Chapter 13
Exploring Factors Driving Satisfaction from Recommendation Algorithm on Netflix

Karolina Olma, Mariia Rizun, and Artur Strzelecki

Abstract The present study aims to evaluate customer satisfaction with the recommendation algorithm used by Netflix. Online streaming platforms have revolutionized the way people consume media content. With the multiplication of choices and the abundance of content, it has become difficult for users to find the materials they are interested in watching. To address this problem, recommendation algorithms have been developed to suggest the content that the user is most likely to find entertaining. The research is conducted through structural modeling equations and data analysis, with the use of data from 274 Netflix users. The results show a positive relationship between personalization, use of search engine, homepage usefulness and satisfaction from using Netflix's recommendation algorithm. The results of this research contribute to our understanding of customer satisfaction with the recommendation system of online streaming platforms.

13.1 Introduction

As technological advancement continues, individuals are increasingly transferring their daily activities to the virtual world. Reading news on online platforms instead of newspapers, seeking advice on forums, and even communicating with friends through instant messaging and social media have become commonplace. Entertainment is also evolving on the Internet, including games, short videos, gossip articles, etc. One notable trend is the extending popularity of Internet television, with a growing number of websites offering a wide selection of films, television shows, game shows, and other forms of entertainment [1]. The popularity of traditional television is decreasing, particularly among younger generations, while interest in streaming platforms such as Netflix, HBOMax, and Disney + is increasing [2].

K. Olma · M. Rizun · A. Strzelecki (✉)
Department of Informatics, University of Economics in Katowice, 1 Maja 50, 40-287, Katowice, Poland
e-mail: artur.strzelecki@ue.katowice.pl

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Recommendation algorithms on these platforms are the foundation of their operation as they influence the type of content presented to the user, which, in turn, ultimately impacts the user's experience with the website [3].

Netflix is an American company that specializes in streaming and film production. Netflix offers a large selection of films, television shows, and other forms of entertainment, which is constantly expanding [4]. Initially, the brand was primarily known as a platform for high-quality film content, but as the company has grown, it has also become known for producing high-quality original films and shows [5]. The website netflix.com can be accessed through Web browsers and through a mobile application on devices connected to the Internet, including smartphones, tablets, smart TVs, media players, and gaming consoles [6]. Subscribed users can watch live content and download certain content for offline viewing; however, this offline viewing option is only available on iOS, Android, and Windows 10 devices [7]. The digital platform is based on a monthly subscription, with the option to choose from different plans, which differ in cost, video quality and resolution, and usage rules [7]. Online television, also known as streaming or video-on-demand (VOD) platforms, are websites that allow to watch video material online without a set schedule or programming lineup [8]. Users can choose to watch any movie at any time [9]. Access to these platforms can be paid, partially paid, or free, eliminating the need for physical copies of the content and taking up less storage space on the device [10]. Subscribers also have more control over their viewing experience through personalized recommendation and rating algorithms and can stop watching at any time [11, 12].

13.2 Study Background

Netflix initially offered a website where customers could rent DVDs and receive them via mail [13]. The company transitioned to online streaming in January 2007, allowing previous subscribers to access the new service for free. By 2010, Netflix expanded to Canada, 2011 to Latin America, 2012 to Europe, and by 2016, it was available in 190 countries [14]. The company's early recommendation system was based on an average number of stars given by viewers. After watching a film, viewers could rate the film on a scale of 1–5 stars. This allowed the company to evaluate films from the viewer's perspective, not just from professional critics. Yet, as the global business grew, the need for a more accurate film rating algorithm emerged, to retain current subscribers and attract new users [15]. In 2009, Netflix received its first award for its innovative algorithm to predict ratings, which is still in use today [16]. Streaming content to individual subscribers also allowed for personalized film recommendations. The system gathered information on how the site was used, such as device, the hour, weekday, and even viewing intensity, allowing the users to have a personalized set of films not only based on personal preferences but also on time and device used [17].

