MASTER

Subscribe or not?

The effect of content on the adoption of a Video on Demand platform

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Subscribe or not? The effect of content on the adoption of a Video on Demand platform

Master Thesis

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Abstract

The amount of Video on Demand (VoD) services is higher than ever, with an expected growth of 1,5 billion users worldwide by 2026. Competition in VoD markets is fierce due to the entry of new platforms, such as ShowTime and HBOMax. This makes it harder for companies to distinguish themselves based on subscription prices. Companies need to find other strategies to grow their market share. Content is the main non-price factor that influences the adoption of VoD platforms (Bhullar & Chaudhary, 2020). The large scope of the platforms and the fierce competition make it harder for users to choose the platform that fits their needs. Understanding from an user perspective what user drives to adopt a platform can help companies make strategic decisions on which content to show. In this context, the study examines the extent to which personalized recommendations on the homepage of a VoD provider will foster the adoption of over-the-top (OTT) services by users in the Netherlands.

To investigate whether content fosters the adoption of VoD the study two different methods are used. The results of the A/B test provide the direct effect of content on the adoption of VoD and the user study results explain the indirect effect of content on the intention to use. The results show that the presentation of content influences new and returning users differently. Therefore, the VoD platform should adapt its acquisition to the different groups. The goal of the user study was to explain the whole adoption process, including the perceptions and their effects on the user attitude towards a system. Contrary to our expectations the results show that non-personalized recommendations are better for adopting users than personalized recommendations. This can be explained by the higher perceived quality of the new series and the top series than the personalized series. The most popular series gave the best results on the intention to use the OTT service.

However, this thesis does provide a starting point for researchers to combine different methods in analysing the whole adoption process of OTT services. Whereas previous literature only incorporated user experience factors, e.g. perceived enjoyment and perceived value (Leowarin & Thanasuta, 2021; Singh et al., 2021; Fernández-Robin, 2019). This study shows that subjective system aspects such as quality and diversity directly affect intent as well. Resulting in a complete user model explaining the effect of content on the adoption of OTT services.

Preface

First, I want to thank my supervisors Martijn Willemsen and Bert Sadowski. Martijn Willemsen was always available for questions and challenged me to think critically during our weekly meetings. Bert Sadowski for taking up the challenge to be my supervisor for a dual degree project. He helped me combine my degrees in one thesis and was always enthusiastic and interested in the HTI and IS sides of the project.

I would like to thank my supervisors of Videoland Daan Odijk and Natascha Hoogeveen. From the start they made me feel at home at RTL. They would frequently check up on me and were always available when I had any company-related questions or problems. I would also like to thank my other colleagues at Videoland: Dirk Krediet, Lucas Vos and Xander Schrijnder, Marcel Stommels, and Daniella Mittemeyer. They helped me with the setup of the studies and were always available for feedback and questions.

I also want to thank my family and friends for their support throughout this project. They were always interested to hear what I was doing in my thesis project. This motivated and fuelled my enthusiasm throughout the project. Apart from that, they were always ready to check my spelling!

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1. Introduction

Netflix, Videoland, Amazon prime, Apple TV, HBO max who hasn't got a subscription to one of those platforms? Video on Demand (VoD) or streaming Over-the-top (OTT) services are more popular than ever. The biggest difference is that Video on Demand only provides video content, whereas OTT also offer audio broadcasts like podcasts. Data is showing us that the top of this market hasn't been reached yet, with an expected growth of 1,5 billion users by 2026 (Statista, 2021a). The potential of the market is enormous and therefore more companies are entering this market, only in Europe already 29 different VoD services are available (Statista, 2021b). This growing competition makes companies focus on distinguishing themselves from each other.

The growing competition in the market of OTT services makes companies invest even more money into marketing campaigns to keep and grow the number of users on their platforms. To make those campaigns successful the companies invest in research about consumer needs. Subscription costs, content, regulation and policies and retention of the audience are the main challenges these OTT media services face today (Mula, 2022).

Initially, the low price of these services attracted a lot of users. However, with the growing market, users subscribe to multiple VoD platforms and slowly shift away from traditional television. The availability and adoption of multiple platforms make them pickier on other factors than price. Content is the main reason for customers now to subscribe and cancel their subscriptions to an OTT service (Mulla, 2022). The growing availability and the large amounts of content on these platforms make it sometimes hard for users to choose the right platform with the right content. Therefore these platforms need to create the best experience possible to gain new users. Thus this study investigates the following research question:

[RQ]: Given the exponential growth of VoD platforms and their disrupting impact on media and advertising industries, how do personalized content recommendations by a VoD service provider facilitate the adoption of these platforms?

This study uses Videoland as a mature platform in the Dutch OTT market to examine personalized content recommendations and their impact on the adoption of an OTT streaming service. The growth of different companies in the OTT market is different across the world. Videoland is a good example of a platform that is still growing in a mature market and with fierce competition from global OTT streaming services, such as Disney+ and HBO Max. This makes the results generalizable for other platforms in mature markets.

This thesis finds an answer to the research question by combining the knowledge from an adoption perspective and an user perspective. The adoption perspective is based on literature from a business point of view described in section 2. In section 4 these theories are tested in the form of A/B tests where direct manipulations on the adoption of OTT services are measured. In section 3 literature and theories from an user perspective are described and a conceptual model is proposed to analyze them. In section 5 the results of manipulations on content on users' attitudes are given answering the research questions from a user perspective. Section 6 gives insights into the unique contribution of combining both the adoption perspective and user perspective in investigating the adoption of VoD platforms. An overview of the sections:

Section 2: a literature review on the global level of the current OTT industry, business models and factors driving the adoption of OTT services.

Section 3: a theoretical analysis of user attitudinal models and the creation of the conceptual model.

Section 4: the empirical part that shows the literature, method and results of the studies on the visibility of content. In this test, the visibility of the general content on the homepage is increased. Another test is where the visibility of the general content on the homepage is decreased. Another study on the homepage where visibility of the fold is increased.

Section 5: the empirical part that shows the literature, method and results of a user study in the context of VoD services that tests the user perceptions and experiences with the type of content presented on the landing page.

Section 6: the summary, conclusion, discussion and implications of the study on the OTT industry. The results of the theory combined with the empirical study will help explain the adoption of OTT services on a higher level.

2. Literature review

The influence of non-price factors has become important because of the fast-changing streaming OTT market for providers to distinguish themselves. Therefore it is important to get an understanding of nature and the direction of innovation in this market. In the literature review, the growth of VoD services will be discussed, from an economic and business point of view.

2.1. OTT industry and business models

OTT stands for "over-the-top" and is any streaming media service offered to viewers via the internet. The name comes from the content being delivered through another platform, i.e., "over the top" of another device (Alonso, 2019). VoD stands for video-on-demand and is the principle of watching a video whenever you choose to watch it. Platforms like Netflix, Videoland and Prime video are OTT and VoD services because they offer on-demand streaming. The difference is that OTT services also offer services apart from video, such as podcasts etc. OTT and VoD are very closely related therefore research on OTT and VoD can be used.

The technological advances of both OTT and VoD services allow users to use the service anywhere they want (Mulla, 2022; Jones, 2009). In combination with trends in data costs, internet accessibility, and Wi-fi free zones these services have made enormous growth last couple of years (Udoakpan & Tengeh, 2020). The advantages that OTT services offer have led users to cancel their linear television, also known as cord-cutting (Fudurić et al., 2018). However, not all users have cancelled their linear television, there is a group who use both. This group of users are known as cord-shavers, they 'shave' time on using linear television and spend that time on the OTT platform. OTT services are a substitute for these users (Udoakpan & Tengeh, 2020).

OTT services have a disruptive effect on the revenue made in the media and advertising industry. It hurts the advertising industry because linear television advertisements become less valuable and do not reach certain audiences, specifically young people (Fudurić et al., 2018). Falling rates in broadcast TV hurt firms' turnover because the price for advertising online is lower than for television (Cha, 2014). Advertisement and media companies need to adjust to the changing market. To gain revenue the VoD platform's business models can be categorized into four groups:

(1) *Ad-based Video on Demand* (AVoD); the revenue comes from advertisements to pay for content and production, e.g. Youtube.

(2) *Subscription-based Video on Demand* (SVoD); allows users to access the entire video library with a subscription, e.g. Netflix

(3) *Transactional Video on Demand* (TVoD); TVoD is where consumers rent or buy content per piece, e.g. the rent option on Prime Video and Apple+.

(4) *Hybrid Business Models*; the elements of the business models are combined. For example, Videoland has a hybrid business model where it combines AVoD and SVod as a value for money. It offers a lower charge for the basic tier users with advertisement interruptions to their services. For a higher price, the plus and premium tier users get no advertisements (Mulla, 2022).

For advertisement companies, an Ad-based Video on Demand service offers an opportunity (51.6% of total revenue) to come into the OTT market (Figure 1). Whereas most VoD services started with an SVoD business model they now tend to shift due to the changing market. SVoD generates nearly twice as much money per user as AVoD (Shahzeidi, 2022; Statista, 2022). Still, AVoD generates more revenue than SVoD (Figure 1). For example, Netflix lost subscribers for the first time in 2022 more than a decade (Telecompaper, 2022b), raising questions about the viability of subscription-based models (Pallotta, 2022). They now offer a new subscription plan with advertisements, thus adopting a hybrid business model, to keep up with the competition.

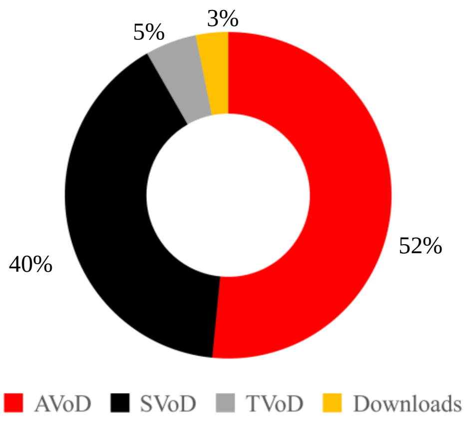


Figure 1, Revenue of different business models of VoD platforms (Shahzeidi, 2022; Statista, 2022).

2.2. The Dutch OTT market

The Dutch market is a mature market that allows us to get a better understanding of the structure and dynamics of these VoD platforms. A good example is Disney+ which used the Netherlands as a test market before launching in the rest of the world (Roxborough, 2019). They used the Netherlands as a test case because of its technical advantages, e.g. a broadband internet penetration of 98% and 7.5 million households small enough for servers to not get overloaded. Nevertheless, the quality of the internet service providers (ISP) is high, The Netherlands is in the top 10 of The Netflix ISP Speed Index, which measures the performance of services/data that travel across the specific ISP network (Netflix, 2022). Consumers in mature markets are used to the fact they have to pay for online content, this can be seen in the huge subscriber rate for multiple services, such as Netflix, Spotify and Videoland. Currently, the biggest VoD platform in the Netherlands is Netflix and the biggest local VoD is Videoland (Figure 2).

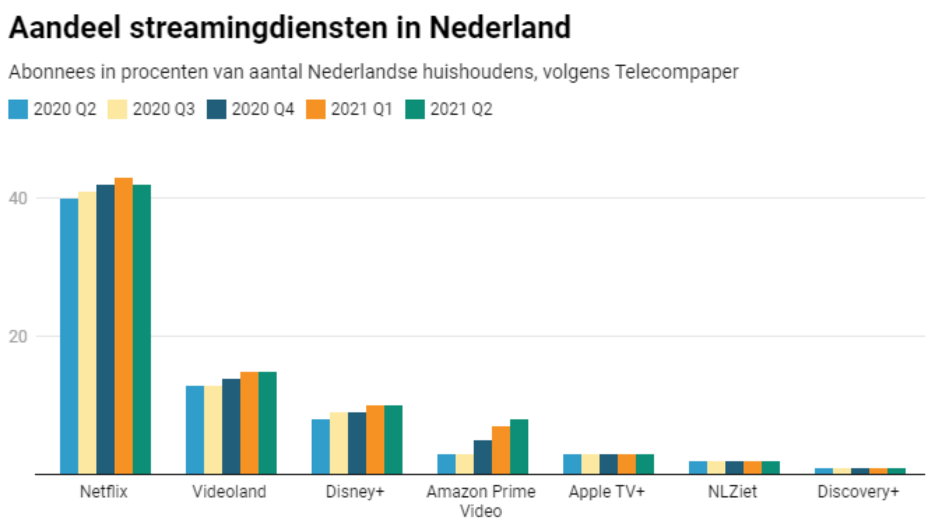


Figure 2, Amount of subscriptions streaming services in the Netherlands per household (Telecompaper, 2021).

The average price of a VoD platform in the Netherlands is €6.25. Viaplay is exceptionally high with a subscription fee of €14,00 (Figure 3). Surprisingly, price is not directly related to the amount subscriptions, Netflix with the most subscriptions is with their pricing on the higher end of the market (almost €8,00). Videoland's pricing is in the middle making it an interesting platform to analyse for this study.

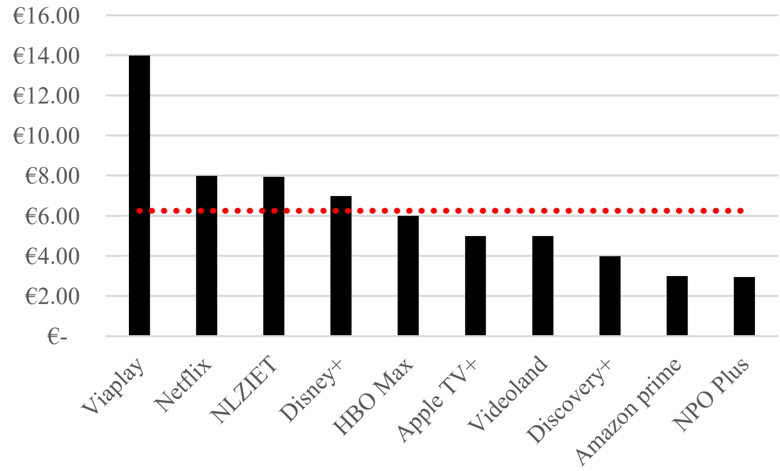


Figure 3, VoD subscription prices where the red line represents the average per month in the Netherlands (Streamwijzer, 2022).

When it comes to the revenue from subscriptions then the revenue for Netflix is 3.5% lower compared to last year. Higher subscription prices could not compensate for the decrease in revenue (Telecompaper, 2022b). In terms of shares in the Dutch OTT market, Netflix's shares have not grown since the first quartile of 2021 (Telecompaper, 2022b). While other VoD platforms, such as Videoland, Disney+, and Prime Video, shares is still growing. The growth of these market shares shows that the market is not yet saturated. Additionally, the amount of "stackers", households with two or more streaming services, is growing allowing a bigger market share for Netflix's competitors (Barnar, 2022). These "stackers" mostly combine Netflix with Videoland, Disney+, Viaplay, Prime Video and HBO Max (Barnar, 2022). Knowing that new competitors will enter the market, it is expected that new stack combinations will occur in upcoming quartiles in the Netherlands (Van den Broek, 2022; Telecompaper, 2022a). Therefore, it is interesting to see which factors can influence the further growth of Videoland in the Dutch OTT market and whether these factors can be applied to other mature markets.

The type of content that users watch differs across VoD services. Videoland has the highest share of customers watching series followed by Netflix and HBO Max. Whereas Viaplay is dominated by customers watching sports, mainly showing the value of Formula 1 for the growth of Viaplay in the Netherlands (Barnar, 2022).

2.3. Impact of user behaviour on the adoption of OTT services

User behaviour influences the factors driving OTT services adoption. These factors can be divided into price and non-price factors. Offering a low price, it encourages users to try a new platform. Whereas non-price factors such as content and the flexibility of the platform can help users keep their subscriptions (Mula, 2022). In the following paragraphs, these user adoption factors are further explained.

2.3.1. Price

Price has a major influence on the adoption rate and engagement of OTT platforms. A low monthly fee encourages new consumers to switch from linear television to OTT platforms. A low fee encourages them to use it only for a specific movie or show, and as an extra experience the service and find out other opportunities (Lee et al., 2016). Price is also a variable identified that significantly affects perceived benefits (Kim & Kim, 2020). Cost-benefit associations have an impact on affective reactions, cognition, and behaviours and are dependent on situational and personal factors (Kamleitner & Hölzl, 2009). Businesses want to highlight the benefits, rather than costs, of their products to increase purchases. Motivating factors for VoD portals are the freedom to watch films and series at any time with the absence of commercials. Furthermore, the content needs to be up-to-date and the offering of a wide variety of films and series (Mikos, 2016). Communicating that a subscription is a way of buying goods and services at a sensible price can help with persuasion (Kim & Kim, 2020).

The landscape is more dynamic in mature markets, e.g. US, Canada and the Netherlands, compared to upcoming markets, e.g. Middle-East and North Africa. This means the competition is high and users have more choices between platforms. They can discover content at a price point they are comfortable with. Resulting that in these dynamic markets consumers make an informed choice by adding and cancelling services in search of the best value for their time and money (Bhullar & Chaudhary, 2020). Especially for SVoD services, where subscribers cancel their subscriptions due to price increases, content changes, or subscription fatigue (Udoakpan & Tengeh, 2020).

2.3.2. Contents

Consumers have more choices on what to watch with the expanding market in OTT platforms. The acceptance and use of a new platform increase when it is different from cable television in satisfying their needs (Cha, 2013). The same study examined whether the genre influences the choice of a particular platform. It distinguished eight different genres of video content, where reality shows were the most popular genre in viewer preferences (>70% of the studied group of people). The genre favourites do differ from the ‘traditional’ cable television, where news and sports are the most popular genres (Fudurić et al., 2020). This difference in the genre might be the result of the on-demand option of Video on Demand, while news and sports can be outdated when watched at a later time.

The problem with most OTT platforms is not the lack of content but the large scope of their content. Consumers get lost in the big amount of choices. Prior studies in e-commerce have shown that recommender systems can significantly reduce information overload, product uncertainty, as well as search time (Xiao and Benbasat, 2007). A recommendation content strip can help filter the scope of content by showing content adjusted to user preferences. They can enable item “discoverability”, meaning that they can increase the visibility of items that would otherwise not be found. It will help users explore and find content that matches their long term-preferences (Jannach & Adomavicius, 2016; Gomez-Uribe & Hunt, 2015; Knijnenburg, Willemsen & Kobsa, 2011). Thus from a business point of view recommender systems can be used to increase product sales or conversion rates, because customers get a better experience with the OTT service.

Recommender systems are already widely used on homepages of VoD services to help users search and find content that fulfils their needs (Alvino & Basilico, 2015). However, most of those recommender systems use complex recommender techniques and algorithms based on a large dataset containing implicit and explicit data of its users (Ko, Lee, Park & Choi, 2022). In this study the adoption of a platform is investigated, there is no information available on the users that want to adopt a service. Thus personalization with implicit and explicit data is not possible. Hence, a more straightforward recommendation method is needed such as an item-based recommender system. An item-to-item recommender system uses in this case certain item, e.g. title of a show or movie, to recommend other items. Targeted advertising for a show or movie can play a part in providing a starting point for personalizing the content on the landing page.

