# Giving and Following Recommendations on Video-on-Demand Services

Jennifer Gutzeit
Heinrich Heine University
Düsseldorf, Germany
jennifer.gutzeit@hhu.de

Isabelle Dorsch
Heinrich Heine University
Düsseldorf, Germany
isabelle.dorsch@hhu.de

Wolfgang G. Stock
University of Graz
Graz, Austria
wolfgang.stock@hhu.de

## Abstract

*This is an empirical paper about giving, receiving, and following recommendations on Video-on-Demand (VoD) services, including results on gender-specific differences. Based upon a model for information behavior on VoD services, we applied an online survey and generated 1,258 valid questionnaires from active VoD users. Participants receive recommendations from the systems once a week on average, but they follow them only occasionally. They give actively recommendations to other people several times a month. Users do not receive recommendations from other sources as often as from the services (only several times a month); however, they follow those recommendations more often. The most important source for receiving recommendations from other sources is face-to-face communication. Obviously, VoD users follow recommendations from other people more than suggestions from algorithmically generated recommender systems. Besides, self-determined content selection following intrinsic motivation is important. The findings are of interest for research on digital and social media and for VoD services.*

## 1. Introduction

### 1.1 Purpose of this paper

Viewers of television, movies in cinemas, downloading platforms, and also of streaming services do not always follow only their own intentions when they are looking for content to watch, but are open to recommendations of others—of the applied services as well as of other sources including other users. In this study, we concentrate on on-demand streaming services, which are mainly consumer-oriented with a focus on passive entertainment [1]. While the users are more or less passive when consuming content for entertainment, they are indeed active when they search for videos or series and are happy to receive and—sometimes—to follow recommendations, both from the systems' recommender systems as well as from other sources.

Video-on-Demand (VoD) services are either free of costs (as, e.g., YouTube or TV media libraries) or behind a paywall (as, for instance, Netflix, Amazon Prime, Sky, or maxdome). For paid services, the situation of a lock-in must be considered [2]. Viewers are locked into one provider—unless they sign multiple contracts in parallel. For instance, one cannot access content from Amazon Prime as a Netflix user or vice versa.

When it comes to the selection of content, perhaps for this evening's entertainment or in a longer perspective to find an interesting new serial, users may exhibit self-determined information behavior, i.e. they are solely intrinsically motivated to determine what they watch [3]. However, they also may follow or give recommendations on specific videos or serials. Or the users may follow the systems' recommendations. We distinguish between (1) algorithmically generated recommendation from the VoD services and (2) all other suggestions distributed online or offline including personal recommendations (by friends, family members, or influencers), be it face-to-face or by e-mail or messages as well as suggestions read in reviews or ads.

Especially technological aspects of VoD services' recommender systems are well studied. We will not discuss the algorithms of the recommender systems in detail, but the user behavior relating to these recommendations, what is new. We found only few articles on information behavior concerning VoD and to the best of our knowledge no single study about giving, receiving, and following recommendations from other sources concerning VoD platforms and their content.

To deepen research on recommendations on streaming media we define four research questions (RQs):

**RQ 1:** How often do users receive algorithmically generated recommendations from VoD services and how often do they follow the system's suggestions?

**RQ 2:** How often do users provide personal recommendations to other users?

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**RQ 3:** How often do users receive suggestions from other sources outside of the VoD services (e.g., personal recommendations from other users) and how often do they follow such suggestions **(RQ 3a)**? From which sources do users receive those recommendations **(RQ 3b)**?

**RQ 4**: For comparison: How often are users intrinsically motivated and follow their own wishes and interests?

In a closer look at users, it is possible to differentiate by demographic variables (as generation and gender). In this study, we prioritize gender over age, as there are already results on generations: Gutzeit et al. [3] found a greater interest of younger users for applying VoD services. The younger active users (aged 10 to 49 years) follow the algorithmically generated recommendations as well as the suggestions from other sources more frequently than the older ones (50+). However, [3] did not discuss gender-specific aspects in detail. Maybe there are gender-specific differences in the users' behavior concerning recommendations. For all four research questions, we are going to report the results separated for women and men.

Our results are important for the scholarly research on digital and social media, as we are able to report on the reception, the following, and the active giving of recommendations from the viewpoint of the users. The results are also useful for studies in sociology and communication research as we can analyze the connections, i.e. the strong and weak ties [4], between users in the context of streaming services. Moreover, as there are results for the different genders, this article is attractive for gender studies. Some findings may be of practical interest for VoD services: Do users accept and follow the systems' recommendation? Is there a kind of competition between the system's recommendations and other suggestions (e.g., by other users)?