The selection of content to watch on Netflix primarily relies on the homepage and the built-in search feature. The homepage uses an algorithm to recommend content to users [18, 19], while the search function uses different algorithms and allows users to find specific titles using keywords, such as popular tags, film titles and genres, or names of actors [20, 21]. The recommendation algorithms of Netflix select movie and cover art that align with the unique interests of the subscriber [18]. However, the limitation is not only the large film database, but also the interface, which must be consistent and organized while also being personalized to the specific account. As a result, each homepage has a different set of films, arranged according to a specific layout. The algorithm first evaluates the individual user's actions on the platform, then creates a personalized ranking of thematic groups, which are then arranged on the homepage in order of potentially most interesting to the customer. This layout of the homepage makes it easy for users to navigate and displays multiple options on a small, limited screen or monitor. The basic indicator of film grouping is their genre, sub-genre, or other video metadata, such as release date [22].

As stated on Netflix's official blog, the challenge is not only selecting and organizing up to 40 rows with around 40–75 movies, out of tens of thousands, but also balancing the discovery of new content with ease of continuing a series or revisiting previously watched content [18]. Netflix continues to improve their algorithms for the main page and recommendations, considering factors such as time of day and device used.

The range of rows in Netflix main page is based on a personalized recommendation algorithm, known as the Personalized Video Ranker (PVR) [23]. The PVR algorithm organizes groups of content, or subsets, based on genre, sub-genre, or other filters, separately for each user, resulting in different sets of movies being displayed on different accounts, even in rows with the same name. Often, personalized content is mixed with popular content in the ranking, allowing users to discover new content. Additionally, the set of rows updates and changes every time the main page is opened. Another row, "Selected for [username]," is curated by the Top-N Video Ranker algorithm, designed to provide personalized recommendations from the entire Netflix catalog [24]. Unlike PVR, it does not limit to selected subsets of the catalog, and the row may consist of content from various themed groups not similar to each other or specially filtered. Moreover, like the previous ranker, Top-N combines the user-chosen content with the most popular content, and takes into account viewing trends over different time frames, such as season or day, and even the device the subscriber is connected to [24]. As a result, "Selected for" row displays different content even when the user simultaneously opens the website on a few devices. Lastly, "Popular Now" row displays the most popular movies of the moment across all Netflix users [25].

As previously observed, the existing literature on Netflix primarily examines its societal impact in various nations, as well as its competition with other TV cables or over-the-top platforms. To the best of our knowledge, no research has been conducted on how Netflix users perceive the recommendation algorithm that provides each user with a distinct content set to view. Identifying this gap, we aim to address it by proposing a theoretical model to elucidate what influences the satisfaction with using the Netflix recommendation algorithm.

This study examines satisfaction with using the platform and the functionality of the homepage and searches based on the content recommended for users. The main purpose of the study is to determine satisfaction from using the recommendation algorithms on the platform. The work is structured as follows: the methodology and hypotheses are covered in the second section, the third part contains data results obtained during the analysis, the fourth part begins the discussion and provides an interpretation of the findings and an overview of the research, the limitations encountered during its conduct, and the practical application of the work. Lastly, we conclude the results.

13.3 Method

The focus of our study was the subjective opinion of Netflix users on the usefulness of recommendation algorithms of the service and satisfaction with displaying personalized results. We have identified four external variables that, as we postulate, impact users' satisfaction with the recommendation algorithm in Netflix. These variables are "use and recommendation," "personalization," "usefulness of homepage," and "use of search engine."

13.3.1 Use and Recommendation

The characteristics of each Netflix user depend on the way and frequency of using the platform [26]. The brand community can be observed on social media profiles [27]. "It is a group of people who share a common interest in a given brand, creating a subculture around the brand with its own values, myths, hierarchy, rituals or vocabulary" [28]. Belonging to such a community causes greater involvement and attachment. One should also remember about the existence of passive users who read information and make decisions based on it [29]. The variable "use and recommendation" was used to examine the respondents' attachment to the brand, their willingness to recommend it to relatives, and to check whether the films watched on the platform were selected based on their familiarity or interest in the cover.

