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The Influence of Recommender Systems and Social Factors on the Content Choices of Streaming Video on Demand Consumers

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Abstract. Streaming Video-on-demand (SVOD) services are getting increasingly popular. Current research, however, lacks knowledge about consumers' content decision processes and their respective influencing factors. Thus, the work reported on in this paper explores socio-technical interrelations of factors impacting content choices in SVOD, examining the social factors WOM, eWOM and peer mediation, as well as the technological influence of recommender systems. A research model based on the Theory of Reasoned Action and the Technology Acceptance Model was created and tested by an n=186 study sample. Results show that the quality of a recommender system and not the social mapping functionality is the strongest influencing factor on its perceived usefulness. The influence of the recommender system and the influence of the social factors on the behavioral intention to watch certain content is nearly the same. The strongest social influencing factor was found to be peer mediation.

Keywords: Streaming Video on Demand; Social Influence; (e)Word of Mouth; Peer Mediation; Technology Influence; Recommender Systems

1 Introduction

Subscription Video on Demand (SVOD) services are booming. A survey by Deloitte[3] showed that 69 % of respondents have subscribed to at least one video streaming provider, a number climbing to 80% in the age group 22-35. SVOD consumers particularly value the possibility to choose from an extensive number of available movies, shows and documentaries without thinking about their individual cost. Consequently, the price for a single content unit is taken out of the selection process, increasing the influence other factors may have on people's consumption choices. While there is previous work investigating content choice behavior in cinema and television (e.g. [1, 2]), only few researchers have so far studied the behavior of SVOD consumers (e.g. [3]). Focusing

[3] https://www2.deloitte.com/content/dam/Deloitte/lt/Documents/technology-media-telecommunications/LT_DI_Digital-media-trends-13th-edition.pdf [accessed: 25.10.2020]

on well-known influencing factors, such as Word of Mouth, electronic Word of Mouth and peer mediation, as well as the role modern recommender systems may play, the work presented in this paper aims to help close this research gap. To do this, the Theory of Reasoned Action [4] and the Technology Acceptance model [5] served as theoretical underpinning for a survey collecting data on people's content choice. The subsequent analysis used structural equation modeling to investigate respective effects. The paper is organized as follows: First, we provide a brief introduction to the influencing factors relevant for the statistical analysis. Next, we proceed with the description of the methodological approach, the data analysis and result discussion. Finally, we reflect on some limitations of the presented work and propose topics for further investigation.

2 Factors Influencing Content Choice

While overall, aspects influencing people's content consumption behavior are certainly manifold, one may subdivide them into social and technical factors. With respect to the former, previous research has shown that informal and non-commercial face-to-face interaction between consumers, i.e. so-called Word of Mouth (WOM), has a significant influence on people's product and service choices [6]. Although this type of communication is usually rather subjective, happening coincidentally in private conversations, and thus difficult to observe [7], it was found that with respect to the field of video consumption both positive (e.g. [8]) as well as negative viewing experiences (e.g. [9]) increase the presence of WOM. It was further shown that high box office revenues, which are usually considered a sign of high quality, may trigger *'me too'* behavior [1] and consequently lead to positive WOM [2].

In addition, it may be argued that the continuing popularity of social media platforms and other Internet-based information channels has eased the sharing of people's opinions and experiences. Thus, today we find many different forms of online communication, leading to a great number of opinions that are available at all times, helping content consumers choose [10, p. 1]. With this so-called electronic WOM (eWOM), Marchand et al. [11] highlight product reviews, such as Amazon's customer reviews, and microblogs, such as Twitter, as particularly important types of informal information exchange, and thus influencial for people's choices. Similar to traditional WOM, it was shown that also eWOM (no matter whether it has a positive or negative connotation) preceding movies and during their first week after release, triggers *'imitation behavior'* [12]. An empirical analysis of revenue data has furthermore revealed that there seems to be a direct association between the number of pre-release *'Likes'* on a movie's Facebook-page and its opening week box office sales [13].

