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Title of proposed study: Drivers of continued use of OTT platforms.

Nature of study: Study will explain variability in consumers' behavioural intent to use OTT platforms.

A research project submitted to the Gordon Institute of Business Science, University of Pretoria, in partial fulfilment of the requirements for the degree of Master of Business Administration.

Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

ABSTRACT

As Over The Top (OTT), platforms continue to gain market share and disrupt traditional linear broadcasters has lead academic, business leaders and legislators to consider if conventional marketing and Information systems models can explain continued use intentions for OTT platforms. While the adoption of technology is crucial to the success of an enterprise, it is continued use that determines the long term sustainability of an enterprise. Understanding the factors that drive continued use intentions of OTT platforms is crucial for developing long-standing sustainable and loyal relationships with customers.

Video-on-demand platforms like YouTube, Showmax, Amazon and Netflix continue to disrupt traditional linear broadcasters and are continuously altering the TV and video marketplace and value chains. These OTT platforms are altering consumer viewing trends, moving away from TV schedules prescribed and dictated by traditional broadcasters, resulting in time-shifted viewing. These changes are no longer limited to time-shifted viewing; consumers are increasingly in control of when and how they view video content, resulting in fragmented viewing patterns, significantly impacting mass media models relied on by the advertising industry.

The results of our quantitative study indicate that the proposed model for continued use explains 69 percent of the variation in continued use intentions. Our findings indicate that consumers are multihoming and using multiple competing platforms, concurrently, which is inconsistent with conventional marketing and IS theory that consumers adopt and use only one competing product. Our findings indicate that the presence of a competing product impacts user continuance intentions, habit and satisfaction. However, the impact size was insignificant for intentions and satisfaction.

KEYWORDS

Continued use; habit; satisfaction; multihoming, and Over-the-Top (OTT).

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CHAPTER 1

1.1 Introduction to the research problem

Over-the-Top (OTT) platforms subscription revenues are projected to make up 35% of global pay-television (pay-TV) revenues by 2023 (Chow & Van Eeden, 2019, p.8). However, despite their growing importance, very little is known about the displacement effect and what framework best explains continued use or post-adoption use of OTT platforms (J. Kim, Kim & Nam, 2016). The rapid adoption of OTT platforms, in particular, the freemium model and the proliferation of these platforms have led marketers, academics, developers, and executives to question which is the most appropriate business model between freemium and subscription-based models (Wlömert & Papies, 2016). Answering this question requires that we understand the continued use intentions of consumers and the factors that drive it.

OTT revenues in South Africa have grown exponentially at a Cumulative Average Growth Rate (CAGR) of 34% between 2014 and 2019. Combined with new market offerings and rapidly changing consumer requirements, these OTT services are continuing to disrupt and fragment the highly dynamic television (TV) and video market. According to The Broadcasting Research Council of South Africa's (BRC) (2018) Establishment Survey, 24% of survey participants indicated that they often use video streaming services (OTT), highlighting the growing importance of OTT services in the video viewing mix.

Video-on-demand platforms like YouTube, Showmax, Amazon and Netflix continue to disrupt traditional linear broadcasters and are continuously altering the TV and video marketplace and value chains (Boehm et al., 2018). These OTT platforms are altering consumer viewing trends, moving away from TV schedules prescribed and dictated by traditional broadcasters, resulting in time-shifted viewing (Schweidel & Moe, 2016). These changes are no longer limited to time-shifted viewing; consumers are increasingly in control of when and how they view video content, resulting in fragmented viewing patterns, significantly impacting mass media models relied on by the advertising industry (Corder & Chipp, 2013 & Chipp & Chakravorty, 2016).

> *"How do you consume entertainment and media content? Ask 20 different people, and you are likely to get 20 different answers, even if some of those people live under the same roof. One parent may watch the first episode of the final season of HBO's epic Game of Thrones on a 60-inch television on Sunday night when it first airs. The other parent might stream it later in the evening on the HBO Go app on an iPad. Their teenager might watch it the next day on his phone, while simultaneously playing a video game. Their daughter, home from university, might download it, and then stream the episode on her laptop four days later" (Chow & Van Eeden, 2019, p.2).*

1.2 What are OTT services?

OTT refers to services that deliver audio, video, and other media that bypass traditional networks (Sujata et al., 2015). In the case of video, video streaming services refer to the delivery of services through the internet and bypassing the traditional broadcasting services that deliver content via cable, satellite, and Over-the-Air (OTA) (Schweidel & Moe, 2016). The initial streaming services were primarily Video on Demand (VoD) and subscription-based (SVoD). The product offering and mix have grown to include both free AVoD (advertiser funded) and paid SVoD (subscription funded with no advertising). Furthermore, some platforms now offer both VoD and linear channels similar to traditional TV broadcasting, further highlighting their growing importance (Prince & Greenstein, 2017) (Sujata et al., 2015).

1.3 The effect of OTT services on other industries

The disruption of OTT services is not limited to video technology. Similar to the video market, telecommunications service providers have experienced a decline in revenues due to a shift in consumer preferences (Sujata et al., 2015). It is estimated that global SMS revenues declined from US$120 billion in 2013 to US$97 billion in 2018. Similarly, the growth of Voice over Internet Protocol (VoIP) is expected to negatively affect telecom companies voice revenues by US$479 billion by 2020. Understanding post-adoption, continued use models are crucial to developing sustainable business models. Similar to the telecoms industry, the rise of the digital channel within the music space has resulted in revenues initially declining then rebounding in recent years. The rebound has been attributed to a better understanding of continued use models. In their paper, *On-demand streaming revenues on music industry revenues*, Wlömert & Papies (2016) found that free on-demand services cannibalised traditional distribution channels. However, they noted that free services attracted new previously inactive customers to the market to the benefit of the industry. They also noticed a decline/cannibalisation in spending from active customers through spending less on the digital channel than the traditional channel. The increase in the overall market size more than compensated for the cannibalisation of traditional streams (Wlömert & Papies, 2016). Thus, it is vital to understand the post-adoption models for OTT platforms to create sustained business models.

1.4 Business strategy implications

The emergence of OTT platforms and their disruption of traditional markets and fast adoption enabled by technology advances in devices, high-speed networks, and superior functionalities developed over time have shifted consumer preferences in favour of OTT platforms (Sujata et al., 2015). In recent years, OTT platforms have increased their market share, and as a result, the TV and video market has become increasingly fragmented. Traditional broadcasters and pay-TV providers have seen their market share decline, and this has coincided with the increased popularity of OTT platforms (Tao, Zhumin, Yujie & Jun 2018; Schweidel & Moe, 2016; Chow & Van Eeden, 2019). Their popularity has led to the rise in new market entrants that are rapidly altering the industry structure, value chain, and ecosystem. These changes pose the following question for business and academia: What model and factors can explain the continued use of OTT platforms?

Fragmentation has led to the consumer having more choice (Chow & Van Eeden, 2019). Consumers are starting to reject bundled channel packages from multichannel video programming distributors (MVPDs), creating and assembling their own bundles from complementary OTT platforms (Chow & Van Eeden, 2019). In some instances, consumers are also creating bundles that include both pay-TV (MVPD) and OTT platforms. In the United States of America (USA), an estimated 64% of OTT users also subscribe to a pay-TV platform (Marketing Charts, 2020). Similarly, in South Africa, 71% of 9 857 MyBroadband readers indicated that they subscribed to an OTT service in a 2018 survey.

In addition to implications for business, the proliferation of global OTT platforms has implications for the countries in which they operate. Most companies that operate OTT platforms operate at a global level, thereby giving them more significant scale and scope compared to traditional and local broadcasters. Furthermore, these platforms have been accused of not paying taxes or not abiding by regulations that local operators are subjected to in the markets they operate, thereby giving them a further competitive advantage on local and traditional players (Candidate, 2018). Understanding the continued use of these platforms is critical for legislators when deciding on legislation aimed at addressing market competitive issues for both global platforms and local/traditional platforms (Swofford, 2020 & Candidate, 2018).

In an increasingly fragmented market, understanding which business model is effective requires retaining a broad customer base. Understanding factors that drive continued use intentions for customers is crucial to adopting an effective strategy and business model.

1.5 Customer retention, satisfaction, habit, and contribution to the existing literature

With consumers seemingly not satisfied with their current bundles and creating their own, the research asks if consumers are satisfied with their OTT platforms and if satisfaction will lead to continued use. The increasing share of the market together with the proliferation of OTT services have shifted the attention from adoption to continued use, and more platforms are focusing on satisfaction and continued use (J. Kim et al., 2016).

In a rapidly shifting TV landscape, content distribution directly to consumers via owned inhouse branded OTT platforms has developed into one of the strategies for content and channel owners (PwC, 2019). The rapid proliferation of these OTT platforms has shifted focus away from adoption to post-adoption (continued use) (Netflix Inc, 2018). Platform owners like Netflix are now diverting their attention to continued use. Furthermore, it has been reported that 65% of millennials are using OTT services exclusively, further highlighting the changing landscape (Flynn, 2020).

> *"The relative service levels, content offerings, pricing and related features of competitors to our service may adversely impact our ability to attract and retain memberships. In addition, many of our members rejoin our service or originate from word-of-mouth advertising from existing members. Members cancel our service for many reasons, including a perception that they do not use the service sufficiently, the need to cut household expenses, availability of content is unsatisfactory, competitive services provide a better value or experience, and customer service issues are not satisfactorily resolved. Further, if excessive numbers of members cancel our service, we may be required to incur significantly higher marketing expenditures than we currently anticipate to replace these members with new members" (Netflix Inc, 2018, p.3).*

Fragmentation, complexity, and fluidity of the media and entertainment market, particularly the OTT market, has put customer retention at the centre of OTT platform business models (Boehm et al., 2018). Both subscription-based and advertising-funded (free) models are profoundly dependent on customer retention to forecast and predict future cash flows. The inability to forecast and predict future cash flows has significant ramifications for both business models. Firstly, the commissioning and acquisition of content transpire months if not years before airing or being available for consumption (Netflix Inc, 2018). Thus, the cash outflows and monetisation of the content occur in advance. Any significant loss of customers will negatively impact the commissioning and acquisition of content. Additionally, the marketing strategies of these platforms are highly dependent on word-of-mouth advertising by current users. Any loss of existing users will drive customer acquisition costs up (Netflix Inc, 2018).

Linear TV has used appointment viewing strategies to influence consumer habits and drive customer retention and loyalty. In an increasingly fragmented market, habitual and consistent use of these platforms is critical for future revenues and cash flows. Thus, we ask if consumers are habitually using OTT platforms and if habit will lead to continued use (Hsiao, Chang & Tang, 2016).

This research will add to the growing research on continued use; the study will focus on OTT platform technology. This technology has been key to disrupting the TV and video market by putting control back into the hands of the consumer, allowing them to view/consume content on a device of their choice at a convenient time for them. Thus, we focus on a technology that is increasing in importance but remains under-researched.

The study will explain the variation in continuance intentions of OTT platforms by examining consumer satisfaction and habitual behaviour. This study aims to understand how these variables interact with the technology in question (OTT services). OTT differs from other products in that consumers broadly adopt new technology (OTT) while concurrently using old technology (pay-TV). Thus, while scholars have regarded OTT platforms as a substitute for pay-TV, they have been utilised as a complementary product (Rich, 2019 & J. Kim et al., 2016).

Furthermore, the research enhances existing literature by building on the work of Hsiao, Chang & Tang (2016) by adding the multihoming and Status Quo Bias (SQB) theories to explain variations in satisfaction and habit. OTT consumers are creating their own bundles and combining competing products. Multihoming explains how consumers purchase competing products, a concept that goes against the traditional marketing convention that a consumer only buys one product. Our theory is that multihoming will result in SQB, the impact of which will vary depending on the user's primary platform (Jiang, Tian & Zhou, 2019: Karahanna & Polites, 2012: Rey-Moreno et al., 2018). Thus, SQB will negatively impact continuance intention for users who do not identify an OTT platform as their primary system. SQB will positively impact continuance intention, satisfaction, and habit for users who identify an OTT platform as their primary system (Jiang, Tian & Zhou, 2019: Karahanna & Polites, 2012: Rey-Moreno et al., 2018).

The future state of the video and TV market is exceptionally reliant on access to customers. The proliferation of OTT platforms has resulted in a fragmented market and moving attention away from adoption to post-adoption (continuance intention) (Boehm et al., 2018). Changing customer orientation and behaviour has implications for content curation and media entertainment business. Understanding how these platforms create and capture value from consumers is key to understanding consumer behaviour, and continued use intentions are key (Chipp & Chakravorty, 2016). Furthermore, the entrance of global OTT players into the South African market and the strategy by local players to launch their own branded OTT platforms have created an urgent need to understand customer retention and, in turn, continuance intention of consumers in this increasingly fragmented market (PwC, 2019). Thus, understanding consumer continuance intentions of this unique technology has become critical.

1.6 Scope

This study focused on the South African market. South Africa’s media and entertainment industry is twice the size of the second-largest market, Nigeria (PwC, 2019). The study collected data from consumers in all nine provinces across various demographics and income levels to get a broad range of consumer views. The critical constructs tested were the intention, satisfaction, and habit (dependent variables) with independent variables of Perceived Usefulness (PU), Perceived Enjoyment (PE), Social Ties (ST), and SQB, and complexity (independent variable). Crucial constructs and sub-constructs were recognised and then used as observed variables to measure the key constructs. The study used both primary account holders and those with access to OTT platforms through the primary account holder.