Hypothesis (H1) Use and recommendation has an impact on the personalization of the displayed results. This impact is significant.

13.3.2 Personalization

Personalization is a set of activities that lead to the delivery of content and the way it is presented specifically for a given customer [29–31]. The variable "Personalization" was used to examine the knowledge of the respondents and their perception about proposal personalization as a result of the operation of the recommendation algorithms on the platform. The efficient operation of personalization algorithms should have a positive effect on the usability of the home page and search engine (the "Use of search engine" by Netflix users).

Hypothesis (H2) Personalization affects the use of a search engine. This impact is significant.

Hypothesis (H3) Personalization affects users' satisfaction. This impact is significant.

Hypothesis (H4) Personalization affects the usefulness of the homepage. This impact is significant.

13.3.3 Satisfaction

Satisfaction is the judgment that a feature of a product or service provides (or provided) a pleasant level of fulfillment associated with consumption, including under- or over-fulfillment. It is a feeling and a short-term attitude that can easily change under different circumstances [32]. The variable was used to examine the level of satisfaction with the possible options for searching and selecting movies on the Netflix platform and the displayed suggestions, which are the result of operation of the recommendation algorithms.

13.3.4 Usefulness of Homepage

Usefulness is a property that indicates that the subject of consideration tends to bring benefits, pleasure, good or happiness to the recipients [33]. The variable was used to test the usefulness of the homepage, including the usefulness of the recommendation algorithms that work when creating the homepage and displaying suggestions to users of the streaming platform.

Hypothesis (H5) Usefulness of the homepage affects users' satisfaction. This impact is significant.

13.3.5 Use of Search Engine

Netflix uses a combination of algorithms and human curation to power its search functionality [34]. The algorithms take into account factors such as a user's viewing history, ratings, and search history to suggest content that may be relevant to them. The search process also involves human curation, with teams of editors and curators working to ensure that the most relevant content is being surfaced to users. Additionally, Netflix also uses machine learning and natural language processing to comprehend the motivation behind user queries and return the most relevant results [35]. The "use of search function" was taken to investigate the usefulness of the search feature, specifically the result of the recommendation algorithms responsible for displaying a personalized order of movies when using the built-in search feature on the Netflix streaming platform.

Hypothesis (H6) The use of a search engine has a significant impact on users' satisfaction.

The resulting theoretical model is to help in the examination of user satisfaction with the proposals displayed on the platform, which translates into the usefulness and effectiveness of the recommendation algorithms used. It was assumed that the use and recommendation have an impact on the personalization of results, and this, together with the usability of the home page and the use of search engine, affects perceived satisfaction. Table 13.1 contains the variables along with the scales describing them and the acronyms that appeared in the survey conducted during the study.

The questionnaire was created using the Google Forms platform, and the survey questions were designed in such a way that the answers could be given using a seven-point Likert scale. This made it possible to collect numerical data relating to seemingly unmeasurable opinions and to quantify the results. To reach Netflix users, a survey was published on thematic groups on Facebook social network, which gather a community interested in materials available on Netflix. The only condition to take part in the survey was the use of services available on Netflix.

The Faculty Research Ethics Committee of University of Economics in Katowice, Poland, accepted minimal ethical risk after it was carried out in compliance with the Declaration of Helsinki (20211215_141726). Informed consent from each participant was collected at the beginning of the survey. The statement was following: "By taking part in this study, you are agreeing to allow us to collect data about your Netflix use and behavior. This data will be used to help us better understand satisfaction from recommendation algorithm on Netflix and will be kept strictly confidential. You are always free to leave the study by contacting us."