The growth between different companies in the OTT market is different across the world and in the Netherlands. The fierce competition makes it harder for companies to distinguish themselves based on price. Consumers have more choices on what to watch and which platforms to stack with the expanding market. In mature markets, non-price factors are weighted heavier than in less mature markets, e.g. Africa (Bhullar & Chaudhary, 2020). To further understand the adoption of OTT platforms we will identify adoption factors from a user perspective in Section 3.

3. Conceptual model

The growth of OTT services is explained in the literature review from a business perspective. However, the user perspective should not be forgotten, because understanding human intrinsic behaviour to adoption can help explain the growth patterns in the market. To evaluate the user perspective a conceptual framework is created. The conceptual model explains which type of content affects which experience-related factors to understand the intention to use an OTT service. The foundation of the framework is based on the framework proposed by Knijnenburg et al. (2012) which brings subjective and objective measurements together to explain the user experience and behaviour of recommender systems. Where user experience (EXP) is caused by objective system aspects (OSA), mediated by subjective system aspects (SSA), and moderated by personal (PC) or situational characteristics (SC).

3.1. Attitudinal models

When it comes to the adoption of technology, the attitudes of users can be used to predict behaviour. These attitudinal concepts are described in attitudinal models. To understand the conceptual model that is used in this study, different attitudinal models are described and their influence on user behavioural intention. Knowing which attitudinal factors are important in the adoption of OTT can provide insights into which experience-related factors (EXP) can have a positive effect in changing these attitudes.

3.1.1. Technology Acceptance

Acceptance is fundamental for the adaptation of new technology or service. One of the fundamental models in the field of Information Technology (IT) is the technology acceptance model (TAM) (Davis, 1989), which posits that the attitude toward a system can be explained by two beliefs:

(1) *Perceived ease of use*, the extent to which using a system will be free of effort.
(2) *Perceived usefulness*, the extent to which using a system will enhance a user's job performance

The system itself forms the external factor that influences this attitude towards the system. Fundamental to TAM is the theory of reasoned action by Fishbein and Ajzen (1975) which states that individual behaviour is driven by the individual's behavioural intention. Attitudinal and normative factors influence this behavioural intention which in turn predicts actual behaviour, according to the theory of planned behaviour (Ajzen, 1985).

Venkatesh et al. (2003) integrated eight behavioural intention models, including TAM, and proposed a new model the Unified Theory of Acceptance and Use of Technology (UTAUT) that explains about 70% of the variance in behavioural intention. The UTAUT model structure includes four components namely, (1) performance expectancy (similar to perceived usefulness), (2) effort expectancy (similar to perceived ease of use), (3) social influence and (4) facilitating conditions. . The UTAUT model includes four moderators; (1) gender, (2) age, (3) experience and (4) willingness to use. The original UTAUT model was developed to explain employee technology acceptance and use in an organizational context. Criticism of these models has been the utilitarian approach to adopting technology systems, in which hedonic attributes are not taken into account.

VoD services are a hedonic product and therefore perceived enjoyment and perceived ease of use are stronger predictors of intention to use than perceived usefulness (van der Heijden, 2004). Hence Venkatesh, Thong & Xu (2012) proposed a new model (UTAUT2) tailoring the UTAUT to a consumer use context incorporating hedonic benefits (Figure 4). They found that adding hedonic motivation (e.g. enjoyment), habit and price value were crucial to add to the scope of UTAUT2 in the consumer environment. Moreover, previous studies in the context of entertainment streaming services found that hedonic motivation, e.g. enjoyment, has a contributing factor to user adoption (Walsch & Singh, 2021; Chen et al., 2018). In this study an adoption of the UTAUT2 model will be used, where only the factors that can be linked to content are adopted in the model.

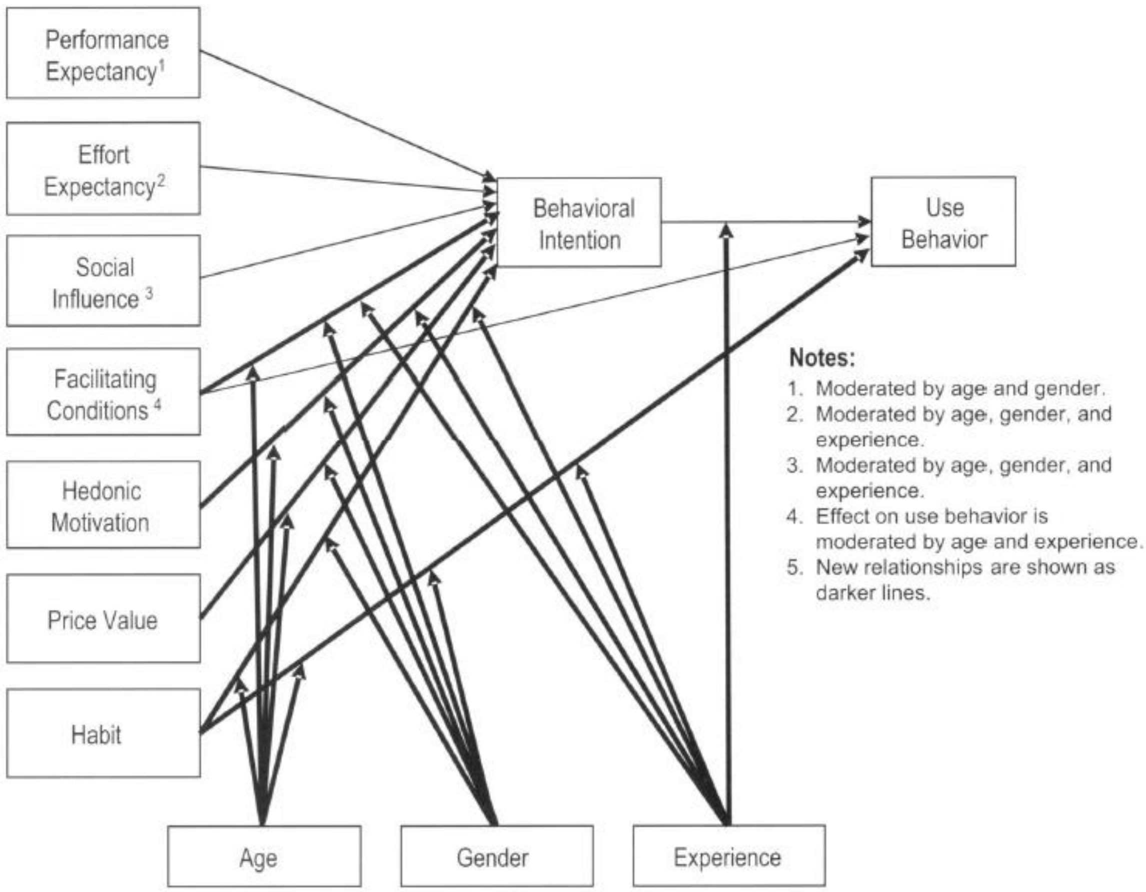


Figure 4, UTAUT2 model (Venkatesh, Thong & Xu, 2012)

3.1.2. Perceived value theory

Perceived value is the customer's overall perception of online content services based on a cost-benefit trade-off (Zeithaml, 1988). Wang, Yeh & Liao (2013) adopted perceived value into the TAM model by replacing perceived usefulness with perceived value as a predictor for purchase intention in a value-based adoption model (VAM). The results of their study indicated that perceived enjoyment, perceived usefulness, and perceived fee have a significant influence on perceived value (Table 1). In turn, consumers that had a high perceived value of using online content services were more likely to purchase the service. Thus service providers should enhance customers' value perception by improving the utilitarian and hedonic benefits of their service to increase purchase intention.

Originally the multidimensional perceived value theory consisted of five broad aspects (1) social, (2) emotional, (3) conditional, (4) epistemic and (5) functional (Sheth et al., 1991). Later, the functional value was divided into two categories: (1) monetary values and (2) convenience values. This was done to make it more appropriate for online services. Oyedele & Simpson (2018) made a model based on the perceived value theory on how a customer perceives the value they receive from video streaming by adding the value components; convenience, monetary, emotional and social alongside cognitive effort and identity salience. These aspects are all closely related to the concepts of TAM, UTAUT and VAM.

(1) *Convenience value* represents the user's perception of the time and effort needed to seek out and use self-service technologies.
(2) *Monetary value* represents the cost-benefit trade-off in line with the findings on perceived fee (Wang, Yeh & Liao, 2013) and price value (Venkatesh, Thong & Xu, 2012).
(3) *Emotional value* relates to the hedonic benefits where the effect includes the enjoyment a customer derives from using the service.
(4) *Social value* is derived from the function of the service capable of enriching the social image of the customer when sharing it with its social group (Sheth et al., 1991). Social value fits with the UTAUT aspect of social influence.

Oyedele & Simpson (2018) found that all perceived value concepts significantly affected recommending an entertainment streaming application (both music and video services) except for monetary value. Emotional and Social values had an influence on identity salience which in turn influenced hours of use. App developers can make apps more engaging by customizing content relating to people's self-identities. For example, HBO addressed in their social media campaigns of "Game of Thrones" different program characters to appeal to certain sub-cultures.

Singh et al. (2021) extended the research of Oyedele & Simpson with six important determinants, (1) effort expectancy, (2) performance expectancy, (3) perceived innovativeness, (4) perceived risk, (5) perceived enjoyment and (6) addiction to heavy viewing. The last four determinants were directly linked to determining continued intention. The factors of the model of Oyedele & Simpson (2018) were linked to determine perceived value. Effort expectancy and performance expectancy of the UTAUT were linked to determine personal innovativeness. Their results showed that convenience value has the strongest impact on the perceived value of a user, followed by monetary, emotional and social value. Overall, there is a significant positive impact of perceived value on users' continued intention to use streaming services (Table 1). In addition, perceived enjoyment, personal innovativeness and addiction all significantly affected continued intention (Table 1).

In our study, a combination of the predictors of the UTAUT2 model and the model proposed by Singh et al. (2021) is used to include all factors in the model. An overview of all the results can be found in Table 1. These factors will be used to determine the user intent, as a user experience measurement (EXP), for using Videoland. As in Knijnenburg et al. (2012), the measurements will provide insights if user experience measurements explain the user intent to subscribe to Videoland.

First of all the user experience measurements are linked to the manipulation of certain objective system aspects, e.g. different types of content. This study is focussing on the non-price factor content and its relation to OTT adoption. The changes in presentation and type of content are done to the purchase intention of VoD services described by Mikos (2016). Content can be linked with two user experience values from UTAUT2 and its extensions, perceived value (Wang, Yeh & Liao, 2013; Venkatesh, Thong & Xu, 2012) and perceived enjoyment (Singh et al., 2021; Venkatesh, Thong & Xu, 2012). Perceived usefulness is not integrated into the model, because it was not significant for hedonic products, especially not for VoD services (Leowarin & Thanasuta, 2021), and rather a predictor of perceived value (Wang, Yeh & Liao, 2013; Venkatesh, Thong & Xu, 2012). Monetary value is not taken into account in this experiment, since it is a price factor. As Figure 3 shows the price of Videoland is below average, the effect can be neglected. Thus non-price factors play a more important role in the adoption of the OTT platform. The non-price factor effort and performance expectancy are not integrated into the conceptual model, since the manipulation does not affect them.

3.2. User experience and subjective system aspects

In the field of human-computer interaction user experience models have been used to investigate the hedonic and experiential aspects of technology use (Hornbæk & Hertzum, 2017). TAM and its adaptations provide representations of the psychological processes and intermediary factors underlying technology acceptance and behavioural intention. Most of the adaptations of TAM incorporate perceived enjoyment, which connects technology acceptance with user experience through its hedonic aspect. A disadvantage of these models is that they are not closely related to the product's qualities (Diefenbach, Kolb & Hassenzahl, 2014). Hassenzahl (2004) proposed a model of user experience where objective aspects, e.g. product features such as content and presentation, are divided into pragmatic and hedonic attributes. These perceptions, in turn, have consequences causing an experiential evaluation (Figure 5). Pragmatics refers to the product's perceived ability to fulfil do-goals. Whereas hedonics refers to the product's perceived ability to fulfil be-goals, like novelty and identification.

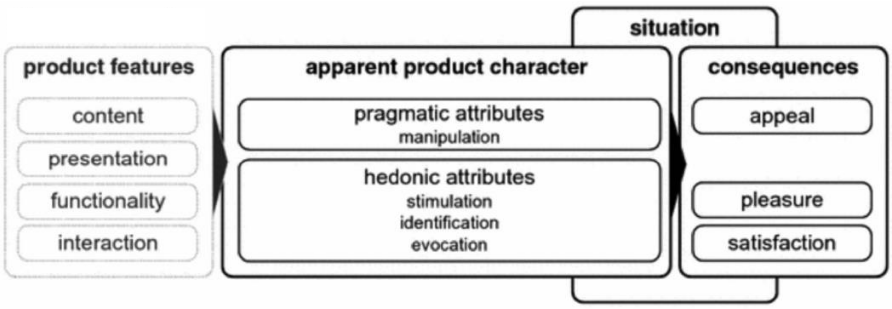


Figure 5, Model for user experience (Hassenzahl, 2004)

A study done by Van Schaik & Ling (2011) proposed an experience-acceptance model that integrated Hassenzahl's model of interaction experience into TAM, to produce a more complete model and to clarify the role of interaction experience in technology acceptance. The results show that both types of hedonic quality were predictors of perceived enjoyment (Table 1). This approach is used in our framework to link the hedonic quality of content to predict perceived enjoyment.

The approach of Hassenzahl's model (2004) of interaction experience can be used in our model as well as subjective system aspects that mediate the experience of the different types of versions of the landing pages that are proposed in this study. The personalized content influences the apparent product character which in turn might influence perceived enjoyment and perceived value. For the objective systems aspects, different versions of landing pages are used. Where the manipulation of these objective system aspects will be linked to the product feature content of Hassenzahl's model. The pragmatic predictors of van Schaik & Ling (2011) are not integrated, because the content does not affect these qualities.

Knijnenburg et al. (2012) proposed to include the subjective systems aspects (SSA) described in Hassenzahl's model in an SEM model to provide a more extensive understanding of how and why features affect the user experience. They are evaluated based on the system feature itself. It is a more practical approach to why certain behaviour, intentions and interaction appear. Therefore, this approach is used in our study and the SSAs added to measure whether the users perceive the personalized content as relevant and fit their needs. (1) perceived recommendation quality and (2) perceived level of personalization. Then (3) perceived novelty and (4) perceived recommendation diversity are SSAs added to measure the difference between the top content and new content conditions and whether this influences the perceived value and enjoyment differently.

Author	Context	Theory	Predictors	Predictors	Dependent variable	Findings
van der Heijden (2004)	Dutch movie website	TAM	PE, PEU and PU		Intention to use	PEU and PE approximately twice as much predictive value to explain intention than PU.
van Schaik & Ling (2011)	Wikipedia	Hassenzahl (2004) and TAM	Goodness, Beauty, Pragmatic quality, Hedonic quality	PU, PEU, PE	Intention to use	PU, PEU and PE all significant predictors for intention to use. PU was mediator of the effect of PEU on Intention to use. Goodness and Beauty do not independently predict intention to use. Both types of hedonic quality were predictors of PE, where only HQ-identification was significant for PU and PEU.
Venkatesh, Thong & Xu (2012)	Mobile internet	UTAUT2	Effort expectancy, performance expectancy, Social influence, facilitating conditions, Hedonic motivation, Price Value, Habit, Gender, Age, Experience	Behavioural intention	Use behaviour	Social influence, performance and effort expectancy direct significant effect on behavioral intent and all moderated by age, gender and experience. Behavioral intention and facilitating conditions signifcant impact on use and moderated by experience. Habit has both a direct effect on use and indirect effect through behavioral intention.
Wang et al. (2013)	E-commerce	VAM	PU, PE, technicality, perceived fee	PV	Purchase intention	PU and PE positive effect on PV, Perceived fee negative effect PV. Technicality not significant. Perceived value positively affect purchase intention
Oyedele & Simpson (2018)	Entertainment streaming services (ESA)	UTAUT		Cognitive effort, CV, MV, EV, SV, identity salience	Hours of use, Recommend	Influenced by EV and SV only identity salience significant effect on use. All perceived value constructs except MV significant for recommendation
Fernández-Robin (2019)	Netflix	UTAUT2		Trust, effort expectance, performance expectance, hedonic motivation, social influence, facilitating conditions, price value	Behavioural intention	Trust, performance expectancy and hedonic motivation are significant predictors for behavioural intention
Singh et al. (2021)	Live streaming services	VAM, UTAUT	Effort expectancy, performance expectancy, CV, MV, EV, SV	PV, personal innovativeness, PE, perceived risk, addiction	Continued intention	CV, MV, EV & SV all significant predictors of PV. Effort expectancy and performance expectancy significant for personal innovativeness. Personal innovativeness, PV, PE and addiction significant for continued intention.
Leowarin & Thanasuta (2021)	SVoD	TAM, VAM and TRA		PU, PEU, Subjective norms, PE, Perceived fee	Purchase intention	All significant except PU

Abbreviations: Perceived usefulness (PU) , Perceived ease of use (PEU), Perceived enjoyment (PE), Perceived value (PV), Convenience value (CV), Monetary value (MV), Emotional value (EV) and Social value (SV)

Table 1. Overview of attitudinal models on OTT services

3.4. User characteristics and user adoption of OTT services

External user factors and user characteristics influence the adoption and acceptance of OTT services. The uses and gratifications theory states that people are affected differently by the same media content, based on their ideas and what they want to do with the media (Samani & Guri, 2019) Meaning that individual personalities, values, background, race, and gender influence consumer's choice (Shobiye et al., 2018).

Viewers adopting OTT services differ in all kinds of ways. Such as differences in the demographic area, for example in South Africa consumers are mostly in the age group of 35 to 45 and from low-income backgrounds (Udoakpan & Tengeh, 2020). Contrary to the more mature market like the US and the Netherlands, where generation Z and millennials are more likely to adopt OTT services. Additionally, young consumers shift in video behaviour by spending more time on OTT platforms than on live tv (Fuduric et al., 2020). When it comes to the Dutch market Netflix, Disney+ and HBO Max show a relatively stronger age trend in intention to subscribe**,** with the highest interest among consumers between 16 and 25 (Barnar, 2022).