As one can find many studies on algorithmically produced recommendations of online services, a main contribution of this study is the additional consideration of further forms of recommendations from other sources as, for instance, face-to-face communication of the users.

### 1.2 VoD services and their recommendation algorithms

VoD services—free of cost, such as YouTube (we excluded the subscription-based service YouTube Premium), or paid, such as Netflix—have created an upheaval in the media industry [5, 6]. In addition, the constant availability of media led to modified consumption behavior, which also gave rise to the behavior of binge watching, i.e. watching series, movies or user-generated videos for hours via the Internet [7]. This is at least associated with a tendency among younger viewers to turn away from conventional media such as television, which are squeezed into a rigid program schedule.

The systems of the VoD services offer recommendations for their users. The applied algorithms work, among others, with users' click-through rates [8] or hints on users' preferred watching habits [9]. Recommendation engines do not offer popular or well-known content, but items being otherwise hard to find [10]. To increase the quality of experience, VoD recommender systems may work with personalized user interfaces [11].

We could identify reports on special algorithms for TV media libraries [12], YouTube [13], and Netflix [14, 15]. However, we do not want to analyze the VoD systems' recommendation algorithms, but the user behavior reacting on them.

### 1.3 Modeling recommendations on VoD services

On live streaming services, there is or may be participation of all users, some presenting a live performance, and others reacting on it [16]. There is a feedback loop between participating users. Concerning on-demand streaming, one cannot find a direct system-supported feedback loop between users when they watch content. However, there are indirect feedback loops when we consider recommendations.

Our research model (Figure 1) is based upon the feedback model of Zimmer et al. [17]. The model presents all aspects seen from the perspective of a single user, here called *User X*. As every user, also *User X* will be described by demographic data (as, for instance, gender), his or her circumstances in the situation (e.g., sitting alone at home), and the respective role. The role is either active (giving recommendations to others) or more passive (following recommendations). It is "more" passive, as there is not only the passively received recommendation, but also the active decision of the user to follow the recommendation or not. Here, the user's motivation plays a crucial role [18]. When the user's intrinsic motivation matches a recommendation, it is likely that the user will follow the recommendation. When there is extrinsic motivation (i.e. the user has eventually no own idea what to watch), the user may follow the recommendation because, for instance, a good friend suggests this piece of content or the system informed her or him that many other people had watched the video. If there is amotivation [18], the user will not follow recommendations.

In the model, there are two feedback loops. One loop is between the user and the VoD service. The user interacts with the system, e.g. by browsing through items, by watching videos, or by following or ignoring system recommendations. The system accumulates all those data and presents its recommendations for specific content (in Figure 1: bold black lines).

The second feedback loop is between *User X* and other people (maybe personal, by word-of-mouth recommendation, or mediated by magazines) and exists independently from the VoD service. Our user gives a personal recommendation on specific content to another user, here *User Y* (bold yellow-brown lines) or she or he receives a recommendation from *User Y* (bold red lines). Obviously, *User Y* has some experience on a video or a service. At this point it is possible to recommend a concrete serial or movie (say, the series "Beauty and the Beast"), a concrete VoD service (as, for instance, Amazon Prime), or both ("Beauty and the Beast" on Prime). Concerning the first aspect, *User X* may indeed watch this series on Prime, but she or he can also buy the DVD [19]. In this study, we concentrate on VoD services and on content.—At this point our empirical investigation starts.