Table 13.1 List of variables, items, and questions

Variable	Item	Question
Use and recommendation	UR1	I prefer to watch movies with an interesting cover
	UR2	I follow the news added to Netflix
	UR3	I only watch movies that I know or associate with
	UR4	I follow the information added on Netflix social media
	UR5	I would happily recommend Netflix to a friend or family
Personalization	P1	I believe the Netflix search results are personalized to the account I'm using
	P2	I believe the home page has rows selected individually for each user
	P3	I believe that the order of the titles in the individual rows of the home page is NOT the same for every user
	P4	I believe that the content of the rows on the homepage is NOT the same for every user
	P5	I believe I know a lot about Netflix's referral algorithms
Satisfaction	SAT1	I think the suggestions on the home page are spot on
	SAT2	I believe that the search results in the search engine are hit
	SAT3	I am happy with the way I search and select movies on Netflix
	SAT4	I believe Netflix has all the search features I would expect
Usefulness of homepage	UHP1	I usually search for movies on the homepage
	UHP2	I spend most of my time on the homepage (except for viewing materials)
	UHP3	I like the design of the Netflix homepage
	UHP4	I find the Netflix homepage to be a standout compared to other streaming platforms
	UHP5	Using the homepage is intuitive and pleasant
Use of search engine	USE1	Most often I search for movies using the search engine on the platform
	USE2	I like how the Netflix search engine works
	USE3	I find the Netflix search engine to be fast and effective
	USE4	I believe that the way the search results are presented is clear

13.4 Results

The questionnaire gathered 274 respondents, including 173 people (63.1%) having their own account on the platform and 101 people (36.9%) using a friend's account. More than half of the respondents, 64.2%, were women. Six people (2.2%) chose not to state their gender. Most of the group (75.6%) were people under 27 years old; 22.6% of respondents were aged 28–57; 1.8% of people were above 57 years old. More than half (68.6%) have secondary or primary education; 30.3% have high education and 1.1% chose vocational education. The last part of the survey was about the frequency of use and the type of content watched. It turns out that most respondents (64.6%) use Netflix only 1–3 times a week, while the number of users, watching movies on the platform 4–6 times a week (18.2%) is slightly higher than the number of people doing it daily (17.2%). The most-watched content on the platform are series (49.3%) and movies (23%). Documentaries gathered 10.2%, while 17.5% of answers were given to "other" types.

Results for the model are the outcome of the structural equation modeling (SEM), carried out in the SmartPLS4 program. The method consists of several key stages: first, the appropriateness of the constructs and variables used must be evaluated, then the structural model can be estimated. The following options were used in this work: PLS algorithm with default configuration settings (weighting scheme: centroidal, maximum number of iterations: 300, stopping criterion: 10^-X with 7 selected), bootstrap with 5000 samples with corrected bias and acceleration in a two-sided distribution.

The first stage of the research is the analysis of the suitability of reflective variables. To do this, the values of their loadings (Table 13.2) were checked.

In Table 13.3, we see that for five reflective variables (UR1, UR3, USE1, UHP1, and UHP2), the loadings are too low. For the variables P3, P4, and P5, the loading is also lower than the accepted 0.7; however, the value is above 0.6, and the decision was made to keep the variables in the model. The next step is to assess the internal consistency reliability and average explained variance (AVE). The assessment was made after removing five items with loading below 0.6.

The values of AVE are at a satisfactory level (Table 13.4). Additionally, all reliability indicator values for each construct are at a satisfactory level, so despite the low

Table 13.2 Loadings

Item	Loadings	Item	Loadings
P1	0.833	UHP1	0.481
P2	0.798	UHP2	0.518
P3	0.642	UHP3	0.849
P4	0.670	UHP4	0.719
P5	0.621	UHP5	0.848
SAT1	0.735	USE1	0.456
SAT2	0.751	USE2	0.902
SAT3	0.904	USE3	0.904
SAT4	0.780	USE4	0.842

Item	Loadings
UR1	0.557
UR2	0.676
UR3	− 0.080
UR4	0.707
UR5	0.775

Table 13.3 Variable reliability and validity

Variable	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
P	0.771	0.819	0.840	0.516
SAT	0.804	0.819	0.872	0.632
UR	0.725	0.732	0.799	0.571
USE	0.869	0.871	0.920	0.792
UHP	0.779	0.785	0.873	0.697

loadings of variables P3, P4, and P5, they remain in the model. The final step in evaluating reflective variable validity is to analyze the HTMT coefficient (Table 13.5), which allows for an evaluation of differential validity.