Apart from age, other user characteristics can influence user intent. A study on live streaming in China showed that there are no differences between males and females in live-streaming audiences. Both males and females watch for approximately 30 minutes to two hours and on average four times a week (Long & Tefertiller, 2020). A study in India confirmed these results for SVoD services specifically the willingness to subscribe declined as age increased and that gender had no significant influence (Nagaraj, Singh & Yasa, 2021). China and India are different from the Netherlands. Checking the gender differences for services in the Netherlands we see that Netflix, Videoland and Disney+ have higher shares among women, while Viaplay and Amazon Prime have higher shares among men (Barnar, 2022) However, these differences are small, especially as services will be shared among couples/families. Thus in the conceptual model both age and gender are only measured as exploratory variables.

3.4. Conceptual framework

The conceptual framework is built to investigate which objective system aspect influences intention to use. The diverse offering and types of content are one of the main reasons for users to adopt an OTT service. Therefore, in this thesis different types of content strips are investigated to find out which type works best. The OSAs are personalized content compared to top content and new content. Top content and new content are already used as content strips to show which content is available on the platform and are therefore added as a control condition. These content types are non-personalized and based on the average of all users on the platform. A more personalized approach towards users might help users to adopt an OTT service because it tailors to users' specific needs. Additionally, personalized content is not yet used or investigated by VoD platforms until now.

The user study investigates whether these aspects influence our intention to use. Therefore, intention to use is the construct that is chosen to measure the adoption of the VoD service. Integrating the knowledge gained from the literature study on attitudinal models (Table 1) and perceived value theory it is expected that perceived value predicts intention to use (Singh et al., 2021; Wang et al., 2013). Perceived enjoyment is measured as the other predictor for intention to use (Leowarin & Thanasuta, 2021; Singh et al., 2021). It is expected that the intention to use caused by different types of content is mediated through both these two constructs (Figure 6).

Integrating this framework with the knowledge we gained from the literature study on Hassenzahl's model (2004) certain aspects of content influence the user experience constructs, these SSA's are integrated as mediators between the OSA and EXP predictors of intention to use. Perceived recommendation quality and perceived recommendation level of personalization are added to measure whether the user sees the personalized content as more relevant and if they perceive them as more personalized (Knijnenburg et al., 2012; Willemsen, Graus & Knijnenburg, 2016). Content perceived as relevant and fits the user's needs increases the perceived value and enjoyment.

Perceived recommendation diversity is added to measure whether the non-personalized content is more diverse compared to the personalized content (Willemsen, Graus & Knijnenburg, 2016). In turn, it measures the effect of diversity on perceived value and perceived enjoyment.

Perceived recommendation novelty is added to measure whether the new content is perceived as more new compared to the personalized content (Ekstrand et al., 2014). In turn, measures the effect of perceived novelty on perceived value and perceived enjoyment.

From the literature on user characteristics of OTT services, only experience is added as a personal characteristic in the model (Figure 6). Age and gender are only measured as exploratory variables.

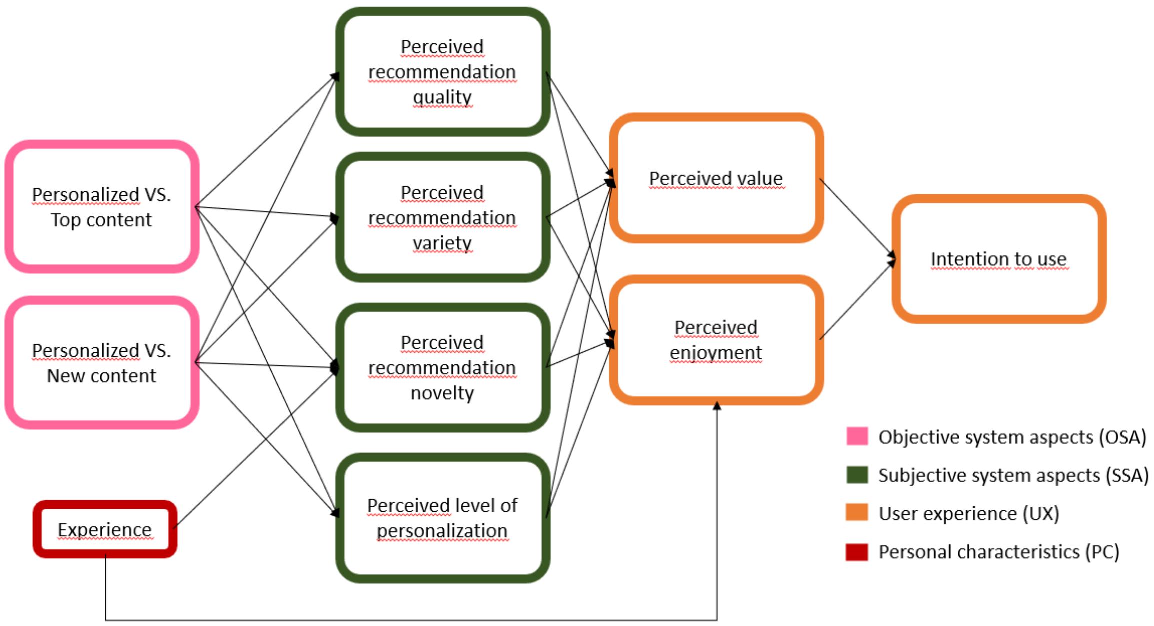


Figure 6, Conceptual structural equation model

3.5. User interaction

User experience and attitudinal models are subjective models to explain user behaviour. The actual behaviour can be measured objectively and might in turn influence the user experience. For example, longer dwell time might influence user satisfaction and in turn, satisfaction might influence the dwell time on the page. In previous literature, several objective measurements have been used to test and evaluate user behaviour on a website.

An online method to evaluate the direct impact of a recommender system is *A/B testing* (Aggarwal, 2016). In A/B testing two or more variations of the system are used where one of the variations can become the winner. For example, for a video platform, one might measure the conversion rate of users clicking on a specific movie or series that was recommended or one might decide to subscribe or not. *Conversion rate* is the observed frequency where the user performs the desired action amongst the people that clicked on the advertisement (Becker et al., 2009). It is used to measure whether a user adopts the system more when a different type of page will be presented. The conversion rate itself is limited in that it does not explain why a user performs a certain action. It simply tells when a user performs an action and if certain actions will be performed more in a different scenario.

Research in the e-commerce sector investigated the associations between website features and conversion rates. Adding certain website features for the customer website flow can enhance purchase intention and conversion rate. When it comes to the visitor greeting page, e.g. the first page a visitor sees, both showing recommended products, as well as featured products, increasing the conversion rate (McDowell, Wilson & Kile, 2016). Therefore, in this study manipulating website features (content presentation) in an A/B test helps to prove that certain website manipulations lead to the adoption of the VoD platform. The conversion rate is used to measure the business value of the personalized recommendation page and to measure the direct effect of objective system manipulation on user behaviour.

The conversion rate provides the connection between actual behaviour and intended behaviour in the conceptual model. As we know from the Theory of Planned behaviour user intent predicts user behaviour. In this case, the user study is connected by user intent to the conversion rates in the A/B study where users' actual behaviour is measured. In section 4 AB tests on content and the presentation on content are done to measure the effects in a real-life setting. These results are limited in that they only explain what works and not why. Therefore in chapter 5, a conceptual model is from an user perspective on why certain manipulations work. The combination of those studies gives insights into the whole adoption process of OTT services.

4. Presentation of content

Videoland operates in a mature OTT market where the competition is high and consumers have more choices to discover content for the price they want. Resulting in consumers making an informed choice by adding and cancelling services in search of the best value for their time and money (Bhullar & Chaudhary, 2020). When we check the price of Videoland it is below average in the Netherlands (Figure 3) therefore we focus on the value of the platform. The value of a service is presented to the user in the form of marketing (advertisements) and on the platform itself, the landing page in this case. A user study done by Videoland and current feedback surveys on the homepage shows that the main user problem is the lack of information on the general content offered by Videoland (Figure 7).

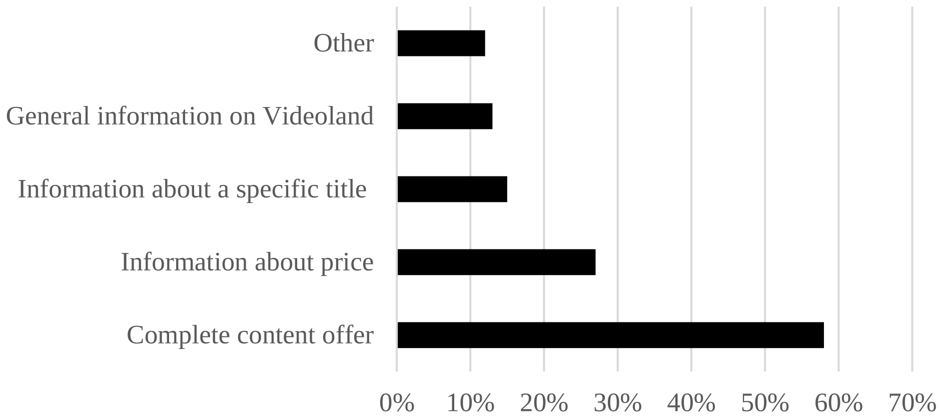


Figure 7, Answer to the question on the homepage: what is the information you are looking for? (Videoland feedback, Nov-May 2022)

As previously discussed in the literature content is one of the most important non-price factors for users to adopt an OTT service (Cha, 2013). Therefore three studies in the form of A/B tests are done on the presentation of content on the homepage to answer the following research question:

[RQ1]: To what extent does the visibility of content shape the adoption of a VoD platform?

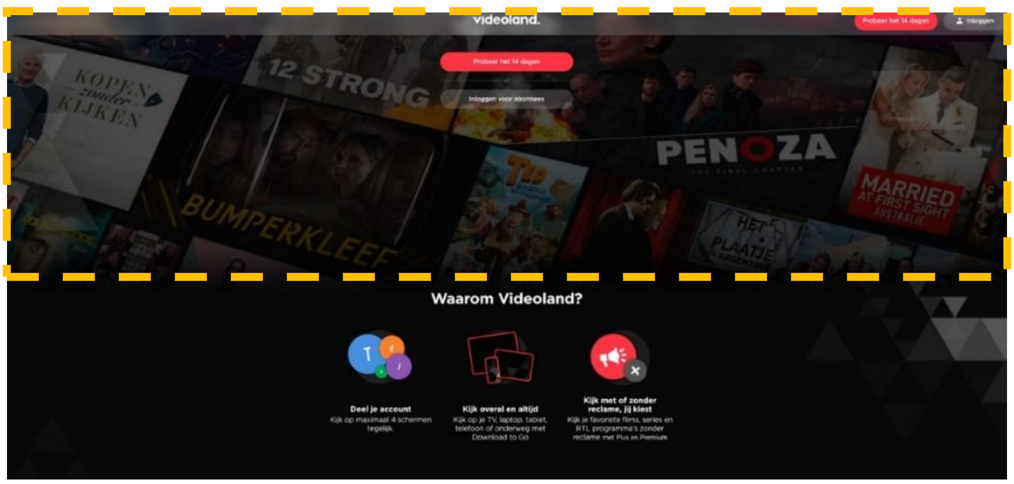


Figure 8, Current interface of the homepage of Videoland. The dashed area is the initial screen (fold).

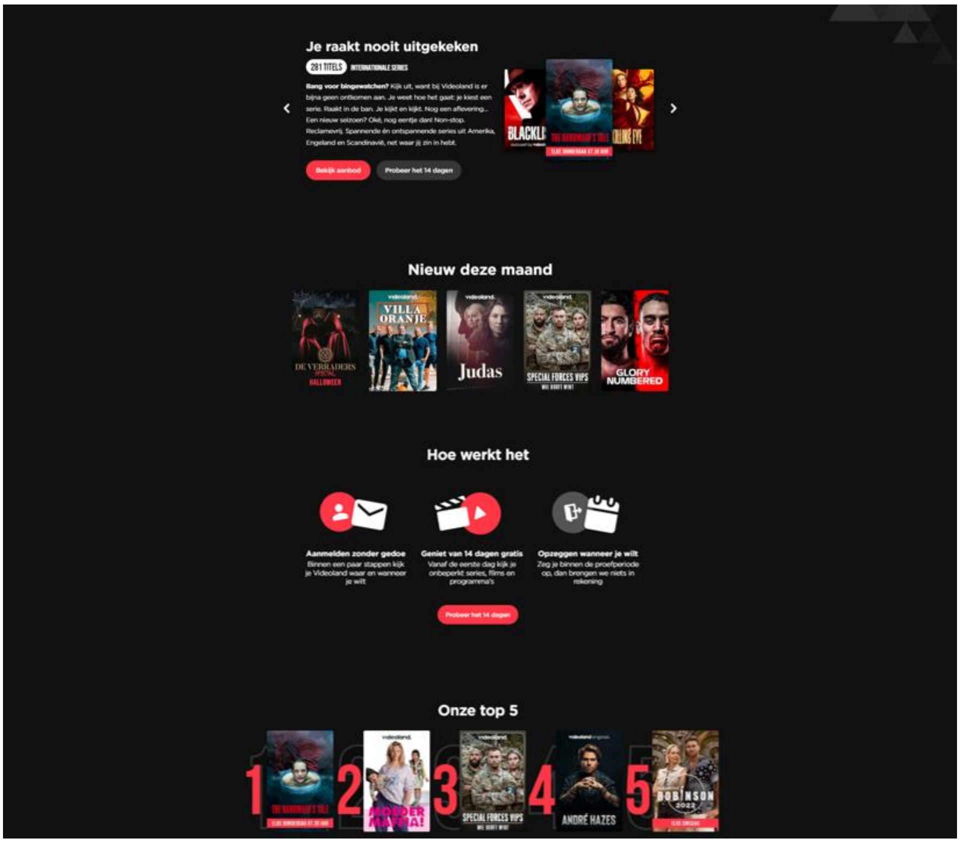


Figure 9, Interface after scrolling down

When checking the design of the homepage (Figure 8) the content offered is shown as a background image above the fold and the content is presented by scrolling the screen halfway to spot two strips with content items (Figure 9). The first content strip is the five upcoming series and movies (New this month) on Videoland and the second content strip is the five most popular series and movies on Videoland. When studying user interaction on the homepage, the heatmap of the homepage from Videoland shows that most of the users do not scroll that far below the fold, i.e. the initial screen when entering the page. This might explain why users lack information about the general content because the content strips are simply not perceived. The fold contains content (Figure 8) with images of titles on the platform. However, the opacity of the images is very low making it hard to see them, especially on a phone. Following these observations we can assume two things: the content strips are often not perceived and/or the content on the background of the fold is not easily perceived. Based on the literature review and the current design this study asks the following questions about the content strip:

> *[SQ1]: Does increasing the visibility of the general content, by moving the content strip higher on the homepage, increase conversion rates?*

The second sub-question tries to answer whether the current background is perceived:

> *[SQ2]: Does decreasing the visibility of the general content, by removing the background of the fold, increase conversion rates?*

4.1. Study 1: increasing visibility below the fold

4.1.1. Setup and expectations

The first study on the presentation of content is to improve the visibility of the general content offered on Videoland. Content plays an important part in the cost-benefit trade-off in deciding to adopt an OTT platform. Informing consumers of about that the content available by subscription arouses enjoyment can be a good way of presenting the cost-benefit trade-off (Kim & Kim, 2020). From previous studies on presentation, we know that *order effects* influence user decision-making, where films on the top left of the initial screen are watched more often than those elsewhere and people are more likely to scan vertically than horizontally (Johnson, 2021; Alvino & Basilico, 2015). Even more, the items that users see first are intuitive and of higher importance than other items seen later (Jesse & Jannach, 2021; Caraban et al., 2019; Sunstein, 2016). Thus placing the content strips higher on the homepage increases the visibility of the content offer and offers a good way of presenting the consumer good. Apart from the presentation, we can distinguish the type of content by experimenting with two types of content strips, namely the Top-5 and New-5. The type of content can influence the perceived value and persuasion of users. Two types of users convert on the homepage: new users and returning users that had a subscription in the past. The returning users are already familiar with the content that is available on the platform. Previous literature suggested that in mature markets users cancel and resubscribe their VoD subscription based on an informed choice of content and price (Bhullar & Chaudhary, 2020; Udoakpan & Tengeh, 2020). Thus it is expected that these users want to reactivate their accounts because they want to see the new shows or seasons that have become available on the platform. Rather than see the information on shows that they have already seen. However, for new users with no experience with the platform, the top content is more interesting because it is the most popular among the current users. It gives an average of what is generally most liked and watched. For the new content, it is yet to be determined whether it will be a success or not. Providing that content positively affects the adoption of OTT services we create the following hypothesis:

[H1]: Showing New-5 content more prominently (above the fold) increases conversion rates compared to the baseline condition (current situation).

[H2]: Showing Top-5 content more prominently (above the fold) increases conversion rates compared to the baseline condition (current situation).

[H3]: The increase in conversion rates relative to the baseline, is higher for new users in the Top-5 condition.

[H4]: The increase in conversion rates relative to the baseline, is higher for returning users in the New-5 condition.

4.1.2. Research design and procedure

An A/B test with three variants was conducted on the homepage of Videoland, e.g. the home page. Control is the baseline condition of the current homepage. Variant 1 was the New-5 content row that shifted upwards and variant 2 was the Top-5 most popular row that shifted upwards (Figure 10). To test hypotheses 1 and 2 the total conversion rates of both new and returning users were measured for all variants, control, the New-5 and the Top-5. For hypotheses 3 and 4 the conversion rate of new users and returning subscriptions were measured. Apart from the type of users the difference between mobile and desktop was measured for exploratory purposes.

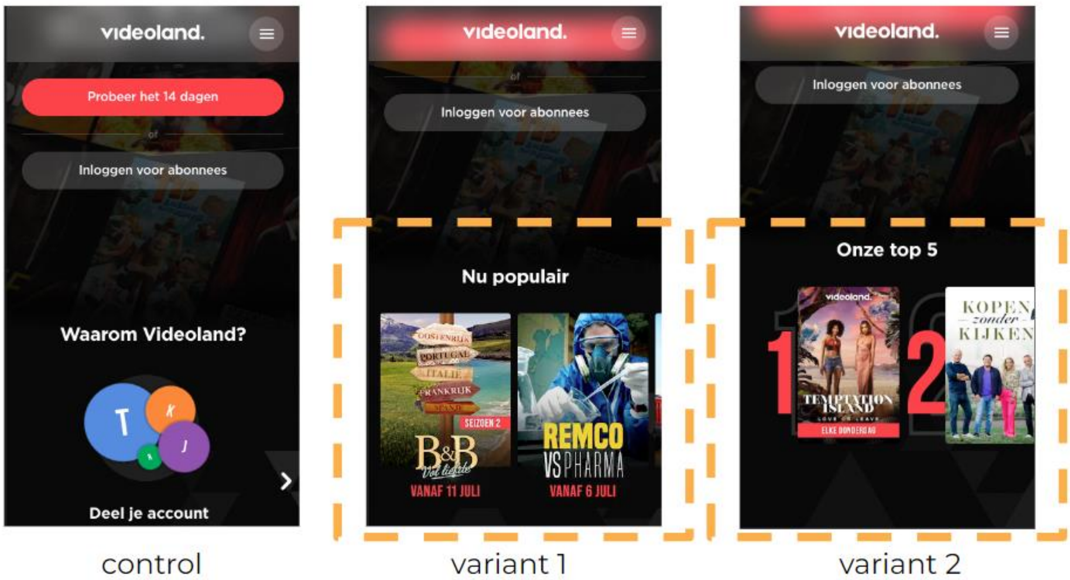


Figure 10, the interfaces after scrolling, where control is the current interface, variant 1 is the new content strip and variant 2 is the top content strip

4.1.3. Results

A chi-squared test is used to test whether the conversion rates are significantly different between the conditions. The chance to beat the control determines the statistical significance and shows the probability that the variation page will perform better than the control version. The chance to beat control is set at a threshold of 80% to be implemented on the page. The chance to beat control is calculated with the use of Bayes' theorem:

$$P\ (A|B) = \frac{P\ (B|A)\ P(A)}{P(B)}$$

The absolute conversions and conversion percentages are anonymised, because of commercial reasons.