While WOM and eWOM communication are defined as forms of informal communication in non-commercial, and therefore private contexts, they do not necessarily happen with peers; i.e. communication partners may not always stand in a closer relationship to each other. Peer relations emerge from a sense of equality and lead to the reciprocation of behaviors of other peer group members (i.e., peer mediation). This requires the reflection of others' ideas and opinions, which eventually leads to a peer group's mutually constructed world view [14, p. 3]. Discussions about consumed media content are, of course, also part of peer relationships, often leading to pressure situations in cases where content is missing or could not be consumed by parts of the group [15, p. 530]. To this end, Nathanson [14] has shown that in adolescent media use, peer mediation has a higher influence than parent mediation, and that peers with similar academic or social problems may be drawn together by their media consumption patterns. A qualitative long-term study carried out among teenage girls in different US middle schools led to similar results. Most girls in peer groups agreed to watch the same shows, read the same magazines and listen to the same music. Their behavioral patterns, as well as clothing choices, were highly influenced by their choice of media, and very similar within the individual peer groups [16]. While most of these peer mediation studies are carried out with children or teenagers, as peer influences are usually stronger and more important during adolescence [14], we see an increasing demand for the investigation of adult peer groups. Although later in life peers may be less influential with respect to defining one's worldview, they are likely to affect media and content consumption behavior. A recent study has for example pointed to an influence of peer mediation on the attitude towards and consequent use of health apps on mobile phones [17].

2.1 Technical Influence

A recommender system tries to predict the probability for a user to consume or buy a product. In order to do this, the system analyzes usage behavior and presents suggestions to help users find the right content, product or service [18]. In general, recommender systems can be divided into two categories: Content-based systems and collaborative filtering systems. The former focus on previous user behavior, while collaborative filtering systems involve preferences of others in their analytical process. Thus, they try to incorporate the previously mentioned social influencing factors (i.e., WOM, eWOM and peer mediation) in their recommendation decision [19]. The aim is to provide the user with a sense of socialization that never happened [20]. Streaming platforms usually use a mix of content-based and collaborative filtering systems. Additionally, online behavior and browser cookies are consistently tracked and analyzed, while users are logged into their media account (e.g., Netflix [3]). This allows the inclusion of data that was generated even before the account was created (e.g., social media and shopping behavior) [21]. Most literature on recommender systems focuses on technical aspects and improvements [22]. Only few studies try to shed light on the influence these systems have on users' decision processes. Pittman and Eanes [3], for example, found that the amount of available content on streaming platforms leaves too many choices for viewers, impeding rational decision making and leading to unsatisfied outcomes. The use of recommender systems, on the other hand, makes them consume content they would not have consumed otherwise. Another study examined the persuasive nature of recommender systems and found that users tend to rely on the system's recommendation when preceding recommendations were satisfactory [23]. Although this persuasive power may also lead to potential negative psychological effects such as excessive use and addictive behavior (e.g. [24]), it is said that the constant technological improvement of recommender systems makes them ever more efficient in helping users choose desired content. Hosanagar et al. [25], for example, discovered that collaborative filtering lets users widen their interests and find more similarities with others. These similarities may also create more WOM and/or eWOM and thus in turn should be considered as a recurring factor influencing content choice.

2.2 Socio-technical Interrelations as a Research Gap

The above shows that most research on content choice focuses on single influencing factors. However, it may be argued that content choice is not only influenced by a single factor, but rather by a multitude of factors. And these factors not only influence viewers in their choice, but also themselves reciprocally. That is, the emergence and success of WOM leads to *'imitation behavior'*, particularly in peer groups [1]. Also, WOM and eWOM communication are difficult to separate, as pure face-to-face WOM is difficult to observe and measure (e.g. [2, 7]). In other words, influencing factors are often examined individually but their synergies are seldom taken into consideration. In addition, most of the extant literature about media content choice is focusing on television or cinema. Choice and decision processes in SVOD, which so heavily pushes the use of recommender systems, is less researched. Also, most literature on recommender systems focuses on technological improvements [22]. While, according to Pittman and Eanes [3], the improvements of these recommender systems will eventually dominate all other influencing factors, it is unlikely that consumers will stop discussing their experiences and impressions via WOM or eWOM. Thus, it seems important to investigate the interrelation between these factors and how they, as a group, eventually influence the consumers' choice of content, leading to the following research question:

To what extent does the mapping of social influencing factors (WOM, eWOM and peer mediation), imitated by recommender systems, affect the content choice of subscription video-on-demand users?