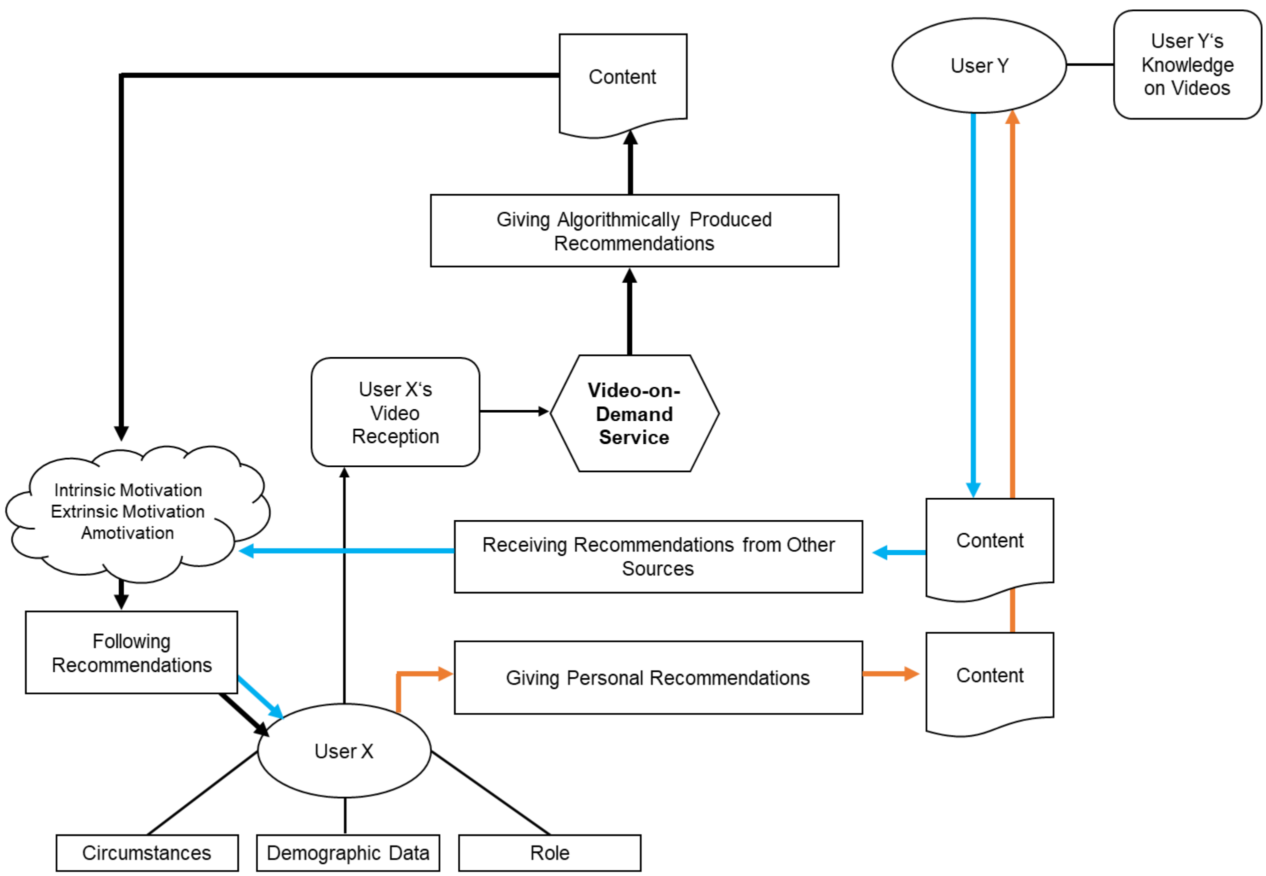


**Figure 1: Intuitive sketch of our research model: Receiving and following algorithmically generated recommendations from VoD services (black), giving personal recommendations to other users (orange), and receiving as well as following recommendations from other sources (blue) (as seen from User X).** ***Source:*** **Following [17], modified.**

## 2. Methods

We investigated the giving, receiving, and following recommendations on VoD services in German-speaking countries. It was distinguished between algorithmically generated suggestions from the services and recommendations from other sources and to other users. We described users by their gender, the VoD services by their machine-generated recommendations, and other users who are in interaction with the initial user and make or receive recommendations actively or passively as well as online or offline.

Online-survey-based questionnaires provide a means of generating quantitative data. Furthermore, they ensure anonymity, and thus, a high degree of unbiasedness to bare personal information, preferences, and own knowledge. Therefore, we decided to work with an online survey. It was active from February 19, 2019 to March 31, 2019. Our procedure was non-probability sampling, more precisely convenience sampling in combination with volunteer sampling [20]. To strengthen the power of the statistical analysis we predefined a minimum of 1,000 usable questionnaires. The power tables provided by Cohen [21] have a maximum of n = 1,000 participants. Therefore, we chose this value of the sample size to ensure statistically significant results, also for smaller subsets as single genders.

As no ethical review board was involved in our research, we had to determine the ethical harmlessness of the research project ourselves and followed suggestions for ethical research applying online surveys such as consent, risk, privacy, anonymity, confidentiality, and autonomy [22].