1.7 Research aims

The research aims to test the statistical significance of factors driving the continued use of other technologies to establish the importance of these factors in driving behavioural intentions concerning the continued use of OTT platforms. The research purports to answer the following questions:

a) What factors and model will explain an individual consumer's behavioural intention to carry on using the OTT platforms they are presently using?
b) Is satisfaction a crucial variable in continued use intentions of OTT platforms?
c) Will OTT consumers habitually use OTT platforms?
d) To what extent will OTT consumers carry on utilising the media they are presently utilising?

1.8 Conclusion and document structure

The rapid adoption and proliferation of OTT platforms have highlighted the need to understand factors that drive continued use intentions for these platforms. Understanding the continued use intentions of these platforms is crucial for marketers, academics, developers, executives, and legislators. It is crucial for deciding on effective business models (freemium/subscription), how traditional and local media operators can compete against global OTT platforms, and for legislators in setting up appropriate laws and regulations to govern the competitive space in which these companies operate. For academics, the research augments the prevailing literature on continued use and the role of habit and satisfaction in continued use intentions. This study attempts to understand the role of satisfaction and habit in determining continued use intentions, thereby contributing to existing marketing and technology continued use literature. The rest of the document will be organised as follows: Chapter 2 reviews the available literature and addresses the relationship between the constructs. Chapter 3 addresses the research questions. Chapter 4 details the research design and methodology. Chapter 5 is the results chapter. Chapter 6 discusses the results, and we conclude the document in Chapter 7.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The study aims to verify theories that impact the continued use of OTT platforms. At the same time, we draw on the original technology adoption and acceptance theories. We focus on continued use as this is an under-researched area, and most of the research focuses on adoption and cord-cutting behaviour, where consumers cancel their subscriptions to MVPD services over cable or satellite in favour of OTT platforms (Hsiao et al., 2016 & Prince & Greenstein, 2017). Furthermore, OTT technologies are unique and continuously evolving and have not yet been researched extensively. Thus, we draw on the research of other technologies like social media applications, fitness wearables, and e-government services (Piehler, Wirtz & Daiser, 2016, Rey-Moreno et al., 2018 & Canhoto & Arp, 2017).

Past research into Information Systems (IS) use has focused on IS adoption as opposed to continued use (Hsiao et al., 2016). IS adoption refers to user acceptance and use of new technology, while continued use refers to post-adoption repetitive use of the technology (Venkatesh, Morris, Davis & Davis, 2003). Thus, we consciously reject existing technologies and methods in favour of new technology (adoption) and once adopted, the consumer continuously uses the new technology (continued use). The foundation of IS adoption theories is based on the Theory of Planned Behaviour (TPB) and the Theory of Reasoned Action (TRA) as the basis of explaining adoption (Venkatesh, Thong & Xu, 2016). The proliferation of computer-enabled mobile devices partly facilitated the shift in focus from adoption in a business setting to mass market consumer adoption. Additionally, research has pivoted from adoption to continued use as the use of applications became prevalent and competition amongst market participants increased (Hsiao et al., 2016).

The study draws on research by Chun Hua Hsiao et al. (2016). Their research paper focuses on satisfaction, habit, and customer value perspectives and their impact on the continued use of mobile social applications. Research from Wang, Harris & Patterson (2013) focuses on the role of the subconscious, in particular the question of whether habit influences satisfaction or satisfaction influences habit. Research by Rey-Moreno, Felício, Medina-Molina & Rufín (2018) focuses on facilitator and inhibitor factors to adopting e-government services in a dual model, and the paper uses SBQ inertia theories to explain continued use. Lastly, we combined the above research with multihoming research by Jiang, Tian & Zhou (2019) and Prince & Greenstein (2017), which challenges the perception and assumption that consumers do not purchase competing products.

Continued use intention versus Behaviour (actual use) versus Habit

Continued use intention is defined as the motivation to perform a particular action or task (Y. Kim & Zhang, 2010). Similarly, continued use refers to constant or consistent use of technology, and equates consistent use to loyalty (Jahanmir, Silva, Gomes & Gonçalves, 2020). Y Kim & Zhang (2010) further define continued use as repetitive behavioural patterns as a result of specific cues that are associated with satisfaction and the perceived value of using the product. Unlike adoption or initial use, continued or persistent behaviour is more complex. It is not an extension or function of adoption behaviour (Limayem, Hirt & Cheung, 2007). While external factors mainly drive initial use, several factors impact continued use. Continued use intention is dependent on the technology itself, the individual, and the environment in which the technology operates. In addition to the PU, Perceived Ease of Use (PEOUS), and social constructs that are critical in the adoption of technology, continued use intentions have additional constructs (habit and satisfaction), further highlighting its complexity (Hsiao et al., 2016). Continued use reconciles the experience of actual use with the individual’s prior notions of the product (Piehler et al., 2016).

Ninety per cent of all digital innovations fail (Jahanmir et al., 2020). While adoption is fundamental to the initial success of a technology, continued usage plays a significant role in the long-term success and financial sustainability of a product. In highly competitive environments, it is crucial not only to promote strategies that drive the increase in users’ continued use intentions but also user loyalty as both are critical for the long-term survival of the technology (Jahanmir et al., 2020). Furthermore, continued use intentions are associated with loyalty, increased market share, and competitive advantage for the technology that can lead to long-term financial sustainability (Kim & Zhang, 2010). It is, therefore, critical that we understand the factors that drive continued use intentions. An intention is an antecedent to action. It is a plan of action that an individual aims to carry out.

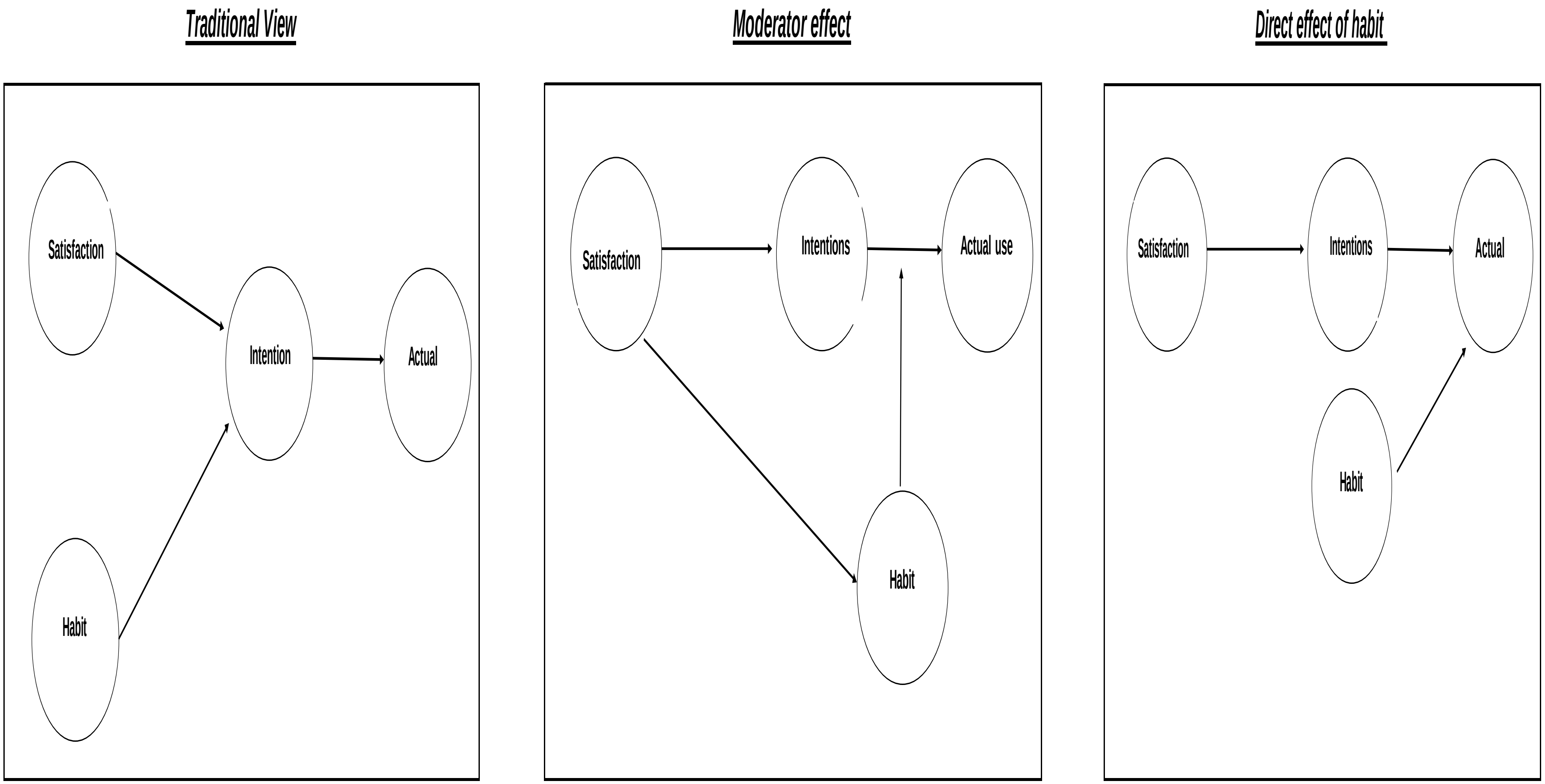
2.2 Continued use intentions versus Usage

The intention to use a particular service or product is proven to explain a significant portion of the variance in use. Thus, differences in the utilisation of technology can be explained by the consumer's intentions before use. The stronger the intention, the more likely that the user will follow through with the action. Earlier studies like Davis, Bagozzi & Warshaw (1989), Venkatesh & Davis (2000), and Kim & Malhotra (2005) found that intentions explained 40%, 34%, and 64% respectively of the variance in use. More recent research like Gieure, Benavides-espinosa & Roig-dobón (2020) found that intentions explained 46% of the variance in actual use.

While there is clarity on the role of intentions on actual behaviour, there is no clear consensus on whether intentions are a cognitive or habitual process. Wang et al., (2013) argue that intentions, which are the mental conscious thought process, play a significant part in the initial stages when the technology is still new to the user. Thus, the consumer makes a conscious decision to continue using the technology. After multiple uses, the consumer shifts from being conscious to subconscious, making the use habitual. Therefore, Wang et al., (2013) conclude that use is determined initially by intentions (conscious), and then habit (subconscious) plays a significant role after that. Other authors like Karahanna & Polites (2012) argue that habit impacts intentions directly and is not a cognitive process but rather a subconscious process. Multiple theories support the various arguments above. The study summarises these into the following categories: the traditional view, the moderator effect, and the direct effect.

The figure below summarises various views and their interactions from the direct effect to the moderating effect. The traditional view shows satisfaction and habit being parallel constructs; the moderator effect shows satisfaction impacting habit and habit being a moderator between intentions and use. Lastly, the direct effect shows habit directly impacting use. All three enjoy varying degrees of support in literature with no clear consensus on the appropriate model (Limayem et al., 2007).

Figure 1 – Different views on theories



Traditional view

Firstly, the TRA and the TPB suggest that human behaviour is rational and planned behaviour, thus providing a theoretical grounding for the conscious cognitive argument (Y. Kim & Zhang, 2010). Confirmation-disconfirmation theories build on TRA and TPB by positing that in a post-acceptance scenario of using technology, the user takes into account prior experience with the system and reconciles it with their expectations to decide to utilise or not to utilise the service (Bhattacherjee, 2001). Thus, the intentions to utilise or utilise to use the system is a cognitive process. Lastly, the habit theories posit that to avoid cognitive overload and promote decision-making efficiency for repeated actions, individuals develop automated responses to certain stimuli, and these automated responses occur subconsciously (Karahanna & Polites, 2012).

While initial technology theories focus on adoption and are based on ideas like the TRA and TPB, more recent views like Venkatesh, Thong & Xu (2016) and Williams, Rana & Dwivedi (2015) have extended the adoption model to explain continued use. At the same time, the basis for TRA and TPB is the belief that rational decision-making guides human decision-making. While this might hold true for adoption when the technology is new and external, and the decision to use the technology is a conscious cognitive process, the same cannot be said for repeated, persistent behaviour as the process becomes automated as use continues after adoption. TRA predicts behavioural intentions and actual behaviour; it theorises that intentions which are the antecedents of actual behaviour are mainly driven by a person’s behavioural and normative beliefs (Charng, Piliavin & Callero, 1988). Behavioural beliefs affect a person’s attitudes towards technology, and normative beliefs are related to subjective societal norms. The basis of TPB is the TRA; however, the main difference between the two theories is behavioural control (Ajzen, 1991). Behavioural control refers to the degree to which an individual has control over the actions that are essential for them to perform a given behaviour (Orbell, Blair, Sherlock & Conner, 2001). Behavioural control impacts both intentions and the auctioning of the intentions. TPB further states that the performance of a behaviour is a function of both intentions and behavioural control. The importance of each factor is dependent on the context and varies across various circumstances and behaviours (Ajzen, 1991).

The TRA and TPB are an essential foundation and connection for continued use predictors. Continued intentions are the most important antecedent for continued use (Limayem et al., 2007). Sheppard (1985) concluded that continuous intentions are a significant factor in actual use. Intentions explain 50% of the variation in use (Gieure et al., 2020). In their study, *Social sharing of online videos*, Yang & Wang (2015) found a strong correlation between intent and actual behaviour. A stronger intention to share videos translated into a high number of videos shared online (Yang & Wang, 2015). Similarly, in Hsiao, Chang & Tang (2016) and Kim & Malhotra (2005), intent was found to be the principal predictor of the actual use of IS. While some authors like Limayem et al. (2007) have criticised the use of continued intentions instead of actual use, multiple theories like TPB, TRA, and confirmation-disconfirmation theory have highlighted the importance of continued use intention as a predictor of actual behaviour (Hsiao et al., 2016).