3 Methodology

Given that the above stated research question investigates a socio-technical problem space, we require a research model which integrates social/personal, as well as technical influencing factors. To this end, the Theory of Reasoned Action (TRA) aims to explain one's behavior based on attitudinal and social factors [4]. That is, an individual's attitude towards a specific behavior and its subjective norms determine the behavioral intention which, eventually, leads to the actual behavior. According to this framework, the attitude towards a specific behavior is influenced by the beliefs about the outcome of said behavior and the evaluations of this outcome [26]. The subjective norms are influenced by normative beliefs about the behavior and the motivation to comply with these norms [4]. Thus, the TRA may serve as a solid basis for our socio-technical research model as it combines both attitudinal and social factors. Social factors are reflected by one's subjective norms, formed by normative beliefs and the motivation to comply with those beliefs. These normative beliefs are a standard that is set by a person's social environment and thus may be represented by the previously discussed social influencing factors WOM, eWOM and peer mediation. The attitudinal factors, on the other hand, are described as one's attitude towards a specific behavior. In our case, attitude towards the behavior of watching content recommended by a streaming platform's recommender system. As this does not entirely align with the TRA's representation of an attitude towards a behavior, given that the behavior is influenced by a technology, we need to further expand our model. To this end, Davis [5] developed the so-called Technology Acceptance Model (TAM), which states that a user's intention to use a technological system is determined by its perceived usefulness, its perceived ease of use, and the user's attitude towards using the system. Both perceived usefulness and perceived ease of use are further influenced by external factors. While previous work has shown that TAM may be used to study the the acceptance of recommender systems (e.g. [27]), it should be highlighted that here the attitude towards use serves as the counterpart to the attitude towards behavior in TRA, eventually reflecting the acceptance of using the technology. This is supported by the fact that TAM in its original form neglects subjective norms and focuses entirely on the user as a single person – an aspect which was often criticized (e.g [28]). Hence, similar to more recent TAM studies (e.g. [29]), we find it necessary to also include these social constructs and consequent influence on the use of the technology, eventually leading to our proposed research model illustrated in Figure 1.

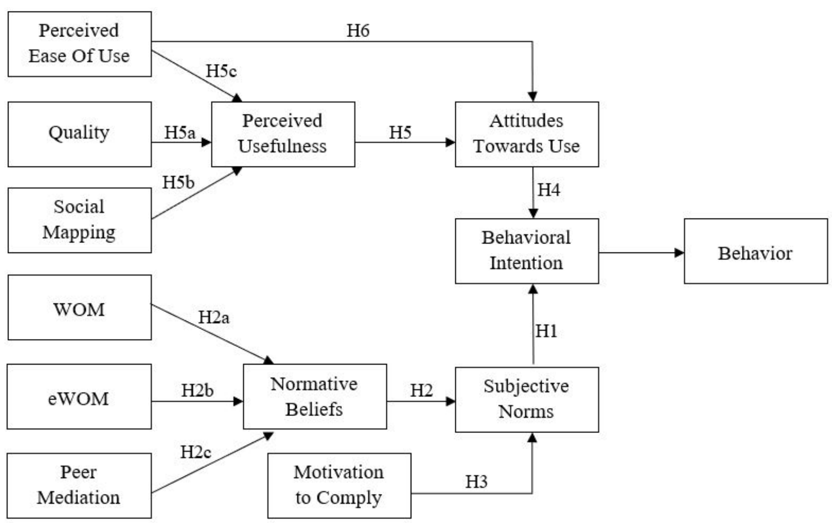

Figure 1. Proposed Research Model Derived from TAM and TRA

4 Hypotheses

Based on the research model described above, we developed a set of 13 hypotheses, focusing on the influence social and technological factors have on consumers' content choice in SVOD. The goal was to better understand how the intention to watch certain content is formed. The analysis thus compares the influences of an individual's social environment and the influences of a technology which tries to imitate this social environment, i.e. the recommender system (cf. Table 1).