With the online survey, we collected data about users, video services, and users' friends and acquaintances. The survey was pretested and then distributed via *UmfrageOnline.*

The first question of the survey, "How often do you watch videos (movies, serials, web videos) online?", allowed us to collect data about the users and an initial screening of participants on use or non-use of video streaming services. In the second question, "Which video streaming services do you use?", we were able to filter out additional non-relevant participants by using the answer option "I do not use video streaming services." Questions 3 to 10 dealt with users' information reception behavior, i.e., how ("alone" or "together with others"), how often ("daily," "weekly," etc.) and where (e.g., "at home," "on the road") they watch videos, and the user behavior described via experiences with recommendations or suggestions ("Have you recommendations / suggestions already received or shared?", "How did you get recommendations?"). Question 11 was dedicated to the intrinsically motivated search for videos without any suggestions or recommendations from others. The last three questions identify the demographic data of each survey participant. In this article, we only use data on genders.

For the questions about the periodicity of use, we applied two 7-point Likert scales [23], the first one ranging from "never" (1) to "occasionally" (as a neutral option in the middle) (4) to "always" (7), the second one from "never" (1) via "several times a month" (4) to daily (7).

As our data were ordinally scaled, we calculated the median, the interquartile range (IQR) as measure of dispersion, and the Mann-Whitney U-test [24] for marking the significance of the differences between the genders. We distinguished between four levels of statistical significance, namely ns (not significant), *: $p \leq 0.05$ (significant), **: $p \leq 0.01$ (very significant), and ***: $p \leq 0.001$ (extremely significant). However, one has to interpret such values of significance levels always with caution [25]. All calculations were performed using SPSS.

## 3. Results

### 3.1 Basic data

Our sample generated N = 1,258 valid questionnaires from participants in German-speaking countries. Of these, 609 participants (48.4%) were male, 644 participants (51.2%) were female, and 5 participants (0.4%) were diverse (the data from these 5 people were not used). All 1,258 questionees were active users of VoD services.

Participating users consume content from VoD services very often; the median is 7 with an IQR of 1. Most users watch content from home (median: 7, IQR: 1), only rarely (median: 2, IQR: 3) on the move. They watch content alone (median: 7, IQR: 1), but also frequently (median: 5, IQR: 2) together with others. Men apply their PCs or laptops as well as their smartphones very frequently (median: 6, IQR: 5); women uses smartphones not as frequently as men (median: 5; IQR: 5) and PCs or laptops even less frequently (median: 4, IQR: 4); however, we have to consider the very high value of dispersion. In regard to all participants, Netflix is used most frequently, followed by YouTube and Prime (Table 1). There are no big differences between the genders for many services. However, female users are more likely to use Netflix and less likely to use YouTube.

**Table 1: Used VoD services by gender**

| VoD service | All | Women | Men |
|---|---|---|---|
| Netflix | 80.9 % | 85.3 % | 76.4 % |
| YouTube | 75.8 % | 70.7 % | 81.4 % |
| Amazon Prime | 68.6 % | 69.3 % | 68.1 % |
| TV media libraries | 35.1 % | 36.5 % | 33.7 % |
| Sky | 22.0 % | 18.3 % | 25.9 % |
| Maxdome | 5.5 % | 5.6 % | 5.4 % |
| Other | 5.9 % | 2.0 % | 9.8 % |
| N | 1,253 | 644 | 609 |

### 3.2 Receiving and following algorithmically generated recommendations of VoD services (RQ 1)

Most algorithmically generated recommendations were received through suggestions from the video streaming services on their platforms than through personalized emails. More than 42% of all participants reported that they never received any e-mail with recommendations.

**Table 2: Receiving and following algorithmically generated recommendations from VoD services by gender**

**(a) Women**

| | Receiving Recommendations* | Following Recommendations** |
|---|---|---|
| (1) | 3.0 % | 3.3 % |
| (2) | 12.6 % | 7.0 % |
| (3) | 9.0 % | 11.2 % |
| (4) | 25.0 % | 45.2 % |
| (5) | 16.0 % | 23.8 % |
| (6) | 22.0 % | 9.2 % |
| (7) | 12.4 % | 0.5 % |
| Median | 5 | 4 |
| IQR | 2 | 1 |
| N = 644 | | |

**(b) Men**

| | Receiving Recommendations* | Following Recommendations** |
|---|---|---|
| (1) | 5.1 % | 3.6 % |
| (2) | 9.9 % | 9.7 % |
| (3) | 6.2 % | 11.5 % |
| (4) | 19.7 % | 44.8 % |
| (5) | 18.1 % | 21.2 % |
| (6) | 22.2 % | 7.9 % |
| (7) | 18.9 % | 1.3 % |
| Median | 5 | 4 |
| IQR | 2 | 1 |
| N = 609 | | |

