decisions, even more than advice and recommendations from peers (Montal & Reich, 2017; Shin, Zhong & Biocca, 2020). However, looking further into what actually makes these systems effective and what convinces people to make use of this system is crucial to continue developing and improving this type of technology. To elaborate, in order to understand the societal impacts of algorithms, it is important and beneficial to understand how users encounter and interact with algorithms, and to what extent these experiences shape users' behavior. As stated by Beer (2017), algorithmic systems can "shape decisions or become integrated into the choices that are made" (p. 5), with these choices becoming part of people's lives. In turn, the behavior and interaction from users play a role in shaping the algorithms, resulting in a co-evolutionary process with societies and technologies like algorithms influencing each other and creating reality together (Just & Latzer, 2017).

Yet, researchers have lacked in investigating the context of recommender systems implemented by streaming platforms and people's responses to it, and specifically, under which conditions people intend to use the system and actually adopt recommendations made by the system. With the rapid implementation of artificial intelligence and algorithm technologies, user experiences are increasingly improving and systems are widely and pervasively used in society, making it essential to address challenges and contexts (Ettlinger, 2018). For instance, while there is something for everybody in the big catalog, navigating it might be difficult at times. Recommender systems have the practical benefit of simplifying choices available to the user, especially the personalization feature of the algorithms helps to narrow down the options for the user. As this factor is there to help users, it might play a role in their decisions and choices, making it a relevant factor to consider in this study. Also, due to the technological aspect of algorithmic recommenders, it might not be as straightforward to investigate concepts such as trust and expertise. However, in this case, it might be interesting to look into these concepts and better contextualize users' perceptions and behaviors. Gaining insights into these conditions and to what extent people's perceptions impact their likelihood of accepting suggestions from algorithmic recommenders, allows for conclusions to be drawn on the social impact and power of algorithmic recommenders.

Thus, to further expand existing literature and current knowledge on this topic, in particular, the factors that influence people's intentions and behavior, this study focuses on Netflix users' perceptions toward the recommender system and the impact on their behavioral intentions and eventual recommendation adoption. To what extent people's perceptions toward algorithmic recommenders and their experience affect their use of platforms that implemented such algorithmic systems, and to what extent attitudes determine behavioral intentions and actual behavior, is reflected upon in this study. By investigating this topic, a better understanding is gained of users' algorithmic experience, their attitudes, intentions and resulting behavior. The findings of the current research can contribute to and build upon existing studies on the impact of algorithms on user perceptions and experiences, as well as their responses to recommendations provided by Netflix's recommender algorithm. Additionally, outcomes can be translated into practical implications for professionals in the field and can potentially serve as a starting point for future research paths while also filling research gaps. All things considered, this thesis aims to answer the following research question:

RQ: To what extent does Netflix's recommendation algorithm and its characteristics influence subscription members' behavioral intentions and recommendation adoption?

1.1. Societal relevance

First of all, in this digital age, various technologies have emerged that are now part of almost every aspect of daily life. Through these new technologies, such as apps and web-based services, people have embraced a digital lifestyle which refines viewing practices and options (Crawford, 2015). For instance, entertainment is not limited to cinemas and cable television anymore, but people increasingly seek on-demand streaming services to watch movies, tv shows, and original content created by the streaming services themselves. With this increase in the use of online services, users are also increasingly encountering artificial intelligence, such as algorithms (Willson, 2017). As stated by Just and Latzer (2017), such algorithmic systems play a role in shaping and forming society's everyday life and reality, while also affecting perceptions and actions. Nowadays, people commonly rely on such algorithms for all kinds of advice and information, as these systems are pervasive and the work of algorithms can be observed everywhere. For example, Google search results, recommendations for accounts to follow on social media platforms, and also the rows of movie recommendations on a streaming platform. In this media landscape with infinite information and entertainment, algorithms act as an ever-present feature and play an important role by offering a form of guidance to quickly and effortlessly find the most relevant content (Seaver, 2019). Importantly, according to Gomez-Uribe and Hunt (2015), 80% of what people consume is recommended by an algorithm. All in all, the focus on streaming services and artificial intelligence, recommender systems in particular, is important in this day and age because on-demand services and algorithms are increasingly being integrated into everyday life and impact the contemporary everyday practices and understandings.

Next, cultural products such as movies and series are increasingly consumed through on-demand streaming services, with Netflix being a major player in the global mediascape (Wayne, 2020). Thus, focusing specifically on Netflix's recommender system generates relevant, contemporary findings. With a streaming platform as widely used as Netflix's, many people are exposed to the recommender system implemented to assist its users in their viewing practices. With this wide exposure and visibility, it can be expected that the recommender has effects on its users, to a yet unknown extent. Especially considering the fact that when users open the Netflix app and log in to their account, they are immediately exposed to the recommender system consisting of rows with suggested movies and shows. So, the algorithm is not only an invisible, hidden, abstract thing, but it is something that influences the way people use Netflix from the moment they open the app.

This study will reveal the extent to which certain factors and the context of the recommender systems impact the usage of that specific recommender system. To achieve that, various factors are measured to investigate whether this affects Netflix users' intentions and actual behavior. The concepts included in this research are perceived source credibility, perceived personalization, attitude, behavioral intentions and the resulting behavior of recommendation adoption. These concepts will be thoroughly discussed in the next chapter. Looking into how users perceive algorithms is important, as these perceptions shape not only their orientation towards it, but also their actions (Bucher, 2017; Just & Latzer, 2017). People's intentions to use the recommender system and the resulting behavior of recommendation adoption impacts the recommender system's success and shows their ability to affect what is being consumed.

Moreover, the findings can be useful for professionals in the field to further develop the functionality and visibility of algorithmic recommenders. According to Varela and Kaun (2019), users are considered "co-producers of content, contributing data and knowledge through their practices to the platform development and consequently to its success." (p. 198). By improving the functionalities of the recommender system with the findings and gained knowledge from this study, professionals can stand out from competitors, while also keeping users satisfied and subscribed by suggesting relevant movies and show to watch out of all the available options. The relevance of this thesis for streaming services such as Netflix is the evaluation of the credibility and personalization of algorithmic recommenders, as well as the attitudes toward it and the resulting intentions and behavior. With new knowledge on the influence of Netflix's recommendation algorithm in particular, the performance of current algorithms and recommender systems can be enhanced to improve the overall user experience and satisfaction in these times of information overloaded platforms.

1.2. Scientific relevance

Previous studies have investigated recommender systems, but in a broader sense rather than focusing on a specific recommender system (Shin, Zhong & Biocca, 2020). Researchers who did focus on Netflix's recommender system, took an industry perspective (Amatriain & Basilico, 2015; Gomez-Uribe & Hunt, 2015). By using Netflix as a case study, the specific approach and techniques implemented by the company can be explored. However, this perspective does not allow for the expansion of understanding and knowledge on consumption and audience experiences. As stated by Turner (2019), research on consumer experiences and their everyday television viewing practices is limited. Also, as stated by Bucher (2017), there is limited research on "the ways in which people experience and perceive algorithms as part of their everyday life and media use" (p. 31). So, to fill this research gap, this study looks into user perceptions of and experiences with algorithms, and the role these factors play in their media use and consumption. The user-centered approach is especially useful to gain a better understanding of how people perceive and use algorithms, also considering the fact that companies that implement such systems are often reluctant to share data and statistics, making it even more interesting to gain insights on Netflix consumer behavior (Barr, 2015). Thus, by focusing on the users, more insight is gained into how Netflix's actual and current consumers perceive the system. As a result, it is revealed to what extent they intend to use it and their actual adoption of the recommendations.

Additionally, websites specifically designed to recommend movies have been thoroughly studied by researchers, but algorithmic recommendation systems from streaming services are relatively new in the research field (Bobadilla, Ortega, Hernando, & Alcalá, 2011). Results from studies that have focused on movie recommendation websites might not be particularly applicable to the context of recommender systems by streaming platforms. By focusing on the algorithmic recommenders from such platforms, another gap is filled and more insights can be gained on movie recommendations in another context.

Therefore, to fill the research gaps, the current study will take a user perspective by distributing an online survey among Netflix users to quantitatively investigate their preference for recommender types, perceived source credibility, perceived personalization, attitude, behavioral intentions and resulting behavior of recommendation adoption. Importantly, by addressing perceived personalization as a potential influential factor, this study fills the gap of limited research on perceived personalization. Perceived personalization is deemed a relevant concept to include in this study, as Netflix's recommendations are personalized and this measurement will indicate whether and to what extent users perceive it to be personalized. In turn, this personalization can have an impact on the effectiveness of the recommender systems and user satisfaction, which can affect behavioral intentions (Tintarev & Masthoff, 2012).

All things considered, by investigating the user perspective, specifically users' attitudes toward, perceptions of, intentions and behavior with this specific type of technology, this research contributes to the broader field of research on the social implications of algorithms and artificial intelligence and allows for a scientifical understanding of the current trends.

1.3. Chapter outline

As discussed above, this thesis focuses on users' perceptions of Netflix's recommender system, and the effects thereof. This thesis is divided in five chapters and is structured as follows. After this chapter with the introduction of the topic of the thesis, its academic and societal relevance and the overall research question, Chapter 2 discusses previous research and theories on recommender systems and intentions. The theoretical background of this study is discussed together with the hypotheses that guide this study. Next, Chapter 3 explains the research design to provide more insights into the quantitative survey research method, the sampling method, the measurements used to test the hypotheses and answer the research question, and the data. Chapter 4 presents the results of the statistical analyses to test the hypotheses. In this section, it is clear whether the hypotheses can be confirmed or rejected. Lastly, Chapter 5 discusses the findings and concludes with an answer to the research question and the hypotheses. Theoretical and societal implications of the research findings are discussed, as well as the limitations of the study and suggestions for future research.

2. Theoretical framework

Before shedding light on the influence of Netflix's recommendation algorithm on subscription members, it is crucial to examine the environments in which this phenomenon takes place. This chapter reviews existing literature on the topic and builds a framework around the theoretical concepts that are applied to the current research. The theory is used to provide the reasoning for the research model and the hypotheses. Also, the relevance and usefulness of theoretical concepts are explored, as these concepts guide this chapter and serve as a backbone in the study.

2.1. Recommender systems

With the rapid growth of internet services and media technologies, many of our actions and interactions take place online, such as buying online and gathering information through search engines (Lü et al., 2012). As people often rely on their peers for recommendations before trying something new or buying a product, recommender systems were developed to also offer help to people in their process of selecting a suitable product from all the options available (Sharma & Singh, 2016). This is especially relevant, as technological advancements and the online environments have led to an increase in the available choices for the consumer. The electronically stored data on what people choose, buy, and watch online creates opportunities for corporations to develop recommender systems. The recommender systems use this data on their users and preferences to predict what the users might like and be interested in in the future.

Recommender systems are especially popular in the entertainment industry (Kumar, Yadav, Singh, & Gupta, 2015). Due to the wide variety of available content that people can watch, recommender systems provide assistance to users through recommendations that have been found to match their interests, needs and preferences (Christensen & Schiaffino, 2011). A firm that has incorporated recommender systems as a major part of its services is the streaming platform Netflix. Netflix uses the content-based filtering algorithm to recommend items based on similarity with the users' previously preferred items (Bobadilla, Ortega, Hernando, & Alcalá, 2011). According to Sharma and Singh (2016), content-based systems revolve around users' past behavior, as products or items are recommended based on similarity with the ones the particular user has already liked in the past. So, when people finish a movie or show from any category on Netflix, the algorithm will recommend more titles from that particular category as it is likely that the user will like titles similar to movies and shows they just finished.

The use of recommender systems has proven to be beneficial and influential, as over 2/3rd of the movies people watch on Netflix were initially recommended by the algorithm (Gomez-Uribe & Hunt, 2015; Kumar et al., 2015). However, it is important to note that how people experience algorithms is related to their perceptions, which then shapes intentions to use the recommender system and the adoption of algorithms (Shin, Zhong & Biocca, 2020). Therefore, the remainder of this chapter proposes hypotheses supported by theory and findings from previous studies to investigate the factors that influence people, and to what extent these factors influence users' decisions and actions in regard to the recommender system.

2.2. Different recommender types

With the rise of big data, algorithms have become a new source of advice (Logg, Minson & Moore, 2019). As algorithms are able to make accurate predictions based on data, many studies have argued that they can perform better than human agents in various areas and contexts (Dietvorst, Simmons, & Massey, 2018; Logg, 2017). However, to what extent people accept and adopt the recommendations differs. In essence, people can have a preference for algorithmic recommender systems over human agents – algorithm appreciation –, whereas other people are more reluctant to follow recommendations by algorithms and prefer human recommendations – algorithm aversion.

2.2.1. Algorithm appreciation and aversion

Algorithm appreciation suggests that people prefer algorithms and are more likely to take advice from an algorithm than from a human being. In the context of news, Thurman, Moeller, Helberger, and Trilling (2019) found evidence for this appreciation for algorithmic recommendations. In the case of news selection, people showed higher levels of preference for recommendations from algorithms than from humans. Notably, the source of the data driving the recommendations has been found to influence the level of appreciation of algorithmic recommendations. When the past behavior of respondents' themselves served as a source for the algorithmic recommendations, more appreciation of algorithmic recommendations was shown than when the source was stated as being the past behavior of respondents' friends. In the case of Netflix, the recommender system and filtering technique is also based on the users' past behavior and they communicate this to the user through headings such as "because you watched…".

Importantly, Castelo, Bos, and Lehmann (2019) state that people generally already know algorithms and its use for tasks such as recommending movies on streaming services. When people are already familiar with such an algorithm for the given task, they are more likely to trust the algorithm and more willing to rely on the algorithm for the task. As many online streaming services, such as Netflix and Hulu, use the same algorithmic recommendation system to recommend items based on the users' past behavior, it can be assumed that consumers are already familiar with this type of algorithm for the specific task. Therefore, they will be more likely to use the algorithm and have a favorable perception of or even preference for the system (Groshek & Krongard, 2016).