5 Research Model and Survey Design

In accordance with the above stated hypotheses we developed a 44-item questionnaire[4]. The first questionnaire section asked participants about the type, number and frequency of use, connected to certain streaming services (Q01-03). Next, we investigated people's intention to consume streaming content in general and after hearing about it (Q04-05). Subsequently, the influence of the social environment was measured with 14 questionnaire items based on the TRA [4]. The first three of these items (Q06-08) assessed the respondents' subjective norms, inspired by the work of Chin et al. [30]. Individual normative beliefs were reflected by items connected to the social influencing factors WOM, eWOM and peer mediation. This is, two WOM items (Q09-10) evaluated individuals' likeliness to watch a movie or show after positive [2] as well as negative WOM communication [8, 9]. Three eWOM items (Q11-13) were phrased similarly to the WOM items, but modified so as to reflect a social media context [12, 13]. A fourth eWOM item (Q14) assessed the respondents interest to actively search for user generated information on cinematic rating platforms, such as IMDB or Rotten Tomatoes [11]. Next, peer mediation was assessed based on four items (Q15-18) which evaluated the respondents in conversing about movies and shows with their peers [14, 31]. Finally, the last item of this block (Q19) assessed the motivation with which people would comply with these subjective norms [4].

Next, a block of 21 question items was used to measure the influence of recommender systems. This question set was mainly based on the TAM literature by Davis [5]. The first three items (Q20-22) evaluated the respondents' attitudes towards recommender systems, where the questions were modified according to the work of Pittman and Eanes [3]. Next, we used four items (Q23-26) from a previous TAM study conducted by Armentano and Christensen [27] assessing the overall perceived usefulness of a recommender system and four items (Q27-30) about its perceived quality with respect to diversity, novelty and match with people's interests [32]. Following, we included items on the recommender systems' mapping of social influencing factors (Q31-36). Here, the items which were used to evaluate the normative beliefs (WOM, eWOM and peer mediation) were aligned with the functionality of recommender systems. These items were taken from the original TAM by Davis [5] and the already mentioned work by Armentano and Christensen [27]. The block concluded with four items inspired by Armentano and Christensen [27], Pu et al. [32] and the System Usability Scale [33], assessing perceived ease of use (Q37-40). The last four questionnaire items of the survey (Q41-44) collected demographic data on age, gender, current occupation and country of origin.

Building upon previous work [34], our target group of the questionnaire was focusing on university students. Young people between the age of 22 and 35 are considered as the most regular users of streaming services[5]. Therefore, the questionnaire was distributed online via different social media channels (e.g. Facebook, LinkedIn, Instagram) as well as through direct contact in Universities in three European countries, i.e. Austria, Finland and Germany (note: countries were determined by the origins of the research team mem-

[4] https://doi.org/10.13140/RG.2.2.26579.60966

[5] https://www2.deloitte.com/content/dam/Deloitte/lt/Documents/technology-media-telecommunications/LT_DI_Digital-media-trends-13th-edition.pdf [accessed: 25.10.2020]

bers). In order to translate the English source questionnaire into German and Finnish the translation-back-translation procedure was applied [35, p. 39]. In addition, we conducted pre-tests in all three of the countries. Copies of the final questionnaire in English and German are available here: (anonymized). They were launched in May 2019 and stayed available for a timeframe of 20 days, during which a total of 253 people participated, 212 of whom completed all questions. Incomplete questionnaires were excluded from further analysis.