**(c) Difference between women and men**

| | |
|---|---|
| Significance/Receiving | 0.004** |
| Significance/Following | 0.134 ns |

* Scale: (1) never, (2) less than once a month, (3) once a month, (4) several times a month, (5) weekly, (6) several times a week, (7) daily
** Scale: (1) never, (2) very rarely, (3) rarely, (4) occasionally, (5) frequently, (6) very frequently, (7) always

We could identify gender-specific differences concerning the perception of recommendations (Table 2). For both genders, the median is 5 and the IQR equals 2, but there are differences in the distribution of the values. Men perceive recommendations of the systems more “daily” (7) than women (18.9% versus 12.4%), and women exhibit higher values on “several times a month” (4) than men (25.0% versus 19.7%).

Receiving and perceiving algorithmically produced recommendations is one thing; following the recommendations is another. Due to the users’ intrinsic and extrinsic motivations to follow a recommendation and their respective amotivation there is a gap between receiving and following those suggestions. While all users receive recommendations on a weekly base (median: 5, IQR: 2), they follow those recommendations only “occasionally” (median: 4, IQR: 1).

About 19% of all women and 25% of all men follow such recommendations only seldom (value 1, 2, and 3), while a third of the female participants and about 30% of the males follow them rather frequently (values 5, 6, and 7). The remaining questionees (about 45% for both gender groups) chose the neutral value 4, which is here the median. For following recommendations from the VoD services, we do not find statistically significant differences between the genders.

### 3.3 Giving personal recommendations to other users (RQ 2)

Now we turn our attention from human-computer interaction to human-human interaction. Women and also men give recommendations several times a month on average (Table 3). Only few people (about 2%) never make recommendations; in contrast, more than 16% of our participants give suggestions several times a week or even daily. The median for active recommendations is 4 (IQR: 2); there is no significant difference between the genders; however, our value ($p = 0.070$) is only slightly above the threshold $p \leq 0.05$.

**Table 3: Giving personal recommendations to other users by gender**

| | All | Women | Men |
|---|---|---|---|
| (1) | 2.3 % | 2.6 % | 2.0 % |
| (2) | 20.4 % | 19.7 % | 21.2 % |
| (3) | 17.2 % | 19.3 % | 14.9 % |
| (4) | 30.3 % | 31.8 % | 28.7 % |
| (5) | 13.7 % | 12.4 % | 14.9 % |
| (6) | 13.4 % | 12.1 % | 14.8 % |
| (7) | 2.7 % | 2.0 % | 3.5 % |
| Median | 4 | 4 | 4 |
| IQR | 2 | 2 | 2 |
| N | 1,253 | 644 | 609 |
| Significance | | 0.070 ns | |

Scale: (1) never to (7) daily

**Table 4: Receiving and following recommendations from other sources by gender**

**(a) Women**

| | Receiving Recommendations* | Following Recommendations** |
|---|---|---|
| (1) | 3.3 % | 0.6 % |
| (2) | 19.6 % | 2.6 % |
| (3) | 17.1 % | 6.2 % |
| (4) | 33.1 % | 35.9 % |
| (5) | 12.8 % | 37.6 % |
| (6) | 11.5 % | 16.3 % |
| (7) | 2.8 % | 1.5 % |
| Median | 4 | 5 |
| IQR | 2 | 1 |
| N = 644 | | |

**(b) Men**

| | Receiving Recommendations* | Following Recommendations** |
|---|---|---|
| (1) | 3.8 % | 1.2 % |
| (2) | 18.1 % | 4.3 % |
| (3) | 13.8 % | 7.6 % |
| (4) | 28.6 % | 33.7 % |
| (5) | 17.6 % | 32.7 % |
| (6) | 14.9 % | 19.2 % |
| (7) | 3.3 % | 1.5 % |
| Median | 4 | 5 |
| IQR | 2 | 1 |
| N = 609 | | |

**(c) Difference between women and men**

| | |
|---|---|
| Significance/Receiving | 0.020* |
| Significance/Following | 0.856 ns |

* Scale: (1) never to (7) daily
** Scale: (1) never to (7) always

### 3.4 Receiving and following recommendations from other sources (RQ 3a)

Similar to the receiving of recommendations from the services, there are gender-specific differences concerning the perception of recommendations from other sources, be it friends, acquaintances, family members, further contacts, ads, or influencers (Table 4). Women and men receive recommendations several times a month on average (median: 4, IQR: 2), but women select more values 3 and 4 (50.2% in contrast to 42.4% of all men) as well as less values 5 and 6 (24.3% versus 32.5%).