		Conversion rates for new users				
Version	**Audience**	**Conversions**	**Conversion %**	**Diff. %**	**Chance to beat control**	**Result**
Control	82,222	[redacted]	[redacted]			
New-5	81,639	[redacted]	[redacted]	-0.16%	47.73%	inconclusive
Top-5	81,827	[redacted]	[redacted]	-9.73%	1.47%	negative

Table 2. Results from conversion rates of new users

Following the research question, moving up the New-5 and Top-5 content does not result in more conversions on the total transactions (Table 2). Comparing the New-5 and Top-5 content to control, we find a significantly lower conversion for Top-5 (p=0.018). The CTBC control of 2%, shows that there is a 98% chance that Top-5 performs worse than the control. There is a non-significant effect (p=0.973) comparing New-5 against the control version. The CTBC of 48% shows that control beating New-5 is likely due to random chance. There is a significantly lower conversion rate of Top-5 compared to New-5 (p=0.016). When checking the viewport of the page visitors, only 4,4% of the total visitors scrolled just below the fold to see the strip (Table 3).

Audience check		
	% Actual	*Actual*
Total	4.4%	11,237

Table 3. Amount of users within the viewport of the manipulation

Total conversion rates						
Version	**Audience**	**Conversions**	**Conversion %**	**Diff. %**	**Chance to beat control**	**Result**
Control	4,006	[redacted]	[redacted]			
New-5	4,170	[redacted]	[redacted]	0.05%	48.23%	inconclusive
Top-5	1,471	[redacted]	[redacted]	-20.98%	4.61%	negative

Table 4. Results of the total conversion rates

In Table 4 we find the results of the A/B/C test for the users that were in the viewport of the manipulation. When checking the sample size there is a sample ratio mismatch, since Top-5 only has 1471 users in its sample whereas control has a sample of 4006 users and in the sample of New-5 are 4170 users. To examine hypothesis 1 for the users that saw manipulation we find a non-significant difference in conversion rates for New-5 compared to the control (p=0.148). The CTBC of 48% shows control beating New-5 is mostly likely due to random chance.

To test hypothesis 2 by comparing the Top-5 against the control and find a non-significant lower conversion rate for Top-5 (p=0.052) (Table 4). However, the CTBC is 5% indicating that 95% of the time control performs better than Top-5. These results are not in line with hypothesis 1, since New-5 is lower than the control strip. Hypothesis 2 is rejected because the Top-5 strip has a lower conversion rate than the control.

Conversion rates for new users						
Version	**Audience**	**Conversions**	**Conversion %**	**Diff. %**	**Chance to beat control**	**Result**
Control	4,006	[redacted]	[redacted]			
New-5	4,170	[redacted]	[redacted]	-4.76%	32.96%	inconclusive
Top-5	1,471	[redacted]	[redacted]	5.65%	59.52%	inconclusive

Table 5. Results on the conversion rates of new users

For hypotheses 3 & 4 the difference in conversion rates is calculated for new and returning users. New and returning users can only be identified when they convert because the system recognizes the bank account. Therefore the audience scores in Table 5 and Table 6 are the same. We can only compare the conversion rates with the total visitors on the page, since we do not know beforehand whether someone is a returned or new visitor (due to privacy constraints). For the visitors that do not convert we do not know whether they had a subscription in the past or not.

To test hypothesis 3 we find a non-significant lower conversion rate for New-5 compared to the control (p=0.876) (Table 5). The CTBC is 33% leaving too much to random chance to be implemented. Comparing the Top-5 against the control we find a non-significant higher conversion rate for Top-5 (p=0.758). The CTBC of 60% shows that it is highly due to random chance. Hypothesis 3 is not supported the Top-5 has a relatively higher, rather than lower, conversion rate to the baseline than the New-5 but is non-significant. Even more, there is also no significant difference between Top-5 and New-5. Top-5 has a non-significant higher conversion rate compared to New-5 (p=0.561).

Conversion rates of returning users						
Version	**Audience**	**Conversions**	**Conversion %**	**Diff. %**	**Chance to beat control**	**Result**
Control	4,006	[redacted]	[redacted]			
New-5	4,170	[redacted]	[redacted]	7.30%	64.63%	inconclusive
Top-5	1,471	[redacted]	[redacted]	-61.10%	0.03%	negative

Table 6. Results of the conversion rates for returning users

To test hypothesis 4 we compare the conversion for Top-5 and New-5 for returning users. There is a significantly lower conversion rate for returning users comparing Top-5 against the control (p =0.0028) (Table 6). The CTBC of 0.1% for Top-5 indicates that control performs better than Top-5 more than 99% of the time. Comparing the New-5 against the control for returning users we find a non-significant higher conversion rate (p=0.650) (Table 6). The CTBC for New-5 is 65% indicating there is a 35% chance that the results are due to random chance. Hypothesis 4 is supported because the conversion rates of New-5 compared to control are significantly higher than Top-5 compared to control.

4.1.4. Conclusion and recommendation

Initially, the Top-5 strip had a significantly negative effect on conversion rates compared to the baseline. New-5 had a non-significant negative effect on conversion rates compared to the baseline, which is not in line with our main hypothesis. When checking the viewport of the manipulation only 4% of the total visitors saw the content strip.

The results for users that saw the content strip still do not support hypothesis 1. Hypothesis 1 expected that showing New-5 content would increase conversion rates compared to the baseline. However, showing New-5 content more prominently (above the fold) did not increase conversion rates compared to the baseline condition (current situation). The results show the opposite effect of hypothesis 2 because Top-5 has a non-significant lower conversion rate instead of a higher conversion rate. Hypothesis 3 is also rejected since the conversion rates for new users are non-significantly higher for the Top-5 strip. Hypothesis 4 expected higher conversion rates for returning users for the New-5 strip. The hypothesis is not supported, because the New-5 strip is not significantly higher.

The initial negative effect of Top-5, in the first A/B test without a viewport check, might be because fewer people saw the manipulation in that group. Top-5 does show to have a negative effect on returning users implying that returning users rather see the information of the platform than the Top-5 strip, but keep in mind there is a sample ratio mismatch in this condition and the number of conversions is low. Overall, traffic and conversion rates are too low for people who saw the content strip to conclude that re-arranging the content strips to the top increases or decreases conversion rates. Another limitation of the study is that the caption of the New-5 strip did not match the content. The strip stated “Popular now/Nu populair”, but a better copy would have been “New this month/ Nieuw deze maand”. The follow-up study investigates other ways to present the content on the homepage.

4.2. Study 2: decreasing visibility of content on the fold

4.2.1. Expectations and set-up

In the second study, we investigate whether the current background of the homepage forms a distraction. The homepage has a background with the content of the platform (Figure 11). The content is faded making it hard to distinguish the different titles. The feedback surveys on the homepage suggest that the titles are poorly visible because they do not know what the content is of Videoland. The current background in this case can form a distraction from the flow. Flow and perceived ease of use are important predictors of user acceptance of technology (Singh et al., 2021; Leowarin & Thanasuta, 2021). To investigate whether this affects conversion rates we ask the following sub-question:

> *[SQ2]: Does decreasing the visibility of the general content, by removing the background of the fold, increase conversion rates?*

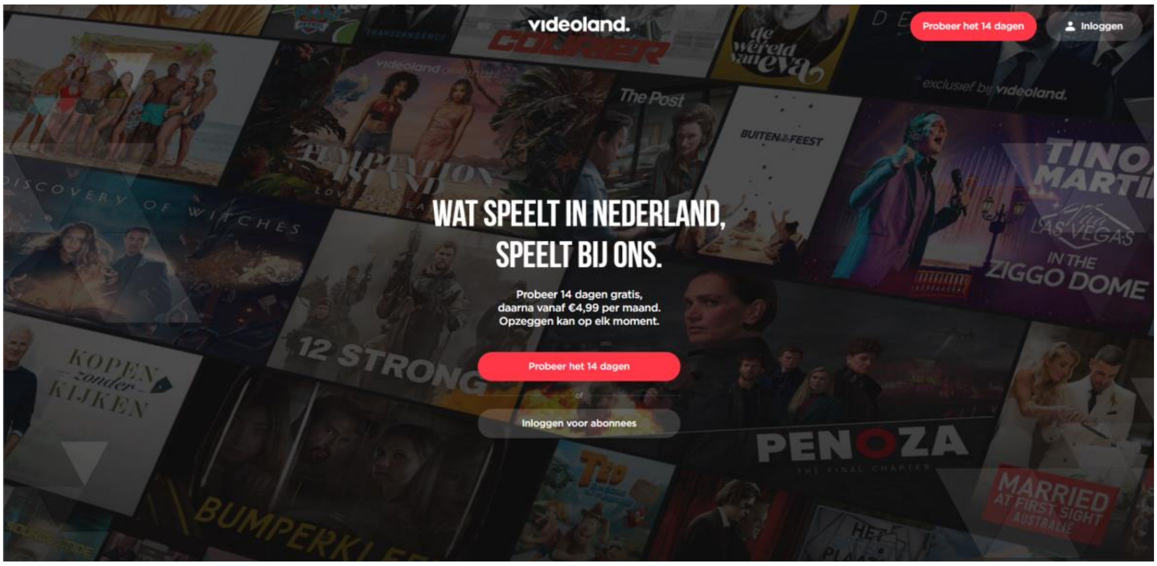


Figure 11, Initial screen of the homepage of Videoland (without scrolling)

There are two design options to improve the flow: the background content is faded and the background is black. Both versions might increase the flow by removing the distraction of the titles. Apart from that other elements such as the subscription button are highlighted. The subscription button improves the desired end goal, increasing conversion rates. Therefore we assume the following hypotheses:

> *[H1]: Showing content less prominently (background faded) increases conversion rates compared to the baseline condition (current situation).*

> *[H2]: Showing no content (background black) increases conversion rates compared to the baseline condition (current situation).*

When it comes to new users previous literature suggested that less informed users might be more likely to try out the free trial period, due to the information gap and the curiosity that is generated by this gap (Gafni & Dvir, 2018; Menon & Soman, 2002). While returning users in the OTT industry make a more elaborate and informed choice in subscribing (Bhullar & Chaudhary, 2020; Udoakpan & Tengeh, 2020). Returning users are familiar with the content on the platform and their choice is more likely to be influenced by the new content that is on the platform. Otherwise, they wouldn't have unsubscribed to the platform if it fulfilled their needs. The impact of hedonic quality (website design) on the intention to use a website is significant on novice users of the system and non-significant on users familiar with a website (Aranyi & van Schaik, 2016). Therefore, it is expected that changing the website presentation of a website has a bigger impact on new users. Leading to the following hypotheses:

> *[H3]: The increase in conversion rates relative to the baseline when the background is faded is higher for new users than for returning users.*

> *[H4]: The increase in conversion rates relative to the baseline when the background is black is higher for new users than for returning users.*

4.2.2. Research design and procedure

An A/B test with three variants was conducted on the homepage of Videoland. Control was the current homepage where the background content was highlighted. Variant 1 was the interface where the background faded and the content becomes less visible. Variant 2 was the interface where the background was black and no content is shown (Figure 12). To test hypotheses 1 and 2 the total conversion rates of both variant 1, faded background, and variant 2, black background, were measured. Apart from the total conversions, the difference between mobile and desktop was measured for exploratory analysis. For hypotheses 3 and 4 the conversion rate of new users and returning subscriptions was measured.

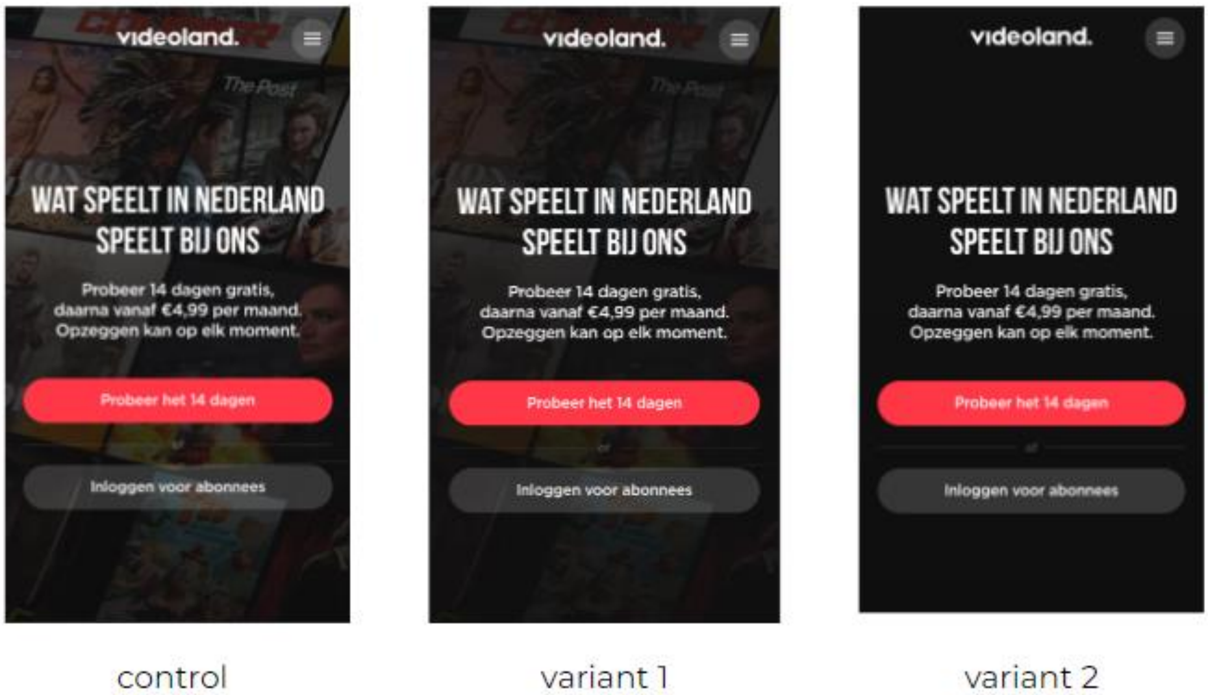


Figure 12, Interfaces used in the A/B test

4.2.3. Results

Total conversion rates						
Version	**Audience**	**Conversions**	**Conversion %**	**Diff. %**	**Chance to beat control**	**Result**
Control	46,615	[redacted]	[redacted]			
Faded	47,287	[redacted]	[redacted]	-4.52%	5.17%	negative
Black	47,083	[redacted]	[redacted]	-5.49%	2.39%	negative

Table 7. Results of total conversion rates

To examine hypothesis 1 we compare the conversion rates of the faded background against the control variant (Table 7). We find a non-significant lower conversion rate for the variant with the faded background (p=0.107). The CTBC of 5% indicates a high chance for the faded content to perform worse than the control. To examine hypothesis 2 we compare the conversion rates of the black background against the control variant (Table 7). We find a significantly lower conversion rate for the variant with the black background (p = 0.049). The CTBC is 3% indicating a high chance to perform worse than the control. The difference between black and faded conversion rates is non-significant (p =0.724).

Conversion rates for new users						
Version	**Audience**	**Conversions**	**Conversion %**	**Diff. %**	**Chance to beat control**	**Result**
Control	46,615	[redacted]	[redacted]			
Faded	47,287	[redacted]	[redacted]	0.00%	49.16%	inconclusive
Black	47,083	[redacted]	[redacted]	-2.57%	24.86%	indication

Table 8. Results from conversion rates of new users

To examine hypothesis 3 for the new users comparing the faded background against the control we find a non-significant difference in conversion rate (p=0.999) (Table 8). The CTBC of 49% indicates that the results are 51% due to random chance.

Whereas for the returning users we find a significantly lower conversion rate for the faded background against control (p=0.017) (Table 9). The CTBC of 1% indicates a high chance to perform worse than the control version.

Conversion rates of returning users						
Version	**Audience**	**Conversions**	**Conversion %**	**Diff. %**	**Chance to beat control**	**Result**
Control	46,615	[redacted]	[redacted]			
Faded	47,287	[redacted]	[redacted]	-9.72%	0.82%	negative
Black	47,083	[redacted]	[redacted]	-8.79%	1.52%	negative

Table 9. Results of total conversions of returning customers

To examine hypothesis 4, for the new users we find a non-significant lower conversion rate for the black background against control (p=0.510) (Table 8). The CTBC of 25% indicates that 75% of the time control wins, only 5% below the threshold.

Whereas for the returning users comparing the black background against the control we find a significantly lower conversion rate for the black background (p=0.032) (Table 9). The CTBC of 2% indicates a high chance perform worse than the control version. Apart from that faded is significantly lower than black (p=0.032).

These results are in line with hypotheses 3 & 4 since we expected that making the content less visible or invisible for users that are returning would have a higher impact on the conversion rate than for the new users.

DESKTOP | Total conversion rates						
Version	**Audience**	**Conversions**	**Conversion %**	**Diff. %**	**Chance to beat control**	**Result**
Control	18,152	[redacted]	[redacted]			
Faded	18,183	[redacted]	[redacted]	-2.54%	31.18%	inconclusive
Black	18,287	[redacted]	[redacted]	-2.63%	30.63%	inconclusive

Table 10. Results of total conversions on desktop

MOBILE | Total conversion rates						
Version	**Audience**	**Conversions**	**Conversion %**	**Diff. %**	**Chance to beat control**	**Result**
Control	27,425	[redacted]	[redacted]			
Faded	28,067	[redacted]	[redacted]	-5.18%	5.49%	negative
Black	27,771	[redacted]	[redacted]	-6.74%	1.89%	negative

Table 11. Results of total conversions on mobile

For exploratory purposes, the difference between mobile and desktop users is checked. The results show that the changes had more impact on mobile than desktop. There was a non-significant lower conversion rate for the faded background on the desktop against the control (p=0.643). There was a non-significant lower conversion rate for the black background on the desktop against the control (p=0.632) (Table 10). The CTBC of 31% shows a high percentage of the results are due to random chance. The higher conversion rate of black against faded was non-significant (p=0.988).