In contrast, algorithm aversion is the phenomenon that people prefer advice from humans over an algorithm's advice (Dietvorst, Simmons, & Massey, 2015). Despite algorithms outperforming human judgment, Logg, Minson, and Moore (2019) suggest that people can have a skeptical attitude toward relying on algorithms. Studies have shown that people prefer recommendations from humans (Dietvorst, Simmons & Massey, 2015; Sinha & Swearingen, 2001). The experiment conducted by Dietvorst, Simmons, and Massey (2015) showed that, in the context of predicting the future, people preferred human recommendations over those of algorithms. However, this preference was only present if they observed the algorithm making mistakes in its performance. When people did not see the algorithm inaccuracy and errors, or when the algorithmic predictions were nearly perfect, they were more likely to prefer the algorithm. Considering the context, the study focused on predicting the future, such as students' performances, and whether their prediction was correct.

In comparison, in the case of Netflix's recommender system, there is no straightforward right or wrong answer. When Netflix recommends a movie, reasonable explanations are provided to help the user understand why that given title is recommended to them (Walek & Foijtik, 2020). This makes it less likely that the user will consider the recommendation to be an error. Also, by providing these explanations, Aggarwal (2016) states that it helps increase the credibility of the system and user loyalty. Thus, despite Dietvorst, Simmons, and Massey's (2015) findings on algorithm aversion, in the case of Netflix's recommender system, people might be less likely to observe the system making mistakes and will express preferences for an algorithm, and even consider the system to be more credible and become more loyal to it.

Additionally, Sinha and Swearingen (2001) conducted an experiment in which they involved human and system recommendations. For the human recommendations, personal friends from participants were contacted to actually recommend items that could be included in the experiment. The findings suggested that participants preferred recommendations made by friends, showing the algorithm aversion. Yet, participants did express a high level of usefulness and overall satisfaction with the recommender systems. Significantly, a limitation in this study regards the bias in favor of the respondents' friends. The recommender source, and with that also the specific friend, was made visible to participants. It could have been the case that the participants would show more algorithmic appreciation when this bias and social desirability toward their friends was not present.

Also important to note is that although algorithmic recommendations were invented in the 1990s, they only became prominent and common in the past decade (Seaver, 2021). Since Sinha and Swearingen's (2001) study was conducted in 2001, algorithmic recommenders were less common and people's familiarity with using these systems was not as present. The unfamiliarity and rareness of such technologies could have potentially influenced their perceptions of or preference for algorithms. This makes it highly relevant to study algorithmic recommenders in a time when algorithms are more widespread, especially when it comes to streaming services. The shifting perceptions of algorithms contributes to the importance of investigating current perceptions and attitudes toward Netflix's recommendation algorithm and the relevance of the current study.

So, while this particular study by Sinha and Swearingen (2001), as well as Dietvorst, Simmons, and Massey (2015), found evidence for algorithmic aversion, the limitations such as bias and familiarity could have affected the results. By eliminating those limitations, the results could have directed toward algorithmic appreciation. As previously discussed, algorithmic appreciation regards the preference for algorithmic recommendations over human recommendations. If the study was conducted in an environment without possible bias toward any of the recommendation sources, the results could have been different, specifically, more toward algorithm appreciation. Thus, previous studies supporting algorithm aversion have to be critically reflected upon as people might not necessarily be averse toward recommendations by an algorithm, but they were affected by the context of the study.

As previous studies have shown, when people perceive recommender systems to be more useful than peer recommendations, they are more likely to accept the algorithmic recommendations (Sinha & Swearingen, 2001). In addition, the familiarity with a recommender system to find movies and shows to watch, as well as the source which the recommendations are based on – users' past behavior –, positively affects people's preference towards algorithmic recommendations (Groshek & Krongard, 2016; Thurman et al., 2019). Therefore, taking the approach of algorithm appreciation as introduced by Logg, Minson, and Moore (2019) and the findings from previous studies, it is hypothesized that people will be more likely to adopt recommendations by Netflix's algorithm than by their peers.

> H_1: People will show higher levels of recommendation adoption for recommendations from Netflix's algorithm than from their friends and family

2.3. Theory of planned behavior

Many social cognitive theories, such as Ajzen's (1991) theory of planned behavior (TPB), have argued that intention to perform a behavior can be looked at to predict actual performance of the behavior. Ajzen (1985) proposes that attitude – one's positive or negative individual perspective on the product – influences intentions, which in turn influences behavior. Behavioral intention is said to be the strongest predictor of actual behavior, as it indicates the probability of someone engaging in a certain behavior. To elaborate, Ajzen (1991) states that people's intention to perform a behavior is at the center of the theoretical model, with the rule that the stronger the intention, the more likely the performance. The intention is an indicator of someone's willingness to attempt or put in effort to perform the behavior. So, according to Ajzen (1991), attitude positively affects behavioral intentions, with the more favorable one's attitude, the stronger their behavioral intentions.

As previous studies have moreover shown, people's behavioral intentions could be predicted by looking at one's attitude. To illustrate, Korzaan (2003) and Ku and Tai (2013) found that, in the context of purchasing online, consumer purchase intention is primarily affected by consumer attitude. One's attitude showed a positive relationship with intentions to make purchases online. Similarly, a study which focused on determinants of intention to use Netflix, found that attitude toward Netflix is positively related to intention to use Netflix (Cebeci, Ince, & Turkcan, 2019). When people showed a favorable attitude toward Netflix, they were more likely to express intentions to use Netflix.

Taking Ajzen's TPB (1991) and findings from previous studies regarding the role of attitudes in determining intended behaviors, it can be expected that there is a positive relationship between attitudes toward Netflix's recommender system and intentions to use Netflix's recommender system. People who express a positive attitude will be likely to express a high level of behavioral intentions to use Netflix's recommender system. Therefore, it is hypothesized that attitude will positively predict behavioral intentions.

> H_2: People's attitude toward Netflix's recommender system will positively predict their behavioral intentions to use Netflix's recommender system

Additionally, while intentions to engage in certain behaviors can be predicted by looking at attitudes, behavioral intentions can be looked at to predict people's action. Although not all intentions result in action, actions are controlled by intentions (Ajzen, 1985). The intention to perform or not perform a certain behavior, ultimately determines that action. As stated by Ajzen (1991), the general rule is that "the stronger the intention to engage in a behavior, the more likely should be its performance" (p. 181).

In line with Ajzen's (1991) statements, previous studies on shopping behavior have found a positive relationship between purchase intention and actual purchase behavior (e.g. De Cannière, De Pelsmacker, & Geuens, 2012; Kytö, Virtanen, & Mustonen, 2019). The study conducted by Kytö, Virtanen, and Mustonen (2019) found that purchase intention predicts purchase behavior, as people who expressed high levels of intentions to purchase a product, eventually also showed behaviors of actually purchasing the product. Similarly, De Cannière, De Pelsmacker, and Geuens (2012) found a significant impact of purchase intention on actual purchase behavior.

While these previous studies have looked at purchasing behaviors and intentions, it can be expected that similar processes are applicable in the context of following recommendations. However, in the case of streaming services, next to the monthly subscription fee, there is no monetary cost to watch a certain movie or show. Rather, there is a time investment, and time is lost when people watch something they do not like. So, as previously discussed, recommender systems are developed to help users find something to watch in the most effective way possible. In the current study, the action regard the user adopting Netflix recommendations, bridging a gap in literature by going beyond purchasing behavior and looking at watching behavior and intentions.

Ajzen's (1991) TPB is a relevant theoretical approach to explain people's behavior as it states that looking at one's behavioral intentions is an effective way to predict actual behavior. With the insights from this theory and previous studies, which found evidence for the relationship between behavioral intentions and actions, it can be expected that behavioral intentions will positively predict people's recommendation adoption. Therefore, it is also hypothesized that people with high levels of behavioral intentions will show higher levels of recommendation adoption than people who report lower levels of behavioral intentions.

> H_3: People with high levels of behavioral intentions to use Netflix's recommender system will show higher levels of recommendation adoption

2.4. Perceived source credibility

As stated by Shin (2021), the recent growth and developments of algorithms have highlighted the importance of a trusted relationship between humans and artificial intelligence. Users will be more likely to accept and adopt a recommendation when they believe the algorithm's information to be credible. The degree to which a source is perceived to be believable, unbiased, or credible can influence people's attitudes and reactions toward the source's information (Hass, 1981). Hence, source credibility is an important and relevant concept to include in the current study on algorithms. Additionally, by looking into this concept, more light can be shed on the relationship between the source of the recommendation and factors that affect users' decision-making process, such as their attitudes and intentions.

A useful approach for this study is Hovland, Janis, and Kelley's (1953) proposed model of source credibility, which states that expertise and trustworthiness are the two important factors that constitute the concept of source credibility. Hovland, Janis, and Kelley (1953) define expertise as the extent to which a communicator is perceived to be a qualified source for discussing a subject and making valid statements. Trustworthiness can be defined as the degree to which the statements made by the source can be considered valid, approved and accepted.

As argued by Chaiken and Maheswaran (1994), when the source of the received information is perceived to be credible, it is likely that argument processing will result in persuasion. Similarly, when comparing highly credible sources and medium credible sources, the recommendation for buying a specific product was more effective when it was communicated by the highly credible source (Harmon & Coney, 1982). So, the more the source is perceived to be credible, the more likely the message is believed by the receivers (Grewal, Gotlieb, & Marmorstein, 1994). People's trust in the received information also plays a role in the process of drawing conclusions regarding their intentions. Previous studies on persuasion and cognition supported the claim that perceived source credibility plays an influential role when it comes to people's attitudes and behavioral intentions (Sternthal, Dholakia, & Leavitt, 1978; Wu & Shaffer, 1987).

Specifically, when a change in attitude or behavior is the goal, highly credible sources were found to be more influential than sources with low credibility (Hovland & Weiss, 1951). In the current study, Netflix's recommender system has the primary goal of wanting to affect users' behavior – that is, make them watch something that is both entertaining and relevant. When people see Netflix's recommender system as a source for recommendations to be credible, as opposed to recommender systems they do not perceive to be credible, the system can have more influence on its users and their attitudes and behavioral intentions. To elaborate, how people perceive recommender systems, particularly the expertise and trustworthiness of the system, can have an influence on the acceptance of recommendations by the algorithm (Luo, Luo, Schatzberg, & Sia, 2013). Additionally, previous studies, e,g. Ohanian (1990), have shown the importance of expertise and trustworthiness on people's degree of persuasion and acceptance of messages.

Moreover, Johnston and Warkentin (2012) found that perceived source credibility positively affected people's attitudes toward the recommendation. When a source is seen as credible, people's attitudes toward the recommender system are more favorable. Similarly, as stated by Kim, Kandampully, and Bilgihan (2018), the higher the level of source credibility, the more positive the attitude. In that case, it was also found that source credibility enhances attitudes toward both the message and the source of the message. Thus, building on these insights about the influential role of perceived source credibility, it can be assumed that the degree to which people perceive Netflix's algorithm as a source to be credible, can influence their attitude toward the recommender system. Therefore, it is hypothesized that there will be a positive relationship between source credibility and users' attitudes toward Netflix's recommender system.

H_4: Source credibility will be positively associated with people's attitudes toward Netflix's recommender system

As previously discussed, expertise and trustworthiness constitute source credibility. In previous studies on expertise, it has been found that endorsers' and salespersons' expertise plays a significant role in consumer purchase intentions (Tsai, Chin, & Chen, 2010; Wen, Tan, & Chang, 2009). The higher the perceived level of expertise, the more likely the intentions to purchase the recommended product. However, these studies have merely used a human source, whereas the current study will focus on an algorithmic source, allowing for another light to be shed on the phenomenon.

Furthermore, Saleem and Ellahi (2017) found that not only the relationship between expertise and purchase intention is significant, but also between trustworthiness and purchase intention. When the source is trusted, meaning that it shows high levels of sincerity and objectivity, the receiver can accept the message without having a reason to question the validity of the information provided. Consequentially, the information is considered more credible, which increases their intentions to use the source for further purposes. All in all, the perceived expertise and trustworthiness, the credibility, of a source are important factors for making a message more persuasive and to increase behavioral intentions.

Thus, to allow for a better understanding of people's intentions to use Netflix's recommender system and the eventual acceptance of Netflix's recommendations, it is crucial to assess the recommender and its perceived credibility. As stated by Mahapatra and Mishra (2017), investigating the extent to which people consider a recommender to be trustworthy and knowledgeable is important as these factors can influence people's acceptance of the recommendation. These findings can be linked to Ajzen's (1991) TPB, which states that credible perceptions toward the source, such as trust and expertise, lead to intention and then actual behavior. So, it can be assumed that perceived source credibility enhances users' behavioral intentions. Therefore, it is hypothesized that source credibility will have a positive impact on users' intentions to use Netflix's recommender system.

H_5: Source credibility will positively affect people's behavioral intentions to use Netflix's recommender system

2.5. Perceived personalization

As firms all over the globe are using the web to reach their consumers while competition is growing every day, one of the strategies firms are adopting in order to retain and attract its consumers is personalized web content (Tam & Ho, 2006). With the use of recommender systems, firms do not only want to assist its consumers in making a choice by recommending products, but they also want each consumer to receive the right recommendation. As a result, the personalization technique is increasingly implemented to present individualized content to users (Greer & Murtaza, 2003). In fact, Netflix has implemented this technique and acknowledges the value of offering people personalized experiences; personalization is now at the core of the video streaming platform (Amatriain, 2013). According to Gomez-Uribe and Hunt (2015), Netflix's recommender system consists of various algorithms that work together to construct what people see on the homepage when they log in: rows with personalized recommendations, which are all different for each subscription member. As previously explained, Netflix uses a content-based system, meaning that the recommendations are based on users' past watching behavior (Bobadilla, Ortega, Hernando, & Alcalá, 2011; Sharma & Singh, 2016).