In comparison to the reception of algorithmically generated recommendations (for both genders the median equals 5), the reception of suggestions from other users is lower (median: 4).

The results for receiving recommendations from other sources (median: 4, IQR: 2) are in line with the results for actively giving recommendations to others (median: 4, IQR: 2). With a relatively small dispersion, users give and take suggestions from other sources several times a month.

When it comes to follow the recommendations from other sources, women and men act more or less in the same way, as we did not find statistically significant differences. However, there are minimal variations. For both genders, they follow suggestions occasionally (4) or frequently (5), but for women the highest relative frequency is reached at 5 (about 38%), for men it is 4 (about 34%).

In comparison to the following of algorithmically generated recommendations (for both genders the median equals 4), the reception of suggestions from other sources is higher (median: 5). Users receive (and perceive) more recommendations through the services, but follow them less; and users receive less suggestions from other sources, but follow them more.

### 3.5 Other sources of recommendations (RQ 3b)

An aspect of the third research questions is directed at the sources of all recommendations besides the services' suggestions. We analyzed groups of people (e.g., family or influencers), channels (for instance, face-to-face, posts, messages), and contents of the sources (e.g., reviews or messages from the VoD services) (Table 5).

The most important sources of such recommendations are face-to-face contacts meaning that two or more users directly speak together (the median equals 5 for both genders). Users also receive recommendations through messengers (as, for instance, WhatsApp) or e-mail. Women get suggestions via this channel several times a month, while men only get recommendations by mail or message once a month.

Users receive suggestions from friends, acquaintances, members of the family, and other personal contacts several times a month on average. However, women exhibit a higher share of contacts several times a month (about 33%) than men (29%), while only 13% of females report contacts on a weekly base in contrast to men (18%).

**Table 5: Other sources of recommendations by gender**

| | Median (IQR) | | |
|---|---|---|---|
| | Women | Men | Diff. |
| Friends, family | 4 (2) | 4 (2) | 0.020* |
| Reviews | 3 (2) | 4 (3) | 0.000*** |
| Influencers | 3 (3) | 3 (3) | 0.641 ns |
| Advertising | 2 (2) | 2 (2) | 0.614 ns |
| Posts by friends | 4 (3) | 4 (3) | 0.786 ns |
| Shared by friends | 4 (3) | 4 (3) | 0.316 ns |
| Face-to-face | 5 (2) | 5 (2) | 0.235 ns |
| Message, e-mail | 4 (3) | 3 (3) | 0.464 ns |
| N | 644 | 609 | |

Scale: (1) never to (7) daily

Both genders receive posts by friends on social media channels. Those posts may be authored by the friends themselves (median: 4) or they are originated by the VoD services and only shared by the friends (median: 4).

Men get suggestions for content through reviews or other editorial articles more often than women (median: 4 versus median: 3 for women). This is the most important gender-specific difference concerning all other sources of recommendations.

Advertising on social media including posts of influencers plays only a minor role for recommendation (median: 3). Finally, advertising on TV or billboard advertising is the least perceived source of recommending VoD services' content. More than 55% of all questionees never or less than once a month receives such recommendations from ads.

### 3.6 Self-determined content selection (RQ 4)

We should not forget that users do not only follow recommendations, but decide also purely on their own interests and wishes, i.e., based upon their intrinsic motivations [18].

For both genders, the median of self-determined content selection is 5 (frequently) with an IQR of 2 (Table 6). Although the median values are the same for the genders, men search intrinsically motivated more frequently (5), very frequently (6), or even always (7) than women, who are more likely to search occasionally (4) on their own initiative. There is a clear indication (especially for male users) that intrinsic motivation and—corresponding—self-determined content selection behavior plays a major role in the selection of videos, too.