Table 1. Hypotheses and their Evaluation

1	Individuals' subjective norms regarding the choice of content to watch will be positively related to their intention to watch content on SVOD platforms.	✓	Influence 24.0 % (t-value=2.244)
2	Individuals' normative beliefs regarding the choice of content to watch will be positively related to their subjective norms.	✓	Influence 38.5 % (t-value=4.731)
2a	WOM in individuals' social environment will be positively related to their normative beliefs regarding the choice of content to watch.	–	Non-significant Influence 2.4% (t-value=0.153)
2b	eWOM in individuals' online environment will be positively related to their normative beliefs regarding the choice of content to watch.	✓	Influence 38.9 % (t-value=2.570)
2c	Peer mediation in individuals' social environment will be positively related to their normative beliefs regarding the choice of content to watch.	✓	Influence 74.8 % (t-value=6.021) Strongest Influence
3	Individuals' motivation to comply to subjective norms about content on SVOD platforms will be positively related to their subjective norms regarding the choice of content to watch.	✓	Influence 19.2 % (t-value=2.155)
4	Individuals' attitude towards the usage of recommender systems regarding the choice of content to watch will be positively related to their intentions to watch content on SVOD platforms.	✓	Influence 20.3 % (t-value=2.194)
5	Individuals' perceived usefulness of recommender systems will be positively related to their attitude towards the usage of recommender systems.	✓	Influence 49.8 % (t-value=8.602)
5a	A recommender system's perceived quality will be positively related to its perceived usefulness.	✓	Influence 67.7 % (t-value=14.823)
5b	A recommender system's mapping of social influencing factors will be positively related to its perceived usefulness.	✓	Influence 16.8 % (t-value=3.432)
5c	A recommender system's perceived ease of use will be positively related to its perceived usefulness.	–	Non-Significant Influence 4.6 % (t-value=1.050)
6	Individuals' perceived ease of use of recommender systems will be positively related to their attitude towards the usage of recommender systems.	–	Non-significant Influence 7.2 % (t-value=0.812)
7	Individual's subjective norms regarding the choice of content to watch will have a greater influence on their intentions to watch content on SVOD platforms, than their attitudes towards the use of recommender systems.	✓	Influence of sub. norms (24.0 %) higher than influence of att. towards use (20.3 %)

6 Results

The statistical analyses on the questionnaire data were conducted using R, R-Studio and SmartPLS 3.0 for structural equation modeling (SEM). In order to compute accurate SEM results, a minimum sample size of ten times the number of structural paths in a model is required [36, p. 47]. As our research model has twelve structural paths and we received 186 complete and applicable responses (note: 26 of the complete 212 responses had to be excluded from analysis as participants declared to not use video streaming services), the required minimum of 120 data sets was fulfilled, for which result accuracy may be assumed. Also, we were able to set the confidence level to 95%, the minimum R^2 level to 0.10 and the statistical power to 80%. Table 2 provides some descriptive summary of the collected data.

Table 2. Descriptive Statistics

Age	$<$ 20 years	2	1.08%
	20 to 29 years	149	80.11%
	30 to 39 years	24	12.90%
	$>$ 40 years	11	5.91%
Occupation	In School	3	1.61%
	Training/Apprenticeship	3	1.61%
	University Student	121	65.05%
	Employee	47	25.27%
	Civil Servant	3	1.61%
	Self-Employed	3	1.61%
	Unemployed/Seeking	2	1.08%
	Others	4	2.15%
Nationality	Austria	66	35.48%
	Germany	62	33.33%
	Finland	43	23.12%
	Others	15	8.06%

6.1 The Measurement Model

With respect to the measurement model, latent variables were measured in a reflective manner [36, p. 38]. Only the normative beliefs construct differs from the rest of the latent variables as it is defined by three other latent variables (i.e. WOM, eWOM and peer mediation) for which a different assessment was required. Becker, Klein, & Wetzels [37] suggest a reflective-formative approach, since the the underlying latent constructs are not similar to each other, but belong to the same higher concept. Figure 2 illustrates the resulting measurement model.

Investigating the resulting relations, it can be seen that R^2 for the target endogenous variable BEH_INT is 15.2%, which means that the two latent variables SUB_NORMS and ATT_USE explain 15.2% of the variance of BEH_INT. Furthermore, the constructs NORM_BELIEFS and MOTIV_COMPLY explain 27.4% of the variance of SUBJ_NORMS and the R^2 value of the reflective-formative concept NORM_BELIEFS