Whereas for total conversion for mobile comparing both conditions have a CTBC < 6%, meaning the chance to perform worse than control is 94%. For the faded background against the control, we find a non-significant lower conversion rate for the faded background (p=0.114). For the black background against the control, we find a significantly lower conversion rate for the black background (p=0.039) (Table 11).

These results are not what you initially expected. The background and its content are more visible when you’re on a desktop than on a mobile. Thus based on the total results it is expected that making the content less visible or invisible for users that are on the desktop would have a higher impact on the conversion rate than for mobile.

4.2.5. Conclusion and recommendation

The study rejects our hypothesis that decreasing the visibility of the general content, by removing the background of the fold, increases the conversion rate. This accounts for both the black background as well as the faded background, where the opacity of the content is lower. The results show that the perceived ease of use and flow is not limited by the current background.

The results show a negative effect of the faded background for the users that resubscribe. There is no difference in conversion rate between the faded background and control for new users. When the background is black it indicates to decrease in the conversion rates of new users. It had a significantly lower conversion rate for users that resubscribe. A possible explanation is that users that resubscribe are familiar with the design of the homepage. The redesigned background fading the content or making it black might be less attractive which in turn affects the conversion rate. This confirms previous research that hedonic quality attributes, e.g. design and aesthetic appeal, play an important role in the intention to use (Aranyi & Van Schaik, 2016). It contradicts the results that only novice users are impacted by design changes, but rather affect returning users.

Surprisingly the conversion rates significantly dropped only for mobile visitors and not for visitors on desktop. It is more noticeable on desktop screens that the background is faded or removed than on a smaller mobile screen. The traffic and conversion rates on desktop are lower than on mobile. It might turn out that if the test runs for another week these results become significant as well.

Another possibility for the lower conversion rates for the black design is that users in the original design perceive the content that is presented in the background. This means that the background content plays a factor in subscribing or not. That is in line with our research question that content does shape the adoption of OTT services and that decreasing visibility has a negative effect on conversion rates. It also confirms the perceived value theory that the benefits should outweigh the costs, in this case paying for content. To test this explanation the next study will test the opposite effect of whether highlighting specific content in the background of the fold can increase conversion rates.

4.3. Study 3: increasing visibility of content on the fold

4.3.1. Setup and expectations

The first study on content presentation showed that not a lot of users scroll below the fold in deciding to subscribe or not, thus this is not the most suitable way to show the value of the OTT platform. From the second study, the results show that fading the background or removing it has a negative effect on conversion rates. Suggesting that the current background does not limit the perceived ease of use of subscribing to Videoland. Changing the background to make the content better visible might enhance the conversion rates based on the theory of perceived value. Thus we ask the following research question:

> *[SQ3]: Does increasing the visibility of content, by changing the opacity of the background and highlighting new content on the fold, increase conversion rates?*

The titles on the current background are faded making it hard for visitors to see which specific titles are on the platform. Bringing some of the content forward might help the user focus on specific content. Apart from that by increasing the opacity of the background, the titles become more visible. Content is the benefit in the cost-benefit trade-off for VoD platforms. By highlighting the content the perceived value should increase which in turn is expected to result in more conversions. Thus the following hypothesis is expected:

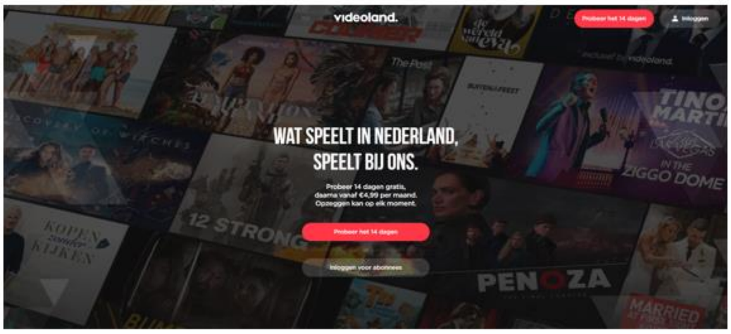
> *[H1]: Showing content more prominently (highlighting background and three titles) increases conversion rates compared to the baseline condition (current situation).*

The results of the second study on the presentation of content showed that removing the background had a significant negative effect, whereas for new users this effect was non-significant. Therefore we expect that highlighting the content will have a bigger effect on returning users than on new users. Previous studies suggested that in more mature markets users constantly switch OTT services based on price and content changes (Bhullar & Chaudhary, 2020; Udoakpan & Tengeh, 2020). Therefore we expect the following hypothesis for users that resubscribe:

> *[H2]: The increase in conversion rates relative to the baseline when the background is highlighted is higher for returning users than for new users.*

4.3.2. Research design and procedure

An A/B test with two variants was conducted on the homepage of Videoland, e.g. the home page. Control, the baseline condition was the current homepage where the background content is all the same opacity (Figure 13). Only two variants are tested due to the time constraints of other experiments that have to take place on the homepage. Variant 1, is the interface where the background has a higher opacity overall making all titles more visible. Variant 1 also has three titles that are highlighted with a red bar. The titles that are highlighted are new seasons of popular series to appeal to both new and returning users (Figure 13). When the only top or only new series are chosen the total conversion rate might not increase, because the effect might be different for new and returning users. To test hypothesis 1 the total conversion rates of both control and variant 1 were measured. For hypothesis 2 the conversion rates of new users and returning subscriptions were measured. Mobile was excluded for this A/B test since the screen is too small to notice the different titles that are highlighted.



Control

variant 1

Figure 13, Interface of the control condition (current) and highlighted condition (variant 1)

4.3.3. Results

Total conversion						
Version	**Audience**	**Conversions**	**Conversion %**	**Diff. %**	**Chance to beat control**	**Result**
Control	51,193	[redacted]	[redacted]			
Highlighted	51,522	[redacted]	[redacted]	-0.64%	39.79%	inconclusive

Table 12. Results of total conversion rates

To examine hypothesis 1 we compare the conversion rates of the highlighted background against the control variant (Table 12). We find a non-significant higher conversion rate for the variant with the highlighted background (p=0.806). The CTBC of 40% shows that the results are more likely due to random chance.

Conversion rates for new users						
Version	**Audience**	**Conversions**	**Conversion %**	**Diff. %**	**Chance to beat control**	**Result**
Control	51,193	[redacted]	[redacted]			
Highlighted	51,522	[redacted]	[redacted]	1.84%	70.46%	inconclusive

Table 13. Results on conversion rates of new users

Conversion rates for returning users						
Version	**Audience**	**Conversions**	**Conversion %**	**Diff. %**	**Chance to beat control**	**Result**
Control	51,193	[redacted]	[redacted]			
Highlighted	51,522	[redacted]	[redacted]	-4.95%	12.23%	negative

Table 14. Results on conversion rates for returning users

To examine hypothesis 2 we compare the conversion rates of the highlighted background against the control variant for new users (Table 13). We find a non-significant higher conversion rate for the variant with the highlighted background (p=0.579). The CTBC of 70% is just below the threshold of 80%.

To examine hypothesis 2 we compare the conversion rates of the highlighted background against the control variant for returning users (Table 14). We find a non-significant lower conversion rate for the variant with the highlighted background (p=0.254). The CTBC of 12% shows it is very likely that the highlighted version is worse than the control.

4.3.4. Conclusion

The study fails to confirm our first hypothesis with a non-significant lower total conversion rate for the highlighted background. In study 2 removing the background had a negative on total transactions on mobile and was inconclusive on desktop. This test was tested only on desktop screens, which might explain the inconclusive results on total conversions. The study rejects our second hypothesis because highlighting the background resulted in significantly more conversion rates for new users and non-significant fewer conversions for returning customers. In study 2 removing the background had a significant negative effect on conversion rates for returning customers. Thus it was expected that highlighting the background would have the opposite effect. However, highlighting the background also had a negative effect on returning users. In study 2 there was no significant increase in conversion rates for new users. In this study, there was a significant increase in conversion rates for new users when the background is highlighted. Combining these results a possible explanation might be that design changes affect returning users negatively because they are familiar with the old design. Whereas for new users its new design either negatively or positively affects them, in this case positively.

4.4. Overall discussion

The empirical studies on the presentation of content show that different presentations significantly affect the adoption of a VoD service. The first study did not result in more knowledge on the effect of moving the content strips higher on the homepage. However, it did show us that only 4,4% of users scroll on the page. The relative conversion rates were higher for the group of users that did scroll. This is probably because it filters out the users that accidentally landed on the homepage. Therefore, this group is interesting to target. It might be that the type of content matters for this group because they show by scrolling that they want more information before subscribing.

The second study shows a negative effect on the total conversion rates when the background is black or the content on the background is faded. Study 2 shows that there was a significantly lower conversion rate on the changed backgrounds for mobile visitors and not for visitors on desktop. These results are surprising because the changes in the background are more evident on desktop screens than on a smaller mobile screen. The relative conversion rates are higher on mobile than on desktop.

The third study studied the opposite effect of study 2 and shows that highlighting the content in the background did not significantly improve the conversion rate for new users. In study 2 fading the background did not result in a significantly lower conversion rate. Suggesting that highlighting the content for new users enhances the perception of the background. The background changes both in studies 2 & 3 negatively affect the conversion rates of users that resubscribe to Videoland. Suggesting that users that are familiar with the design do not like the changes. The A/B test on the presentation of content contradicts the study of Aranyi & van Schaik (2016), where the impact of hedonic quality on perceived enjoyment and in turn on intention to use had a significant effect on novice users of the system and a non-significant effect on users familiar with a website. For studies 2 & 3 changing the presentation (hedonic quality) only significantly affected returning users.

Apart from that, the negative effect on the highlighted background for returning users might be explained by the content that is on the background. The content on the background has not changed in the past 6 months and consists of a lot of old titles. These titles become automatically more visible because the background opacity is increased. The three titles that were highlighted are new because they released a new season rather than being completely new shows (first season). It might be that returning users did not watch the shows that released a new season, meaning that highlighting three shows is not enough to convince returning users. However, a follow-up study has to be done to check this assumption.

5. Study 5: an user study on the type of content

As previously discussed in the literature content is one of the most important non-price factors for users to adopt an OTT service, but research is lacking on whether the type of content that is presented matters in user acceptance (Cha, 2013). Especially in a mature OTT market, the offering of services is high and consumers have more choices to discover content for the price they want (Bhullar & Chaudhary, 2020). Consumers in the Dutch OTT market make informed choices on adding and cancelling services in search of the best value for their time and money.

Companies launch marketing campaigns for new series available on their platform to convince users to join their platform. After a click on the campaign, they get redirected to a landing page or homepage where they can subscribe and find more information on the platform. Simply presenting content on that page might not be enough to convince them to adopt the service. The type of content can easily not match their preference, because of the large scope of content that these platforms own. Therefore, this study will focus on whether the type of content matters in the adoption of OTT services.

When it comes to the type of content, Videoland offers different content strips on their platforms, such as the most popular content (Top 10 most-watched that week) and the newest content (latest releases), as well as different genre strips. It also offers users 'recommended for you' content on the platform. These recommendations are created with two different models depending on the user data available. A more complex model is used for users with more data, i.e. those who watched several series and films. Whereas for new users that have not watched any content the recommendation is made with an item-to-item recommender. This last recommender system is used in our study for personalized content. Where the advertisement (title of film or show) that is clicked functions as an item. Each title has an item profile which represents the important characteristics of that item, e.g. genre, actors release year. The recommender system calculated the top 10 most relevant titles based on that advertisement title. Then 5 five of these titles were presented in the personalized condition. This gives users a more relevant list of titles compared to popular or new content.

The user study on the type of content aims to test how personalized recommendations compared to popular and new content affect user perceptions and experiences towards adopting an OTT service. The proposed evaluation model in Section 3 can be used to help find an answer to our research question of how, why and which specific content can help with the adoption of OTT services by answering the following question:

[RQ2]: To what extent does the type of content, in the form of personalized recommendations, shape the adoption of a VoD platform?

5.1. Dataset

To select the right content for the user study the database of *Videoland.nl* containing all series, movies and television programs were used. The titles selected for the advertisements in the experiment are based on their release date, genre, language and campaigns that are online during the experiment. In both sets, there are Dutch and International titles as well as a variety of genres. The set of advertisements needed to be diverse because in the real world you would only click on a series or film that you like. In this way, the chance is high that each participant at least likes one advertisement. The series that are selected: are Younger, Expeditie Robinson, Blacklist, Handmaid's tale, and Temptation Island. The films that are selected are Midsommar, Spy Who Dumped Me, Wolf of Wallstreet, Transcendence, and Huisvrouwen bestaan niet 2.

After the titles for the advertisement were selected for the experiment these titles could be used as input for the item-based recommender system that selected the personalized content. The recommender system calculated the top 10 most relevant titles of that advertisement. The top 10 from the item-based recommender were checked on whether or not the overlap between items was too big, e.g. when Temptation Island NL leads to recommendations of the same show such as Temptation Island USA and Australia.

For the non-personalized condition, the "Newest five movies and series" and "Top five most popular movies" at that time on Videoland were selected. The most popular content is based on the data of the current users of Videoland. Whereas the new content is simply the series that most recently became available on Videoland.

5.2. Setup and expectations

Previous studies on behavioural intention have shown that both perceived value and perceived enjoyment had a significant effect on continued intention (Oyedele & Simpson, 2018; Singh et al., 2021). Where the latest study by Leowarin & Thanasuta (2021) showed that perceived enjoyment had also a significant effect on purchase intention. Perceived value is the customer's overall perception of online content services based on a cost-benefit trade-off (Zeithaml, 1988). The effects of perceived value and perceived enjoyment are shown in the conceptual model in Figure 6.

Personalized recommendations are items selected based on the advertisement title they clicked on. These recommendations should (somewhat) match the content that the user likes (otherwise they would choose a different title in the advertisement list). The personalized content is more relevant for the initial title apart from that the five titles match the genre of each other. Whereas the non-personalized content can differ a lot in genre and does not always match the title of the advertisement. Therefore, providing personalized content increases the perceived quality of content and the perceived level of personalization. Thus the following hypotheses are expected (Figure 6, Conceptual structural equation model):

> *[H1]: Personalized recommendations compared to new content have a positive effect on perceived quality.*

> *[H2]: Personalized recommendations compared to top content have a positive effect on perceived quality.*

> *[H3]: Personalized recommendations compared to new content have a positive effect on the perceived level of personalization.*

[H4]: Personalized recommendations compared to top content have a positive effect on the perceived level of personalization

The top content is generally more diverse since the content represents the whole platform rather than a specific genre which is the case with personalized recommendations. Furthermore, diversity within the item list reduces choice overload and increases satisfaction (Willemsen et al., 2016). Additionally, it gives a better overview of the scope of the content on the platform. Thus the following hypotheses are expected (Figure 6, Conceptual structural equation model):

[H5]: Top content compared to personalized recommendations has a positive effect on perceived diversity.

[H6]: New content compared to personalized recommendations has a positive effect on perceived diversity.

Results of a study done by Cha (2013) showed that when consumers perceive the new video platform to be different from television in satisfying their needs, the likelihood of using the new video platform increases. New content has a higher perceived novelty. The perceived novelty is different for users who re-subscribe than for completely new users because they are already familiar with the platform. Therefore, the following hypotheses are expected:

[H7]: Top content compared to personalized recommendations has a positive effect on perceived novelty.

[H8]: New content compared to personalized recommendations has a positive effect on perceived novelty.

In turn, the perceived value and perceived is positively influenced by perceived quality, personalization, diversity and novelty. When the content is more relevant the perceived enjoyment and the value for money should go up since the user will perceive the series shown as more fun. When the titles are diverse it shows a wider variety of the scope of content that the platform offers. The scope of content is one of the factors that influence perceived value and perceived enjoyment (Bhullar & Chaudhary, 2020). When the titles are new then the platform offers content that the user hasn't watched yet, thus increasing the perceived value as well as the perceived enjoyment. The effects are represented as arrows in the conceptual model in Figure 6.

Experience is measured by whether users previously had a subscription to Videoland or not. Users that had a subscription are already familiar with the content on the platform. Perceived novelty measures whether users are familiar with the content thus it is likely that the perceived novelty scores are lower for experienced users than new users. Perceived enjoyment measures whether users think using the platform will be fun. Experienced users have experience with the platform hence are more likely to know the platform will be fun than new users. Thus the following hypothesis is expected:

[H9]: Experience has a negative effect on perceived novelty.

[H10]: Experience has a positive effect on perceived enjoyment

5.3. Research design and procedure

The experimental set-up was initially in a within-subject design where a combination of personalized with top content or new content was presented (Figure 14). Within-subject designs have greater statistical power than between-subject designs because it reduces errors associated with individual difference. A major drawback of the within-subject design is the effect that participants take part in one condition can impact the performance or behaviour in all other conditions, a problem known as a carry-over effect. To limit the impact of the carry-over effect the conditions differentiated in films vs series.

Films and series were randomly assigned over trials. Thus in the first trial, they either had to choose between advertisements of films or series. This makes the trials feel a bit different from each other and less like repeated tasks. However, they still had to fill in the same questionnaire and decide whether they intended to subscribe or not. Thus the possibility of a spill-over effect was still present. The same accounted for the Personalized-New order and the Personalized-Top order both manipulations were randomly assigned over the trials. Randomizing the personalized, top and new content and series vs films over the trials allows the study to be analysed between-subject design on the first trial (Figure 14) if the carry-over effect occurs. The sample size was also calculated for a between-subject design.

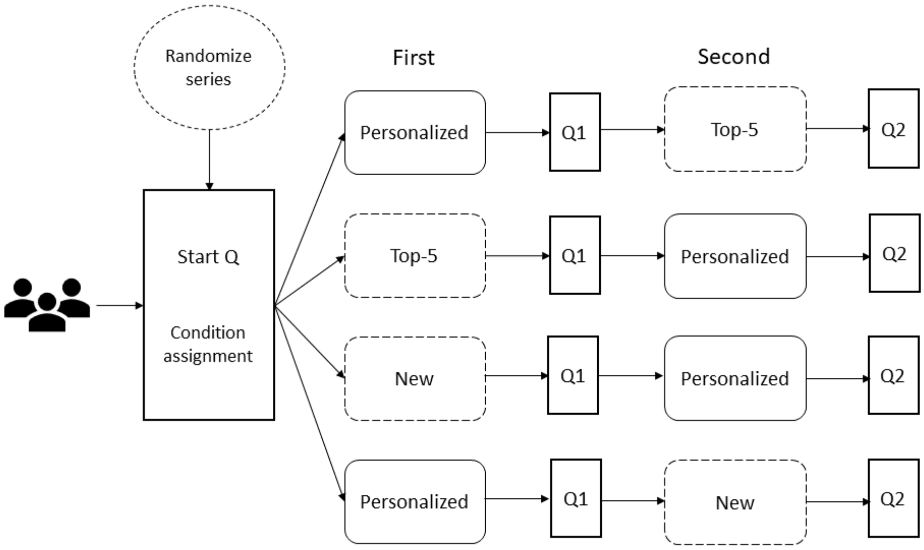


Figure 14, Initial experimental design (Within-between design)

Participants first had to fill in demographic questions and whether they currently or previously had a Videoland subscription. After that, they were redirected to either the *Buienradar* or *RTL Nieuws* website interface. On that page, they had to choose between different advertisements for either series or films (this advertisement click personalizes the content) which redirected them to the Videoland homepage (Figure 15).