It can be observed that none of the values have reached the critical value of 0.85, indicating that all constructs are independent of each other. After removing the unnecessary items, the model, along with the estimated coefficients, appears as follows (Fig. 13.1).

Figure 13.1 shows that the strongest relationships are observed between satisfaction and use of search engine, as well as personalization and usefulness of homepage. However, the weakest relationship is between usefulness of homepage and satisfaction. The next stage in the study involves analyzing the results of the estimation based on the paths in the model and evaluating the hypotheses reflected through specific paths.

Table 13.4 HTMT value matrix

	P	SAT	UR	USE
SAT	0.615			
UR	0.474	0.663		
USE	0.376	0.831	0.474	
UHP	0.434	0.752	0.581	0.575

Table 13.5 Results confirming hypotheses and value of the paths

Hypothesis	Path	Coefficient	*F*-square	*T*-Statistics	*P*-Value	Supported
H1	UR → P	0.346	0.136	5.801	0.000	Yes
H2	P → USE	0.339	0.130	5.759	0.000	Yes
H3	P → SAT	0.269	0.169	5.675	0.000	Yes
H4	P → UHP	0.363	0.152	5.608	0.000	Yes
H5	UHP → SAT	0.266	0.144	5.503	0.000	Yes
H6	USE → SAT	0.485	0.488	11.688	0.000	Yes

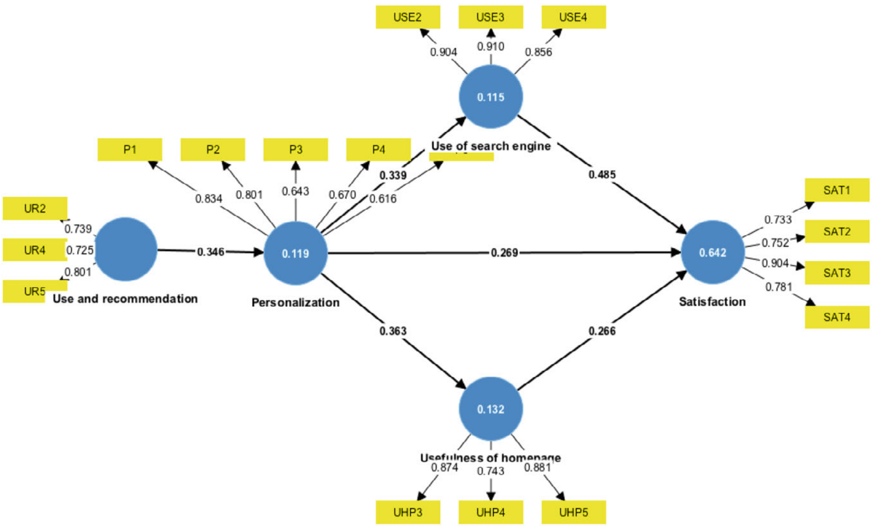

Fig. 13.1 Model with estimated coefficients

Table 13.6 *R*-square overview

Variable	*R*-square
Personalization	0.119
Satisfaction	0.642
Use of search engine	0.115
Usefulness of homepage	0.132

As seen in Table 13.6, all hypotheses based on these paths are confirmed. The values of the determination coefficient *R*-square are presented in Table 13.6. Analysis of these indicators allows for checking the significance of individual variables.

Three coefficient of determination values (*R*-square) are relatively low—for personalization, use of search engine, and usefulness of homepage, indicating a weak or moderate fit to the model. However, the value for satisfaction is 0.642, which means the model accounts for 64.2% of the variation in satisfaction from using recommendation algorithms on Netflix. Therefore, this *R*-square value can be considered significant.