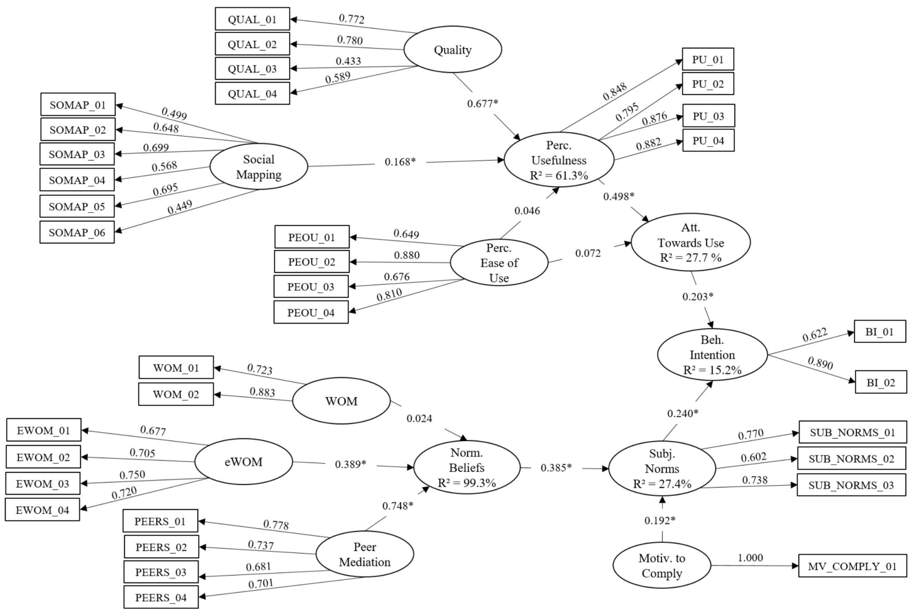

Figure 2. SEM Results, (* = significant with p < 0.05)

is at 99.3%, showing that the reflective concepts WOM, EWOM and PEERS explain 99.3% of the variance of NORM_BELIEFS. Also, the variance of ATT_USE is explained by the PERC_USEF and PERC_EASE, with an R^2 value of 0.277. Finally, PERC_USEF has an R^2 value of 61.3%, which means that the latent variables QUALITY, SOCIAL_MAP and PERC_EASE explain $61,3\%$ of its variance.

6.2 Inner Model Path Coefficient Sizes and Significance

The inner path coefficients of the model explain the effect strength between latent constructs. Usually, effects close to 0 are not significant. In order to validate significance, t-values were calculated through a bootstrapping algorithm (5000 sub-samples). Table 3 lists the respective results. As the significance level was set to 5%, t-values above 1.96 define a significant relationship [36].

6.3 Convergent Validity

The convergent validity explains the extent to which a concept's indicator correlates positively with the other indicators of the same concept. Two measures are commonly used to evaluate the convergent validity: The outer model loadings and the average variance extracted (AVE) [36]. The outer loadings are the relationships between reflective constructs and their indicator variables. They show how good a measure reflects the actual latent construct. Hair et al. [36] recommend values of 0.7 or higher for reliable indicators. However, they argue that it is common to obtain weaker indicators in social

Table 3. Inner Model Path Coefficient Sizes and Significance

	Path coefficient	t-value
ATT_USE - BEH_INT	0.203	2.194
EWOM - NORM_BELIEFS	0.389	2.570
MOTIV_COMPLY - SUBJ_NORMS	0.192	2.155
NORM_BELIEFS - SUBJ_NORMS	0.385	4.731
PEERS - NORM_BELIEFS	0.748	6.021
PERC_EASE - ATT_USE	0.072	0.812
PERC_EASE - PERC_USEF	0.046	1.050
PERC_USEF - ATT_USE	0.498	8.602
QUALITY - PERC_USEF	0.677	14.823
SOCIAL_MAP - PERC_USEF	0.168	3.432
SUBJ_NORMS - BEH_INT	0.240	2.244
WOM - NORM_BELIEFS	0.024	0.153

science studies, especially with newly developed scales. Given the exploratory nature of our study, some of our questionnaire items did not have a validated research background. Thus, indicator loadings between 0.4 and 0.7 should be accepted. Additionally, the bootstrapping procedure highlighted statistical significance for all outer loadings. Table 4 shows the indicators with outer loadings between 0.4 and 0.7.