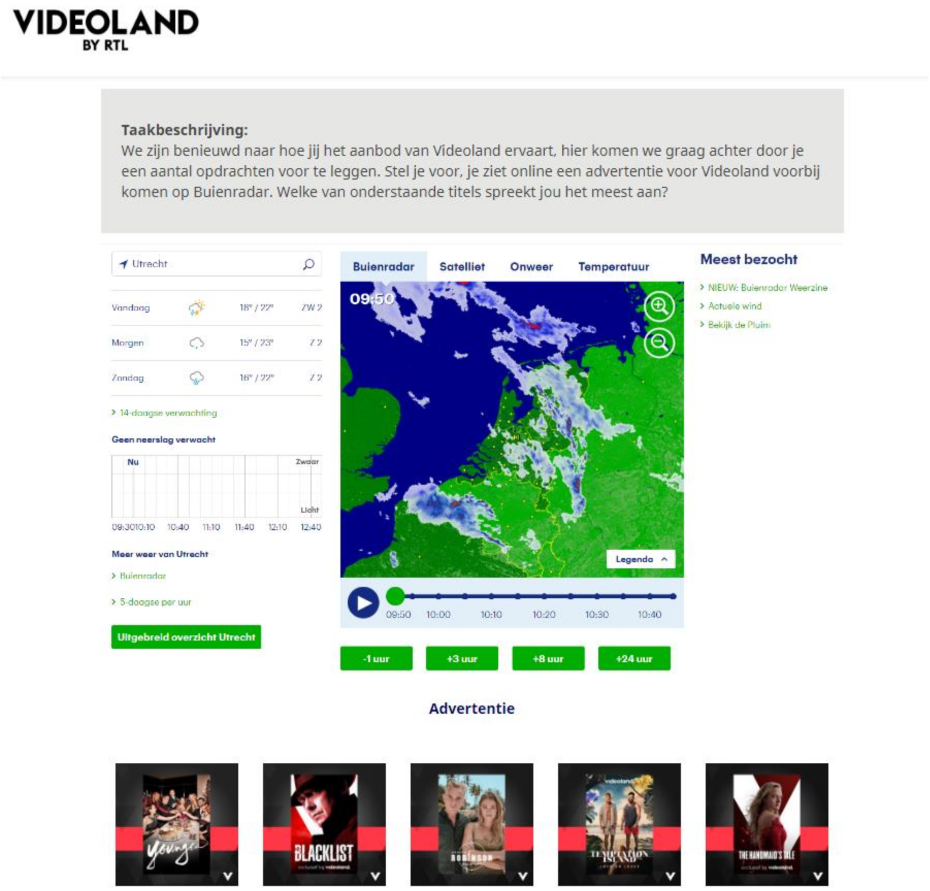


Figure 15, Interface of the advertisement selection

Then the landing page either showed a strip with generic content (new content or top content) or specific content (personalized based on an item of the advertisement) (Figure 16).

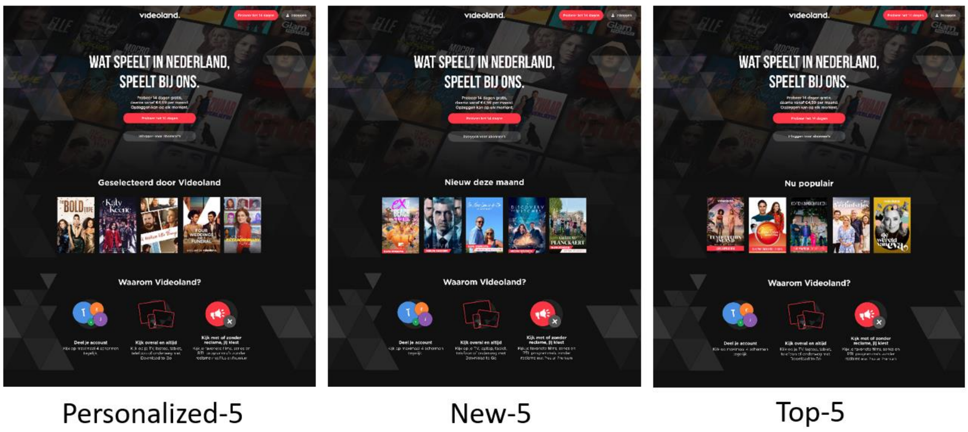


Figure 16, Different conditions after the advert selection

After that, they had to answer a survey containing questions about their perceived novelty, diversity, personalization, quality, value, enjoyment and intention to use. Then the experiment was repeated where they had to choose between different advertisements for films and were redirected to a generic or specific content page depending on their previous variant. After this, they filled in the same questionnaire (Figure 14) for the experimental setup.

The appropriate sample size was determined by performing an a-priori power analysis in GPower 3.1 (Faul et al., 2009), using ”F-Test: Repeated measures, within-between interaction” Under a power of 0.9, a medium effect size f = 0.25, $\alpha = 0.05$, the design required minimum sample size of 174. This sample size of users is also sufficient for a stable factor estimate and SEM mode, according to the suggestion of using at least 5 participants per item (24 items x 5 = 120) by Nunnally (1978) or other guidelines that propose 200 participants for a typical SEM model like ours.

In total 215 participants (M_{age} = 29 years, SD_{age} = 11.17, Ranging between 15-69 years old) fully completed the study. Furthermore 110 of the participants identified as male, 94 of the participants identified as female, and 10 of the participants identified as other. 140 participants never had a Videoland account, 75 of the participants currently have a Videoland account and 20 of the participants had a Videoland account in the past. Participants were recruited via RTL.NL and Prolific. In total 15 participants completed the survey on RTL.nl and 200 on Prolific. Living in the Netherlands and fluency in Dutch were required to be included in the experiment since Videoland is only available in the Netherlands and targets the Dutch market with Dutch series and shows. Furthermore, participants in Prolific received €1,05 as compensation for their participation during a single 5 min session.

First, we check the selection of the advertisements that were chosen (Figure 17). Blacklist and Handmaid’s tale were by far the most chosen advertisements of the series. The film advertisements chosen were more equally distributed with the Wolf of Wallstreet and Transcendence being the most popular. After the advertisement click the user was directed to one of three conditions (personalized, new and top). There seems to be no overrepresentation of a certain advertisement in one of these conditions. This is checked because the advertisement determines the content presented in the personalized condition.

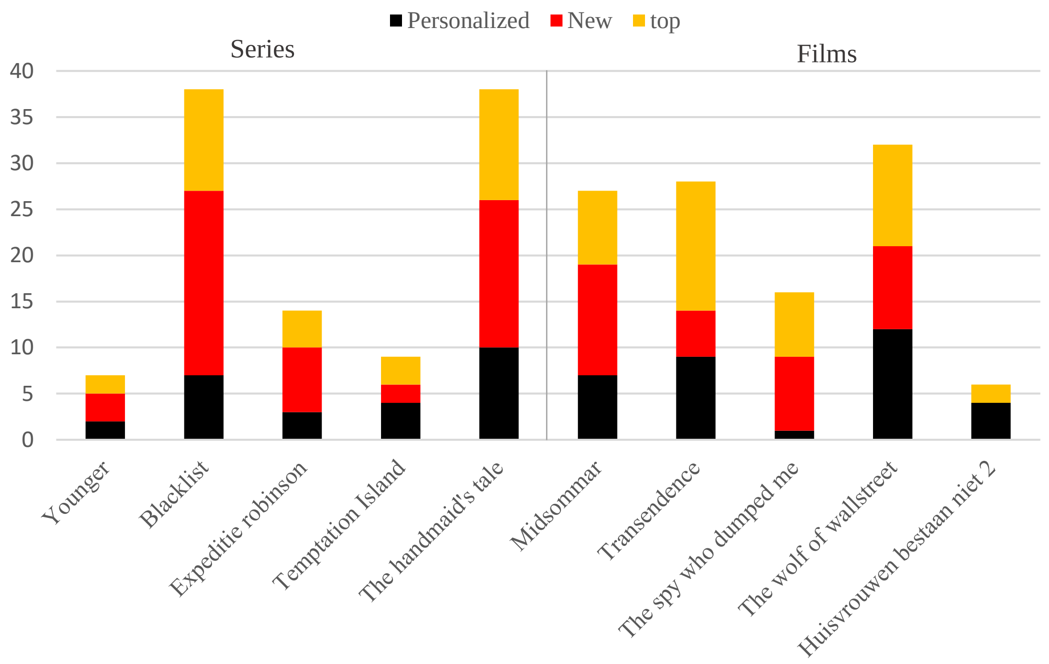


Figure 17, Chosen advertisements in the experiment split by series and films and per condition

5.4. Measures

Appendix A presents the measurement items for each construct both in English and the Dutch version used in the study. For all of the measures, respondents were asked to indicate their level of agreement with each of the measurement statements using a five-point Likert scale (1= completely agree, 5- completely disagree). Perceived recommendation quality, which is related to the relevance of the content presented, was measured with four question items adapted from Knijnenburg et al. (2012). The perceived level of personalization was measured by three items adapted from Graus, Willemsen & Snijders (2018). Four question items were adapted from Willemsen, Graus & Knijnenburg (2016) to measure the perceived recommendation diversity. Three items from Ekstrand et al. (2014) were used to measure perceived recommendation novelty. Three items were adapted from previous studies to measure the perceived value of Videoland (Singh et al., 2021; Wang et al., 2013). To measure perceived enjoyment four items were adapted from the study by Singh et al. (2021). Three items were adapted from Fernàndez-Robin (2019) and Pu, Chen & Hu (2011) to measure behavioural intention. Many prior studies, as well as the present study, have tested the validity and reliability of the measurement items for each construct. The experience was measured by whether people currently have a Videoland account or had an account in the past.

Apart from these constructs, some factors that were not included in the conceptual SEM were measured. Choice satisfaction measured whether users liked the film or series advertisement that they clicked on. This factor was added because in the real world people only click on an advertisement they like. Furthermore, the choice led to certain recommendations. A low choice satisfaction could therefore negatively influence the personalized recommendations condition.

5.5. Statistical analysis

A structural equation model (SEM) is a statistical procedure where it tests the measurement model and all hypotheses at the same time (Knijnenburg & Willemsen, 2015). Structural equation modelling was used to find an answer to the research question and find support for the hypotheses. An SEM model was created using Lavaan in Rstudio.

First, a Confirmatory factor analysis (CFA) was done to check the factor loadings of the latent variables. Factor loadings of included items are shown in Table 15. The construct of perceived novelty was not internally consistent. The questions for that construct had an AVE of 0.172 and Cronbach's Alpha of 0.238. This shows that the collection of questions does not reliably measure the same construct. The latent variable is therefore not added to the model.

Perceived personalization had a high correlation with perceived quality with a covariance of 1.02 meaning they are positively correlated. Therefore the perceived personalization and quality were merged. The first item of perceived personalization was loaded on the construct of perceived quality. Checking the modification indices the results show that the first item of the perceived diversity scale cross-loaded onto quality, value and enjoyment. Therefore this item was excluded from this scale.

The values of AVE and Cronbach's alpha are good, indicating convergent validity. The results of the CFA analysis showed that the items measure the constructs as intended (Table 15) with all AVEs larger than 0.5. The Cronbach's alpha values further confirmed the reliability of the constructs. The Cronbach's alpha values ranged from 0.857 to 0.939 (Table 15).

CONSTRUCT	ITEMS	FACTOR LOADING
Perceived quality	**1. De series vind ik leuk**	**0.940**
Alpha: 0.906	**2. De series spreken mij aan**	**0.993**
AVE: 0.763	**3. De series zijn relevant**	**0.736**
	4. Ik vind geen van de series leuk	**-0.738**
	5. De series vind ik persoonlijk interessant[a]	**0.927**
Perceived diversity	**1. De lijst van series is gevarieerd**	
Alpha: 0.857	**2. De series lijken erg op elkaar**	**-0.859**
AVE: 0.703	**3. De meeste series zijn van hetzelfde genre**	**-0.865**
	4. De series in de lijst verschillen veel van elkaar	**0.788**
Perceived enjoyment	**1. Het gebruiken van Videoland lijkt me leuk**	**0.926**
Alpha: 0.917	**2. Het gebruiken van Videoland lijkt me plezierig**	**0.931**
AVE: 0.799	**3. Het gebruiken van Videoland lijkt me vermakelijk**	**0.904**
	4. Het gebruiken van Videoland lijkt me niks	**-0.807**
Perceived value	**1. Videoland heeft een goede prijs-kwaliteit**	**0.726**
Alpha: 0.869	**verhouding**	**0.917**
AVE: 0.773	**2. Gezien de abonnementskosten is Videoland het geld**	
	waard	**0.976**
	3. Videoland is de moeite waard	
Behavioural intent	**1. Ik verwacht een Videoland abonnement te nemen**	**0.941**
Alpha: 0.939	**2. Ik verwacht in de toekomst Videoland te gebruiken**	**0.972**
AVE: 0.906	**3. Ik verwacht Videoland vaak te gebruiken**	**0.942**

Table 15. Measures and items used in the online experiment. Items without a reported factor loading were excluded from the final model

[a] This item was originally asked as the third item of the perceived personalization scale, but in hindsight fitted much better with the quality scale

5.6 Results

First, the conceptual SEM is used to run the same model separately on the data of the first and second trial. First, a saturated model was created that includes paths that are not in the conceptual model, because there may be additional effects that were overlooked. The saturated model was first to run on condition 1 and had a good model fit: ($\chi2(153) = 194.890$, $p < 0.001$, CFI = 0.999, TLI = 0.999, RMSEA = 0.033, 90% CI [0.013, 0.048]). In the initial model, the condition factors were not significant. Participants either had to choose films or series in the condition, therefore an interaction variable is added to the model. These factors improved the model and affect the construct proposed in the model. Then the model factors with a non-significant model weight were removed one by one to optimize the SEM model.

This resulted in a saturated model for condition 1 that had a reasonable model fit: ($\chi2(208) = 393.575$, $p < 0.001$, CFI = 0.983, TLI = 0.980, RMSEA = 0.064, 90% CI [0.055, 0.074]). Then the same model ran for condition 2, which did not have a good model fit: ($\chi2(208) = 828.336$, $p < 0.001$, CFI = 0.971, TLI = 0.967, RMSEA = 0.118, 90% CI [0.109, 0.126]). The RMSEA is above .06 indicating a poor model fit. As suggested by Hu and Bentler (1999) where RMSEA above .06 and a CFI and TLI below .95 indicate relatively good model-data fit in general. Therefore, the final SEM model was created on the dataset of the first condition of the participants and the analysis is done on the first trial between subjects.

Several exploratory variables were added, such as age, gender, experience and choice satisfaction. Only the factors with significant weights were kept in the model resulting in a final model with good model fit: ($\chi2(242) = 319.100$, $p < 0.001$, CFI = 0.994, TLI = 0.996, RMSEA = 0.039, 90% CI [0.026, 0.050]). The final model is shown in Figure 18 and displays the effects found (the β-weight, standard error and p-value).

The final model shares many similarities with the conceptual model in section 3 (Figure 6). Similar to the model there is a positive direct effect of perceived value and perceived enjoyment on intent. Additionally, in line with our theory perceived quality is a mediator of intention to use via perceived enjoyment and perceived value. Confirming hypothesis 10, experience has a direct positive effect on perceived enjoyment (Figure 18). The exploratory variables age and gender did not have a significant effect on any of the constructs.

There are a few differences with the initial model (Figure 6), enjoyment was expected to have a direct effect on the intention to use. Whereas in Figure 18, based on the results of our SEM, enjoyment was found to have an indirect effect on the intention to use via perceived value. The effect of perceived diversity on intent is not mediated by any of the experience constructs. Instead perceived diversity has an indirect effect on the intention to use via perceived quality. The effect of perceived quality on intention to use is only partially mediated: there is also a direct positive effect of quality on intention to use.

Both experience and whether or not participants had a Videoland subscription had a significant effect on perceived enjoyment. However, the factors covariate and only experience is included. Experience is added because it contains both participants that have a subscription as well as participants that had a subscription in the past. Choice satisfaction was not taken into account in the conceptual model or hypotheses but was found to have a direct effect on both perceived quality and perceived value.

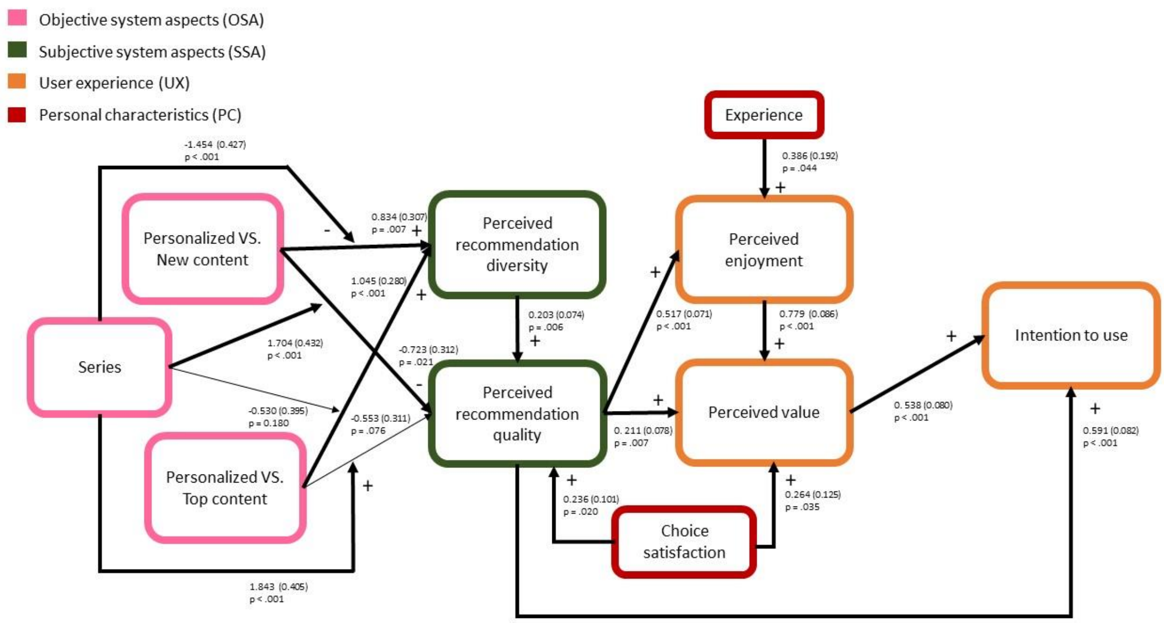


Figure 18, Final SEM

To better understand the effects of our manipulations, the marginal effects of all the conditions are plotted on the subjective constructs as presented in Figure 20 and Figure 19. Looking at the SEM (Figure 18), we see that non-personalized “top content” and “new content” items with interaction on the series have a higher perceived quality than the personalized content with interaction on the series. The marginal effect of quality is higher for the top series and the new content than for the personalized series (Figure 19). These effects were only present for series and not for films.