The study of continued use of technology necessitates that we consider the phenomena of user experiences with the technology improving over time. Expectation Confirmation Theory (ECT) allows us to address this phenomenon in continued use models (Piehler et al., 2016).

> *“The theory postulates a post-acceptance scenario of usage where the prior experience with the system is taken into consideration” (Piehler et al., 2016).*

ECT, therefore, suggests that a consumer’s level of satisfaction determines their repurchase intentions (Piehler et al., 2016). It further states that post-adoption use or repurchase is a function of pre-adoption expectation, PU, and expectancy confirmation (Kim & Zhang, 2010). ECT literature is essential in the study of OTT platforms as it highlights the importance of post-adoption expectations as opposed to pre-adoption expectations as the adoption decisions are fundamentally different from continuance decisions. Furthermore, it highlights the importance of the internal environment in which the technology operates rather than external factors (Y. Kim & Zhang, 2010).

In summary, the traditional view supported by the TRA, TPB, and ECT posits that habit has no direct or moderator effect on actual use but rather an indirect effect through intentions (Limayem et al., 2007). This view, however, is not without criticism. The basis of habitual behaviour is its non-cognitive nature or automatic antecedents. Thus, for authors like Charng, Piliavin & Callero (1988), it is implausible to, therefore, state that habit does not directly impact actual behaviour. Hsiao et al. (2016) argue that intentions are a function of habit. Habitual behaviour will lead to stronger intentions to use. SQB theories support the notion that intentions are impacted by inertia which is, in turn, affected by habit and switching costs (Karahanna & Polites, 2012).

Direct effect

The direct effect refers to the relationship between habit and intentions to use, whereby habit and intentions are parallel constructs and habit has a direct relationship with use. Authors like Charng et al. (1988), have claimed that intentions and habit are parallel constructs. They contend that historical actions have a direct impact on future actions. Thus, habitual behaviour is likely to lead to future usage or action directly. Limayem et al. (2007) summarised that the question of which predictor (preceding factor) is more impactful is dependent on the phenomenon that is under review. A study on food consumption produced mixed results with some food items showing habit as a more robust predictor while intention was a stronger predictor on other food items. A separate survey of blood donation found habit to be a stronger predictor (Limayem et al., 2007).

Moderator effect

The moderator effect is habit being an arbiter between intentions and use. Thus, it determines the strength of the association between intention and use. The moderating effect theory theorises that planned or reasoned character diminishes the more an individual performs a particular action (Limayem et al., 2007). Thus, in instances where an individual has an established action, one can expect the strength of intentions towards a specific behaviour to be weak as the automaticity of the habit develops. In instances where the habit is not yet formed, intentions' strength is much more robust. Accordingly, for authors like Verplanken, Aarts, Van Knippenberg & Van Knippenberg (1994), the influence or strength of intentions on actual behaviour is moderated by habit (frequently repeated unconscious behaviour).

Reasoned or planned behaviour

Continued intentions are a function of planned action as they reconcile pre-use expectations with post-use feeling to form conscious decisions to use or not use a product. Continued intentions are more suited in post-adoption technology as they focus on the internal context in which the technology operates, unlike adoption, which focuses on external factors (Y. Kim & Zhang, 2010). Additionally, continued use intentions reconcile perceptions of the product before use and the user's experience from past use. Thus, intentions are based on a constant feedback loop between expectations, past use, and recent experience. If an individual views the use of a particular technology to be a pleasant experience, then continued use intentions expectations are high, and it is more likely that the user will use the technology in future (Jahanmir et al., 2020).

The debate of whether continued use intentions and habit are parallel constructs in literature is ongoing. Authors like Piehler et al. (2016) argue that habit impacts actual usage directly and that actual use is a function of intentions and habit. They say that habit and intentions are parallel constructs that do not affect each other. Limayem, Hirt & Cheung (2007) argue that habit plays a regulating role between intentions and actual use.

> *"Habit is proposed to exert a moderator (suppressor) effect on the relationship between intention and continued IS usage behaviour. The habituation perspective suggests that intention should be a relatively good predictor of later behaviour in an unstable context, but in a stable context, where the behaviour is presumably under the direct control of stimulus cues, their predictive validity should decline" (Limayem et al., 2007).*

In the case of OTT technology study, we theorise that given that the context is unstable due to consumers utilising multiple channels to access video entertainment, the existing theory states that consumers are using OTT services to supplement their linear TV packages. Thus, they further contribute to the unstable context/ environment for OTT use, and therefore, intention will be the primary determinant of continued use.

In their study of continued use of social media platforms, Hsiao, Chang & Tang, (2016) argue that the intention to continue using technology is a function of habit. Unlike Piehler et al. (2016), the two constructs are not parallel, but intentions are a function of habit and satisfaction. Hsiao, Chang & Tang (2016) hypothesise that habitual use of technology will lead to strong continuance intentions. Similarly, SQB theories postulate that the incumbent system habit causes inertia and inertia directly correlates to continuance intentions. Thus, intentions are a function of habit (Karahanna & Polites, 2012).

This study agrees with the view that actual usage is a function of both conscious cognitive thought (intentions) and the subconscious (habit). However, this view requires us to measure intentions and the ensuing actual use of technology. This approach is better suited to longitudinal studies. This study is cross-sectional given the time limitations. Thus, our proposed research model will measure intentions, not actual use similar to Hsiao et al. (2016).

2.3 Habit

Having addressed the relationship between intentions and actual use, this section of the study will address the role of habit in continued use intentions and habit. Similar to the debate on habit, intention, and actual usage, there is no agreement amongst authors on the link between satisfaction and habit. Habit has been a crucial concept in the marketing field. Habit is a central concept in marketing consumer behaviour, particularly relational marketing, which, unlike transactional marketing focuses on the fostering, generating, and cultivation of enduring customer relationships for the long-term gain of the company

(Tadajewski, 2019). Thus, the relationship focuses on driving the continued use of a product or service by marketing the usefulness, enjoyment, and social factors that drive habitual use of the products. This section will begin by reviewing the definitions of habit in existing literature, then review the antecedents of habit and address the complicated relationship between habit and satisfaction, and conclude by stating which model best addresses continued use intentions for OTT platforms.

Definitions

Various authors in different fields have defined habit in several ways. Landis, Triandis & Adamopoulos (1978) in their social behaviour study defined habit as regularity of an act in the behavioural history of an entity. Charng, Piliavin & Callero (1988) defined habit as the semiautomatic enactment of well-learned action. Bergeron, Raymond, Rivard & Gara (1995) theorised habit as past experience of use quantified in terms of the regularity of behaviour. Orbell, Blair, Sherlock & Conner (2001) emphasised that the actions repeated in an unconscious state constitute habit. They also hypothesised habit as to infer activities that have turned into instinctive responses in particular situations and are done somewhat subconsciously. Limayem et al. (2007) defined habit as automaticity as a result of learned behaviour. They further emphasised the importance of a stable environment as the degree to which individuals tend to carry out actions automatically within a stable environment as a result of past learnings. Hsiao et al. (2016) adopt the theory from Kim & Malhotra (2005) that past behaviour can lead to favourable feelings towards behaviour (satisfaction), and this can lead to habitual use. Tadajewski (2019) defined habit as an action that has become automated as a result of past activities that promote efficiency, avoid cognitive overload, and decision paralysis. The repeated actions result in a decline in consciousness and more automated responses to cues (Tadajewski, 2019).

Antecedents

Based on the above definitions, it is clear that habit has the following antecedents. The antecedents/precursors of habit can be listed as follows: frequency of a behaviour, satisfaction, and stable context (Tadajewski, 2019). While there is some agreement in the literature on the above three precursors of action, this research agrees with the notion from Limayem et al. (2007) that extensiveness of use is another critical antecedent. Antecedents define the environment or conditions necessary for habit formation. They are essential in understanding how habits arise in the context of continuance intention (Limayem et al., 2007). In a practical sense, they can be useful in developing strategies intended to assist in influencing habit development amongst consumers/users of OTT platforms (Limayem et al., 2007).

Frequency of behaviour

It is argued that the more frequently a task or action is performed, the more likely it is that the action will move from a cognitive conscious state of mind to a non-cognitive and non-conscious state of mind. Familiarity is key to explaining this phenomenon (Limayem et al., 2007). Repeated action is likely to lead to familiarity with the system, and together, repeated action and understanding would drive unconscious use of the system, which will result in habitual use (Charng et al., 1988). However, the frequency of behaviour does not necessarily indicate the presence of habitual action. In contrast, behaviour that is not performed routinely (daily or weekly), or previous behaviour is unlikely to illustrate habit. The frequency of behaviour does always incorporate automaticity of action; thus, Limayem et al. (2007) caution the use of frequency and past behaviour as measures of habit.

In addition to the frequency of use, habit formation requires a stable or relatively stable environment. Thus, if conditions are consistently changing, it requires the user to engage with the cognitive elements when deciding consistently. Thus, the formation of unconscious actions is disrupted by consistent cognitive monitoring. A stable environment does facilitate the construction of habitual behaviour. This stability, however, should not be misconstrued with no changes in the environment. Stability may only be interrupted if there are significant changes within the environment or context of use (Limayem et al., 2007).

Comprehensiveness of use

Limayem et al. (2007) defined comprehensiveness of use as the magnitude to which a user utilises the functions offered by a particular technology. The comprehensiveness of use is likely to impact the strength of a habit. Thus, the more functions a user utilises, the stronger the habit they have will be formed.

Satisfaction

Lastly, we look at the satisfaction antecedent. Satisfaction is an essential condition for repeated behaviour. If a consumer evaluates an experience positively, it is likely to lead to repeat behaviour under the same circumstances (Tadajewski, 2019). In this circumstance, satisfaction is a prerequisite for the formation of habitual behaviour. The repetition of this satisfactory action leads to movement from conscious to subconscious; however, the repeated nature of these actions leads us to an important question in marketing research about the relationship between habit and satisfaction.

Some authors like Hsiao et al. (2016) and Wang et al. (2013) agree with Limayem et al. (2007), who have similarly implied that the repeated nature of actions to become subconscious actions is a result of a consumer deriving some satisfaction from the performed activity either through enjoyment or efficiency in the performed task. Thus, habit is a function of satisfaction. This narrative does not find support from other authors who have argued that habit impacts satisfaction. They argue that habit is a key factor for feelings towards satisfaction (Hsiao et al., 2016). This theory can be linked to the fact that the subconscious is not static but ever-evolving with experiences, insights, and associations drawn from everyday life. Thus, bad habits or experiences can lead to a negative impact on satisfaction and vice versa (Tadajewski, 2019).

Similar to the debate on whether habit and intention are parallel constructs, some authors like Hsiao et al. (2016) and Wang et al. (2013) have put forward the notion that habit and satisfaction are parallel constructs in determining continuance intentions. For these authors, there is no direct relationship between the two constructs. Furthermore, they argue that there are other factors like perceived switching costs that encourage the continued use of a service. Incumbent system habit will cause the consumer to persist with the incumbent system despite recognising that the other system is more effective at the same task (Karahanna & Polites, 2012). This explains how our subconscious habits influence us despite not being satisfied with the service. It clarifies how we persist with certain decisions despite being irrational, thus putting forward the notion that continued use is not only subjected to the cognitive domain but strongly influenced by habit and past use (Karahanna & Polites, 2012). This view is further supported by Kim & Malhotra (2005). They argue that cognitive intention will drive use while habit is not fully developed; however, once use becomes habitual, it becomes a significant predictor of use. We, therefore, argue that habit and satisfaction are parallel constructs, and both have a direct effect on intentions as represented in the traditional view above.

Hypothesis 1: Individual habit will positively influence on continuance intention

2.4 Satisfaction

In the section above, we addressed the habit construct. We addressed the antecedents of habit of which satisfaction was one. We concluded the section by adopting the traditional view that states that habit and satisfaction are parallel constructs with separate independent direct relationships with continued use intentions as depicted by the traditional view. This section will address the association between satisfaction and continued use intentions as depicted by the traditional view.

Satisfaction has its roots in marketing research. Satisfaction implies that we repeat specific actions and behaviours on the basis that we gain some sort of satisfaction from them (Bergeron et al., 1995). It implies that satisfaction is a cognitive function where the consumer compares their expectations to the actual results; however, habit also affects satisfaction. Satisfaction occurs when a product or service meets or surpasses customer expectations (Du Plessis, Strydom & Jooste, 2018). Satisfaction itself does not guarantee customer loyalty (Du Plessis et al., 2018). Thus, satisfaction is continuously checked against available information. Consumers are continually searching for choice, which explains why some consumers who are satisfied with a brand can still switch allegiances despite being satisfied (Du Plessis et al., 2018).

Du Plessis, Strydom & Jooste (2018) argue that satisfaction is not one-directional in favour of consumers. Firms can also be satisfied with customer relationships if the relationship is profitable and prolonged to allow a firm to extract profits. Similarly, for OTT platform owners, meeting and exceeding customer expectations is key to driving referrals, and lower customer acquisition costs and lifetime value through subscriptions and advertising (Netflix Inc, 2018).