Table 4. Lower Outer Loadings

Measure	Latent Construct	Outer Loading
BI_01	BEH_INT	0.622
SUB_NORMS_02	SUBJ_NORMS	0.602
EWOM_01	EWOM	0.677
PEERS_03	PEERS	0.681
QUAL_03	QUALITY	0.433
SOMAP_01	SOCIAL_MAP	0.499
SOMAP_02	SOCIAL_MAP	0.648
SOMAP_03	SOCIAL_MAP	0.699
SOMAP_04	SOCIAL_MAP	0.568
SOMAP_05	SOCIAL_MAP	0.695
SOMAP_06	SOCIAL_MAP	0.449
PEOU_01	PERC_EASE	0.649
PEOU_03	PERC_EASE	0.676

Table 5. AVE

Latent Variable	AVE
ATT_USE	0.713
BEH_INT	0.590
EWOM	0.509
PEERS	0.526
PERC_EASE	0.577
PERC_USEF	0.724
QUALITY	0.435
SOCIAL_MAP	0.361
SUBJ_NORMS	0.500
WOM	0.651

The lower outer loadings of BI_01 and SUBJ_NORMS_02 are rather unexpected, since both constructs are derived from the TRA standard items by Fishbein and Ajzen [4]. Additionally, SUB_NORMS_02 is the exact counterpart to SUB_NORMS_01. The lower outer loadings may be explained by questionnaire items which were either derived from different research papers, and thus have no similar validated concept or lack a clearly validated research background. Especially the measures of SOMAP_01-06 were newly developed from extant literature. However, since there are no similar studies available and this research is exploratory, it was decided to keep all indicators in the construct. Such should not only provide initial data, but also appeal to future research to develop novel research constructs, especially with respect to the social mapping context. As a second measure one should consider the Average Variance Extracted (AVE), which is the mean of the squared loadings of the indicators associated to a certain latent construct. An AVE of 0.5 or higher shows that the construct explains more than half of its indicator's variance. Therefore, AVE below 0.5 indicates that more variance remains on the (measurement) error than on the construct [36]. Table 5 shows the AVE of our constructs. Single item constructs have been removed, since AVE is irrelevant for them. For the constructs QUALITY and SOMAP the AVE is smaller than 0.5, while all the other concepts seem rather stable, for which one may argue that the lower outer loading of some measures seems compensated in the whole picture. Additionally, the stop criterion was reached after 64 of 300 iterations of the PLS algorithm, which furhter underlines the reliability of the values [38].

6.4 Internal Consistency Reliability

In order to assess the internal consistency reliability of a PLS-SEM model, two measures are recommended. The first measure is Cronbach's α, which represents the reliability through computing the intercorrelations of the observed indicator variables. In general, a Cronbach α of 0.7 or higher is considered satisfactory. However, in exploratory research such as ours, values between 0.6 and 0.7 may be accepted as well. Cronbach's α is considered a rather conservative approach, since it tends to underestimate the internal consistency reliability [36, p. 135]. Additionally, Cortina [39] argues that it is very dependent on the number of measured items, resulting in lower values with smaller item numbers. The results should thus be treated cautiously and the composite reliability should be observed as an additional verification. This measure takes the different outer loadings into account and can be examined in the same way as Cronbach's α. Values above 0.95 are not desired, since it would imply that the indicators of a certain construct are redundant. The composite reliability is known to overestimate the values, and therefore it is always recommended to observe both values [36, p. 136]. Table 6 shows our Cronbach α values as well as the composite reliability of the model's underlying latent constructs. Single item constructs were again removed, as the measures are not applicable for them. It can be seen that constructs with low Cronbach α measures have rather low values, but in contrast, acceptable or high composite reliability values. The comparison of both show the internal consistency reliability of the underlying latent constructs.