According to Noar, Harrington, and Aldrich (2009), this strategy of personalizing is effective because messages tailored to the individual are perceived to be more relevant, likeable and memorable. Thus, personalized messages often have a bigger impact on people and spark more behavioral change than non-personalized messages. Significantly, personalized advertising results in more positive consumer responses, such as improved attitude and intentions, because the receiver perceives personalized ads to be more relevant (De Keyzer, Dens, & De Pelsmacker, 2015). If the recommendation is not in line with the consumer's interests, the message will not be considered relevant and consumer responses will not improve or enhance. Netflix tries to eliminate this risk of users not being interested or perceiving it as irrelevant, by personalizing the recommendations and being transparent about it by labeling the rows on the homepage accordingly (Gomez-Uribe & Hunt, 2015). For example, rows are named 'because you watched' followed by the name of a previously watched movie or show, and 'top picks for' followed by the name of the Netflix user.

As said by Komiak and Benbasat (2006), personalized recommender systems generate relevant and better choices for that particular consumer, making it more likely that the consumer will believe that the system only looks at the user's preferences and not of any other party. This also contributes to users perceiving the system to be unbiased. Despite the firm's efforts to generate a personalized system, in order to be effective, users have to recognize and perceive the message as being personalized (De Keyzer, Dens, & De Pelsmacker, 2015). If people think the recommender system understands, knows, and considers their needs, they have recognized the message as being personalized. In essence, the extent to which people perceive recommender systems to understand and represent their personal needs is known as perceived personalization (Komiak & Benbasat, 2006).

Perceived personalization is an important concept to look at, as the effectiveness of a message can be superior when the recipient perceives it to be personalized, despite it actually being personalized or not (Li, 2016). Netflix's recommendations can be highly effective if users perceive it to be personalized, which in this case was the intention of Netflix's system. Importantly, these individualized recommendations can play a role in the way people interact with the recommendations they are presented, as well as their attitudes and intentions.

Particularly, why one decides to accept a recommendation or not could be explained by looking at the extent to which they perceive the recommendation to be personalized.

2.5.1. Perceived personalization influencing attitudes and behavioral intentions

Previous studies in various digital environments have already found evidence for personalization improving the effectiveness of a message, recommendation, or advertisement (Kalyanaraman & Sundar, 2006; Tam & Ho, 2006). In particular, perceived personalization has been found to significantly impact attitudes and behavioral intentions (Li, 2016; Xu, 2006). To illustrate, Li (2016) found that perceived personalization has a positive impact on both attitude and purchase intention. When people perceived the message to be personalized, they showed a more favorable attitude and higher levels of purchase intentions. Importantly, when it came to attitudes, Xu (2006) noted that perceived personalization does not only enhance favorable attitudes, but it also improves attitudes from people who initially did not have a favorable attitude. Taking these insights, it is hypothesized that the more Netflix's recommendations are perceived to be personalized, the more favorable the attitude toward the recommender system is.

H_6: Perceived personalization will positively affect attitudes toward Netflix's recommender system

Additionally, Komiak and Benbasat (2006) found that perceived personalization has a significant impact on user intentions to adopt the recommendation. When people perceived the recommender system to have high levels of personalization, they expressed more intentions and willingness to rely on the system to make a decision. Similarly, as stated by Kim and Gambino (2016), positive perceptions of the given information and favorable attitudes formed by perceived personalization toward the whole site should result in greater intentions to revisit the site and make use of the recommender system. Thus, taking the claims and insights from previous studies, it can be assumed that when recommendations are perceived to be personalized, users are more likely to express desires to use the recommender system. Therefore, it is also hypothesized that perceived personalization will positively affect behavioral intentions toward Netflix's recommender system.

H_7: Perceived personalization will positively affect behavioral intentions to use Netflix's recommender system

This approach is especially useful as previous studies focusing on algorithms have lacked in investigating the concept of perceived personalization and its influence on people's acceptance of recommendations (e.g. Weber, 2019). By exploring the concept of perceived personalization in the current research, more insights can be gained on the potential influence of personalization on people's responses to algorithmic recommendations and the connection with algorithm appreciation.

Moreover, studies on perceived personalization have often used a general and minimal personalization, for instance only based on gender (De Keyzer, Dens, & De Pelmacker, 2015; Li & Liu, 2017). Although this shows that even a minimal degree of personalization can already result in positive effects, considering that consumers indeed recognize the message to be personalized, looking into Netflix's more personalized recommender system will fill this gap of research on different levels of personalization. The incorporation of other aspects that can make the recommendation more personally relevant, such as tastes and preferences in the case of Netflix, is important since it likely that consumer responses are impacted by these aspects in different ways.

2.6. Summary

To sum up, the current study will investigate the key factors influencing behavioral intentions, and to what extent these intentions influence the adoption of the recommendations presented by Netflix to its users. This will expand the TPB model as proposed by Ajzen (1985), as well as the concepts of algorithm appreciation (Logg, Minson, & Moore, 2019) and algorithm aversion (Dietvorst, Simmons, & Massey, 2015).

As seen in the research model (see Figure 2.1.), it is first posed in H_1 that recommender type will have a significant impact on recommendation adoption. People can have a preference toward either algorithms or human recommendations, but previous studies found a clear tendency toward algorithm appreciation, also considering the limitations of algorithm aversion studies. Thus, it is predicted that people will show higher levels of recommendation adoption for Netflix's recommendations, than for peers'.

Next, H_4 proposes that source credibility has an effect on attitude, as the extent to which people perceive a recommender source to be trustworthy and knowledgeable can influence their perception of the algorithm. In turn, attitude affects behavioral intentions (H_2), because a more favorable attitude toward Netflix's algorithmic recommendations is expected to positively affect behavioral intentions to use Netflix's recommender system. To test the mediation effect, H_{8a} is proposed, which states that attitude will mediate the effect of source credibility on behavioral intentions. Source credibility is also predicted to positively effect behavioral intentions (H_5).

Additionally, attitude will mediate the effect of perceived personalization on behavioral intentions, as proposed in H_{8b}. It is predicted that perceived personalization will influence attitude (H_6), which in turns affects behavioral intentions (H_2). Perceived personalization is also expected to positively affect behavioral intentions (H_7).

Finally, the TPB model (Ajzen, 1985) suggested that behavioral intention is a key determinant of actual behavior. Therefore, it is also expected that behavioral intentions will have a significant impact on recommendation adoption (H_3).

All in all, this research model includes relevant and important concepts in order to answer the research question: *"To what extent does Netflix's recommendation algorithm and its characteristics influence subscription members' behavioral intentions and recommendation adoption?"*. This study will generate more insights in and understanding of user experiences, intentions, and behavior regarding Netflix's recommender system. Moreover, by focusing on a contemporary topic such as Netflix's recommender system and investigating concepts such as perceived personalization with a user perspective, various gaps in academic literature will be filled.

H_{8a}: Attitude will mediate the effect of source credibility on behavioral intentions

H_{8b}: Attitude will mediate the effect of perceived personalization on behavioral intentions

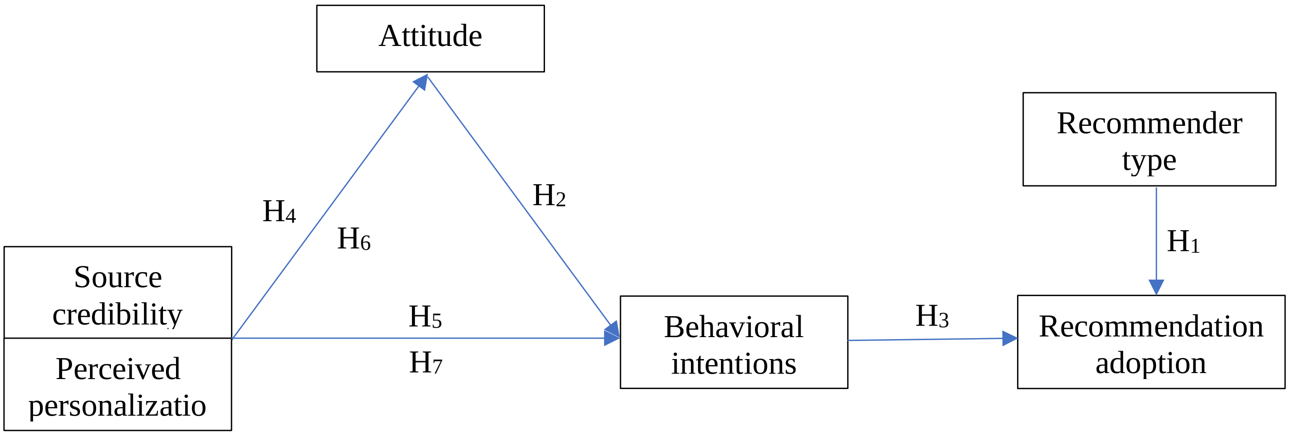


Figure 2.1. Model of hypotheses 1 – 7

3. Method

This chapter discusses and justifies the methodological approach of the current study. Through this approach, the hypothesized model, as shown in the previous chapter, is tested. The first part of this chapter explains the quantitative approach of the research and the choice for a survey. This section is followed by the research design, which explains the survey structure, the conducted pretests and the sampling methods. Next, the participants section illustrates the sample through descriptive statistics. The chapter continues with an in-depth operationalization of all the variables included in the research design and mediation approach. Lastly, after the steps taken to ensure reliability and validity are reflected upon, the method of data analysis is explained.

3.1. Choice of method

This research aims to investigate users' perceptions toward Netflix's recommender system and the influence on behavioral intentions and the adoption of the recommendations. Specifically, behavioral intentions and recommender type are expected to influence recommendation adoption. Importantly, this study includes a mediated path, with perceived source credibility and perceived personalization affecting behavioral intentions through the mediated aspect of attitude.

By taking a quantitative approach, more insights can be gained on the influences of different concepts and explanations for the relations between concepts can be sought (Wrench, 2017). Through a deductive approach, the hypotheses derived from previous studies and theories, such as the theory of planned behavior (Ajzen, 1991) and concepts such as algorithm appreciation (Logg et al., 2019) and aversion (Dietvorst et al., 2015), as thoroughly discussed in the previous chapter. The formulated hypotheses can be tested through validated measurements, allowing for numerical data to be gathered for statistical analysis (Neuman, 2014). Furthermore, quantitative research is an appropriate method to explain phenomena with numerical data that are analyzed using statistics (Muijs, 2010).

As this research seeks a broader explanation, rather than an in-depth understanding of individual cases, quantitative research helps to understand effects and relations of the population of Netflix users (Golafshani, 2003). The results from the research can be used to draw conclusions about a wider population, supported by data. Through quantitative research, and survey research in particular, large amounts of data can be collected. As stated by Lawrence (2014), surveys can be used to ask many questions to measure many variables, and numerous hypotheses can be tested within one survey. Additionally, surveys are a systematic method for gathering information from a sample to describe a larger population using statistics (Groves et al., 2011). As qualitative research focuses on generating meanings from and interpreting specific cases of a phenomena, the aim is not to generate generalizability and objectivity (Slevitch, 2011). In contrast, quantitative research aims to measure the phenomenon under study and analyze the data for relationships and trends with the purpose of drawing conclusions on a larger population (Watson, 2015). By proposing hypotheses, testing, and verifying them, while also controlling for confounding factors that can influence outcomes, quantitative research helps to achieve objectivity and generalization – when the sample size is sufficient to ensure representativeness (Slevitch, 2011).

So, by using quantitative survey research, this study can investigate relationships between variables to describe the larger population of Netflix's subscription members (Punch, 2003). The online distribution and easy access to the survey contributes to this larger population, as participants can be reached on a global level and within a short time frame. And by allowing people from all ages above 18, different backgrounds, and educational levels to participate in the research, it is made possible to obtain a more diverse and robust sample that is representative of a large population.

However, some previous studies have argued that survey research is not the most suitable method for assessing causal effects. For instance, Mercer, Kreuter, Keeter, and Stuart (2017) stated that nonprobability surveys lack the aspect of random respondent selection, which is an essential condition for making unbiased inferences about population parameters and causal effects. Notably, by not including treatment conditions, where respondents are assigned to one of the conditions that reflect the independent variables in the study, internal causality arises as an issue. Since there are no comparison groups, groups do not differ in terms of their value on the independent variable due to treatment and non-treatment, and there is no random assignment of conditions. These aspects are strengths of experimental research, between-subjects designs in particular, to test causal hypotheses (Check & Schutt, 2011).

So, survey research might be less suitable to assess causality among the variables. Yet, there are strong reasons to believe that there might be causal relationships between various variables. For instance, as argued in Chapter 2, perceived source credibility and perceived personalization are expected to affect attitude, which in turn can affect behavioral intentions. By including a mediation model, a better understanding is gained of the process by which the independent variables affects the dependent variable.

All in all, a quantitative approach and an online survey is the most appropriate research method for this thesis to analyze attitude and its mediated aspect in this study, as well as other relations between the concepts among the target population of Netflix users, as displayed in the conceptual model (Figure 2.1.).

3.2. Research design

For this study, the survey software Qualtrics was used to create the questionnaire. In order to reach the target population, Netflix users, the distribution of the survey was online through various sampling methods. The questions participants were asked were based on statements as demonstrated in previous studies. These measurements were carefully chosen and adapted to fit the context of the current study – that is, Netflix's recommender system. The statements as used in the survey (Appendix A) are originally from studies by Pu and Chen (2010), Cheung, Luo, Sia, and Chen (2009), and Hyan Yoo and Gretzel (2008).

3.2.1. Survey structure

When respondents opened the survey distributed by the researcher, they were first provided an introduction to the research topic and a few ethical concerns. These ethical concerns were taken into account to protect respondents, guard their privacy, and to eventually present results that accurately reflect the respondents' answers and information (Oldendick, 2012). Respondents were asked for their consent and they were informed that they can withdraw from the study and skip questions without any consequences. Additionally, their data was used for the purpose of this study and was not shared with any other parties, and their answers were anonymous and cannot be traced back to them.

After consent was given, the survey continued with the filter questions. The participant requirements to be able to proceed with the survey included an age of 18 or higher and a current subscription to Netflix. Following the filter questions, respondents were asked questions about the streaming services they use, the length of their Netflix subscription, and their Netflix usage. Additionally, the effects of the COVID-19 pandemic were briefly touched upon through questions about their current use compared to before the pandemic, and their assessment of the quality of Netflix's recommendations since the pandemic. Their overall familiarity with Netflix's recommender system was also asked to make sure the sample is sufficiently familiar with the topic in question. For illustration purposes, a screenshot was taken from the researcher's own Netflix profile and arrows were added to emphasize the features of the recommender systems (see Q8 in Appendix A).