While there is no clear, direct causal relationship between satisfaction and loyalty (Wang et al., 2013), the correlation between continuance intention and satisfaction is a lot clearer and well supported in academic literature (Wang et al., 2013). The research proposes that performance expectations mainly influence satisfaction with OTT platforms. PE (as media is primarily for entertainment purposes) and PU (their ability to allow the consumer to be served content at convenience: time and device) drive performance expectations. Similar to Tadajewski (2019), we agree with the notion that we only repeat or continuously use a product or service on condition that we gain some satisfaction. Consumers will reconcile expectations against actual performance. If these performance expectations are met or superseded, the resulting satisfaction will lead to continued intention. Previous studies like Kim & Zhang (2010) and Hsiao et al. (2016) have found a positive association between satisfaction and continuance intentions. ECT provide the basis in explaining the relationship between satisfaction, intentions, and continued use in an environment where user experience is increasing from continued use. Bhattacherjee (2001) describes post-use satisfaction as a function of pre-use expectations, product performance expectancy confirmation. ECT reconciles these three functions and theorises that satisfaction determines intentions to repurchase. Thus, we propose that:

Hypothesis 2: Satisfaction has a positive influence on continuance intention

The study identified the two constructs that are predicators for continued use intentions. It then reviewed past literature to identify which variables explained both satisfaction and habit. The review of the literature on past continued use models identified PU, PE, and ST as factors that impact satisfaction habit and intentions. Additionally, the review of the literature highlighted the fact that consumers are utilising multiple competing products at the same time (multihoming). This variable will be discussed below.

2.5 Hedonic

Perceived Enjoyment (PE)

Hedonic needs refer to an individual’s or consumer’s need for fun, excitement, or pleasure (Venkatesh, Thong & Xu, 2012). It is the gratification, amusement, and pleasure that users generate from utilising a product or service (Canhoto & Arp, 2017). Hedonic motivation is a critical predictor of consumer behaviour (Venkatesh et al., 2012). Understanding the entertainment value sort is key to understanding continuance intentions.

Hedonic motivation is of primary importance since OTT platform use is primarily for entertainment purposes (Prince & Greenstein, 2017). While OTT platforms are available for both video and music entertainment, our focus is on the video platforms. TV and video content consumption are the prime use of free and leisure time (Prince & Greenstein, 2017). They are thus highlighting the importance of hedonic motivation to this study.

Similar to Hsiao et al. (2016), we believe that the pleasure trait derived from consuming content from these platforms evoke positive feelings from the consumer that will result in greater satisfaction and intention to utilise the platform.

Habit is the unconscious repetition of a task. It is a critical construct in continued use models as it accounts for unconscious behaviour. Habit makes use of information obtained from past use and relies on cues to activate action (Karahanna & Polites, 2012 & Venkatesh et al., 2012). Satisfaction, therefore, plays an integral part in how these experiences are perceived, stored, and therefore impact the automation of consumer actions. Enjoyment will drive satisfaction and satisfaction positively impacts habit (Hsiao et al., 2016). Excitement or pleasure from use will positively impact satisfaction and habit. Thus, we posit:

Hypothesis 3: Perceived Enjoyment directly and positively impacts continuance intention
Hypothesis 4: Perceived Enjoyment will positively influence consumer satisfaction
Hypothesis 5: Perceived Enjoyment will positively influence habit formation

2.6 Utilitarian

After addressing the hedonic factors of the proposed model, the study proceeded to discuss the utilitarian factors. Davis (1989) suggests that consumers use or not use a technology based on the purported advantage that the technology will give the user a relative advantage. He intimates that a positive user performance relationship and the enduring nature of this relationship determines the extent to which the consumer considers that the system will add value to the task they are trying to perform.

The utilitarian motivation reflects the user's attitude towards the job to be done by the technology. Usefulness is a significant factor in continuance intention. Some have argued that it reflects the relative advantage of the technology and represents the consumer's subjectivity on how performance improves by the use of the technology (Hubert et al., 2019).

PU of the technology and PEOUS drive the utilitarian construct. Once a consumer has deemed a particular technology to be useful, the consumer will then consider the ease of use of that technology. Utilitarian motivation explains a significant share of the variation in behavioural intention (Hubert et al., 2019). However, Hsiao et al. (2016) contend that within the utilitarian construct, PU has been confirmed to be a consistent predictor intention; however, PEOUS has not been a dependable predictor of intention. Furthermore, OTT technologies' competitive advantage is their ability to allow consumers to consume content at their convenience and on a device of their choice as compared to traditional linear TV. We thus conclude that usefulness is a necessary construct, and we will disregard ease of use. Thus, we posit:

Hypothesis 6: Perceived Usefulness will positively impact consumer continuance of use intention

Consumers' PU is closely related to satisfaction. They are both cognitive functions that reconcile expectations and actuality. If a consumer deems a technology user-friendly, the consumer's expectations have likely been met or exceed, and the consumer is satisfied with the technology (Hsiao et al., 2016). The usefulness of the technology results in satisfaction. Thus, we posit:

Hypothesis 7: Perceived Usefulness will positively impact consumer satisfaction

Similarly, consumers are likely to continue using technology if they deem it useful (Hsiao et al., 2016). This continued use of the technology will move from conscious to subconscious. The repetition leads to the formation of habits. Habit is vital to video consumption. For decades, TV consumption has been based on linear viewing and appoint viewing, thus dictating to viewing habits. OTT consumption, both free and premium, rely on consumers continuously using their platforms, understanding OTT viewing habits in understanding continued use.

Hypothesis 8: Perceived Usefulness will positively impact consumer habit

2.7 Social influence

After discussing the utilitarian and hedonic factors, the study moved to social factors that drive user satisfaction, habit, and intentions. Social effect discusses the extent to which a person considers that people within their reference group or people who are important to them are of the view that they should use a particular technology (Venkatesh et al., 2003). Social influence occurs in a specific context; social context defines what is tolerable within a social group. The use of a technology creation is mostly dependent on the context in which it is deployed, thus highlighting the importance of technical and social contexts (Canhoto & Arp, 2017), compared to PU and PE that are linked to the actual technology itself. At the same time, social influence is a context related factor as it relates to the environment in which the technology operates. In the study of facilitators and inhibitors, social influence was considered to be a facilitator of continued use (Rey-Moreno et al., 2018). Context related factors are essential in the sense that they may override a predisposition towards technology and are critical to driving intentions. Similarly, OTT companies rely on social influence as part of their efforts to entice and retain consumers.

> *"In addition, many of our members rejoin our service or originate from word-of-mouth advertising from existing members. If our efforts to satisfy our existing members are not successful, we may not be able to attract members, and as a result, our ability to maintain and/or grow our business will be adversely affected" (Netflix Inc, 2018).*

The presumption is that customer satisfaction will lead to customer retention. By retaining a broad base of satisfied customers, a business can rely on the social influence of current members to get people within their social circle to use the technology, resulting in innovation diffusion (Sun, 2013). The diffusion of technology results in the general use of technology within social circles (Hsiao et al., 2016). The widespread use of technology in these societal circles will directly impact continued use intentions (Hsiao et al., 2016).

In addition to social influence having a direct bearing on continued use intentions, the research contends that social influence has a direct and positive effect on satisfaction and habit (Venkatesh et al., 2003). The relationship between social influence, satisfaction, and habit is dependent mainly on the proportion of people within the social group that is participating in a shared activity. The ratio and frequency of use by users within a social context will impact satisfaction and habitual use. If an action is being performed frequently by members of the group, it is likely to become part of the group's conversation and dynamics. The desire to be relevant and belong will lead to high-frequency use, and the sense of belonging will lead to satisfaction. Social influence is thus directly influenced by behavioural intention, habit, and satisfaction. Thus, we propose:

Hypothesis 9: Social influence has a positive influence on behavioural intentions
Hypothesis 10: Social influence has a positive influence on consumer satisfaction
Hypothesis 11: Social connections and interactions have a positive influence on consumer habit

2.8 Multi-purchase/Multihoming

The research identified that OTT users are using multiple platforms, including competing platforms. It then proceeded to discuss how the use of multiple competing platforms impacts on user habit, satisfaction, and continued use intentions. The existing marketing literature is primarily based on the assumption that consumers do not purchase competing products simultaneously (Jiang et al., 2019).

> *"We say a user is multi-homing when he/she participates on multiple competing platforms concurrently" (Etworks, Koh & Fichman, 2014).*

The use of multiple competing products has an impact on the frequency and comprehensiveness of use and therefore, will impact user habit, satisfaction, and continued intentions. Etworks et al. (2014) state that platform owners risk misspecifying user behaviour by assuming that users are only utilising their platforms and not anticipating user behaviour on competing platforms. They further specify that negating consumers' multihoming behaviour can lead platform owners to incorrect and ineffective competitive strategies.

Similar to video gaming consumers, OTT platform users acquire and utilise competing products concurrently - a concept referred to as multihoming or multi-purchase (Jiang et al., 2019). In the USA, an estimated 54% of OTT users also subscribe to a pay-TV platform (Marketing Charts, 2020). In South Africa, 71% of pay-TV (DStv) subscribers also subscribe to OTT services (Rich, 2019). Thus, while OTT and pay-TV platforms are often thought of as substitutes, in many instances, they are used as complementary services.

Similar to the inertia theory, which is defined as the continuation of habitual behaviour despite the presence of superior alternatives (Karahanna & Polites, 2012), inertia and SQB theories have been used to explain facilitating and inhibiting factors in the adoption of new technology (Rey-Moreno et al., 2018). This research contends that these factors continue to influence post-adoption use and are not only relevant to the acceptance of new technologies. With pay-TV and OTT technologies, a significant portion of consumers (54% in the US and 71% in South Africa) subscribe to or utilise both platforms. The presence of two or more products with a high frequency of use will result in daily/frequent decisions on which system to use despite the adoption of both. Thus, in situations where there are competing products, consumers will be biased towards their primary technology. Watching TV is no longer a lean-back experience controlled by the broadcaster (Mancuso & Stuth, 2012). The availability of applications and second-screen viewing (use of another device like a tablet, cell phone or laptop while watching TV) allows the consumer to make their own selections and research content they are currently watching or want to watch (Cauwenberge, Schaap & Roy, 2014). Thus, when faced with a decision, incumbent system habit and switching costs will initially play a significant role in deciding what to watch and what platform to use resulting in SQB (Karahanna & Polites, 2012). We posit that consumers will initially choose to watch a platform that they are more familiar with (their primary platform) and when their expectations are not met, they will then enquire what is available on the other platform.

The actions of consumers that consider pay-TV to be their primary platform will be impacted by inertia when presented with a choice between pay-TV and OTT platforms. Thus, the incumbent system habit and switching costs will lead to continued use of pay-TV and negatively impact the continued use, habit, and satisfaction of OTT platforms (Karahanna & Polites, 2012). For users who identify OTT platforms as their primary platform, SQB will positively impact satisfaction, habit, and continuance intentions (Karahanna & Polites, 2012).

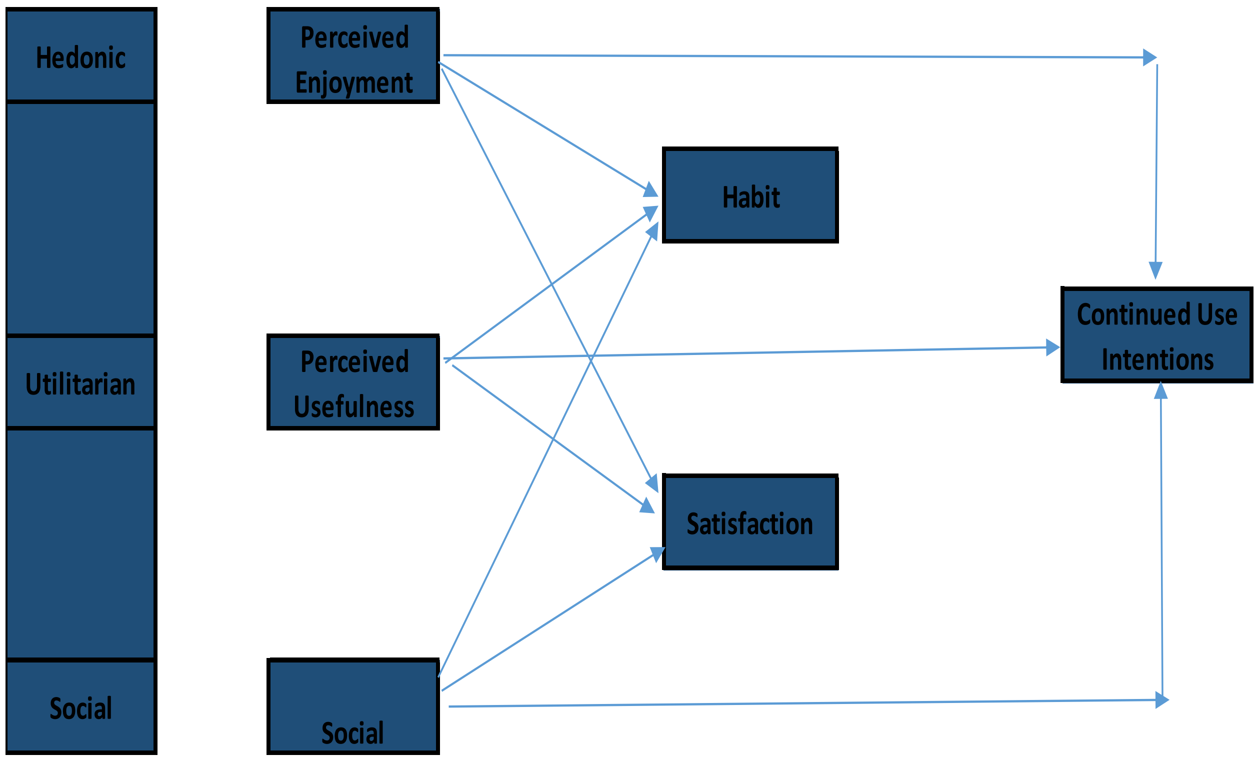
In the context of OTT platforms in South Africa, we theorised that most OTT usage is occurring in conjunction with linear TV consumption (Rich, 2019). We further posit that OTT technologies vary from linear TV in two main technological aspects, method of delivery (the internet) and the recommendation function. One is a prerequisite for OTT use, and the other is a back-end function of the technology that users cannot elect to utilise. Thus, comprehensiveness is dependent on the use of one technology or platform. We theorise that consumers who only utilise OTT platforms as opposed to both OTT and linear platforms are more likely to comprehensively use OTT technology and likely to develop more substantial habitual use. This argument is supported in Verplanken, Aarts, Van Knippenberg & Van Knippenberg (1994) who argue the distinction between general and specific use. We argue that general use which connects to the comprehensiveness of use is likely to happen where there are no competing products. This notion is further highlighted by Tao, Zhumin, Yujie & Jun, (2018) who found the use of OTT platforms to be high during holiday periods in households that had both OTT and linear technologies. Thus, we posit that:

Hypothesis 12: Multihoming will negatively impact continuance intention, satisfaction, and habit for users who do not identify an OTT platform as their primary system

Hypothesis 13: Multihoming will positively impact continuance intention, satisfaction, and habit for users who identify an OTT platform as their primary system

The study proposes the model below to explain the factors that drive the continued use of OTT platforms. The result of the model will be compared for variation between groups that identify OTT as a primary platform and group that identify linear TV as the primary platform.