13.5 Discussion

Netflix is a relatively new streaming service and a fairly young form of entertainment. As a result, there is limited literature available with research on it. However, it is worth noting that the company runs its official blog, where it publishes information about the functioning of the recommendation algorithms implemented in the service. This has allowed for the presentation of information in the theoretical introduction to the study carried out.

The study was based on users' subjective perceptions of the chosen streaming service. All the hypotheses presented were confirmed. This means that being a part of the brand community, as well as the resulting use and recommendations from the Netflix streaming platform, significantly affect the way the personalized search results are displayed. In turn, this has a significant impact on users' satisfaction with the recommendation algorithm. Personalization has a positive impact on using the search engine and the usefulness of the homepage. The usefulness of the search results displayed, and the usefulness of the homepage also positively impact satisfaction.

In prior studies, various theories and methodologies were employed to examine the acceptance and satisfaction of using Netflix. Despite the differences in approach, these studies mainly addressed two topics: platform adoption acceptance [33] or overall satisfaction with the service [34, 36, 37]. Our research specifically examines the factors that influence satisfaction with the recommendation system. Nevertheless, our findings have similarities that can be compared with the previous studies.

Melo-Mariano et al. [38] studied the modified technology acceptance model (TAM), and they indicated that "the intention to use Netflix platform in Brazil is influenced by perceived enjoyment, perceived usefulness and perceived ease of use." In our study, we used homepage usefulness and confirmed its significant impact on satisfaction. Cebeci et al. [39] used an extended TAM model with three external variables (knowledge, self-efficacy, and technology anxiety) and confirmed that "self-efficacy and knowledge are positively related to perceived ease of use, knowledge and perceived ease of use are positively associated with perceived usefulness, perceived usefulness predicts attitude, attitude predicts intention to use, and technology anxiety attenuates the positive effect of perceived usefulness on attitude." Our work uses homepage usefulness, as it can be compared to perceived usefulness. Martins and Riyanto [37] studied the influence of six external variables like "attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty on customer satisfaction" on Netflix in Indonesia and found that all have a significant positive effect. However, there is no further explanation of what these variables represent.

Lestari et al. [40] examined system quality, content quality, customization, price level, psychological risk, and enjoyment as external factors influencing "attitude to use and its implications on continuance intention to use Netflix." They found that "there is a positive relationship between system quality and enjoyment of attitude to use. Furthermore, there is a negative influence between the price level and attitude to use; however, content quality, customization, and psychological risk did not affect the attitude to use Netflix." We can describe system quality as similar to our homepage usefulness and use of search engine and as well, we also confirmed a positive effect on satisfaction. Shin and Park [41] "compared the users' expectation, satisfaction, and dissatisfaction between Netflix and Korea-based over-the-top (K-OTT) services in South Korea. Respondents showed higher expectations and satisfaction with Netflix than with K-OTT service." In their study, they examined the overall satisfaction from using Netflix, whereas our study explores satisfaction from using Netflix recommendation algorithm.

Pratama et al. [42] used the UTAUT2 theory to analyze variables affecting subscription interest on Netflix in Indonesia. "Results showed that behavioral intention, content availability, facilitating conditions, habit, performance expectancy, price value, and social influence variables had a significant impact on subscription intentions on Netflix." Still, the subscription intention goes before getting satisfaction from using the service. Our research further explores the users' behavior. Camilleri and Falzon [43] integrated two theories. First, the TAM, and second, "the uses and gratifications theory to understand motivations to use online streaming services." They proved that "the perceived usefulness and ease of online streaming services were significant antecedents of intentions to use online streaming services." They did not examine a particular streaming service, but the overall intention to use it.

Netflix, video-on-demand services, and streaming platforms are relatively new in the entertainment market, so there have been few studies conducted on the topic [44]. The information that has been published so far has allowed for the definition of variables that are important in the subjective perception of the functioning of the streaming platform. This work can serve as a basis for creating new marketing actions and help to identify the target group of the streaming service product [45]. The work may contribute to further research on the development of this type of leisure activity, the impact on the audience of the content provided, and the relationships between the elements of the platform.