Next, the questions for the dependent variable were asked: attitude, behavioral intentions, and recommendation adoption. After these questions, the questions were asked for the independent variables: source credibility and perceived personalization. The last part of the survey contained questions regarding the respondents' demographic background. When the respondent finished the survey, a thank you message with contact information was presented.

3.2.2. Survey pretests

After the creation of the survey and before starting the actual data collection, six pretests were conducted to test the questionnaire. This small pretest sample consisted of three females and three males, recruited from the researcher's personal network. Conducting pretests does not only determine if respondents understand the formulated questions, but it also evaluates and increases the validity and reliability of the measurement (Pallant, 2016). Three participants of the pretests took the questionnaire while being on a phone call with the researcher, allowing for real-time feedback. The other three participants gave their feedback after taking the questionnaire by themselves.

A few small issues came forward and solutions were applied to the survey before officially distributing it. Firstly, while the participants expressed their familiarity with the recommender system, a brief explanation of the system was still preferred to make sure they were on the right track. So, the illustration in the survey was then accompanied by a short explanation of the system. Next, the item 'Netflix's recommender system takes my needs as its own preferences' from the perceived personalization measurement was found to be vague, which resulted in the adjustment of the item to 'Netflix's recommender system considers my needs'. Also, some participants were used to the order of answer options being 1 (strongly agree) to 5 or 7 (strongly disagree). As the answer options in this survey ranged from strongly disagree to strongly agree, the first question with these answer options stated in bold that respondents were asked to answer the questions based on a scale of 1 (strongly disagree) to 5 (strongly agree). The pretests were also useful to get an accurate estimation of the time it takes to fill in the survey, which confirmed the estimated duration as displayed by Qualtrics.

3.2.3. Sampling method

After the last adjustments were made, the final version of the survey (see Appendix A) was distributed through several sampling methods. In quantitative research, non-probability sampling methods are considered less appropriate due to subjectiveness in selecting the sample, making it not representative of the population (Etikan, Musa & Alkassim, 2016). However, it is deemed useful when random sampling is impossible, such as in this case where it is difficult to assemble a sample frame with a population as large as Netflix users within the time and costs constraints. To specify, in the current study, the population is defined as Netflix users above 18 years old. As the language of the survey was English, Netflix users who understand English were targeted. This limits the target audience of Netflix users to those who can speak English, filtering out people who do not understand English and could not fill out the survey. To recruit respondents for the survey, the nonrandom sampling methods purposive, snowball and volunteer sampling were used. The participants were recruited between the 14th and the 22nd of April.

Firstly, the survey was distributed on the social media platforms Facebook and Instagram. An appealing graphic was created for a Facebook post and an Instagram story (see Appendix B). On Facebook, the graphic was accompanied with a short textual explanation of the research. On Instagram, the story post directed people to the researcher's bio, which contained the link to the survey on Qualtrics. The story post reached 216 people in total, and combined with the Facebook post, five people shared the post with their own network.

Additionally, purposive sampling was conducted. The survey was distributed on ten selected Reddit groups and forums, such as 'netflix'[1] and 'SampleSize'[2]. These communities were found to be relevant and fitting to reach the target population. Despite the voluntary and non-individualized nature, with the choice to participate strongly relying on the respondents, by only posting it on highly relevant forums, people are more likely to participate as opposed to distributing it on random forums (Vehovar, Toepoel, & Steinmetz, 2016). It was also attempted to distribute the survey on three Facebook groups such as 'Netflix Recommendations'[3], but the owners of the group did not approve.

An additional sampling method was SurveySwap. This platform reduces bias and makes a varied sample, as participants come from different countries, colleges, backgrounds, educational levels, and age groups. SurveySwap strictly keeps an eye on its users' behavior, for example by tracking respondents' completion time, and removes users that have shown to not take it seriously. This contributes to the reliability of the responses. In total, 69 responses, both valid and invalid, came from SurveySwap.

[1] https://www.reddit.com/r/netflix/
[2] https://www.reddit.com/r/SampleSize/
[3] https://www.facebook.com/groups/613870175328566

Finally, six social ties were asked to share the survey with people who meet the requirements and are unknown to the researcher.

3.3. Participants

In total, 426 survey responses were recorded. Firstly, in the process of data cleaning, the pretests (n = 6) and previews (n = 2) were removed from the dataset. Next, participants who did not complete the survey were considered partial data, thus, these unusable responses were excluded (n = 90). Approximately ⅓ of these participants stopped at the questions regarding their number of years subscribed and hours spent on Netflix per day. Another ⅓ had stopped at the attitude questions, and the other ⅓ stopped at different moments in the survey. Additionally, six participants did not consent to participating in the survey and withdrew from the study.

Furthermore, people who did not meet the sampling criterion were removed from the dataset. Firstly, respondents who are younger than 18 were filtered out (n = 6) and those who answered 'no' to the question whether they are currently subscribed to Netflix were also removed (n = 15). Next, the median of the duration in seconds was calculated, which was 373. By taking 40% from 373 seconds, a duration of 149 seconds was established. Respondents with a completion time lower than 149 seconds were excluded from the dataset (n = 11). This ensures that the dataset does not include participants who speeded through the survey without thoroughly reading and answering the questions. Finally, the dataset was checked on straight lining, and this resulted in one participant being removed as they provided the same answer to each question. After data cleaning, the usable dataset is established at 289 participants.

3.3.1. Socio-demographic background

In this study, age, gender, educational level, and country were part of the respondents' socio-demographic background. The age of the participants ranged from 18 to 76 years old (M = 27.43; SD = 1.34) with 63.7% females and 33.2% males. Regarding gender, four participants selected the option 'prefer not to say', and five participants selected 'other'. While two participants did not specify their gender in the provided text entry box, three participants were non-binary (n = 2) or agender (n = 1). In this study, the most named highest educational level was Bachelor's degree (48.1%), followed by high school graduate (14.9%), and Master's degree (13.5%). Due to the open nature of the study, meaning that there is no restriction or requirement in terms of nationality, the sample obtained a total of 25 different nationalities. The most prominent countries are the Netherlands (53.3%), United States of America (19.0%), and United Kingdom of Great Britain and Northern Ireland (3.8%).

3.3.2. Streaming services

From a list of various streaming services, people were asked to select the services they are subscribed to. As the study required participants to be subscribed to Netflix, most of the participants had selected this platform (96.2%). Additionally, Disney+ (37.4%), Amazon Prime Video (33.9%), and Videoland (18.7%) were other popular streaming services among the participants. The answer option ‘other’ was provided with a text entry box in which respondents could name other streaming services not listed. 30 participants made use of this, which resulted in 18 additional streaming services with the most popular being Paramount+ ($n = 4$), Hayu ($n = 3$), and NLZIET ($n = 2$).

On average, people were subscribed to Netflix for 4.62 years ($SD = 2.63$) and spent 1.63 hours per day on watching Netflix ($SD = 1.22$). This average usage of 1.63 hours per day, 98 minutes, matches with statistics that show a daily use of 85 minutes per day (Statista, 2020). This indicates that the sample in this study matches the characteristics of the population, which reinforces the validity. When asked to compare current Netflix usage to Netflix usage before the pandemic, most participants assessed their Netflix usage to be about the same (37.7%), slightly higher (36.7%), or much higher (14.5%). As for the familiarity with Netflix’s recommender system, most people expressed that they were very familiar (42.2%), extremely familiar (38.4%), or moderately familiar (14.2%). Additionally, compared to before the pandemic, most participants assessed the quality of Netflix’s recommendations to be about the same (67.5%), somewhat better (18.7%), or somewhat worse (10.0%).

Table 3.1. Descriptive statistics for single-item continuous variables age, years subscribed, and Netflix usage in hours per day, ($N = 289$)

Variables	*M*	*SD*
Age	27.43	1.43
Years subscribed	4.62	2.63
Netflix usage in hours per day	1.63	1.22

Table 3.2. Frequencies for categorical variables gender, nationality, educational level, streaming platforms, Netflix usage comparison, familiarity, and recommendation quality (N = 289)

Variables	Items	%	*N*
Gender	Woman	63.7%	184
	Man	33.2%	96
	Other (non-binary, agender)	1.7%	5
	Prefer not to say	1.4%	4
Educational level	Bachelor’s degree	48.1%	139
	High school graduate	14.9%	43
	Master’s degree	13.5%	39
	Some college but no degree	12.8%	37
	Other (less than high school degree, associate degree in college, doctoral degree, professional degree)	10.7%	31
Nationality	The Netherlands	53.3%	154
	United States of America	19.0%	55
	United Kingdom of Great Britain and Northern Ireland	3.8%	11
	Other (Argentina, Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, India, Indonesia, Ireland, Luxembourg, Malaysia, Portugal, Romania, Russian Federation, Serbia, Singapore, Sweden, Switzerland, Viet Nam)	23.9%	69
Streaming platforms	Netflix	96.2%	278
	Disney+	37.4%	108

	Amazon Prime Video	33.9%	98
	Videoland	18.7%	54
	HBO	12.5%	36
	Hulu	12.5%	36
	AppleTV+	7.6%	22
	ESPN+	4.5%	13
	Discovery+	2.4%	7
	Other (Acorn, Canal+, CBC Gem, Crave, Crunchyroll, Hayu, Hoichoi, NLZIET, NPO, Paramount+, Peacock, Rakuten Viki, SHOWTIME, Sky, Stan, STARZ, YouTube premium, Ziggo Sport)	11.1%	30
Usage comparison	Much higher	14.5%	42
	Slightly higher	36.7%	106
	About the same	37.7%	109
	Slightly lower	5.9%	17
	Much lower	5.2%	15
Familiarity	Extremely familiar	38.4%	111
	Very familiar	42.2%	122
	Moderately familiar	14.2%	41
	Slightly familiar	4.5%	13
	Not familiar at all	0.7%	2
Quality	Much better	3.1%	9
	Somewhat better	18.7%	54
	About the same	67.5%	195
	Somewhat worse	10.0%	29
	Much worse	0.7%	2

3.4. Operationalization

Whereas the previous chapter and the research model (Figure 2.1.) provided the theoretical foundation, this section establishes a way to make the theory under study measurable. The operationalization process, as explained by Neuman (2014), concerns the transformation of concepts into variables, and having concrete statements and survey questions to measure these variables. This section explains how the theoretical concepts as discussed in the previous chapter are operationalized for the online survey. Specifically, it is explained how the variables perceived personalization, source credibility, attitude, behavioral intentions, and recommendation adoption were measured. Finally, the control variables are also discussed.

3.4.1. Attitude

The attitude scale was taken from Pu and Chen (2010). Six items were included that measured users' overall feeling toward Netflix's recommender system (M = 3.31, SD = .76). By looking into users' satisfaction, it can be determined what users feel and think as they make use of the recommender system. Through the six items, users were able to express their preferences and opinions about the system. The questions were formulated on a 5-point scale that asked participants about their overall feelings toward the recommender system (1 = strongly disagree to 5 = strongly agree). Higher scores indicate more positive attitudes.

The item 'Netflix's recommender system made me confused about my choice' was negatively worded, thus it was reverse coded for further analyses. Through the reversed item, participants who did not pay attention to the questions can be identified (Neuman, 2014). Before performing the principal components analysis, the suitability of the data for factor analysis was assessed, and all assumptions regarding sample size, the ratio of participants to items, and the strength of the relationship among the items were met (Pallant, 2016).

The six Likert-scale based items were entered into factor analysis using Principal Components extraction with Direct Oblimin rotation based on Eigenvalues (> 1.00), KMO = .86, χ^2 (N = 289, 15) = 485.12, p <.001. The resultant model explained 53.8% of the variance in *attitude*. As expected, only one component was extracted with an Eigenvalue of >1, and the Scree plot clearly showed a bend at the second component. This was expected based on the original scale, established by Pu and Chen (2010), which also contains one component. The factor loadings of individual items onto the one factor found and the reliability score are presented in Table 3.3. Moreover, the reliability was tested for all items of the unidimensional scale. A Cronbach's α of .81 was revealed, indicating that the scale has good reliability.

Table 3.3. Factor and reliability analyses for scale for attitude (*N* = 289)

Item	*Attitude*
Overall, I am satisfied with Netflix's recommender system	.85
I am convinced of the quality of the movies and shows recommended to me	.77
I am confident I will like the movies and shows recommended to me	.82
Netflix's recommender system made me more confident in my decision on what to watch	.67
The recommended movies and shows made me confused about deciding what to watch	.50
Netflix's recommender system made me more confident in my decision on what to watch	.74
R^2	53.8%
Cronbach's α	.81
Eigenvalue	3.23

3.4.2. Behavioral intentions

The behavioral intentions scale was taken from Pu and Chen (2010) to measure users' intention to use Netflix's recommender system, the continuance and frequency of this usage, willingness to recommend the system to friends, and their intention to watch the recommendations. Six items were included that measured user intention to use Netflix's recommender system (M = 3.26, SD = .87). Respondents were asked to answer the questions based on a 5-point scale (1 = strongly disagree to 5 = strongly agree). Higher scores indicate more intentions to use Netflix's recommender system to find something to watch. Before performing the principal components analysis, the suitability of the data for factor analysis was assessed, and all assumptions regarding sample size, the ratio of participants to items, and the strength of the relationship among the items were met (Pallant, 2016).

The six Likert-scale based items were entered into factor analysis using Principal Components extraction with Direct Oblimin rotation based on Eigenvalues (> 1.00), KMO = .89, χ^2 (N = 289, 15) = 1072.12, p <.001. The resultant model explained 66.4% of the variance in *behavioral intentions*. As expected, only one component was extracted with an Eigenvalue of >1, and the Scree plot clearly showed a bend at the second component. This was expected based on the original scale, established by Pu and Chen (2010), which also contains one component. The scale showed good reliability with a Cronbach's α of .89. The factor loadings of individual items onto the one factor found and the reliability score are presented in Table 3.4.