Figure 2 – Model to explain the factors that drive the continued use of OTT platforms


Hedonic
Utilitarian
Social
Perceived Enjoyment
Perceived Usefulness
Social
Habit
Satisfaction
Continued Use Intentions

CHAPTER 3: RESEARCH QUESTIONS

3.1 Purpose of the research

The examination aims to test if deviations in continuance intentions of OTT-platforms users can be clarified by satisfaction, habit, social preferences, and SQB. The objective is to confirm if these constructs are statistically significant when explaining differences in OTT technology continuance intentions.

The model used in the study aims to verify the elements that affect behavioural intent concerning the continued use of OTT platforms. Additionally, the research aims to test the statistical significance of factors driving the continued use of other technologies to establish the importance of these factors in driving behavioural intentions concerning the continued use of OTT platforms. The research purports to answer the following questions:

3.2 Research question 1

What factors and model will explain individual consumers' behavioural intention to continue using the OTT platforms they are currently using?

With the adoption of OTT platforms migrating from early adopters to the early majority stage, platform owners are shifting their focus from the adoption of OTT platforms to continued use. With COVID-19 also increasing the time spent at home and thereby increasing adoption of these technologies, the focus has shifted from adoption to continued use intentions. While intention does not explain the full variance in use, it plays a significant role in explaining variations in use as highlighted by previous research. The TV video market is a highly competitive and disruptive environment with the success of OTT platforms highly dependent on adoption, continued use/customer retention, and continued use intentions. It is, consequently, crucial to comprehend what dynamics drive these continued use intentions.

Hypothesis 1: Individual habit will have a positive influence on continuance intention
Hypothesis 2: Satisfaction has a positive influence on continuance intention
Hypothesis 3: Perceived Enjoyment directly and positively impacts continuance intention
Hypothesis 6: Perceived Usefulness will positively impact consumer continuance of use intention
Hypothesis 8: Social influence has a positive effect on behavioural intentions

3.3 Research question 2

The study aims to understand if OTT users will habitually use OTT platforms. Linear TV uses appointment viewing to create user habit, and this must lead to linear TV viewing becoming habitual over the years. To replicate the success of linear TV, some authors argue that for OTT platforms to be successful, habitual use will be critical (Schweidel & Moe, 2016 & Prince & Greenstein, 2017). The study, therefore, asks the question:

Will habitual use become prevalent among users of OTT platforms?

Hypothesis 1: Individual habit will have a positive influence on continuance intention
Hypothesis 5: Perceived Enjoyment will positively influence habit formation
Hypothesis 8: Perceived Usefulness will positively impact consumer habit
Hypothesis 10: Social connections and interactions have a positive influence on consumer habit

3.4 Research question 3

Continued use intentions have been linked to customer loyalty which, in turn, correlates to customer satisfaction. The research, therefore, aims to understand if satisfaction is a crucial variable in continued use intentions. If satisfied, OTT platform users will have higher continued use intentions amongst platform users.

Hypothesis 2: Satisfaction has a positive influence on continuance intention
Hypothesis 4: Perceived Enjoyment will positively influence consumer satisfaction
Hypothesis 7: Perceived Usefulness will positively impact consumer satisfaction
Hypothesis 9: Social influence has a positive effect on consumer satisfaction

3.5 Research question 4

To what extent will OTT consumers continue consuming the media they are presently using?

The research aimed to understand which platform consumers considered to be their primary platform. Also, the research checked if there were any statistical differences in habit and satisfaction between users who only use OTT platforms and multihoming users.

Hypothesis 11: Multihoming will negatively impact continuance intention, satisfaction, and habit for users who do not identify an OTT platform as their primary system
Hypothesis 12: Multihoming will positively impact continuance intention, satisfaction, and habit for users who identify an OTT platform as their primary system

CHAPTER 4: RESEARCH METHODOLOGY

4.1 Methodology

The study's objective was to establish which factors were statistically significant in a consumer's continued use intention of OTT platforms. The study utilised set theory from Chun Hua Hsiao, Chang & Tang (2016), and the unified theory of acceptance and use (Venkatesh et al., 2016), to examine and explain continuance intention. The study's philosophy was positivism, akin to the setting of a scientist as the research focused on observable social and socio-physiological constructs to yield law-like simplifications (Saunders & Lewis, 2018). The scientific method is the technique recognised by the positivism philosophy; the study has a structure and begins with a concept and continues to gather data that either corroborates or contradicts the concept (Creswell, 2014). Sampling, collection, and measurement of data allows for generalisations, inferences, and extrapolations. The research design highlights the relationships between independent variables (PU, PE, and ST), and impact latent variables (habit and satisfaction) and how these impact continuance intention (Hsiao et al., 2016, Venkatesh et al., 2003, Venkatesh et al., 2012 & Venkatesh et al., 2016). The research built on the above with the addition of the multihoming construct and linked it to SQB and relative advantage theories. The study aimed to construct, test, and access a model explaining consumers' continuance intentions of OTT platforms.

Research into continuance intentions theory is well developed. However, similar to research in technology adoption models, continuance intentions are reliant on on the user, context, and the technology features in question (Canhoto & Arp, 2017). Given the theory is a well-developed theory in technology acceptance and continued use field, a deductive approach was considered appropriate for the study. A deductive approach comprises the testing of a hypothetical proposition by means of a research strategy specifically designed to gather data to test it (Saunders & Lewis, 2018). The research was quantitative, and the deductive approach is normally used in quantitative research (Creswell, 2003).

A mono-quantitative method approach was used to collect data, and data were gathered using a solitary gathering technique (Saunders & Lewis, 2018). Information was gathered using a questionnaire. The techniques stereotypically utilised in explanatory studies can typically comprise questionnaires, interviews, observations, and analysis of secondary data (Saunders & Lewis, 2018). The study was confirmatory and concerned itself with factors driving OTT platforms' continued usage intentions within the South African context. A quantitative approach was deemed to be appropriate (Rich, 2019), combined with statistics and figures (Lee, 1992). The analysis was quantitative as the study did not seek to develop new theory, but rather confirm the applicability of the existing theory in a different context in terms of country and technology (Creswell, 2016).

The independent variables: PE, PU, ST, and SQB were measured to establish their linear relationship with latent constructs of habit and satisfaction, which in turn impact continuance intentions.

4.2 Context of the study

The study focused on the South African OTT market. South Africa has the second-largest economy in Africa by Gross Domestic Product (GDP); however, South Africa's media and entertainment industry is twice the size of the second-largest market, Nigeria (PwC, 2019). The study collected data from current users of OTT platforms in South Africa to establish the factors that influence continuance intentions based on philosophies found in earlier research. The research was designed to be explanatory.

Furthermore, the South African market is unique in the sense that when compared to other nations where OTT use is highly prevalent, it is characterised by low fibre penetration rates as compared to European countries where the rates are average. Additionally, the internet data rates in South Africa are among some of the most expensive in the world. Despite the challenges above, internet penetration rates continue to grow, and OTT platform use continues to disrupt existing market players.

> *"We highlight the fact that relative to markets with high levels of OTT penetration (e.g. the United States and Canada), South Africa has low levels of internet penetration, slow internet speeds and comparatively high data prices, all of which limit the potential substitution of pay-TV with OTT services. This requires original thinking and application of economic principles about relevant markets, in this country-specific context" (Rich, 2019).*

The research was cross-sectional. The study was conducted at a point in time and represented current thinking and views of current OTT platform users (Saunders & Lewis, 2018). In their longitudinal model of continued IS use, Kim & Malhotra (2005) collected data in two-month intervals to establish how users' evaluations can change over time as their familiarity with IS increases. This type of approach requires significantly more time than is available for this study. Thus, the research will not cover how consumers' behaviour changes over time but instead focus on factors driving continuance intentions at a point in time.

Consideration was given to the impact of COVID-19 on the research methodology. The study was conducted in South Africa while the country was on level one lockdown restrictions. While level one restrictions represent the least restrictive of the lockdown phases, the study was conducted after the initial lockdown period when citizens were confined to their houses for two consecutive months. This unprecedented period resulted in the number of households utilising OTT platforms to rise by 5,2 million, according to Flynn, (2020). This sharp increase has been attributed to the lockdown period. The study noted that these events could skew OTT consumers' responses towards continued use intentions. The study also noted research by Tao et al. (2018) on temporal viewing patterns that notes the use of OTT platforms increasing during weekends and public and school holidays when consumers have more time. This research contends that the lockdown period is similar to holiday seasons when consumers spend more time at home, and thus, the time spent at home should, therefore not distort the findings of the study.

The study utilised a research questionnaire. Questionnaires are appropriate for collecting information over a significant size of respondents, and the data are typically examined statistically (Saunders & Lewis, 2018).

4.3 Population

The research study limited the population to those users who were using OTT services at the time of the survey as the main objective of the study is to access continuance intentions. As highlighted above, the survey was based on OTT consumers in South Africa. The study focused on consumers that already had access to OTT platforms such as Netflix, Amazon, Showmax, Amazon Prime Video, YouTube, Disney+, Apple TV, and DEOD. This list is not an exhaustive list of OTT platforms available in the South African market.

OTT is defined as video streaming or transmitting video content via the internet that circumvents traditional cable, broadcast, and satellite providers (Schweidel & Moe, 2016). The study population was limited to current users of OTT platforms since the study is focusing on continued use intentions. The study made use of screening questions to ensure that only present users of OTT platforms were selected.

The research included both the primary and secondary subscribers to OTT platforms; thus the population was not limited only to include registered account holders but individuals like family members who can access the platforms as a secondary user. Chow & Van Eeden (2019) highlight how multiple people can utilise one subscription in various ways. Showmax accounts allow consumers up to six profiles on one subscription; for Netflix, a consumer can set up five profiles (Showmax, 2020 & Netflix, 2020). This notion is further supported by the second-screen viewing theory, which purports that individuals and families are increasingly using portable mobile technologies to multitask while consuming TV content (Lowenstein-Barkai & Lev-On, 2018). While the research could have focused on the decision-maker (the person responsible for paying the subscription or making a choice), this would have negatively impacted the diversity of the research.

4.4 Unit of analysis

The unit of analysis refers to an object or element that a study aims to explain or quantify (Babbie, 2016). In this study, individual consumers, not family units or account holders (person responsible for paying the subscription), were used as the unit of analysis; thus, the research specifically targeted individual consumers. The unit of analysis was limited to OTT platform users in South Africa.

4.5 Sampling method and size

A non-probability sampling technique was utilised since there are no accessible databases of all OTT consumers in South Africa publicly available; thus, probability sampling was not realistic as the entire population is unidentified.

The study distributed questionnaires on websites, online communities, WhatsApp, and Facebook. These platforms require an internet connection; a prerequisite for OTT platform use. Multiple sources of data were utilised to reduce the risk of using one source, also to assist with data triangulation and ensure the diversity of the sample. Pre-screening questions were used to ensure that respondents were above the age of 18.

An online community was used as the primary method to distribute the questionnaire. The online community is a network of people who provide interactive and accurate feedback, primarily on video content consumption. While the online community was the central platform to recruit participants, the study also recruited participants via WhatsApp and Facebook to avoid bias and a skewed sample in terms of demographics. In addition to demographics, the study used pre-screening questions and quotas to ensure that the sample was not skewed towards a particular group.

In addition to the above quota, sampling was used to ensure the diversity of the population. While it has been argued that streaming services cater to all ages, genders, and income levels, Netflix's age profile has shifted over time from being skewed towards 18 to 24-year-olds (51%) before 2015 to being more evenly distributed post-2017 with 18 to 24-year-olds reducing their share to 33% and the 55+ age category moving from 12% to 21% (civicscience, 2020). The South African market, however, is skewed towards the younger demographic. The Broadcasting Research Council of South Africa's (BRC), (2018) Establishment Survey showed that 70% of users are below the age of 35 compared to 33% for the USA (civicscience, 2020). Similar to earlier acceptance and use models, more recent research from the likes of Canhoto & Arp (2017) and Hsiao Chang & Tang (2016) also base their samples on adults below the ages of 35 and 30 respectively. This study used quota sampling to guarantee that the sample was representative of the population across gender, age, and income.