Higher perceived quality in turn leads to higher perceived enjoyment (Figure 18). Both top and new series score higher on enjoyment compared to personalized series (Figure 19). Higher perceived enjoyment in turn leads to higher perceived value (Figure 18). Both top and new series score higher on perceived value compared to personalized series (Figure 19). The effect of quality on perceived value is only partially mediated by perceived enjoyment: there is also a direct positive effect of perceived quality on perceived value (Figure 18).

In the SEM (Figure 18), perceived value in turn leads to a higher intention to use. The marginal effects of intent are higher for the top series than for the series and both are higher than the personalized series (Figure 20). These results are confirmed with the indirect paths in the SEM where the new series positively affects intent via perceived quality and perceived value 0.426 ($p < 0.05$). The total indirect paths in the SEM confirm the results where both indirect paths of the conditions top and new series via quality via enjoyment via value on intent have a significant effect of 0.333 ($p < 0.05$) and of 0.396 ($p < 0.05$).

Looking at the SEM (Figure 18), the perceived quality of intent is only partially mediated by perceived value. There is also a direct positive effect of perceived quality on the intention to use. These results are confirmed with the indirect paths in the SEM where the strongest indirect paths are via perceived quality to intent for both top of 1.075 ($p < 0.001$) and new of 0.906 ($p < 0.003$). Thus intent increases directly via perceived value and perceived quality. Both quality and value are higher for the top and new series than for the personalized series (Figure 19) rejecting hypotheses 1 & 2.

Hypothesis 5 is confirmed with the higher perceived diversity for top series and films than personalized series and films. New content series have a lower perceived diversity than personalized series, rejecting hypothesis 6. New series has a lower perceived diversity than the personalized series (Figure 19). The indirect path of the new series on intent via perceived diversity and perceived quality in the SEM model has a negative effect of -0.174 ($p < .05$) The negative effect of new series on diversity resulted in a lower score of the new series on intent (Figure 20). The positive effects of new and top films via diversity and quality resulted in a higher score on intent.

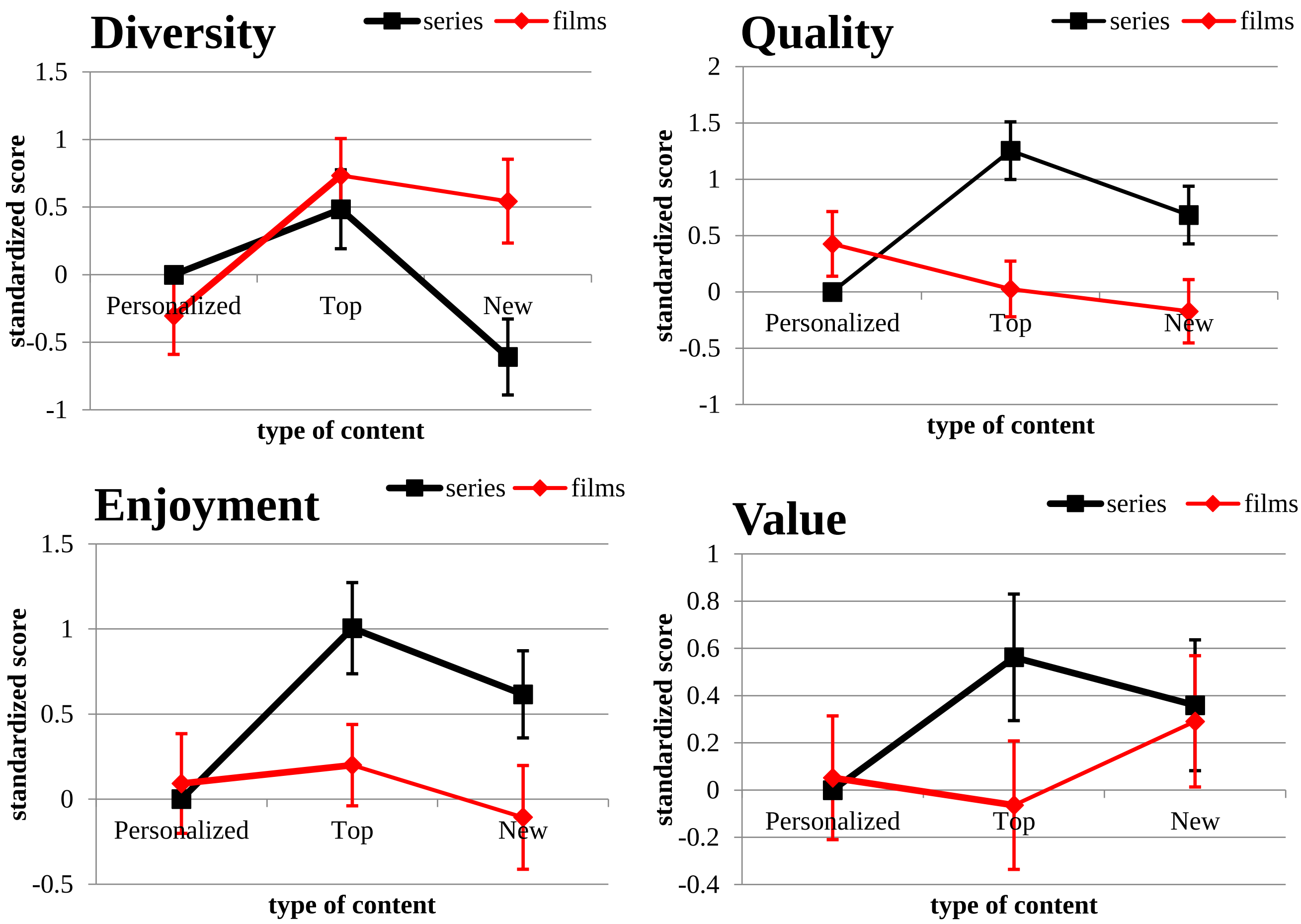


Figure 19, Marginal effects of the different conditions on the subjective constructs in the SEM model. Error bars represent 1 standard error from the mean.

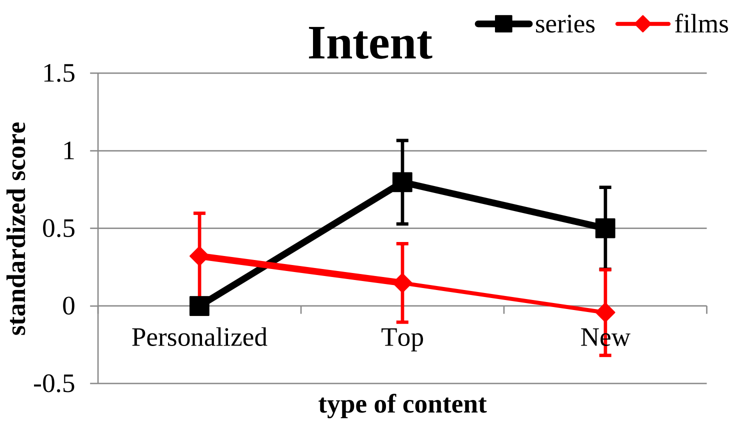


Figure 20, Marginal effect of all the conditions on intent

5.7 Discussion

The goal of study 5 was to show how personalized recommendations affect user intent by positively enhancing user subjective system aspects. The results show that personalized recommendations decrease the subjective system aspects resulting in a lower intent compared to the non-personalized condition, but only for series (for movies there are no differences). The marginal effects on the perceived quality show that personalized series are higher for top and new series (Figure 19). The most popular titles are generally the most liked and often show where the quality of the platforms lies. This might explain the higher marginal effect of the top content on perceived quality. The items of the new series consisted of some popular shows on Videoland that might explain the higher score on perceived quality for new content. Both non-personalized conditions being higher suggests that the quality of the items presented by the recommendations from the advertisement was not very good.

Surprisingly the most chosen advertisement titles were “The Blacklist” and “The Handmaid’s Tale” (Figure 17). These titles did not match the genre with the items presented for the top and new series. Even though the items in the non-personalized did not match the genre of the advertisement the perceived quality of non-personalized was higher compared to the personalized sets. This suggests that the content of the advertisement does not have to match the content on the homepage to have a higher perceived quality.

Videoland differentiates itself with local content and its marketing point is reality shows. It might be that the offering of other genres is lacking, limiting the quality of the items presented in the recommended set of content. It is also possible that one input (the advertisement) is not adequate to make a good set of recommendations to present on the homepage.

Users seem to base their intention to use on both perceived quality and perceived diversity of the content. Top series scores higher than personalized series on perceived diversity. Which is in line with hypothesis 5 expected diversity to be higher for the top content. The new series compared to the top series score lower in the graph on user intent (Figure 19). The lower score can be explained by the scores on perceived diversity. New series scores lower compared to personalized series on perceived diversity (Figure 19). In the new series condition were three Dutch shows and two international shows in the genres of drama, reality, fantasy and romance. This might be the reason for the slightly lower score of the new series on diversity (Figure 20). The lower diversity of the new content mediated in a lower intent score. The mediating effect of perceived diversity suggests that users want a diverse item sets rather than a set with the same type of content items, especially when it comes to films.

The model shows that the experience affected the perceived enjoyment. This is not surprising because users that have or had an account in the past already know that it can be enjoyable to use. The direct effect of choice satisfaction shows the effect of liking the advertisement they chose increases the perceived quality and perceived value of the items that were then presented on the landing page.

Overall the study shows to support that different types of content sets have different effects on user intent to adopt an OTT service. The model in the study shows to validate different theories on the factors that are relevant to intent. The effects of the conditions on intent are mediated by perceived quality, perceived enjoyment and perceived value. This confirms our conceptual model presented in Figure 6. The lower perceived quality affects the lower perceived enjoyment which in turn affects the perceived value. Different than predicted upfront, the SEM model supports the model of Wang et al. (2013) where perceived value is a mediator of perceived enjoyment on perceived intent. The model proves that product perceptions, perceived quality and perceived diversity are relevant for predicting intent. As proposed in van Schaik & Ling (2011) and Hassenzahl (2004) perceived quality influences perceived enjoyment. Additionally, the direct effects of perceived quality on intent suggest that intent increases when the content items perceived quality is high and the diversity between these items is high.

6. Conclusion and recommendations

6.1. Conclusion

This thesis investigated how the non-price factor content shapes the adoption of OTT services. The study shows evidence that content is important for the adoption of OTT services. The design changes in content presentation in the A/B tests prove that changing the presentation of content (OSA) either negatively or positively affects user adoption of a VoD platform.

The trade-off in the presentation of content on the adoption of Videoland shows that there is a significant difference between new users and returning users. Therefore, the acquisition of new users should be approached differently than that of returning users. For new users highlighting the content on the background and three titles suggest an improvement in the adoption of the platform. Highlighting the content had a negative effect on returning users. The results show no improvements in presentation for returning users and should therefore be further investigated.

The user study showed that users have more intention to adopt a VoD platform for series than for films. Films are often only watched once making it cheaper to rent on a TVoD platform than pay for a subscription on an SVoD. Series are watched over a longer period making an SVoD more desirable when it comes to value for money. Additionally, current users of Videoland use Videoland mainly to watch series (Barnar, 2022).

Furthermore, it shows that it is hard to make a good set of content recommendations based on the content in the advertisement that a user clicked on. Therefore, it is easier and better for companies to show popular content on the homepage to convince new users to adopt their platform.

The results provide additional theoretical insights into existing work. The user study adds to the current literature factors that are relevant for intention to use in the area of OTT services. It confirms the current literature on OTT services that perceived enjoyment influences perceived value (Wang et al., 2013). In turn perceived value predicts intention to use (Wang et al., 2013; Singh et al., 2021).

Where previous literature (Table 1) only incorporated user experience factors, e.g. perceived enjoyment and perceived value, this study shows that subjective system aspects such as quality and diversity directly and indirectly affect intent as well. In turn, the study shows that all these factors explaining user intent can be manipulated by changing objective systems aspects in this case the type of content.

Despite the contradictory results of our hypotheses, this thesis shows the applicability of the model in a VoD context. The combination of both attitudinal factors, as well as perceptions of the manipulations, help explain the influence of content on the whole adoption process. It also explains why the results of the manipulation differ from the theoretical assumptions stated in the hypotheses.

6.2. Limitations

The user study tried to mimic the real world, but we know that there is always a difference between a controlled experiment (where users get paid) and the real world. The theory of planned behaviour comes closest by predicting intention to use and actual behaviour. However, if the user model was tested in the form of an A/B test this could have confirmed that the results apply to the real world, where things such as price can form a barrier between intention to use and actual use. This was unfortunately not possible due to the planning of other tests on the homepage by Videoland.

This study used only one platform to test whether content influences the adoption of OTT services. Research on other platforms in the same market is needed to see whether they apply to other platforms. A limitation of the empirical studies on the Videoland homepage is that they only measure whether content on the homepage influences the adoption of OTT services and not what content does in other situations for the platform. It might be that advertisements on television are enough to prove the influence of content on the adoption of VoD platforms.

The first study lacked data to conclude whether re-arranging the homepage and different content strips helped with the adoption of Videoland. In the third study, the data collected was limited by only including desktop visitors, these results can't be applied to mobile visitors. Apart from that, the design in study 3 was not very different from the original design. A more disruptive design where the content pops up on both mobile and desktop can help with testing the effect of content rather than design.

The sample of the user study consisted of 75 people that already had a subscription to Videoland these people can be biased in their answers to certain questions. For example, the questions on perceived enjoyment state whether users think it will be fun to use Videoland, users that have an account probably think it is fun otherwise they would unsubscribe. The same accounts for the questions on the intent that ask if they think they will use the platform users. There was no direct effect on intent but these people would normally be new subscribers in the real world (i.e. included in the a/b test).

The user had a trial with either series or films that were presented on the homepage and a mix of both series and films was not tested. Whereas for the A/B test only a mix of series and films was tested. To get more insights on whether series or films work better for SVoD these things should be tested separately.

6.3. Future research

Future research should further investigate ways to present content on the homepages of VoD platforms. It should investigate whether certain devices matter in the decision-making of a VoD platform to adapt to these needs. Additionally, designs can be adapted to the customer journey that is specific to a device.

The results of the presentation on content show a difference in the effect of content presentation between new users and returning users. A/B testing whether different types of content help with the highlighted presentation can provide insights into whether the content influenced the results or the design. Furthermore, A/B testing more designs can help find the best way to present content in a real-life setting.

The perceived novelty was not implemented in the final SEM. Therefore, the results of the user study give no insights whether the novelty of new titles affected user intent. The studies on presentation highlighted new content but the other content that was in the background was a bit outdated. Measuring the effect of novelty can help explain why certain presentation manipulations resulted in opposite effects. The perceived novelty of content on the homepage might also help explain the difference in the adoption of VoD platforms between new users and returning users.

The findings of the user study should be tested in a real-world situation in the form of an A/B test. Where the Top-5 content, New-5 content and personalized content are visible on the fold. This could provide insights whether the intention to use can predict actual behaviour. It also shows the influence of other factors that were not incorporated in the final model that influence the adoption of OTT services. The results of the user study in a real-world situation can prove that the mixed method approach works for analysing the adoption of OTT services.

A follow-up study can investigate how personalized recommendations can be improved. The final model can be used to evaluate whether a different type of recommender improves the perceived quality of the items which in turn increases the intention to use. One way to improve the recommender is by implementing external data, e.g. data from IMDB, in recommending item-2-item. Additionally, a study can be done where a mix of films and series is presented on the homepage compared to only series or films.

For Videoland it would be interesting what different type of content does over time and whether there are shifts in the market that cause these results. When a new platform enters the market that targets a certain group whether that influences the adoption rates of Videoland. Showing content that differentiates itself from that platform might help with competing in the dynamic market. Apart from that future research on OTT platforms should investigate whether the influence of content on the adoption of OTT services differs between different markets and platforms. It might be that for new platforms the market content has a different effect and different types of content should be presented than established platforms, such as Videoland and Netflix.

References

Aggarwal, C. C. (2016). *Recommender systems* (Vol. 1). Cham: Springer International Publishing.

Ajzen, I. (1985). From intentions to actions: A theory of planned behaviour. In *Action control* (pp. 11-39). Springer, Berlin, Heidelberg.

Alonso, C (2019). What is OTT (over-the-top)? Retrieved from: https://www.stateofdigitalpublishing.com/digital-platform-tools/what-is-ott-over-the-top/

Alvino, C. & Basilico,J. (2015). Learning a Personalized Homepage. Retrieved from: https://netflixtechblog.com/learning-a-personalized-homepage-aa8ec670359a

Aranyi, G., & Van Schaik, P. (2016). Testing a model of user experience with news websites. *Journal of the Association for Information Science and Technology*, *67*(7), 1555-1575.

Attfield, S., Kazai, G., Lalmas, M., & Piwowarski, B. (2011, February). Towards a science of user engagement (position paper). In *WSDM workshop on user modelling for Web applications* (pp. 9-12).

Azzahro, F., Ghibran, J. V., & Handayani, P. W. (2020, October). Customer Satisfaction and Willingness to Pay OnDemand Entertainment Streaming Service: The Role of Service Quality and Perceived Values. In *2020 International Conference on Information Technology Systems and Innovation (ICITSI)* (pp. 179-184). IEEE.

Barnar, V. (2022, November). Video behaviour of Dutch consumers 2022-Q3. Comprehensive market research on Dutch video consumers, the devices they use to watch the video, their subscriptions to premium and OTT channels, and time spent consuming TV and other video content. In *Telecompaper*. Retrieved from https://www.telecompaper.com/.

Becker, H., Broder, A., Gabrilovich, E., Josifovski, V., & Pang, B. (2009, November). What happens after an ad click? quantifying the impact of landing pages in web advertising. *In Proceedings of the 18th ACM conference on Information and knowledge management (*pp. 57-66).