Table 3.4. Factor and reliability analyses for scale for behavioral intentions (N = 289)

Item	*Behavioral intentions*
I will use a recommender such as Netflix's to find movies and shows to watch	.88
I will use Netflix's recommender system again	.88
I will use Netflix's recommender system frequently	.88
I prefer to use Netflix's recommender system in the future	.87
I will watch the recommended movies and/or shows, given the opportunity	.78
I will tell my friends about Netflix's recommender system	.56
R^2	66.4%
Cronbach's α	.89
Eigenvalue	3.99

3.4.3. Netflix recommendation adoption

The recommendation adoption scale was taken from Cheung, Luo, Sia, and Chen (2009). It was adapted to the context of Netflix's recommendations. Five items were included that measured users' adoption of Netflix's recommendations (M = 4.42, SD = 1.32). The questions were formulated on a 7-point scale (1 = strongly disagree to 7 = strongly agree). Higher scores indicate higher levels of the adoption of Netflix's recommendations. Before performing the principal components analysis, the suitability of the data for factor analysis was assessed, and all assumptions regarding sample size, the ratio of participants to items, and the strength of the relationship among the items were met (Pallant, 2016).

The five Likert-scale based items were entered into factor analysis using Principal Components extraction with Direct Oblimin rotation based on Eigenvalues (> 1.00), KMO = .85, χ^2 (N = 289, 10) = 776.22, p <.001. The resultant model explained 66.1% of the variance in *Netflix recommendation adoption*. As expected, only one component was extracted with an

Eigenvalue of >1, and the Scree plot clearly showed a bend at the second component. This was expected based on the original scale, established by Cheung, Luo, Sia, and Chen (2009), which also contains one component. The scale showed good reliability with a Cronbach's α of .87. The factor loadings of individual items onto the one factor found and the reliability score are presented in Table 3.5.

Table 3.5. Factor and reliability analyses for scale for Netflix's recommendation adoption (N = 289)

Item	*Netflix recommendation adoption*
Netflix's recommendations…	
… have enhanced my effectiveness in making decisions on what to watch	.90
… made it easier for me to decide what to watch	.88
… have motivated me to decide what to watch	.86
The last time I looked at Netflix's recommendations I watched one of the recommended movies or shows	.78
… contributed to my knowledge of presented movies and shows	.61
R^2	66.4%
Cronbach's α	.87
Eigenvalue	3.30

3.4.4. Peer recommendation adoption

The recommendation adoption scale was taken from Cheung, Luo, Sia, and Chen (2009) and was adapted to the context of peer recommendations. Five items were included that measured people's adoption of peer recommendations (M = 5.30, SD = 1.32). Questions were formulated on a 7-point scale (1 = strongly disagree to 7 = strongly agree). Higher scores indicate higher levels of the adoption of recommendations by friends and family. Before performing the principal components analysis, the suitability of the data for factor analysis was assessed, and all assumptions regarding sample size, the ratio of participants to items, and the strength of the relationship among the items were met (Pallant, 2016).

The five Likert-scale based items were entered into factor analysis using Principal Components extraction with Direct Oblimin rotation based on Eigenvalues (> 1.00), KMO =

.89, χ^2 (N = 289, 10) = 1212.96, p <.001. The resultant model explained 78.5% of the variance in *peer recommendation adoption*. As expected, only one component was extracted with an Eigenvalue of >1, and the Scree plot clearly showed a bend at the second component. This was expected based on the original scale, established by Cheung, Luo, Sia, and Chen (2009), which also contains one component. All items from the scale loaded onto one factor and showed excellent reliability with a Cronbach's α of .93. The factor loadings of individual items onto the one factor found and the reliability score are presented in Table 3.6.

Table 3.6. Factor and reliability analyses for scale for peer recommendation adoption (N = 289)

Item	*Peer recommendation adoption*
My friends' and family's recommendations…	
… made it easier for me to decide what to watch	.88
… have enhanced my effectiveness in making decisions on what to watch	.90
… have motivated me to decide what to watch	.86
The last time I received recommendations from friends and family, I watched one of the recommended movies or shows	.78
… contributed to my knowledge of presented movies and shows	.61
R^2	78.5%
Cronbach's α	.93
Eigenvalue	3.93

3.4.5. Perceived source credibility

The perceived source credibility scale was taken from Hyan Yoo and Gretzel (2008). The scale was adapted to fit the context of Netflix's recommender system. 16 items were included that measured people's credibility perceptions of Netflix's recommender system (M = 4.48, SD = .99). Questions were formulated on a 7-point scale that asked participants about the expertise and trustworthiness of Netflix's recommender system (1 = strongly disagree to 7 = strongly agree). Higher scores indicate higher levels of perceived credibility toward Netflix's recommender system. Before performing the principal components analysis, the suitability of the data for factor analysis was assessed, and all assumptions regarding sample size, the ratio of participants to items, and the strength of the relationship among the items were met (Pallant, 2016).

The 16 Likert-scale based items were entered into confirmative factor analysis using Principal Components extraction with Direct Oblimin rotation based on Eigenvalues (> 1.00), KMO = .93, χ^2 (N = 289, 120) = 2697.87, p <.001. The resultant model explained 64.1% of the variance in perceived source credibility. Three components had an Eigenvalue of >1, and the Scree plot showed a bend at the fourth component. However, for the purpose of this study, two components were extracted to match the original scale, which contained two subscales.

The items ‘Netflix’s recommender system is reliable’ and ‘Netflix’s recommender system is dependable’ loaded on the first factor, expertise, instead of on trustworthiness as originally established. The items ‘Netflix’s recommender system can be trusted’ and ‘Netflix’s recommender system is there to help me’ loaded on both factors, but they loaded stronger on trustworthiness. Additionally, the item ‘Netflix’s recommender system is consistent in the recommendations it provides’ also loaded on both factors, but the difference was .01. As this difference was small, it was decided to assign the item to the same factor as the original scale – that is, trustworthiness. The items loaded onto two factors and showed good reliability with a Cronbach’s α of .88 for the first factor, and a Cronbach’s α of .87 for the second factor. The factor loadings of individual items onto the two factors extracted and the reliability scores are presented in Table 3.7. The factors found were:

Expertise. The first factor included eight items related to Netflix’s recommender system’s ability to provide valuable recommendations.

Trustworthiness. The second factor included eight items related to Netflix’s recommender system’s reliability and intentions.

Table 3.7. Factor and reliability analyses for scale for perceived source credibility (N = 289)

Item	*Expertise*	*Trustworthiness*
Netflix’s recommender system…		
… helps me find things I really like	.85	
… provides useful suggestions	.81	
… makes decisions easier	.79	
... is reliable	.79	
... is dependable	.79	

… can provide me with more valuable recommendations than human beings	.65	
… has access to and can process more information than human beings	.55	
… offers suggestions that I might not have thought of	.44	
… is designed with the best intentions in mind		.82
… is a good way to get suggestions from a neutral source		.82
… is not biased		.80
… wants me to find an option that best fits my needs		.69
… is there to help me	.34	**.58**
… can be trusted	.39	**.52**
… is a good way to learn about different movies and shows		.35
… is consistent in the recommendations it provides	.35	**.33**
R^2	48.3%	8.5%
Cronbach's α	.88	.87
Eigenvalue	7.73	1.35

3.4.6. Perceived personalization

The perceived personalization scale was taken from Komiak and Benbasat (2006). It was adapted to the context of Netflix's recommender system to measure the extent to which users perceive the system's recommended movies and shows to be personalized. Three items were included that measured people's perceived personalization (M = 4.11, SD = 1.35). Questions were formulated on a 7-point scale that asked participants about Netflix's recommender system and to what extent they believe that the recommendations are based on their personal needs, interests and preferences (1 = strongly disagree to 7 = strongly agree). Higher scores indicate higher levels of perceived personalization. As previously explained, the item 'this recommender system takes my needs as its own preferences' was adjusted to 'Netflix's recommender system considers my needs' with the intention to make the essence of the statement clearer for the respondents.

Before performing the principal components analysis, the suitability of the data for factor analysis was assessed, and all assumptions regarding sample size, the ratio of participants to items, and the strength of the relationship among the items were met (Pallant, 2016).

The three Likert-scale based items were entered into factor analysis using Principal Components extraction with Direct Oblimin rotation based on Eigenvalues (> 1.00), KMO = .69, χ^2 (N = 289, 3) = 603.61, p <.001. The resultant model explained 82.7% of the variance in *perceived personalization*. As expected, all three items loaded onto one factor, which had an Eigenvalue of >1, and the Scree plot clearly showed a bend at the second component. This was expected because the original scale, established by Komiak and Benbasat (2006), contains one component. The scale showed good reliability with a Cronbach's α of .89. The factor loadings of individual items onto the one factor found and the reliability scores are presented in Table 3.8.

Table 3.8. Factor and reliability analyses for scale for perceived personalization (N = 289)

Item	*Perceived personalization*
Netflix's recommender system…	
… understands my needs	.95
… knows what I want	.92
… considers my needs	.85
R^2	82.66%
Cronbach's α	.89
Eigenvalue	2.48

3.4.7. Control variables

While aspects such as participants' socio-demographic background are not of primary interest in the current study, they can influence outcomes and need to be controlled for. The demographic variable age acts as a control variable in the mediation analysis to control for potential confounders. To illustrate, Dimmick, McCain, and Bolton (1979) stated that media use and age are significantly associated. More specifically, it has been found that perceptions of and attitudes toward technologies, as well as technology acceptance, tend to vary among ages (Arning & Ziefle, 2008; Assaker, 2020). So, as age can influence people's attitudes toward, perceptions of, and intentions with technologies, and with that also the outcomes of this study, the variable needs to be controlled for.

Additional variables that might affect the outcomes, are the respondents' familiarity with the recommender system and their Netflix usage. Previous studies found that familiarity with brands or products influences perceptions and purchase intentions (Park & Stoel, 2005; Shukla & Banerjee, 2014). Thus, it can be the case that in the current study, people who are more familiar with Netflix's recommender system might answer statements in the survey differently than people who are not familiar with the recommender system. Similarly, respondents' Netflix usage in hours per day can also influence their overall assessment of the recommender system. When Netflix is only used a few minutes per day, as opposed to a few hours per day, the user is less exposed to the recommender system and chances might be smaller that they regularly rely on the system to decide what to watch.

The control variables age, familiarity, and Netflix usage were entered as covariates in the mediation analysis (Hayes, 2017).

3.5. Validity and reliability

In the process of constructing the research design, various steps were taken to achieve, preserve, and improve the validity and reliability of this survey research. These steps will be explained in this section to provide insight into how measurement accuracy and internal consistency was ensured.

3.5.1. Validity

Muijs (2004) defined validity as the extent to which the concept under study is measured accurately. To measure abstract concepts, instruments that indirectly measure these concepts have to be used, such as questionnaires. However, it is important to use the right measurement instrument that contains the right measures of the concept. Thus, the use of pre-established scales, scales that have been developed and tested in previous studies, ensures that the measurements are good indicators of the concepts. The scales all consisted of various items so respondents could provide answers to questions that yield the same definition. So, as stated by Hyman, Lamb, and Bulmer (2006), validity can be ensured by making use of existing scales that have been extensively tested.

A factor analysis was conducted for each scale to help explore and confirm the relationships between the items of the scale (Knekta, Runyon, & Eddy, 2019). The total number of dimensions can also be identified through this statistical method. This way, content validity is ensured through factor analyses of all the scales included in the current study. The results of the factor analyses confirmed that the scales match with the original scales, except for the source credibility scale. Two items loaded on a different dimension, and three items loaded on both dimensions. The other scales matched the scales as tested by previous studies.

Importantly, the internal validity of this study is enhanced by including control variables in the analyses (Behi & Nolan, 1996). Next to the independent and dependent variables, other variables that can have an impact on the outcomes should be controlled for. In this case, age, familiarity with Netflix's recommender system and Netflix usage were deemed relevant to include in the analyses and control for its potential influence. Thus, to limit the influence of confounding variables, and to potentially explain relationships found, they should be controlled for. This also helps in establishing causal relationships between the variables that were of interest in the hypotheses (Cahit, 2015). Variables that were not controlled for are alternative explanations for the results.

An additional potential factor that could influence outcomes is nationality. As explained by Gomez-Uribe and Hunt (2015), the Netflix video catalog differs per country, which affects the algorithm's recommendations for users from different countries. This could also affect people's perceptions and usage of the recommender system. However, this variable is not controlled for in the current study, but it is a suggestion for future studies, especially those conducting cross-national studies.

Lastly, as previously discussed, survey research is a less appropriate method for making unbiased inferences about casual effects. For instance, it is not the case that there was random assignment of participants, making the assessment of causality among the variables more difficult (Mercer, Kreuter, Keeter, & Stuart, 2017). More importantly, this study did not contain treatment conditions, where respondents are randomly assigned to one of these conditions that reflect the predictor variables in this study (Allen, 2017). Thus, all respondents were given the same questionnaire and were part of one group, rather than receiving different conditions and being part of an experimental or control group. In contrast, experimental research, studies with a between-subjects design in particular, are suitable to test causal hypotheses because they have comparison groups, the variation in the independent variable came before assessment of change in its dependent variable, and there is random assignment of the conditions (Check & Schutt, 2011). The lack of random assignment is an issue of internal validity, since relationships can be seen, such as a significant effect of perceived personalization on attitude, while it could actually be the case that attitude influences perceived personalization.

3.5.2. Reliability

Reliability regards the accuracy of instruments, namely, the extent to which there is no measurement error (Muijs, 2004). The reliability of the current study is preserved by measuring theoretical concepts with existing scales that have proven to be reliable. Although the original scales have been slightly adapted to fit the context of the current study, reliability checks and factor analyses confirmed the reliability of each scale and verified the factors of the measurements. The reliability scores of the scales were established between .81 and .93. Therefore, this study has shown good and excellent reliability.

Additionally, samples that were unusable were removed in the data cleaning process, reducing the risks of outliers, straight liners, and other unreliable responses impacting the accuracy of the scales. All in all, this study has proven to measure concepts accurately and consistently.