The study made use of explanatory, descriptive statistics, and Structural Equation Modelling (SEM) to study the data. The minimum sample size was calculated based on the number of paths directed to any construct. The sample size ought to be ten times the number of construct paths. This method has, however, been criticised for not taking into account reliability and therefore, can be misleading (Hair, Sarstedt, Ringle & Mena, 2012). Hair, Black, Babin & Anderson (2010) argue that for SEMs, the minimum sample size required is 200 respondents. The study received 364 responses with 315 respondents qualifying to be part of the study.

4.6 Measurement instrument

The study made use of a survey questionnaire as an instrument for the research study. The questionnaire was disseminated via the internet by means of the following methods: online communities, and Whatsapp messaging groups. The questions were adapted from questionnaires from earlier research papers like Hsiao, Chang & Tang (2016), Karahanna & Polites (2012), and Venkatesh et al. (2016). The questions were revised and modified to consider variations in the technology being verified, for example, mobile technology versus OTT technology and geographical/cultural variations, for example, Hong Kong versus South Africa.

The instrument was pretested on 15 individuals before distribution. This pretesting allowed the study to access the adequacy of the research instrument if there was any bias in the questionnaire and allowed for adjustments before broader distribution.

The research questions were designed to quantify the association between continuance intention and the latent variables of satisfaction and habit. The following constructs measured the latent variables: PU, PE, ST, and SQB. By utilising and adjusting questions from preceding studies, we safeguarded content and construct validity by ensuring the questions gathered sufficient data to meet objectives and only gathered data which we intended to measure (Saunders & Lewis, 2018). Furthermore, the questions were piloted with industry experts and consumers to confirm the extensiveness and validity of the items being requested.

A self-administered Google Forms questionnaire was used as a measurement instrument. The instrument had four main sections. Section A was the introduction to the research, outlining the objectives and explained what OTT platforms are. It also assured respondents of the confidentiality and anonymity of the study and made them aware that participation was voluntary.

Section B was screening questions. The screening was to ensure that all respondents were people currently subscribing to OTT platforms or who had access to OTT platforms in their household. Since the study was about continued use, only individuals who answered “YES” to the qualifying question were allowed to proceed.

Section C had demographic questions to collect information about the respondent's age, gender, education, income, and home province.

Section D covered the questions in the proposed research model. The items in this section were split into two paths, depending on whether the consumers were using OTT services in conjunction with linear TV. This section further explored which platform, OTT or linear, was the primary viewing platform for video consumption to establish how this would impact OTT consumer habits and bias.

To ensure the dependability of the research and consistency of the results, the research study made use of measurement scales. The research adopted scales from prior research on continued use. The scales were adopted from Venkatesh et al. (2012) and measured using a five-point Likert scale, with the anchors being “STRONGLY DISAGREE” and “STRONGLY AGREE”.

4.7 Data-gathering process

The research study made use of an online questionnaire using Google Forms. It provided respondents with a link to the questionnaire via websites, company intranets, and messaging groups. Based on the sample size, this was the most efficient way of data collection given the time constraints. The study aimed to keep the questionnaire to under 10 minutes. For most survey forms, it is best to have the survey completion time under 10 minutes; preferably, five minutes as these studies achieve higher completion rates (SurveyMonkey, 2020). Data were gathered over two weeks. The response rate and demographics were monitored daily to ensure that the minimum sample size was achieved and that the sample was representative and not skewed towards a particular demographic.

4.8 Analysis approach

Descriptive statistics were executed on the information gathered to determine the statistical validity and an ensuing test application. The data were evaluated using IBM SPSS software. The primary investigative method employed was SEM. SEM is used to evaluate unobservable underlying constructs.

After data collection, the data were coded in SPSS before any analysis was performed. The coding manual is provided in the appendix. After the information was coded, we ran descriptive statistics to gain insights into the sample. Descriptive statistics provide a summarised visualisation of the characteristics of the sample.

SEM was chosen as the primary method to analyse and interpret the data. The proposed model represents a set of interrelated variables that cannot be measured directly. As the relationships between the latent variables are multifaceted and convoluted, there is the need to use a method that allows for the simultaneous analysis of the latent variables as well as measurement errors (Piehler et al., 2016). As highlighted in the literature review, the association between habit, satisfaction, and intention is complicated with a debate on which variable has a direct, moderating, and mediating impact on the other. SEM allows us to test these multiple relationships as well as estimate an error. SEM combines multiple methods like path analysis, regression analysis, and factor analysis. It is, therefore, not limited to on one method, further contributing to its flexibility (Hair et al., 2012).

The data were analysed in two main areas. Firstly, the reliability of the measurement model was tested using Composite Reliability (CR) and Cronbach's Alpha. Reliability refers to data gathering and analysis techniques that can yield consistent findings in other studies (Saunders & Lewis, 2018). After checking for reliability, we also checked for discriminant validity. Discriminant validity is confirmed when two constructs are seen as distinct but correlated (Hsiao et al., 2016).

After the measured model was confirmed through convergence (reliability) and discriminant validity, we then tested the structural model. The model was assessed using the goodness of fit measures like Chi-square, NFI, NNFI, CFI, IFI GFI. In addition to the goodness fit tests, the study also conducted hypothesis testing by analysing the independent sample t-tests. The study also examined the standardised path coefficients to analyse the dependency amongst the variables.

4.9 Quality controls

Data are the lifeblood of any statistical study (Wegner, 2018). For the information gathered to be of high quality, it must be appropriate, clean, and in the precise format for examination. Cleaning data is an essential step before analysis and often involves reformatting, corrections, and combining data sets to enhance the data.

After the data were gathered, we evaluated it for partial surveys, typographic inaccuracies and outliers. This review was to guarantee that inaccurate or incomplete data were not counted in the analysis and did not end in low-quality statistics. According to Bollinger & Chandra (2005), it is practice to clean data by removing data where the variable is larger or smaller than the thresholds in order to reduce the impact of measurement error. However, they warn to exercise caution as it may make matters worse in some cases.

To confirm the validity and reliability, CR and Average Variance Extracted (AVE) will be used to ensure the validity and reliability of the measurement constructs (Hair et al., 2012).

4.10 Limitations

Since this study is restricted to OTT platforms within South African, there might be qualitative dynamics that are distinct to South Africa that might not be exposed by previous continuance models. Because the research was limited to South Africa, the results cannot be generalised to an Africa or global context.

Additionally, with the research being cross-sectional, it provides a picture at a point in time. Circumstances of the contributors may change over time. The impact of COVID-19 on participants' responses is unknown as the study was conducted after the lockdown period - a timeframe where individual movement was significantly restricted, and people were primarily confined to their homes for two months, and video consumption increased significantly. The perceptions of OTT platforms could be skewed due to this unusual period.

The study measured intentions and not actual use. As highlighted in the literature review, this approach is not without criticism. While intentions are a strong predictor of use, the context of use (environment), individual, technology in question, and comprehensiveness of usage and frequency of use impact the role habit plays and might result in habit impacting use more significantly than intentions.

The study is cross-sectional and does not account for changes over time. Continued use changes as users gain experience over time. Experience gained over time from previous use or repurchase shapes expectations, and these expectations are reconciled with a user’s experience to confirm or disconfirm whether expectations are satisfied. Thus, longitudinal studies could be better suited to explain changes over time.

Measurement scales were adopted from previous studies to measure satisfaction, habit, and intentions. Scales can be elaborated to include comprehensiveness of use and loyalty measures. Satisfaction, habit, and intention questions and scales are primarily based on the assumption that consumers are using one product when, in fact, consumers are using multiple products.

CHAPTER 5: RESULTS

5.1 Introduction

The study aims to confirm whether PU, PE, ST, satisfaction, and habit are significant factors in explaining OTT users' continued intentions. This chapter will present and explain the results of the investigation. To understand the results, the chapter will begin by explaining the context of the study by detailing the sample size and characteristics. After that, the chapter will address the validity and reliability of the measurement model. The chapter will address both convergence and discriminant validity. This section will also cover factor analysis and test for differences. Finally, the chapter will address the SEM by assessing the model fit and hypothesis testing. The study utilised SPSS 26, AMOS 26 and SmartPLS to test the proposed model.

5.2 Sample

A survey instrument was designed based on previous technologies continued use studies. The research did not have access to a comprehensive list of OTT users in South Africa, and therefore random, non-probability sampling was utilised. The study distributed the survey via email and WhatsApp. The study aimed to obtain a minimum of 200 responses based on research by Hair, Black, Babin & Anderson (2010) that argued that the minimum sample size required for SEM is 200 respondents. In total, 364 people responded to the research survey.

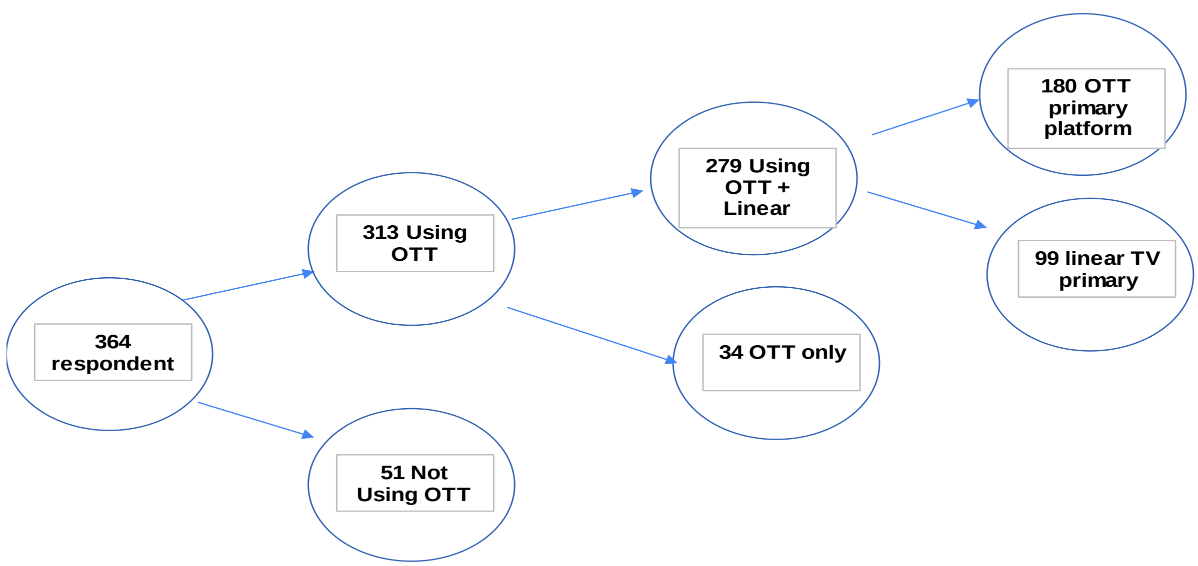
The research instrument made use of qualifying questions to ensure that only current users of OTT platforms formed part of the study. Of the 364 respondents to the survey, 13,5% (51 respondents) indicated that they were not using OTT platforms, and the survey immediately concluded. The remaining 313 respondents indicated that they are current users of OTT platforms and could continue with the survey.

As highlighted by the literature review, 53% of the respondents highlighted that they utilise two or more OTT platforms, thus supporting the notion that users are creating or curating their own video entertainment bundles. The most popular platforms amongst the respondents were Netflix with 74,3% of respondents indicating that they subscribe to the platform followed by Showmax at 48,9%, YouTube at 30,5%, Amazon Prime Video at 9,2%, and Apple TV at 8,6%. Only 12,1% of the respondents indicated that they use other platforms outside of the five mentioned above.

The study asked respondents if they utilise linear services in conjunction with their OTT platforms. Furthermore, the respondents who answered “YES” were also asked which platform, OTT or linear, was their primary/preferred platform when watching video content. Eighty-nine per cent (279 respondents) indicated that they use OTT services in conjunction with their OTT platforms. Of the 279 respondents, 180 respondents indicated that they use OTT platforms as their primary viewing platforms, with the remainder indicating that they use linear TV as their primary platform.

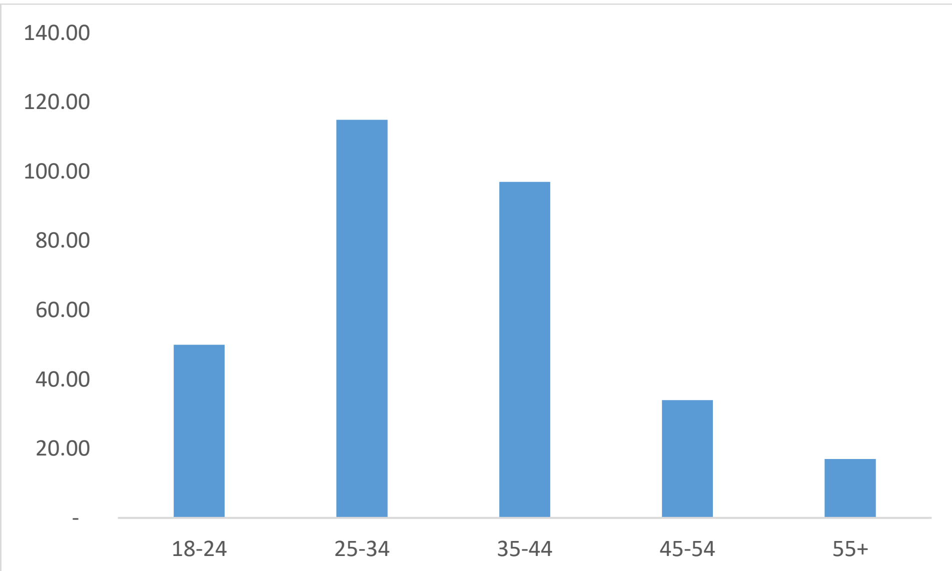
5.3 Descriptive statistics

Figure 3 – Respondents mapping



Fifty-three per cent of respondents were below the age of 34, and 43% were 34 and above. The figure below highlights the age distribution of the respondents. The data support the notion that the age profile of OTT technology is skewed towards the younger demographic as supported by the Establishment Survey, which had a skew of 70% to 30% (The Broadcasting Research Council of South Africa, 2018). It also supports the view that Netflix's age profile has shifted from being skewed towards 18 to 24-year-olds (51%) before 2015 to being more evenly distributed post-2017 with 18 to 24-year-olds dropping to 33%, and the 55+ age category increasing from 12% to 21% (civicscience, 2020).