Bettiga, D., Bianchi, A. M., Lamberti, L., & Noci, G. (2020). Consumers Emotional Responses to Functional and Hedonic Products: A Neuroscience Research. *Frontiers in Psychology*, *11*, 559779. https://doi.org/10.3389/fpsyg.2020.559779

Bhullar, A., & Chaudhary, R. (2020). Key factors influencing users' adoption towards OTT media platform: An empirical analysis. *In Int. J. Adv. Sci. Techno*l. (Vol. 29, Issue 11, pp. 942–956). https://www.scopus.com/inward/record.uri?eid=2-s2.0-85125626066&partnerID=40&md5=4cd952c5e8c2c45272a9f8367658c336

Bollen, D., Knijnenburg, B. P., Willemsen, M. C., & Graus, M. (2010, September). Understanding choice overload in recommender systems. In *Proceedings of the fourth ACM conference on Recommender systems* (pp. 63-70).

Camilleri, M. A., & Falzon, L. (2020). Understanding motivations to use online streaming services: integrating the technology acceptance model (TAM) and the uses and gratifications theory (UGT). *Spanish Journal of Marketing-ESIC*.

Caraban, A., Karapanos, E., Gonçalves, D., & Campos, P. (2019). 23 ways to nudge: A review of technology-mediated nudging in human-computer interaction. *In Proceedings of the 2019 CHI conference on human factors in computing systems (CHI '19)*. https://doi.org/10.1145/3290605.3300733

Cha, J. (2013). Predictors of television and online video platform use: A coexistence model of old and new video platforms. *Telematics and Informatics*, *30*(4), 296-310.

Chen, C. C., Leon, S., & Nakayama, M. (2018). Converting music streaming free users to paid subscribers: social influence or hedonic performance. *International Journal of Electronic Business, 14*(2), 128-145.

Chen, L., & Pu, P. (2009). Interaction design guidelines on critiquing-based recommender systems. *User Modeling and User-Adapted Interaction*, *19*(3), 167-206.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly,* 319-340.

Diefenbach, S., Kolb, N., & Hassenzahl, M. (2014, June). The'hedonic'in human-computer interaction: history, contributions, and future research directions. In *Proceedings of the 2014 conference on Designing interactive systems* (pp. 305-314).

Dupret, G., & Lalmas, M. (2013, February). Absence time and user engagement: evaluating ranking functions. In *Proceedings of the sixth ACM international conference on Web search and data mining* (pp. 173-182).

Ekstrand, M. D., Harper, F. M., Willemsen, M. C., & Konstan, J. A. (2014, October). User perception of differences in recommender algorithms. In *Proceedings of the 8th ACM Conference on Recommender systems* (pp. 161-168).

Faul, F., Erdfelder, E., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G* Power 3.1: Tests for correlation and regression analyses. *Behaviour research methods, 41*(4), 1149-1160.

Fernández-Robin, C., McCoy, S., Yáñez, D., & Hernández-Sarpi, R. (2019, July). Netflix, Who Is Watching Now?. In *International Conference on Human-Computer Interaction* (pp. 202-216). Springer, Cham.

Fudurić, M., Malthouse, E. C., & Lee, M. H. (2020). Understanding the drivers of linear television cord shaving with big data. *Journal of Media Business Studies*, *17*(2), 172-189.

Gafni, R., & Dvir, N. (2018). How content volume on landing pages influences consumer behaviour: empirical evidence. In *Proceedings of the Informing Science and Information Technology Education Conference, La Verne, California,* 35-53. Santa Rosa, CA: Informing Science Institute. https://doi.org/10.28945/4016

Giorgio Brajnik & Silvia Gabrielli (2010) A Review of Online Advertising Effects on the User Experience, *International Journal of Human-Computer Interaction, 26*:10, 971-997, DOI: 10.1080/10447318.2010.502100

Gomez-Uribe, C. A., & Hunt, N. (2015). The Netflix recommender system: algorithms, business value, and innovation. *Acm Transactions on Management Information Systems (This), 6*(4), 1–19. https://doi.org/10.1145/2843948

Graus, M. P., Willemsen, M. C., & Snijders, C. C. P. (2018). Personalizing a parenting app: parenting-style surveys beat behavioural reading-based models. In A. Said, & T. Komatsu (Eds.), *Joint Proceedings of the ACM IUI 2018 Workshops: Tokyo, Japan, March 11, 2018* (CEUR Workshop Proceedings; No. 2068). CEUR-WS.org.

Guo, Q., & Agichtein, E. (2012, April). Beyond dwell time: estimating document relevance from cursor movements and other post-click searcher behaviour. In *Proceedings of the 21st international conference on World Wide Web* (pp. 569-578).

Gutman, J. (1982). A means-end chain model based on consumer categorization processes. *Journal of Marketing*, *46*(2), 60-72.

Hamilton, R., Ferraro, R., Haws, K. L., & Mukhopadhyay, A. (2021). Travelling with companions: The social customer journey. *Journal of Marketing*, *85*(1), 68-92.

Hassenzahl, M. (2004). The interplay of beauty, goodness, and usability in interactive products. *Human-Computer Interaction*, *19*(4), 319-349.

Hassenzahl, M., Diefenbach, S., & Göritz, A. (2010). Needs, affect, and interactive products–Facets of user experience. *Interacting with computers*, *22*(5), 353-362.

Hornbæk, K., & Hertzum, M. (2017). Technology acceptance and user experience: A review of the experiential component in HCI. *ACM Transactions on Computer-Human Interaction (TOCHI)*, *24*(5), 1-30.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*, 1–55. https://doi.org/10.1080/10705519909540118

Huei-Huang Kuan, Gee-Woo Bock & Vichita Vathanophas (2008) Comparing the effects of website quality on customer initial purchase and continued purchase at e-commerce websites, *Behaviour & Information Technology*, 27:1, 3-16, DOI: 10.1080/01449290600801959

Iyengar, S. S., & Lepper, M. R. (2000). Why Choice is Demotivating: Can One Desire Too Much of a Good Thing. *Journal of Personality and Social Psychology*, *79*(995), 1006.

Jannach, D., & Adomavicius, G. (2016, September). Recommendations with a purpose. In *Proceedings of the 10th ACM conference on recommender systems* (pp. 7-10).

Jannach, D., & Jugovac, M. (2019). Measuring the business value of recommender systems. *ACM Transactions on Management Information Systems (TMIS)*, *10*(4), 1-23.

Jesse, M., & Jannach, D. (2021). Digital nudging with recommender systems: Survey and future directions. *Computers in Human Behavior Reports*, *3*, 100052.

Johnson, E. J. (2021). *The Elements of Choice: Why the Way We Decide Matters.* Simon and Schuster.

Johnson, E. J., Shu, S. B., Dellaert, B. G., Fox, C., Goldstein, D. G., Häubl, G., ... & Weber, E. U. (2012). Beyond nudges: Tools of choice architecture. *Marketing Letters*, *23*(2), 487-504.

Kamleitner, B., & Hölzl, E. (2009). Cost-benefit associations and financial behaviour. *Applied Psychology*, *58*(3), 435-452.

Khan U., Dhar R., Wertenbroch K. (2004). *Inside Consumption: Consumer Motives, Goals, and Desires.* Abingdon: Routledge, 144–165.

Kim, S., Baek, H., & Kim, D. H. (2021). OTT and live streaming services: Past, present, and future. *Telecommunications Policy*, *45*(9), 102244.

Kim, Y. J., & Kim, B. Y. (2020). The purchase motivations and continuous use intention of online subscription services. *International Journal of Management*, *11*(11).

Knijnenburg, B. P., Willemsen, M. C., & Kobsa, A. (2011, October). A pragmatic procedure to support the user-centric evaluation of recommender systems. In *Proceedings of the fifth ACM conference on Recommender systems* (pp. 321-324).

Knijnenburg, B. P., Willemsen, M. C., Gantner, Z., Soncu, H., & Newell, C. (2012). Explaining the user experience of recommender systems. *User modeling and user-adapted interaction, 22*(4), 441-504.

Ko, H., Lee, S., Park, Y., & Choi, A. (2022). A Survey of Recommendation Systems: Recommendation Models, Techniques, and Application Fields. *Electronics, 11*(1), 141.

Lalmas, M., Lehmann, J., Shaked, G., Silvestri, F., & Tolomei, G. (2015). Promoting positive post-click experience for in-stream yahoo Gemini users. In *Proceedings of the 21st ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 1929-1938).

Lee, M., Choi, H., Cho, D., Lee, H., 2016. Cannibalizing or Complementing? The impact of online streaming services on music record sales. Procedia Comput. Sci. 91, 662–671. https://doi.org/10.1016/j.procs.2016.07.166.

Leowarin, T., & Thanasuta, K. (2021). Consumer Purchase Intention for Subscription Video-on-Demand Service in Thailand. *TNI Journal of Business Administration and Languages*, *9*(1), 14-26.

Long, Q., & Tefertiller, A. C. (2020). China's new mania for live streaming: Gender differences in motives and uses of social live streaming services. *International Journal of Human-Computer Interaction*, *36*(14), 1314-1324.

Malewar, S., & Bajaj, S. (2020). Acceptance of OTT video streaming platforms in India during covid-19: Extending UTAUT2 with content availability. *Journal of Content, Community and Communication*, 89-106.

Mavlanova, T., Benbunan-Fich, R., Koufaris, M., & Lang, G. (2015). The effect of positive and negative signals on the perceived deceptiveness of websites in online markets. *Journal of theoretical and applied electronic commerce research*, *10*(1), 19-34.

McDowell, W. C., Wilson, R. C., & Kile Jr, C. O. (2016). An examination of retail website design and conversion rate. *Journal of Business Research, 69*(11), 4837-4842.

Mikos, L. (2016). Digital media platforms and the use of TV content: Binge-watching and video-on-demand in Germany. *Media and Communication*, *4*(3), 154-161.

Mulla, T. (2022). Assessing the factors influencing the adoption of over-the-top streaming platforms: A literature review from 2007 to 2021. *Telematics and Informatics*, 101797.

Nagaraj, S., Singh, S., & Yasa, V. R. (2021). Factors affecting consumers' willingness to subscribe to over-the-top (OTT) video streaming services in India. *Technology in Society, 65*, 101534.

Netflix (2022, September 9). *The Netflix ISP Speed Index.* Retrieved from: https://ispspeedindex.netflix.net/global

Oyedele, A., & Simpson, P. M. (2018). Streaming apps: What consumers value. *Journal of Retailing and Consumer Services, 41*, 296-304.

Pallotta, F. (2022, October 13). *Netflix with ads is here. Here's everything you need to know.* CNN Business. Retrieved from: https://edition.cnn.com/2022/10/13/media/netflix-ads-plan-cost/index.html

Pu, P., Chen, L., & Hu, R. (2011, October). A user-centric evaluation framework for recommender systems. In *Proceedings of the fifth ACM conference on Recommender systems* (pp. 157-164).

Ramasoota, P., & Kitikamdhorn, A. (2021). "The Netflix effect" in Thailand: Industry and regulatory implications. *Telecommunications Policy, 45*(7), 102156.

Roxborough, S. (2019, September 26). *Why Disney+ Quietly Launched in the Netherlands First.* The Hollywood reporter. Retrieved from: https://www.hollywoodreporter.com/business/digital/why-disney-quietly-launched-netherlands-first-1243068/

Samani, M. C., & Guri, C. J. (2019). Revisiting uses and gratification theory: A study on visitors to Annah Rais homestay. Jurnal Komunikasi: *Malaysian Journal of Communication*, *35*(1), 206-221.

Shahzeidi, A. (2022). Top OTT Statistics for 2022. Retrieved from: https://www.uscreen.tv/blog/ott-statistics/

Sheth, J. N., Newman, B. I., & Gross, B. L. (1991). Consumption values and market choices: Theory and applications (pp. 16-74). *Cincinnati, OH: South-Western Pub.*

Shobiye, T., Naidoo, G. M., & Rugbeer, H. (2018). Factors that Influence one's choice for viewing public television in South Africa. *Alternation Journal*, *25*(1), 394-424.

Singh, S., Singh, N., Kalinić, Z., & Liébana-Cabanillas, F. J. (2021). Assessing determinants influencing continued use of live streaming services: An extended perceived value theory of streaming addiction. *Expert Systems with Applications*, *168*, 114241.

Starke, A., Asotic, E., & Trattner, C. (2021, September). "Serving Each User": Supporting Different Eating Goals Through a Multi-List Recommender Interface. In *Fifteenth ACM Conference on Recommender Systems* (pp. 124-132).

Statista (2021a). Subscription video-on-demand (SVOD) subscriptions and subscribers worldwide from 2020 to 2026. Retrieved from: https://www.statista.com/statistics/1235801/global-svod-subscriptions-and-subscribers/#statisticContainer

Statista (2021b). Leading SVOD companies in the EU 2020, by revenue. Retrieved from: https://www.statista.com/statistics/1235801/global-svod-subscriptions-and-subscribers/#statisticContainer

Statista (2022). Digital Media Report - Video-on-Demand. Retrieved from: https://www.statista.com/outlook/amo/media/tv-video/ott-video/worldwide?currency=EUR

Streanwijzer (2022). Beste streamingdiensten in 2022: 28 alternatieven voor Netflix. Retrieved from: https://www.streamwijzer.nl/beste-streamingdiensten-alternatief-netflix-nederland/

Sunstein, C. R. (2014). Nudging: A very short guide. *Journal of Consumer Policy*, *37*, 583–588. https://doi.org/10.1057/s11369-018-00104-5

Telecompaper, (2022a). Dutch Consumer Television Market-rapport. Retrieved from: https://www.telecompaper.com/research/dutch-consumer-television-market-2022-q1--1426527

Telecompaper, (2022b). Nederlandse tv-markt ziet omzetdaling in Q2 verder toenemen Retrieved from: https://www.telecompaper.com/news/nederlandse-tv-markt-ziet-omzetdaling-in-q2-verder-toenemen--1437967

Udoakpan, N., & Tengeh, R. K. (2020). The impact of over-the-top television services on pay-television subscription services in South Africa. *Journal of Open Innovation: Technology, Market, and Complexity*, *6*(4), 139.

Van den Broek, M. (2022). Ondertussen, op de Nederlandse televisiemarkt. Retrieved from: https://www.marketingfacts.nl/berichten/ondertussen-op-de-nederlandse-televisiemarkt/

Van der Heijden, H. (2004). User acceptance of hedonic information systems. *MIS Quarterly*, 695-704.

Van Schaik, P., & Ling, J. (2011). An integrated model of interaction experience for information retrieval in a Web-based encyclopaedia. *Interacting with Computers*, *23*(1), 18-32.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425-478.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 157-178.

Walsh, P., & Singh, R. (2021). Determinants of Millennial behaviour towards current and future use of video streaming services. *Young Consumers*.

Wang, Y. S., Yeh, C. H., & Liao, Y. W. (2013). What drives purchase intention in the context of online content services? The moderating role of ethical self-efficacy for online piracy. *International journal of information management, 33*(1), 199-208.

Willemsen, M. C., Graus, M. P., & Knijnenburg, B. P. (2016). Understanding the role of latent feature diversification on choice difficulty and satisfaction. *User Modeling and User-Adapted Interaction, 26(*4), 347-389.

Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: Use, characteristics, and impact. *MIS Quarterly*, 137-209.

Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: a means-end model and synthesis of evidence. *Journal of Marketing, 52*(3), 2-22.

Appendix 1

Construct	Item
Demographics	D1: What is your age?
	D2: What is your gender?
	D3: Do you have a Videoland account?

Construct	Item
Demografische gegevens	D1: Wat is je leeftijd ?
	D2: Wat is je geslacht?
	D3: Heb je een Videoland account?

Construct	Item
Perceived recommendation quality (Knijnenburg et al., 2012)	PERQ1: I liked the series shown by the system.
	PERQ2: The shown series fitted my preference.
	PERQ3: The shown series were relevant.
	PERQ4: I didn’t like any of the shown series.
Perceived level of personalization (Graus, Willemsen & Snijders, 2018)	PERP1: The homepage shows a series I find interesting
	PERP2:: The homepage contains series that are more relevant to the general public than to me
	PERP3: The homepage does not show which series I find interesting
Perceived recommendation diversity (Willemsen, Graus & Knijnenburg, 2016)	PERD1: The list of series and movies was varied
	PERD2: All the series and movies were similar to each other.
	PERD3: Most of the series and movies were from the same genre
	PERD4: Many of the movies in the list differed from other movies in the list
Perceived recommendation novelty (Ekstrand et al., 2014)	PERN1: Videoland has a series that I did not know about
	PERN2: Videoland has a series that I am familiar with
	PERN3: Videolands offer pleasantly surprised me
Perceived Value (Singh et al., 2021; Wang et al., 2013)	PV1: Overall, the use of Videoland delivers me good value
	PV2: Compared to the fee, I need to pay Videoland offers value for money
	PV3: Considering the time I put into using Videoland, it is worthwhile.
Perceived Enjoyment (Singh et al., 2021)	PE1: Using Videoland will be fun.
	PE2: Using Videoland will be enjoyable.
	PE3: Using Videoland will be pleasurable
	PE4: Using Videoland will be entertaining.
Behavioural intention (Fernàndez-Robin, 2019; Pu, Chen & Hu, 2011)	BI1. I am willing to purchase Videoland
	BI2. I plan to use Videoland in the future
	BI3. I plan to use Videoland frequently

Construct	Item
Perceived recommendation quality (Knijnenburg et al., 2012)	PERQ1: De series vind ik leuk
	PERQ2: De series spreken mij aan
	PERQ3: De series zijn relevant
	PERQ4: Ik vind geen van de series leuk
Perceived level of personalization (Graus, Willemsen & Snijders, 2018)	PERP1: De series vind ik persoonlijk interessant
	PERP2: De series zijn meer relevant voor het algemene publiek dan voor mij specifiek
	PERP3: De pagina laat series zien die niet bij mij passen
Perceived recommendation diversity (Willemsen, Graus & Knijnenburg, 2016)	PERD1: De lijst van series is gevarieerd
	PERD2: De series lijken erg op elkaar
	PERD3: De meeste series zijn van hetzelfde genre
	PERD4: De series in de lijst verschillen veel van elkaar
Perceived recommendation novelty (Ekstrand et al., 2014)	PERN1: Videoland heeft series die ik nog niet ken
	PERN2: Videoland heeft series waar ik al bekend mee ben
	PERN3: De series op Videoland verassen me
Perceived Value (Singh et al., 2021; Wang et al., 2013)	PV1: Videoland heeft een goede prijs-kwaliteits verhouding
	PV2: Gezien de abonnementskosten is Videoland het geld waard
	PV3: Videoland is de moeite waard
Perceived Enjoyment (Singh et al., 2021)	PE1: Het gebruiken van Videoland lijkt me leuk
	PE2: Het gebruiken van Videoland lijkt me plezierig
	PE3: Het gebruiken van Videoland lijkt me vermakelijk
	PE4: Het gebruiken van Videoland lijkt me niks
Behavioural intention (Fernàndez-Robin, 2019; Pu, Chen & Hu, 2011)	BI1. Ik verwacht een Videoland abonnement te nemen
	BI2. Ik verwacht in de toekomst Videoland te gebruiken
	BI3. Ik verwacht Videoland vaak te gebruiken