3.6. Method of data analysis

For the data analysis, the statistical software IBM SPSS Statistics 26 was used. Specifically, Hayes' (2017) PROCESS macro was used to conduct the mediation analyses. As stated by Hayes (2017), through the PROCESS modeling, hypotheses can be empirically tested to gain a better understanding of causal associations. Moreover, the analysis shows under which circumstances and conditions, how and when, X affects Y.

Furthermore, all the regression analyses that have to be conducted to test the hypotheses as discussed in the previous chapter, can be done in one step. As a result, not only H_{8a} and H_{8b} can be tested with this mediation analysis, but also H_2 - H_7 can be tested within this analysis. After, the analysis provides an overview of all the direct, indirect, and conditional effects (Hayes, 2017). The bootstrap sample was set at 5000.

PROCESS model 4 was used to test H_2, H_4, H_5, H_6, H_7, H_{8a}, and H_{8b}. This model was carried out once with the independent variable being source credibility, and once with the independent variable being perceived personalization. Behavioral intentions was entered as the dependent variable, and attitude was the mediator. PROCESS model 6 was used to test H_3. In this model, behavioral intentions acted as a second mediator, and Netflix recommendation adoption as the outcome variable. H_1 was not included in the mediation analysis, but was tested through a paired-samples t-test.

4. Results

This chapter focuses on the results of the statistical analyses conducted in IBM SPSS 26 in order to confirm or reject the hypotheses of this thesis. To test H_2 – H_{8b}, three mediation models using PROCESS model 4 and model 6 with 5000 bootstrap samples are conducted (Hayes, 2017). The first section reports the results of the paired-samples t-test to test the first hypothesis. This is followed by the first mediation model, which depicts the indirect and direct effect of source credibility on behavioral intentions, mediated by attitude. Next, the second mediation model is presented, with the indirect and direct effects of perceived personalization on behavioral intentions, mediated by attitude. All models include age, Netflix usage, and familiarity as covariates. The effects of these potential confounding factors are also explored. Lastly, after presenting the findings from each test, an overview with accepted and rejected hypotheses is presented.

4.1. Multicollinearity check

Before starting with the analyses, a check for multicollinearity was conducted. It is important to check the relationship among the independent variables, to avoid wider confidence intervals that result in less reliable estimated coefficients in the model (Alin, 2010; Pallant, 2016). All the variables were entered into a bivariate regression analysis to check how much the variables correlate with each other. In this case, only behavioral intentions and Netflix recommendation adoption had a high correlation of .83. However, since this relationship is what is hypothesized (see Figure 2.1.), other estimates are not impacted. Therefore, this correlation can be discarded and the study can continue with the statistical analyses.

4.2. Netflix vs peer recommendation adoption

To test H_1, a paired-samples t-test was conducted to evaluate the difference between respondents' adoption of recommendations by Netflix and by friends and family. There was a statistically significant difference between the adoption of Netflix recommendations (M = 4.43, SD = 1.31) and the adoption of recommendations by friends and family (M = 5.32, SD = 1.30), $t(286) = -7.96$, $p < .001$ (two-tailed). The mean increase in peer recommendation adoption was 0.88, 95% CI [-1.10; -.66]. The eta squared statistic (.29) indicated a large effect. As the peer recommendations have scored significantly higher than Netflix recommendations, H_1 can be rejected. People do not show higher levels of recommendation adoption for recommendations from Netflix's algorithm than from their friends and family, but instead, the other way around.

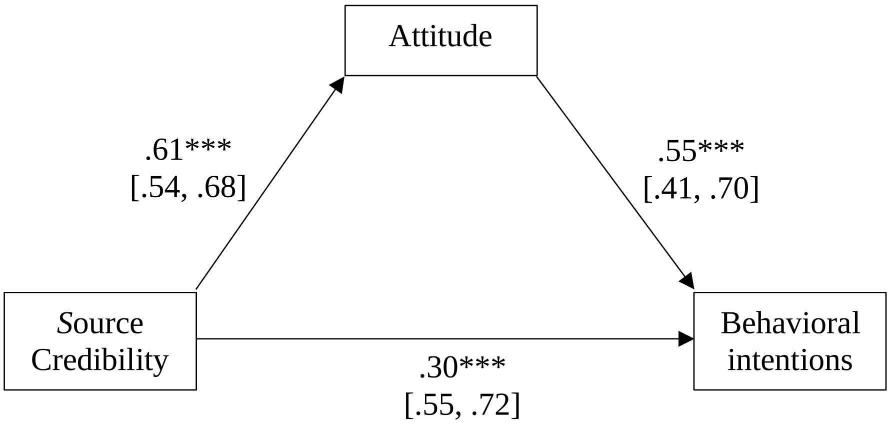
4.3. Mediation analysis of source credibility, attitude, and behavioral intentions

To test H_2, H_4, H_5, and H_{8a}, Hayes' (2017) PROCESS model 4 was used to create the mediation model (see Figure 4.1.). The model was found to be significant, $F(5, 229) = 75.58$, $p < .001$, $R^2 = .62$.

In step 1 of the mediation model, the regression of source credibility on behavioral intentions, ignoring the mediator, was significant and positive, $b = .63$, $p = <.001$. Step 2 showed that the regression of source credibility on the mediator, attitude, was also significant and positive, $b = .61$, $t(230) = 17.91$, $p <.001$. Step 3 of the mediation process showed that the mediator (attitude), controlling for source credibility, was significant and positive, $b = .55$, $t(229) = 7.54$, $p = <.001$. Step 4 of the analyses revealed that, controlling for the mediator (attitude), source credibility was a significant and positive predictor of behavioral intentions, $b = .30$, $t(229) = 5.06$, $p = <.001$. The indirect effect of X on Y was significantly greater than zero, with an effect of .34, 95% CI [.24; .44].

This model shows that there are positive, significant associations between source credibility and attitudes, attitudes and behavioral intentions, and source credibility and behavioral intentions, with attitudes mediating the effect of source credibility on behavioral intentions. In other words, people who perceive Netflix's recommender system as a source to be credible, have a more positive attitude towards it, and these people with positive attitudes show higher levels of behavioral intentions to use the system. Additionally, those that perceive the system to be credible, also show higher levels of behavioral intentions to use the system. Thus, it is found that in this model, attitude mediates the effect of source credibility on behavioral intentions.

Therefore, H_2, H_4, H_5, and H_{8a} can be accepted. The effects reported in this section are visualized in Figure 4.1.



Notes: Age, familiarity and Netflix usage entered as covariates.
****p* < .001.

Figure 4.1. Mediation model source credibility (PROCESS model 4)

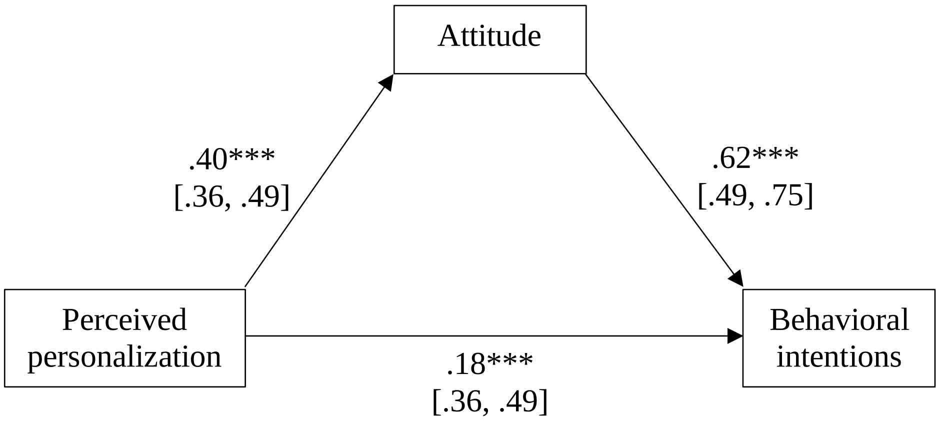
4.4. Mediation analysis of perceived personalization, attitude, and behavioral intentions

To test H_2, H_6, H_7, and $H_{8b,}$ Hayes' (2017) PROCESS model 4 was used to create the mediation model (see Figure 4.2.). The model was found to be significant, $F(5, 232) = 74.13$, $p < .001$, $R^2 = .62$.

In step 1 of the mediation model, the regression of perceived personalization on behavioral intentions, ignoring the mediator, was significant and positive, $b = .43$, $p = <.001$. Step 2 showed that the regression of perceived personalization on the mediator, attitude, was also significant and positive, $b = .40$, $t(233) = 14.60$, $p <.001$. Step 3 of the mediation process showed that the mediator (attitude), controlling for perceived personalization, was significant and positive, $b = .62$, $t(232) = 9.37$, $p = <.001$. Step 4 of the analyses revealed that, controlling for the mediator (attitude), perceived personalization was a significant and positive predictor of behavioral intentions, $b = .18$, $t(232) = 4.77$, $p = <.001$. The indirect effect of X on Y was significantly greater than zero, with an effect of .25, 95% CI [.18; .31].

This model shows that there are positive, significant associations between perceived personalization and attitudes, attitudes and behavioral intentions, and perceived personalization and behavioral intentions, with attitudes mediating the effect of perceived personalization on behavioral intentions. In other words, people who perceive Netflix's recommender system to be personalized, have a more positive attitude towards it, and these people with positive attitudes show higher levels of intentions to use the system. Additionally, those that perceive the system to be personalized, also show higher levels of behavioral intentions to use the system. Thus, it is found that in this model, attitude mediates the effect of perceived personalization on behavioral intentions.

Therefore, H_2, H_6, H_7, and H_{8b} can be accepted. The effects reported in this section are visualized in Figure 4.2.



Notes: age, familiarity and Netflix usage entered as covariates.
***p < .001.

Figure 4.2. Mediation model perceived personalization (PROCESS model 4)

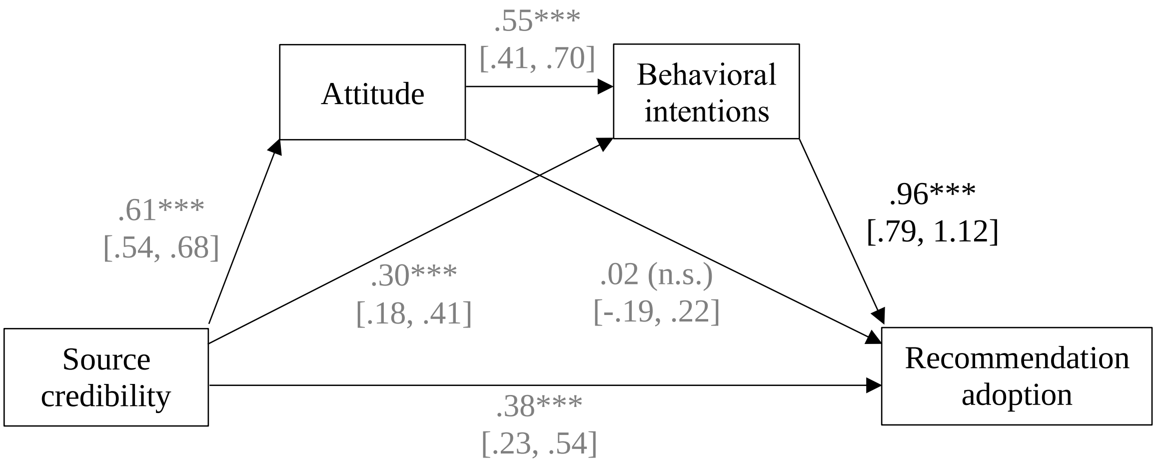
4.5. Behavioral intentions and recommendation adoption

Using PROCESS model 6 (Hayes, 2017), the variables behavioral intentions and recommendation adoption are included in the model to test H_3 (see Figure 4.3.). The coefficients from previously tested hypotheses with model 4 can also be found in Figure 4.3., but are not further reported in this section because there were no meaningful differences between the models.

In this model, source credibility acted as the independent variable. The model was found to be significant, F(6, 228) = 111.84, p < .001, R^2 = .75. The regression of behavioral intentions on Netflix recommendation adoption was significant and positive, b = .96, t(228) = 11.58, p <.001.

The model was also run with perceived personalization as the independent variable, to ensure the overall model is consistent. Likewise, the model was found to be significant, F(6, 230) = 103.60, p < .001, R^2 = .73. It was found that in this model with perceived personalization, the regression of behavioral intentions on Netflix recommendation adoption is also significant and positive, b = 1.02, t(230) = 12.22, p < .001.

This shows that there is a positive, significant association between behavioral intentions and Netflix recommendation adoption. People who have higher intentions to use Netflix's recommender system show higher levels of adoption of Netflix's recommendations. Therefore, H_3 is confirmed and can be accepted. The effects reported in this section are visualized in Figure 4.3.



Notes: Age, familiarity and Netflix usage entered as covariates.
***p < .001.

Figure 4.3. Mediation model recommendation adoption (PROCESS model 6)

4.6. The impact of age, Netflix usage, and familiarity

As previously discussed (see §3.4.7.), age, familiarity, and Netflix usage might affect outcomes, so, they need to be controlled for. These variables were entered as covariates in each of the analyses. The control variable familiarity negatively predicts the dependent variable of the regression, in this case behavioral intentions, when source credibility acts as the predictor variable without controlling for the mediator (attitude) (b = -.16, t(230) = -3.34, p = .001). Familiarity also negatively predicts the dependent variable behavioral intentions, when perceived personalization is entered as the predictor variable without controlling for the mediator (attitude) (b = -.16, t(233) = -3.22, p = .002).

4.7. Hypothesis testing

Table 4.1. provides an overview of the confirmation of the hypotheses. Support was found for eight out of the nine posed hypotheses. There was no support for the first hypothesis, thus, it is rejected.

Table 4.1.