Figure 4 – Age profile of respondents



To ensure the diversity of the sample, the study also requested respondents to fill in their gender, race, monthly income, geographical location, and education level. Fifty-three per cent of respondents were male, and 47% female. Sixty-one per cent of the respondents were black, 16% white and the rest were various other ethnicities as represented in Figure 5 below. Statistics South Africa (2019) estimates that the black race represents 79% of South Africans, and the white and coloured races represent 8% each (Statistics South Africa, 2019). In addition to ethnicity, the study also strived to get diversity in terms of geographical location. Fifty-six per cent of the respondents were from Gauteng, with 14% being from the Western Cape, and 13% from KwaZulu-Natal. According to Statistics

South Africa (2018), Gauteng only accounts for 25% of the total population, followed by KwaZulu-Natal at 19% and the Western Cape at 11,5%.

Given that the technology in question requires an internet connection and that the fibre penetration in South Africa is mainly centred around urban centres (Rich, 2019 & PwC, 2019), it is justified that most responses came from provinces with the largest urban centres and the highest internet penetration rates in the country. Figure 6 highlights the geographical distribution of the respondents. Figure 7 highlights the education level and Figure 8 the income levels of the sample.

Figure 5 – Ethnicity of respondents

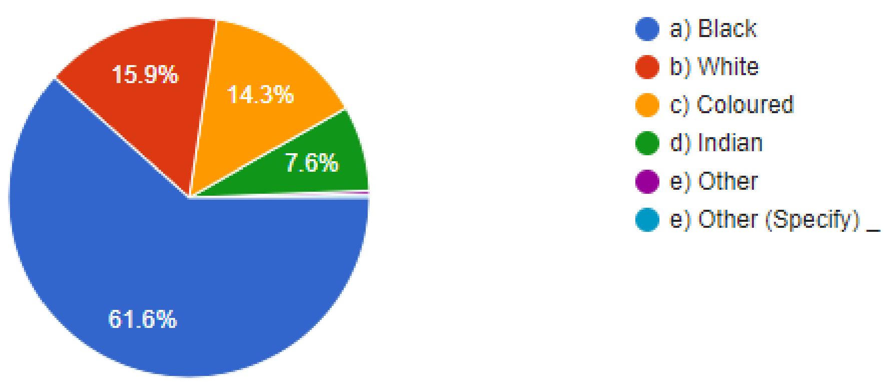


Figure 6 - Geographical location of respondents

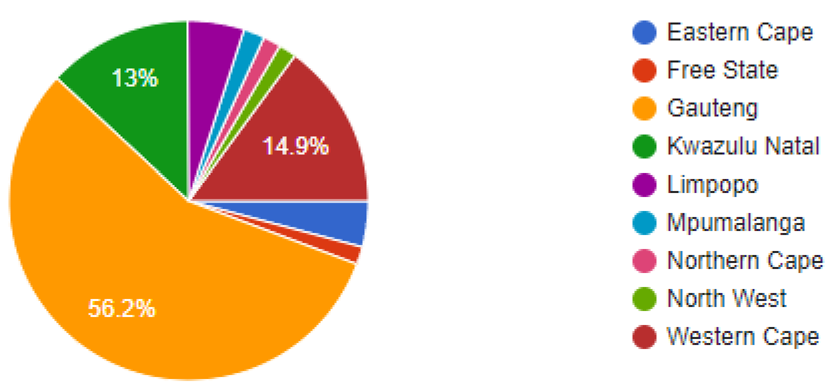


Figure 7 - Education level of respondents

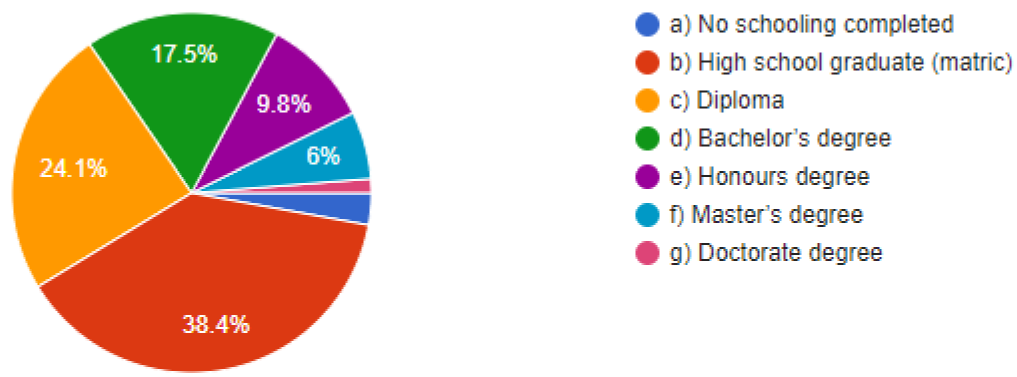
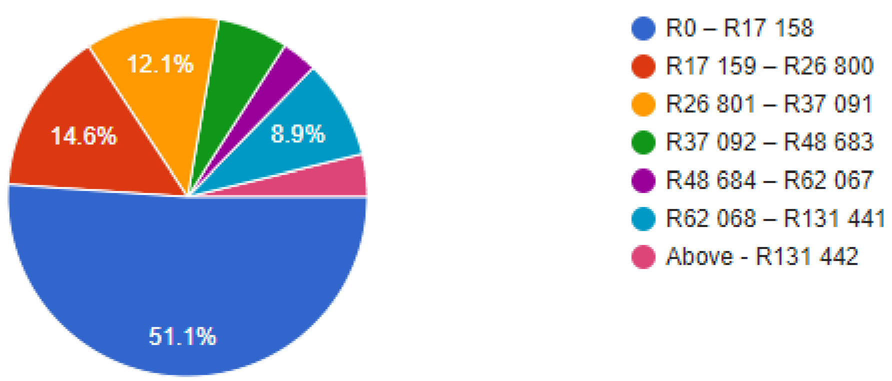


Figure 8 - Income levels of respondents



The data collected represented the South African OTT market. The data were diverse, with no pronounced skew towards a particular demographic.

Means and standard deviations of responses

The table below highlights the means and standard deviations of the questions. The means for the constructs range from 3,79 being the lowest to 4,56 being the highest. There was a general agreement with the questions asked as highlighted in the table as most of the respondents either strongly agreed or agreed. General agreement percentages varied from 70% to 91% while the general disagreement ranged from 1% to 13%.

Table 1 - Summary of responses

		General Disagreement	Neither Disagree Nor Agree	General Agreement	Total	Means	Standard Deviation
PU1	Using OTT/Streaming services help me manage my spare time more effectively.	8,6%	21,4%	70,0%	100,0%	4,02	1,04
PU2	Using OTT/Streaming services is the best use of my leisure time.	7,0%	18,2%	74,8%	100,0%	4,08	1,00
PU3	Using OTT/Streaming will improve my performance in managing my personal life.	12,5%	24,9%	62,6%	100,0%	3,79	1,14
PE1	Using OTT/Streaming services is pleasurable for me.	2,2%	12,5%	85,3%	100,0%	4,35	0,80
PE2	I have fun using OTT/Streaming services.	1,0%	14,4%	84,7%	100,0%	4,42	0,78
PE3	I find using OTT/Streaming services to be enjoyable.	1,0%	10,9%	88,2%	100,0%	4,47	0,74
SO1	People in my social circle use OTT platforms.	4,5%	16,0%	79,6%	100,0%	4,23	0,92
SO2	People in my social circle regularly discuss what they have watched on OTT platforms.	10,2%	14,7%	75,1%	100,0%	4,10	1,08
SO3	People in my social circle recommend that I use OTT platforms.	9,3%	16,9%	73,8%	100,0%	4,04	1,07
HA1	The use of OTT/Streaming services is natural for me.	4,8%	16,6%	78,6%	100,0%	4,17	0,87
HA2	The use of OTT/Streaming services has become automatic for me.	5,8%	16,0%	78,3%	100,0%	4,18	0,95
HA3	Choosing OTT (streaming) when I want to watch TV or video content is something I do as a matter of habit.	9,6%	17,6%	72,8%	100,0%	4,05	1,06
HA4	I find using OTT (streaming) for TV or video content the easiest thing to do.	5,1%	12,1%	82,7%	100,0%	4,28	0,90
HA5	I would rather use OTT (streaming) over anything else.	9,6%	20,1%	70,3%	100,0%	4,00	1,12
HA6	When I have alternatives for watching video content, I prefer using OTT platforms.	5,8%	17,9%	76,4%	100,0%	4,12	0,96
HA7	I do not need to devote a lot of mental effort to decide that I will use OTT (streaming) to watch.	8,9%	18,5%	72,5%	100,0%	3,99	1,02

HA8	Selecting OTT (streaming) to watch video content does not involve much thinking.	6,4%	19,8%	73,8%	100,0%	4,08	0,95
HA9	Choosing OTT (streaming) to watch video requires very little mental energy.	10,5%	17,9%	71,6%	100,0%	3,92	1,09
SA1	I think I made the correct decision in using OTT services.	3,5%	10,2%	86,3%	100,0%	4,41	0,85
SA2	My experience with using OTT services has been satisfactory.	1,6%	10,2%	88,2%	100,0%	4,41	0,75
SA3	I am satisfied with the OTT services I use.	3,8%	9,3%	86,9%	100,0%	4,43	0,85
INT1	I intend to continue using OTT services in the future.	1,6%	7,3%	91,1%	100,0%	4,56	0,75
INT2	I will always try to use OTT services in my daily life.	5,1%	19,8%	75,1%	100,0%	4,16	1,00
INT3	I will keep using OTT services as regularly as I do now.	2,9%	12,5%	84,7%	100,0%	4,38	0,87

After analysing the characteristics of the sample, the study analysed data from the survey in two stages. Firstly, we analysed the measure model to ensure the integrity of the measure being utilised in the study. Thereafter, the study examined the structural model for hypothesis analysis and testing. To check the measurement model, the study tested the validity and reliability of the model.

5.4 Confirmatory Factor Analysis (CFA)

The study performed a Confirmatory Factor Analysis (CFA) using SmartPLS. The CFA was to establish the structural validity of the scale. The following items were removed from the model: PU3, HA7, HA8, and HA9. The factor loading for these items was below the recommended cut-off of 0,5 (Samar, Ghani & F Alnaser, 2017). The loadings for the remaining constructs are depicted in the figure below.