6.5 Discriminant Validity

The discriminant validity evaluates how constructs are distinct to each other; i.e. whether they are unique and not covered by other constructs in the model. It is recommended to assess the discriminant validity with two measures. The first approach is to examine the cross-loadings, which means to compare any construct outer loadings with their cross loadings with other constructs. The outer loadings of a construct should always

Table 6. Cronbach's α and Composite Reliability

Construct	Cronbach's α	Composite Reliability
ATT_USE	0.658	0.829
BEH_INT	0.329	0.736
EWOM	0.679	0.806
PEERS	0.698	0.816
PERC_EASE	0.750	0.843
PERC_USEF	0.873	0.913
QUALITY	0.561	0.745
SOCIAL_MAP	0.662	0.767
SUBJ_NORMS	0.522	0.748
WOM	0.478	0.787

be higher than its cross loadings [36, p. 138]. To this end, our data did not show any problematic cross-loadings. The second measure of discriminant validity is the Fornell-Larcker Criterion. This method compares the square roots of the AVE values with the correlations of latent variables. Each construct AVE square root should be higher than its correlations with any other constructs [36, p. 139]. Results show one problematic value, i.e. QUALITY – PERC_USEF. Since it is only one problematic case, which does not appear in the cross-loadings, it was decided to not remove any indicators. The problematic value may be explained by the rather similar wordings of the PU and QUAL questions; e.g. PU_01 *"I think the movies and shows that are suggested to me are attractive"* and QUAL_02 *"The recommended movies or shows that I already knew before (e.g. from the cinema or television) are usually movies that I like"*. Given the rather complex distinction between the concepts quality and usefulness, especially in an entertainment context, the wordings are quite similar.

7 Conclusions, Limitations and Potential Future Research

The objective of the presented work was to examine the influences of recommender systems and social influencing factors on consumers' SVOD content choices. Especially the recommender systems functionality that tries to map these social influencing factors was examined. This was approached by examining the influence of the social mapping functionality on consumers' perceived usefulness of a recommender system. Results show that the social mapping functionality has a moderate influence on the perceived usefulness. The strongest influence derived from the recommender system's quality. The attitude towards the use of a recommender system and the subjective norms had a relatively similar moderate influence on the behavioral intention. This shows that both factors are important and considerable. The strongest influencing factor on the formation of subjective norms seems to be peer mediation. This supports the assumption that people rely highly on the opinion of close friends and family members regarding their content choices. Surprisingly, WOM communication had no significant influence on normative beliefs at all. Since the influence of WOM on movie choices is reported by a wide range of studies, this result may be caused by a mistake in the research design. Perceived ease of use had neither a significant influence on the perceived usefulness, nor on the attitude towards use. The reasons for this are quite obvious, since there is practically no complexity in using a video streaming platform. This raises the question whether the concept of perceived ease of use may not become obsolete in leisure contexts, where user interfaces are fairly simple to use. Regarding subjective norm, it can be underlined that the opinion and influence of peers is the most trusted factor in content choice. Regarding the attitude towards the usage of a recommender system, it is the quality of the system's functionality, followed by the social mapping functionality, which are most influential.

With respect to the limitations of our work, it was already highlighted that some question blocks lacked validity, as they were derived from different sources. Especially the examination of social mapping resulted in a low validity. Additionally, our approach to combine two research frameworks was new and not previously validated. However, as already mentioned before, most literature studies recommender systems from a technological point of view. There is a lack of critical analysis of their actual influences and therefore, our approach was meant to be rather exploratory. Furthermore, despite all methodical limitations, the model gained solid results and has shown reliability and validity. It is a first step to enable and support further research. To this end, as recommender systems and social factors are not alone influencing the content choice of video streaming users, future research should examine different factors, such as for example 'binge behavior'. Also, further studies aiming to validate our research model are necessary, especially regarding the influences of the recommender system's social mapping functionalities.

It should also be highlighted that the frameworks used as a basis for our research model were developed for other contexts. For example, TAM was developed for business contexts and thus does neither account for today's omnipresence of social media nor other social influence factors [28]. Our attempt to overcome this lack by pairing the model with the TRA may be seen as a first step but requires additional exploration and validation.

In times of the COVID-19 pandemic, it might also be argued that streaming behaviour changes in the context of personal contact restriction. Since peer mediation and personal communication are not very apparent in this setting, there could be a stronger shift to influences from recommender systems and online communication. Future studies are needed to shed light on these special circumstances and their impact on future behavior after the pandemic.

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