Confirmation of the Hypotheses

H #	Hypothesis	Support
H_1	People will show higher levels of recommendation adoption for recommendations from Netflix's algorithm than from their friends and family	No
H_2	People's attitude toward Netflix's recommender system will positively predict their behavioral intentions to use Netflix's recommender system	Yes
H_3	People with high levels of behavioral intentions to use Netflix's recommender system will show higher levels of recommendation adoption	Yes
H_4	Source credibility will be positively associated with people's attitudes toward Netflix's recommender system	Yes
H_5	Source credibility will positively affect people's behavioral intentions to use Netflix's recommender system	Yes
H_6	Perceived personalization will positively affect attitudes toward Netflix's recommender system	Yes
H_7	Perceived personalization will positively affect behavioral intentions to use Netflix's recommender system	Yes
H_{8a}	Attitude will mediate the effect of source credibility on behavioral intentions	Yes
H_{8b}	Attitude will mediate the effect of perceived personalization on behavioral intentions	Yes

5. Conclusion

The following chapter gives an overview of the findings of this research by providing a cohesive discussion and conclusion. The first section presents the results of this study, and discusses them through the practical and societal implications. Next, the limitations of this study are discussed, followed by suggestions for future research in this research area of streaming services' algorithms and their recommender systems. Finally, this chapter ends with a conclusion and an answer to the overall research question.

5.1. Discussion

As seen in Table 4.1., support was found for eight out of the nine posed hypotheses. This section takes a closer look at the results and literature implications. The results of this study provide insights into Netflix users' intentions to use the recommender systems and their actual recommendation adoption by assessing their perceptions and attitudes. Specifically, it is evaluated to what extent users perceive the source to be credible and the recommendations to be personalized, as well as their attitudes toward the recommender system.

First of all, it was found that participants evaluated Netflix as a source to be credible, which positively correlated with their attitudes toward Netflix's recommender system. The more people perceive Netflix to be credible – trustworthy and knowledgeable –, the more positive their attitudes toward the system. This confirms Shin's (2021) statements on the importance of a trusted relationship between humans and technologies such as AI. Trusting the source of advice, and believing it is not only trustworthy but also knowledgeable, plays a significant role in generating positive attitudes. Additionally, source credibility was a significant indicator for behavioral intentions, confirming that people's acceptance of recommendations is related to their perception of the source in terms of trustworthiness and expertise (Mahapatra & Mishra, 2017). Developing a recommender system is one thing, but ensuring that the source is perceived to be trustworthy and knowledgeable is another important factor to generate favorable attitudes and eventually affect acceptance of the recommendations. This shows the importance of human factors, such as trust in the system, in determining the technology's success. Taking an audience perspective is also shown to be important, as the data generated from this perspective can be used to further develop and improve algorithms.

Similarly, Netflix's recommendations were perceived to be personalized by its users, which also positively correlated with attitudes. The more people perceive the recommender system and its recommendations to be personalized, the more positive their attitudes toward the system. Although previous studies already found evidence for personalization improving the effectiveness of a message, particularly when it regards attitudes and behavioral intentions, this finding is especially interesting, since this concept has been underexplored by studies in the research field of recommender systems (Li, 2016; Tam & Ho, 2006). To elaborate, this finding fills a gap by contributing to more insights into the role of personalization in streaming consumption, since web-based personalization has mainly only been studied in the contexts of e-commerce and social media marketing. When Netflix users perceive the algorithm's recommendations to be personalized to their needs and interests, they develop a more positive attitude and show more intentions to use the system to find something to watch. This shows the influential role of personalized recommendations by algorithmic recommenders on user attitudes and behavior in the streaming industry.

Additionally, while researchers (e.g. De Keyzer, Dens, & De Pelmacker, 2015) have focused on a general and minimal personalization, such as gender, this study shows that the elaborate and personalized recommender system from Netflix also impacts consumer responses. This is the first study which found evidence for the impact of perceived personalization on users in the context of video streaming, enhancing the importance of personalization as a possible explanation in various studies on algorithmic recommendations. These significant relations between perceived personalization and attitude, and source credibility and attitude also indicate that Netflix's attempts to be a credible source and provide personalized recommendations are successful, as it positively affects users' attitudes toward Netflix's recommender system.

In turn, attitude was found to be positively associated with behavioral intentions. The more positive one's attitude, the more intentions one has to use Netflix's recommender system. This is a particularly important finding, since the eventual goal of the developers of the recommender system is to help its users decide what to watch. Moreover, this finding is in line with the social cognitive theory of planned behavior (Ajzen, 1991). This theory proposes that attitude positively predicts behavioral intentions, which has been proven in this study.

Importantly, evidence was found for the mediating role of attitude. That is to say, attitude was found to mediate the effect that source credibility and perceived personalization have on behavioral intentions. In other words, attitude as a mediator explains the relationships between source credibility and behavioral intentions, as well as perceived personalization and behavioral intentions. These findings indicate something other studies have not explicitly found yet, namely that attitude acts as a mediator in these relationships, strengthening our understanding of the relations between the variables. This outcome indicates that it is highly beneficial for Netflix to improve the credibility of their system and continue to provide personalized recommendations, as it leads to positive attitudes, which in turn positively affects users' intention to make use of the system to find something to watch. If the relationships were found to be non-significant, it could mean that either Netflix's attempts to come across as a reliable source that provides personalized recommendations are not successful, or people's perceptions and attitudes are not as important in the process of relying on algorithms to find something to watch. However, the findings indicate the significance of user perceptions and attitudes for the success of recommender systems.

Next, intentions to use Netflix's recommender system was found to be positively associated with recommendation adoption. When people express intentions to use the recommender system to find something to watch, they are more likely to actually watch the recommended movies or shows. This finding supports Ajzen's (1991) theory of planned behavior, which proposed that behavioral intentions can be looked at to predict actual behavior. People with higher intentions to use Netflix's recommender system, are more likely to also report high levels of the adoption of recommendations by Netflix. This finding shows the importance of behavioral intentions, as this impacts users' eventual recommendation adoption. It also becomes clear that people do not only passively engage with recommender systems, but make conscious decisions by converting their intentions into behaviors. Users have plans to use the system and as a result, they decide to use the system and to adopt recommendations presented to them.

In addition, algorithm aversion and appreciation are assessed by looking into people's adoption of recommendations by Netflix and recommendations by friends and family. Although there were strong reasons to expect higher levels of recommendation adoption for recommendations by Netflix's system, this study supports findings from previous studies on algorithm aversion (e.g. Dietvorst, Simmons, & Massey, 2015; Sinha & Swearingen, 2015), in the context of video streaming. The assumption that people would show higher levels of recommendation adoption for recommendations from Netflix's algorithm than from their friends and family was not confirmed, as participants reported that they adopt more recommendations by friends and family, than recommendations by Netflix. Despite the findings showing overall favorable perceptions and attitudes toward Netflix's recommender system, this particular finding indicates a tendency toward algorithm aversion.

The insights also support claims by Yeomans, Shah, Mullainathan, and Kleinberg (2019), who stated that the aversion toward algorithmic recommenders can be explained by looking at the subjective nature of contexts in which recommendations are made. The connection with personal tastes, moods, and emotions make entertainment related recommendations a subjective matter, and combined with a lack of understanding for how the algorithm operates, despite the algorithm's accuracy, people find it easier to understand the human recommendation process. Consequentially, people have more understanding for recommendations from a human and show aversion toward algorithms. Another explanation for this finding is the possible bias toward friends and the observed errors. Firstly, because this was not an experimental study, there were no actual recommendations from friends. As a result, respondents could have estimated their recommendation adoption with a particular and random friend or family member in mind. Sinha and Swearingen (2001) compared algorithmic and peer recommendations, and similarly stated that anonymized recommendations could prevent this bias. Thus, respondents in this study might have been biased, in favor of peers' recommendations. Secondly, it was argued in Chapter 2 (see §2.2.1.) that in this case, as opposed to the experiment conducted by Dietvorst, Simmons, and Massey (2015), there are no straightforward right or wrong recommendations, making it less likely that people observe an error and choose human recommenders over an algorithmic recommender. However, it can be the case that people consider certain features of the recommendation algorithm to generate errors. For instance, as stated by Gomez-Uribe and Hunt (2015), people use Netflix with different moods each time, making it necessary to recommend a diverse selection of movies and shows to accommodate each mood. Also, since it is common that one account is shared with multiple people, recommendations are also made diverse to offer something relevant to different users of the same account. With many rows of diverse content, it can be likely that there will be recommendations considered irrelevant and an error. In that case, the concept of serendipity might offer more insights into users' experiences with unexpected discoveries (Kotkov, Wang, & Veijalainen, 2016).

All in all, these findings demonstrate that users who show high levels of perceived source credibility and perceived personalization toward Netflix's recommender system, and therefore a more positive attitude, also show more intentions to use the system to find something to watch. Moreover, users with more intentions to use the system, are also more likely to actually watch something that was recommended by Netflix. However, when it comes to recommendations from friends and family, versus recommendations from Netflix, users are more likely to watch something recommended by their peers.

5.2. Practical and societal implications

This thesis looked into the influence of Netflix’s recommender system on users’ behavioral intentions and actual behavior. Specifically, the aim was to investigate the role of source credibility and perceived personalization, and attitude as a mediator in this phenomenon. It has been shown that users’ attitudes and perceptions toward Netflix’s recommender system in fact also correlate with their intentions to use the system and their actual behavior of adopting recommendations. However, it has been found that users have a preference for their friends’ and family’s recommendations. Overall, the findings of this study might be particularly interesting for Netflix and professionals in the streaming services industry to further develop and improve their recommender systems. To elaborate, this study shows the conditions under which users are likely to accept the recommendations provided by Netflix’s recommender system – that is, when they perceive the source to be credible, the recommendations to be personalized, and have a positive attitude. Insights into these conditions are highly important and useful to professionals who develop and implement such recommender systems.

Furthermore, this thesis showed that the extent to which users perceive Netflix to be a credible source and the recommendations to be personalized, positively affects their attitudes. Streaming services, Netflix in particular, can highly benefit from the implementation of strategies which will specifically contribute to users’ perceived source credibility and perceived personalization. For example, such strategies can include better communication toward the user, by being more transparent regarding the personalization of recommendations. Although Netflix already includes rows such as ‘because you watched’ followed by the title of a previously watched movie or show, more information could be provided to further explain why that particular title was recommended. Movies and shows on Netflix often include a percentage to represent the match, for instance, ‘80% match’, but no further explanation is provided for this number. So, Netflix could be more transparent about which movies, shows, genres, or actors this number was based on to communicate the personalization to the user. This strategy can also increase credibility, by showing users that the recommendation algorithm is able to provide valuable recommendations, can be relied on to find something relevant, and has the best intentions in mind for the user.

By positively affecting these factors, users’ attitudes will also be positively affected, which in turn will positively affect their intentions to use the recommender system to find something to watch. This is particularly interesting for streaming platforms, as this whole process will eventually also positively affect the actual behavior of recommendation adoption and watching what was recommended, which is the ultimate goal.

Also, in order to have an effective recommender system, it is crucial to consider the factors that can influence users' adoption of recommendations from a specific recommender system. So, the findings were contextualized by also looking into the differences in the adoption of recommendations from different recommender types – that is, peers and Netflix. The results showed that people prefer recommendations from friends and family over recommendations from Netflix, despite attitudes toward Netflix's recommender systems being positive. With the gained knowledge on the factors that affect consumer behavior, streaming platforms are able to not only work on these factors to further improve perceptions and attitudes, and with that also the actual use of the system, but in the long run it might also affect recommender type preferences in favor of Netflix.

All things considered, the findings provide professionals in the field with more insights on how users perceive such systems and how this influences the success of the algorithm. In particular, Netflix can benefit from these insights and improve its recommender system in order to strengthen their position in the industry and compete against other streaming services. To elaborate, this study shows the importance of personalized recommendations and the source's credibility in everyday experiences with algorithms. As these results can specifically be applied to Netflix's recommender system, it can be the case that competitors, such as Disney+, do not have similar or even lower levels of personalization, which could negatively affect the successes of the system. Furthermore, the findings of this research provide a framework with potential influential factors and contribute to the improvement and development of algorithmic recommenders.

5.3. Limitations

The research for this thesis was carefully prepared, designed and carried out. The hypotheses derived from theoretical concepts and previous studies, and as discussed in §3.5.1 and §3.5.2., the research design was carefully set up and carried out to ensure the validity and reliability of this study. However, as with any research, there are limitations regarding the choices that had to be made and the constraints of the study. The most significant limitations are discussed in this section.

First of all, while survey research has its benefits, it has been found to be a less suitable method to assess causality. Since there were no experimental and control groups, there is a lack of random assignment, resulting in an issue of internal validity. Relationships between variables were found, but because there were no conditions that reflect the predictor variables in this study, it is possible that the established relationships could in fact have been different. For example, relationships between source credibility and attitude, and perceived personalization and attitude have been found. While it was specifically found that perceived source credibility and perceived personalization impacted attitude, it could have been the case that attitude actually has an impact on those two factors instead. When people have a positive attitude toward Netflix's recommender system, they might have stronger and different perceptions regarding the source's credibility or the degree of personalization. However, the theoretical concepts and potential relationships in this study were thoroughly assessed. There were strong reasons to believe that there might have been causal relationships between the concepts in the current directions, which can be seen in the results. And by including a mediation model, the assessment of the relationships is strengthened.

Additionally, with more than half of the respondents being female, Dutch, and with an educational level of Bachelor's degree or higher, this study had a skewed sample. Thus, a limitation regards the generalizability of the results of this study. The aim is to be able to generalize the results to all Netflix users, but with this skewed sample, and therefore the bias, it could be argued that the results are only generalizable for highly educated Dutch female Netflix users. But, it has been found that overall, the sample is valid. For instance, the average for watching time found in this study matches the average watching time found in previous studies and available statistics. In addition to the selection process being well-designed, this study has proven validity and with that also the generalizability of the findings.

Another limitation regards the sampling method. Since the respondents were recruited through non-probability sampling and thus chose to participate, there might have been self-selection bias. Consequentially, the representativeness of the sample could have been negatively affected. For instance, people who decided to take part in this survey, might have been more motivated by their interest in Netflix and the recommender system than those who do not have favorable views on the platform. However, the descriptive statistics showed that the respondents from all levels of Netflix usage, years subscribed, familiarity, etc. took part in the study and responses to questions regarding perceptions and attitudes also ranged between all levels and answer options. Thus, while it can be said that although instead of non-probability sampling, probability sampling could have been beneficial to ensure generalizability, the sample in this study has shown that it is diverse, making the outcomes more generalizable to the population of Netflix users.