This study presents a novel approach to understanding the satisfaction from Netflix recommendation algorithm by incorporating four variables into the model. These variables (use and recommendation, personalization, use of search engine, and homepage usefulness) provide an expanded comprehension of the factors that influence individuals' satisfaction from using recommendation algorithms in Netflix. The inclusion of these variables is unique in comparison with previous studies, which have primarily focused on other theories and variables not well suited for measuring satisfaction from using a recommendation system. This focus on the recommendation system provides a fresh perspective on a well-studied topic and could potentially lead to improvements in this area for the benefit of users.

13.5.1 Practical Implications

The theoretical and empirical parts of the research deal with the constantly growing brand that is Netflix, specifically its recommendation algorithms used to create the main page of the streaming service and the built-in movies search engine. It is important to note that the company is interested in knowing the opinions of its users, which can be seen from the constantly updated profiles on social media sites, where much of the published content motivates the audience to engage in constant interaction. Therefore, the research results can serve as support for future updates of the recommendation algorithms and help representatives of the brand understand the relationships between the listed variables.

Netflix users can broaden their knowledge about the algorithms working in the service, which will allow them to use this form of entertainment in a more conscious manner. The viewer who is familiar with the principles of the search engine has the opportunity to understand its limitations and effectively select phrases that match their intention when searching for content. Additionally, knowledge of the algorithms that create the main page allows for a quick overview of the content.

The study can also be a source of knowledge for other streaming platforms and related industries, as it not only indicates the operation of recommendation algorithms on the world's largest streaming service, but it also indicates the subjective perception of their results. The findings of this study can therefore be used as the foundation for the work of programmers and for building a positive image of the service and brand by the gathered user community. Building a positive relationship with the user and taking care of the satisfaction and usefulness of the widgets available in the service brings financial benefits to the company, as a satisfied customer will not want to cancel their subscription and thus will fulfill the monthly payment obligation. In such a situation, the brand becomes recognizable, builds, expands, and stabilizes its target community, and can achieve good sales results, while users can enjoy their access to a satisfying and useful form of entertainment.

13.5.2 Limitations

Entertainment through streaming platforms or video-on-demand is rapidly developing along with technological advancements, causing a lot of information to become outdated. The choice of material to watch does not have to rely on the recommendation algorithms of the streaming platform. Often, the user's choice is motivated by recommendations from friends or ratings given to the movie on websites such as IMDb, or Rotten Tomatoes. Since we have only studied the dependence of users' satisfaction from the recommendation algorithms on Netflix and did not consider the fact that the users may prefer websites as IMDb to form their opinion about movies, we see a certain limitation here. By including several movie databases in the research, we could have revealed more about the factors affecting viewer's satisfaction from using Netflix.

13.6 Conclusions

This study focuses on the constantly evolving entertainment field of online streaming platforms, which offer users a wide range of movies, TV shows, entertainment programs, and documentaries. The primary objective of the study was to determine the satisfaction from using the recommendation algorithms applied on these platforms and to examine the viewers' subjective opinions of such content. The research was conducted electronically using a questionnaire, and SEM was used to analyze the data that was obtained. This approach allowed verification of previously established hypotheses.

The study confirmed all six hypotheses. The hypotheses about the impact of use and recommendations on personalization, personalization on the use of search, homepage usefulness and satisfaction, as well as the impact of the use of search and homepage usefulness on satisfaction were found to be validated. This means that the display of personalized results on the Netflix homepage is significant in terms of the usefulness of recommendation algorithms when creating the homepage and in terms of overall satisfaction with the platform.

The users' affiliation to the brand community and the resulting way they use the streaming platform have a big impact on the effectiveness of the algorithms and thus their effectiveness, usefulness, and satisfaction with the displayed and personalized results. As a result, viewers who use someone else's account may have a distorted perception of the recommendation algorithms, affecting their satisfaction with their performance and the usefulness of the homepage, where most rows are based on the already viewed movies or frequently watched movies and TV genres.

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