**Table 6: Self-determined content selection**

| | Women | Men |
|---|---|---|
| (1) | 1.4 % | 0.7 % |
| (2) | 3.1 % | 2.0 % |
| (3) | 7.1 % | 5.7 % |
| (4) | 29.0 % | 20.7 % |
| (5) | 27.2 % | 32.7 % |
| (6) | 26.7 % | 29.6 % |
| (7) | 5.4 % | 8.7 % |
| Median | 5 | 5 |
| IQR | 2 | 2 |
| Sign. | 0.000*** | |
| N = 1,258 | | |

Scale: (1) never to (7) daily

### 4. Discussion

Overall, our empirical online survey study (n = 1,258) on receiving and following recommendations on Video-on-Demand (VoD) services illustrates content selection behavior in VoD services is not influenced or even determined by just one factor, but by a combination of three aspects: firstly, algorithmic recommendations from the services, secondly, suggestions from other sources, and thirdly, self-determined active search behavior.

In a certain balance, all three factors determine the user behavior. Content selection resulting from following recommendations by algorithms occurs least frequently (median: 4), intrinsic self-determined selection behavior and following the suggestions from other sources are about equally frequent (median: 5) (Figure 2).

Users of video streaming services move in a cycle between machine-generated suggestions, recommendations and exchange of opinions from and with other fellow human beings, and self-determined content search behavior. This cycle does not necessarily flow in one direction but can flow in several directions due to the factors mentioned—i.e., algorithms influence users through their recommendation, users influence algorithms (through their using behavior on the services), users influence each other and create groups of like-minded people, and self-determined information behavior has an effect on algorithms (which evaluate the behavior shown) and (insofar as content is actively recommended) on other viewers.

Similarly, Siles et al. [26] conclude a steady interactive exchange of algorithmic cultures and algorithms as cultures and sees both as simultaneously instead of sequential. "[U]sers enact algorithmic recommendations as they incorporate them into their daily lives, but these algorithms are designed to adjust to these enactments in order to colonize users" [26, p. 19].

In summary, and with respect to our research questions, our participants receive algorithmic recommendations from VoD services once a week on average and follow them occasionally (**RQ 1**). Personal recommendations to other users are actively given several times a month (**RQ 2**). Likewise, users receive recommendations from other sources several times a month (**RQ 3a**). That is not as often as from the services (as shown by **RQ 1**). However, our results also reveal that users follow those suggestions from other sources more often. Thus, such suggestions seem to be more important for the users' content selection behavior than algorithmically generated recommendations. Thereby, the most important source for receiving recommendations is face-to-face communication (**RQ 3b**). In terms of users' own intrinsic motivation to follow their own wishes and interests, most of our participants indicate a rather strong self-determined content selection behavior. The majority is doing so once a week (**RQ 4**).

Research on VoD services and their recommendation is still a newer area as the VoD systems themselves has not existed for so long. At the same time, VoD is quickly developing in terms of the overall services' offers, their variations, and their functions.