Moreover, for this survey research, self-reported measures were used to not only estimate people's Netflix usage in hours, but also to measure their recommendation adoption. For this study, the respondents' own generalizations and memories were relied on, and people might not always be aware of the influence of the algorithm on their behavior. Consequentially, they might inaccurately estimate and report their actual usage and behavior, resulting in skewed results.

Lastly, to measure source credibility, the validated scale for perceived source credibility was taken from Hyan Yoo and Gretzel (2008). Originally, the scale consisted of two subscales: expertise with seven items, and trustworthiness with nine items. However, a confirmatory factor analysis was carried out and the results showed that not all items loaded onto the same component as suggested in literature. Two items loaded on expertise instead of on trustworthiness, and three items loaded on both factors. This suggests that the items that loaded on different components might actually measure different constructs. Although, the items that loaded on both factors showed small differences between the factor loadings. Despite the differences with the original scale, good reliability was found for each of the components and the scale in its entirety. So, it can be concluded that the data is still reliable and conclusions can be drawn on a larger population.

5.4. Suggestions for future research

Next to taking into account the limitations discussed in the previous section and acting accordingly, this section presents additional suggestions for future research. Overall, the findings from this study can serve as a starting point to further explore this field of research. By implementing the following suggestions, the gained insights on the topic can be expanded to better understand and explain the phenomenon.

With the limitation of survey research to assess causality, it is suggested to conduct an experimental research. To better assess the causality of the concepts included in this study, a between-subjects study design with randomized and controlled experiments is suggested. For instance, the conditions can regard different degrees of perceived personalization to compare behavioral intentions. This way, self-reported measures do not have to be used, as actual behavior will be measured through the various conditions and the researcher is less dependent on the users' memories and generalizations. In addition, by bringing together the moment of data collection and the moment of media use, as opposed to asking respondents about the media use which took place before the study, the validity also improves (Naab, Karnowski, &

Schlütz, 2019). All in all, it can be evaluated whether the independent variable manipulation was effective and caused the significant differences between groups (Allen, 2017).

Also, considering that catalogs among countries differ, people across countries could perceive and use Netflix's recommender system differently (Gomez-Uribe & Hunt, 2015). This study did not include nationality as a control variable, which leaves out the possibility that country might have affected the outcomes. Thus, it might be beneficial to control for nationality in addition to the control variables already included in this study. Additionally, to account for the bias and potential confounding influences in the sample as previously discussed, gender and educational level can also be controlled for by including it as a covariate in the analysis. For future research, this step might be less necessary if from the beginning, a more diverse sample is obtained to make the results more generalizable to the whole population of Netflix users.

Finally, it is recommended for future studies to expand the research by including other factors that could potentially affect the relationship between users' behavioral intentions and eventual recommendation adoption. According to Ajzen (1991), perceived behavioral control is the perception people have regarding the extent to which they believe the performance of the behavior to be easy or difficult. When two people express the same level of behavioral intentions, their confidence determines who is more likely to actually succeed in the performance of a given behavior. In other words, Netflix users might express the same level of intentions to use the system, but the users who are more confident in their abilities to use the system are more likely to actually adopt a recommendation than the users who have doubts. In this case, since a relationship between behavioral intentions and recommendation has already been found, perceived behavioral control could potentially act as a moderator. By looking into and including perceived behavioral control as a variable, specifically a moderator, this relationship can strengthen and more understanding and insights can be gained on the relationship between behavioral intentions and recommendation adoption.

5.5. Conclusion

With recommender systems becoming more prominent and essential in many industries, they have become a new field of research. The fast growth of Web 2.0 and technologies such as artificial intelligence have resulted in new challenges, possibilities and opportunities of such systems for not only researchers and professionals in the field, but also for its users. Therefore, to gain more insight into user behavior as a result of algorithmic recommender systems, this thesis aimed to investigate users' perceptions of and attitudes toward Netflix's recommender system, and the influence of these factors on behavioral intentions and recommendation adoption. The research question in this study was:

To what extent does Netflix's recommendation algorithm and its characteristics influence subscription members' behavioral intentions and recommendation adoption?

To answer the research question, Netflix's recommendation algorithm influences its users in the sense that the extent to which they perceive the system to be credible and the recommendations to be personalized, affects their attitudes. In turn, their attitudes affect their intentions to use the system to find something to watch. As a result, the higher their intentions to use the system, the more likely they are to actually watch something that was recommended by Netflix. Netflix as a recommender type, however, is less effective in persuading people to watch a recommended movie or show than users' friends and family.

As far as is known, this thesis is the first study to examine perceptions, attitudes, and behavior from the users of Netflix, the biggest streaming platform to date. By conducting this study from a user perspective, a new field of research is explored and the research field of algorithmic recommenders in general is expanded. Building on the theory of planned behavior (Ajzen, 1991) and concepts such as algorithm appreciation (Logg, Minson, & Moore, 2019) and algorithm aversion (Dietvorst, Simmons, & Massey, 2015), this thesis showed significant relations between perceptions, attitudes, intentions, and behavior. In particular, the importance of perceived personalization for perceptions toward and use of recommender systems has been proven, filling research gaps and serving as a starting point for future studies on the further impacts of technologies such as artificial intelligence.

To conclude, this thesis and its gained insights serve as a starting point for future research to further look into not only people's perceptions of algorithms, but also the factors and contexts that play a role in the formation of these perceptions and the extent to which this eventually affects intentions and behavior. Researchers in the field of media and communication, as well as culture and society, are encouraged to continue exploring this topic and expanding knowledge on this evolving industry. With the results from this thesis, previous studies, and future studies in this field of research, we can deepen our understanding of the complex relationship between society and technologies and learn more about how they affect one another.

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Appendix A. Survey questions

Welcome,

Thank you for your participation in this survey. Your input is highly appreciated and valuable!

I am a Media & Creative Industries student at the Erasmus University Rotterdam. This survey is part of my Master's thesis research regarding Netflix's recommendation algorithm. For the purpose of this research, you have to be **18 years or older** and **subscribed to Netflix** to participate. This survey will take approximately **5-10 minutes** to complete. All the collected data will only be used for the purpose of this study, and will not be shared with third parties. Your participation in the survey is entirely anonymous and voluntary. There are no right or wrong answers, your honest assessment is what I am interested in. Please read the instructions provided carefully and fill out the survey in its entirety. If you wish to stop the survey at any point, you can do so. If you have any remaining questions do not hesitate to contact me via: 465192nn@eur.nl. Thank you very much for your time!

Q1 Please select one of the following:

- ○ I consent to taking part in this research and confirm I agree to each of the statements above
- ○ I withdraw from participating in this research.

Q2 How old are you?

▼ Younger than 18 ... 99

Q3 Are you currently subscribed to Netflix?

- ○ Yes
- ○ No

Q4 Which streaming services are you subscribed to?

- ▢ Amazon Prime Video
- ▢ AppleTV+
- ▢ Discovery+
- ▢ Disney+
- ▢ ESPN+
- ▢ HBO
- ▢ Hulu
- ▢ Netflix
- ▢ Videoland
- ▢ Other: ____

Q5 How many years have you been subscribed to Netflix? (e.g. 1.5, 4, etc.)

____

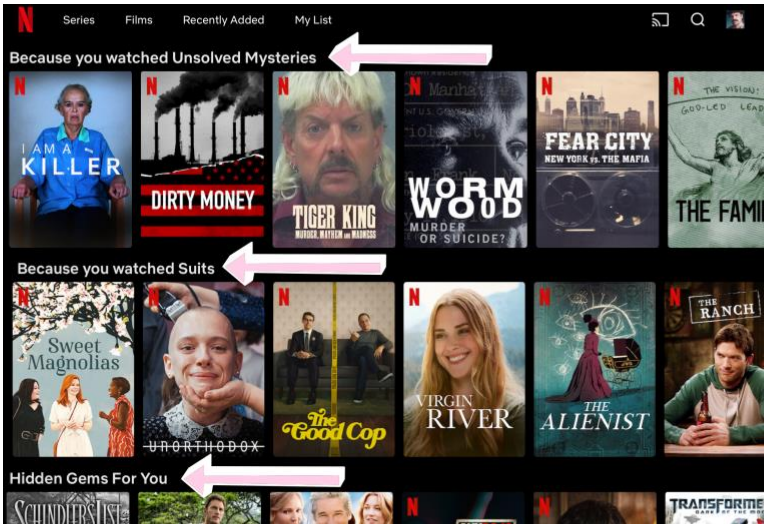
Q6 On average, how many hours per day do you use Netflix? (e.g. 0.5, 4, etc.)

____

Q7 Please think about your Netflix usage before the pandemic and your current Netflix usage. Compared to before the pandemic, my current Netflix use is...

- ○ Much higher
- ○ Slightly higher
- ○ About the same
- ○ Slightly lower
- ○ Much lower

Q8 Netflix has a wide catalog with movies and shows you can watch. When you log in, you see various rows with different types of content recommended to you. To what extent are you familiar with Netflix's recommender system as just explained and seen in the picture below?



- Extremely familiar
- Very familiar
- Moderately familiar
- Slightly familiar
- Not familiar at all

Q9 Since the COVID-19 pandemic started, how would you assess the quality of Netflix's recommendations?

- Much better
- Somewhat better
- About the same
- Somewhat worse
- Much worse

Q10 Please indicate your overall feeling toward Netflix's recommender system on a scale of strongly disagree to strongly agree.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
Overall, I am satisfied with Netflix's recommender system (1)	○	○	○	○	○
I am convinced of the quality of the movies and shows recommended to me (2)	○	○	○	○	○
I am confident I will like the movies and shows recommended to me (3)	○	○	○	○	○
Netflix's recommender system made me more confident in my decision on what to watch (4)	○	○	○	○	○
The recommended movies and shows made me confused about deciding what to watch (5)	○	○	○	○	○
Netflix's recommender system can be trusted (6)	○	○	○	○	○

Q11 To what extent do you agree with the following statements regarding using Netflix's recommender system?

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I will use a recommender such as Netflix's to find movies and shows to watch (1)	○	○	○	○	○
I will use Netflix's recommender system again (2)	○	○	○	○	○
I will use Netflix's recommender system frequently (3)	○	○	○	○	○
I prefer to use Netflix's recommender system in the future (4)	○	○	○	○	○
I will tell my friends about Netflix's recommender system (5)	○	○	○	○	○
I will watch the recommended movies and/or shows, given the opportunity (6)	○	○	○	○	○

Q12 Please indicate to what extent Netflix's recommendations have an impact on you.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Netflix's recommendations made it easier for me to decide what to watch (1)	○	○	○	○	○	○	○
Netflix's recommendations have enhanced my effectiveness in making decisions on what to watch (2)	○	○	○	○	○	○	○
Netflix's recommendations have motivated me to decide what to watch (3)	○	○	○	○	○	○	○
The last time I looked at Netflix's recommendations I watched one of the recommended movies or shows (4)	○	○	○	○	○	○	○
Netflix's recommendations contributed to my knowledge of presented movies and shows (5)	○	○	○	○	○	○	○

Q13 Not only algorithms such as Netflix's system provide you with recommendations, but also the people around you. To what extent do the recommendations by your friends and family affect you?

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
My friends' and family's recommendations made it easier for me to decide what to watch (1)	○	○	○	○	○	○	○
My friends' and family's recommendations have enhanced my effectiveness in making decisions on what to watch (2)	○	○	○	○	○	○	○
My friends' and family's recommendations have motivated me to decide what to watch (3)	○	○	○	○	○	○	○
The last time I received recommendations from friends and family, I watched one of the recommended movies or shows (4)	○	○	○	○	○	○	○
My friends' and family's recommendations contributed to my knowledge of presented movies and/or shows (5)	○	○	○	○	○	○	○

Q14 Now, I would like to know your general opinion on Netflix's recommendations.

Netflix's recommender system...

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
provides useful suggestions (1)	○	○	○	○	○	○	○
makes decisions easier (2)	○	○	○	○	○	○	○
is a good way to learn about different movies and shows (3)	○	○	○	○	○	○	○
offers suggestions that I might not have thought of (4)	○	○	○	○	○	○	○
has access to and can process more information than human beings (5)	○	○	○	○	○	○	○
helps me find things I really like (6)	○	○	○	○	○	○	○

Q15 Netflix's recommender system...

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
can provide me with more valuable recommendations than human beings (1)	○	○	○	○	○	○	○
is reliable (2)	○	○	○	○	○	○	○
is dependable (3)	○	○	○	○	○	○	○
is designed with the best intentions in mind (4)	○	○	○	○	○	○	○
can be trusted (5)	○	○	○	○	○	○	○

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
is not biased (6)	○	○	○	○	○	○	○
wants me to find an option that best fits my needs (7)	○	○	○	○	○	○	○
is a good way to get suggestions from a neutral source (8)	○	○	○	○	○	○	○
is consistent in the recommendations it provides (9)	○	○	○	○	○	○	○
is there to help me (10)	○	○	○	○	○	○	○

Q16 Netflix's recommender system…

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
understands my needs (1)	○	○	○	○	○	○	○
knows what I want (2)	○	○	○	○	○	○	○
considers my needs (3)	○	○	○	○	○	○	○

Q17 Finally, I would like to ask you some questions about your background. In which country do you currently reside?

▼ Afghanistan ... Zimbabwe

Q18 What gender identity best describes you currently?

○ Man
○ Woman
○ Prefer not to say
○ Other ____

Q19 What is the highest level of school you have completed or the highest degree you have received?

○ Less than high school degree
○ High school graduate
○ Some college but no degree
○ Associate degree in college
○ Bachelor's degree
○ Master's degree
○ Doctoral degree
○ Professional degree

Thank you so much for filling in my survey, I really appreciate it! If you have any further questions, comments or complaints, please do not hesitate to get in touch with me (465192nn@eur.nl) or my supervisor, Dr. João Ferreira Goncalves (ferreiragoncalves@eshcc.eur.nl). You can close this window now.
Best regards, Nhu Anh Nguyen.

Appendix B. Social media advertisement (Instagram Story & Facebook post)