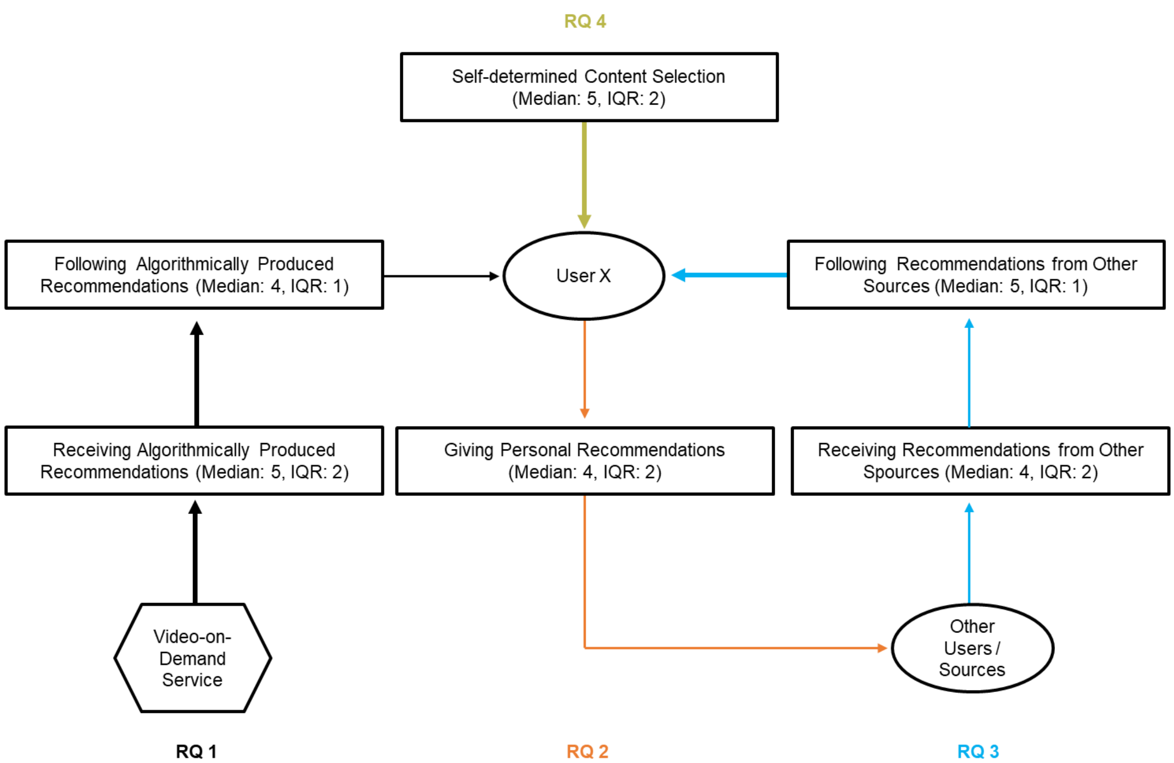


**Figure 2: Overview on the results: Receiving and following algorithmically generated recommendations (black, RQ 1), giving personal recommendations to other users (orange, RQ 2), receiving and following recommendations from other sources (blue, RQ 3), and self-determined content selection (yellow-brown, RQ 4). Bold lines: strong influence (median: 5), normal lines: slightly less influence (median: 4).**

A scholarly literature review of recommender systems in the television domain [27] analyzes recommended item types, approaches, algorithms, architectural models, output devices, user profiling, and evaluation of TV content and TV-related content (mostly no VoD) available on the Web. The majority of their analyzed literature is concerned with recommending TV contents and only few articles deal with the recommendation of TV-related item types. However, VoD was not considered. Based on this, it would be interesting to analyze VoD recommendations versus TV recommendations. Besides, Netflix (80.9%), YouTube (75.8%), and Amazon Prime (68.6%) were the most used VoD services in our study. What about the more specialized providers? In how far does giving and following recommendations function for them? What differences exist in comparison to more established VoD services? And how will both, also in comparison with TV recommendation, further evolve over time?

Within our participants, gender-specific differences between women and men have only a marginal impact on handling recommendations. That is in line with [28], although their study focuses on the evaluation of research paper recommender systems and not on VoD recommendations. However, women recognize algorithmic recommendation less on a daily basis than men, but more occasionally. Men are more often intrinsically motivated in their content selection than women. And men receive and perceive more often recommendations from reviews.

Siles et al. analyze the "domestication" of Netflix users. Based on Silverstone [29], for Siles et al. [26] domestication takes place through personalization ("ways in which individualized relationships between users and the platform are build"), integration of algorithmic recommendations into cultural aspects, the rituals for incorporation, resistance to various aspects of the platform, and the conversion of private platform consumption into a public issue. The interviews with 25 Netflix users located in Costa Rica reveal "how users incorporate Netflix into their daily life and how Netflix seeks to colonize users and turn them into ideal consumers through recommendation algorithm" [26, p. 17]. Like the authors already state by themselves, work on VoD from the user-centered perspective in their everyday life is rather limited and should be extended in terms of services, and the comparison of demographics, as for example, region, age, or gender.

And what impact can the different use cases have? What about the excessive use of VoD? For example, Hasan et al. [30] found out the use of recommender systems in online video streaming services together with a lack of self-control, lack of self-esteem, and use motive of information seeking, impacts a user's excessive use of the service.

Are there dangers of filter bubbles (acceptance of too many recommendations from the services) [31] or echo chambers (acceptance of too many personal recommendations) [32]? According to Zimmer et al. [33, 34] it is a little bit of both, but no real danger. The most important actors are the users themselves.

One of our main results is that recommendations from other sources and self-determined content selection outperform automatically generated recommendations from the VoD services. For the VoD companies this is a strong recommendation to rethink their algorithms and—if possible—to optimize them (or to accept that other sources of recommendation are simply more useful for the audience). For information systems research, these results ask for the enhanced investigations of non-algorithmic recommendations (by other people or other sources) instead of the restricted emphasis only on recommender systems.

Our study attracted many participants but was limited to users in German-speaking countries. How does it look globally? Are there differences between our survey participants and others? In how far do more specific providers or new functions impact giving and following recommendations? Are users even aware of the effects of external recommendations, i.e., the possibility of third-party control by algorithms and other users?

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