Figure 9 - Confirmatory Factor Analysis

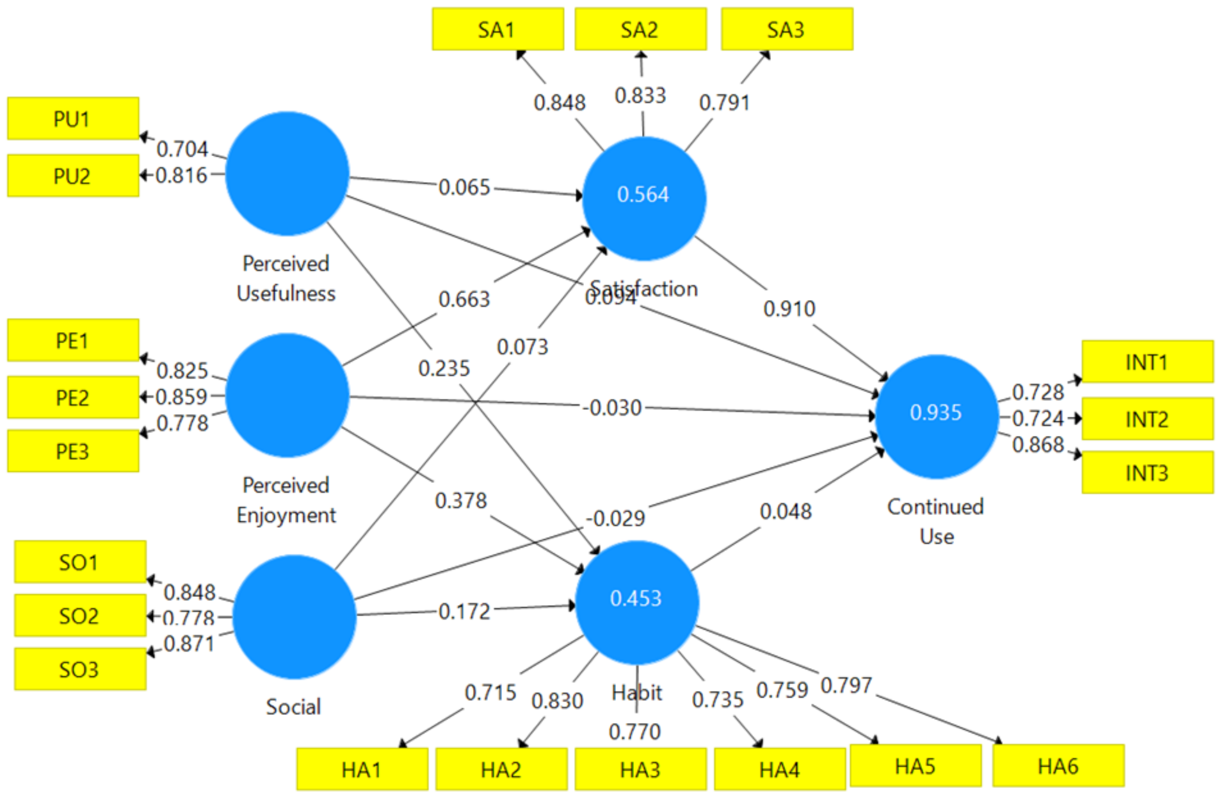
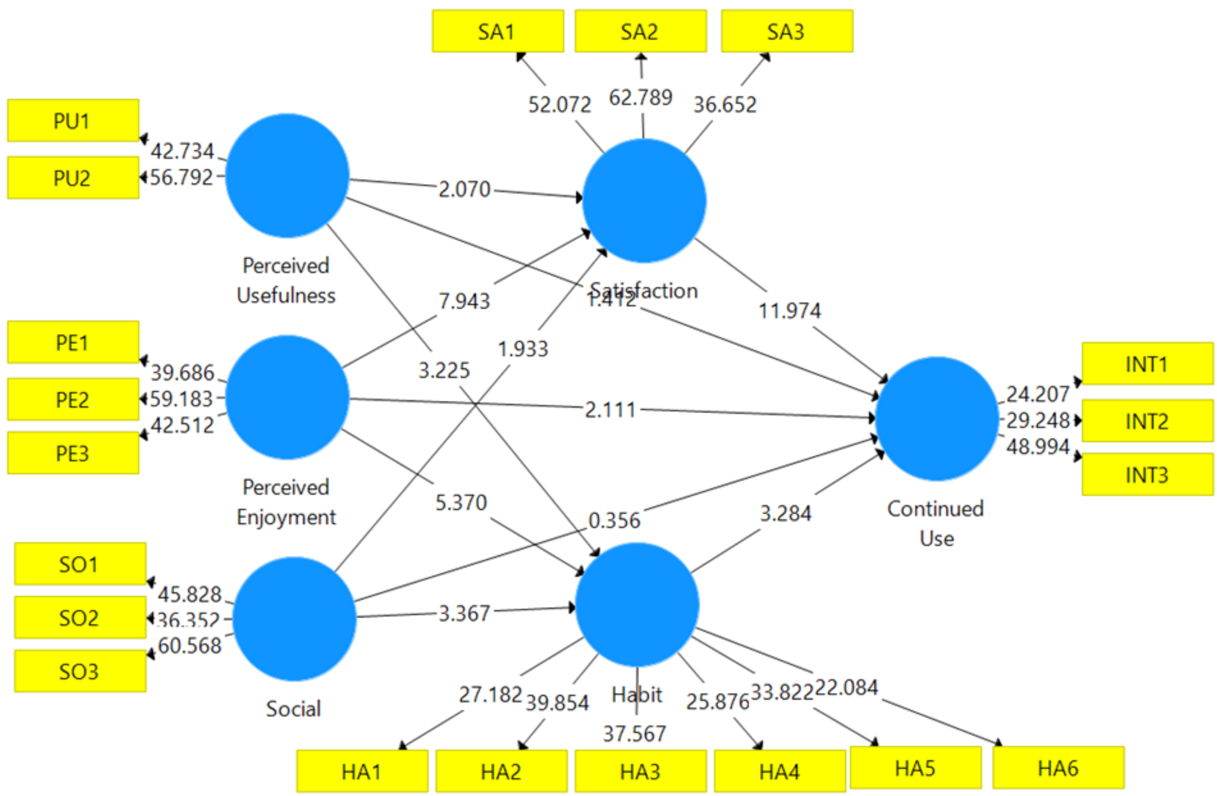


Figure 9b T-Statistics



5.5 Validity

Convergent validity

Validity was measured in two ways. Firstly, we tested for convergence validity and then for discriminant validity. Convergence validity measures how close the variables correlate with other variables within the model. On the other hand, discriminant validity measures how variables differ or how uncorrelated or different constructs are.

> *"Convergent validity refers to how closely the scale is related to other variables and other measures of the same construct. Not only should the construct correlate with related variables, but it should not correlate with dissimilar, unrelated ones. A determination along the latter lines is*

referred to as discriminant validity" (de Vet et al., 2011; Streiner et al., 2015).

Converged validity was established using factor loadings. Table 2 below highlights the factor loadings obtained. All the factor loadings are above the recommended threshold of 0,6 (Chin, 1998).

In addition to the above, convergent validity was measured using CR and AVE. The AVE ranged from 0,659 to 0,796 and exceeded the proposed cut-off levels of 0,5 (Fornell & Larcker, 1981). In addition to AVE, the CR was above the cut-off of 0,7, thereby demonstrating convergence validity.

Table 2 - Composite Reliability and Average Variance Extracted

	Composite Reliability (CR)	**Average Variance Extracted (AVE)**
Continued Use	**0,890**	**0,731**
Habit	**0,921**	**0,659**
Perceived Enjoyment	**0,915**	**0,783**
Perceived Usefulness	**0,880**	**0,786**
Satisfaction	**0,917**	**0,787**
Social	**0,921**	**0,796**

Figure 10 - Composite Reliability

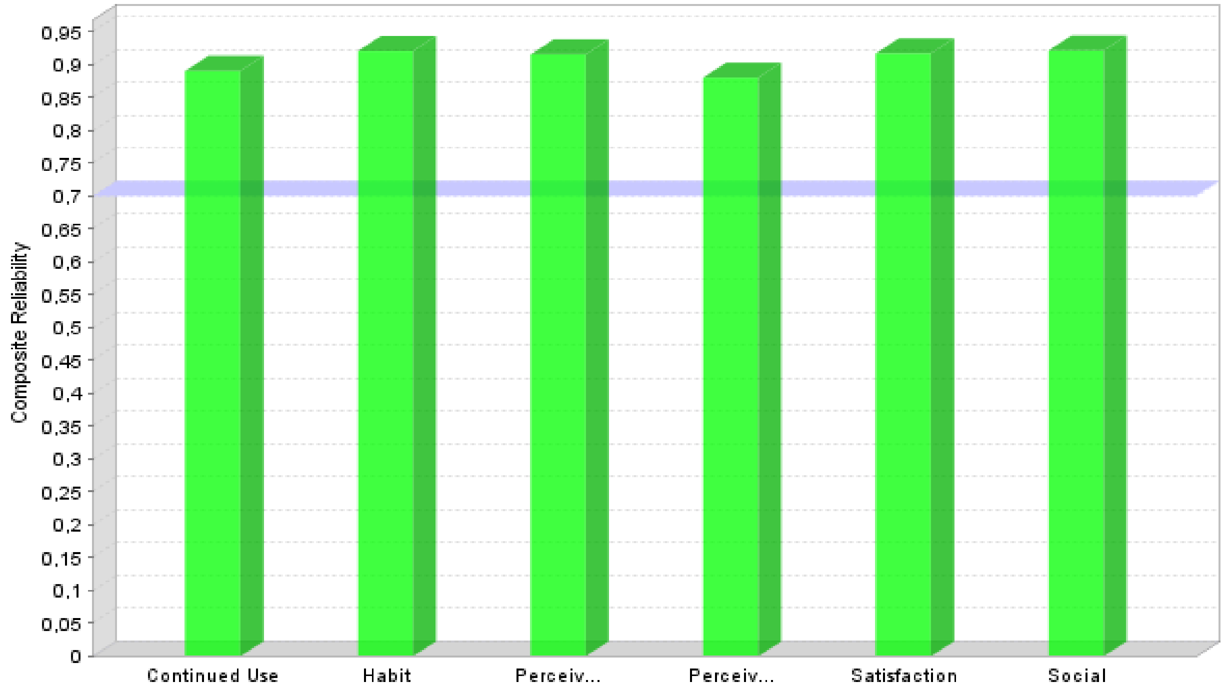
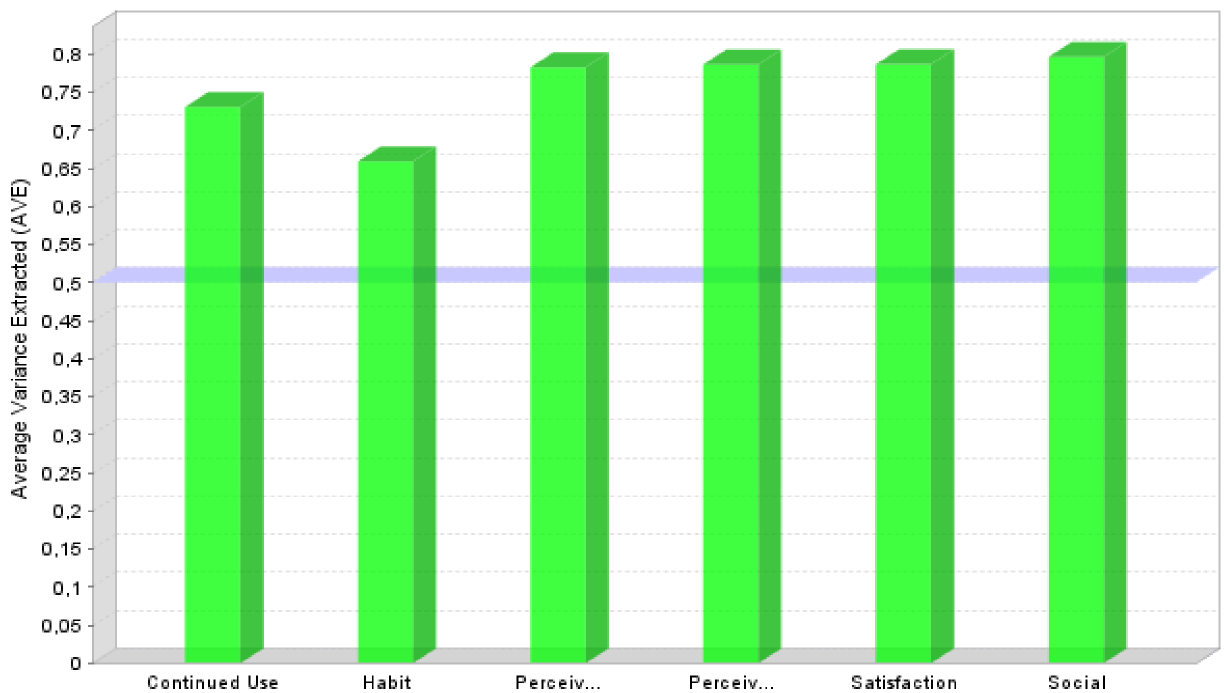


Figure 11 - Average Variance Extracted



Convergent validity was confirmed as the factor loadings were above the threshold of 0,6. Furthermore, the CR and AVE are above the recommended levels of 0,7 and 0,5, as depicted in Figure 10 and 11.

Discriminant validity

Having confirmed convergence validity, we moved on to discriminant validity. Discriminant validity is the extent to which constructs measure distinct concepts (Fornell & Larcker, 1981). It is measured by checking that the average variance shared between each construct and its measure is greater than the variance shared between the construct and other constructs (Liliana, Clipa & Tzafilkou, 2020). The table below depicts the square root of AVE (in bold) being greater than corresponding columns and rows values, which indicate that the measure is distinct/discriminate (Samar et al., 2017).

Table 3 - Discriminant validity

Fornell-Larcker Criterion

	Continued Use	Habit	Perceived Enjoyment	Perceived Usefulness	Satisfaction	Social
Continued Use	**0,855**					
Habit	0,664	**0,812**				
Perceived Enjoyment	0,618	0,558	**0,885**			
Perceived Usefulness	0,457	0,460	0,548	**0,887**		
Satisfaction	0,817	0,680	0,646	0,438	**0,887**	
Social	0,371	0,419	0,475	0,325	0,401	**0,892**

In addition to the above, discriminate validity can also be measured by looking at the cross-loadings of the indicators (Hsiao et al., 2016a). The outer loadings of the indicator and its associated constructs should be greater than the loadings on all other constructs. The table below indicates that a construct loaded higher in its own construct as shown by the numbers depicted in bold and loaded lower on other constructs. According to Hair et al. (2012), this further demonstrates discriminant validity.

Table 4 - Cross loadings

	Intention	Habit	Perceived Enjoyment	Perceived Usefulness	Satisfaction	Social
HA1	0,468	**0,790**	0,457	0,297	0,471	0,374
HA2	0,536	**0,844**	0,503	0,402	0,567	0,420
HA3	0,522	**0,846**	0,453	0,390	0,555	0,349
HA4	0,520	**0,796**	0,480	0,330	0,559	0,282
HA5	0,546	**0,816**	0,372	0,438	0,524	0,333
HA6	0,630	**0,776**	0,448	0,373	0,624	0,281
INT1	**0,834**	0,512	0,548	0,242	0,697	0,301
INT2	**0,836**	0,570	0,453	0,465	0,601	0,270
INT3	**0,893**	0,618	0,574	0,464	0,780	0,370
PE1	0,535	0,534	**0,860**	0,522	0,552	0,453
PE2	0,576	0,510	**0,909**	0,460	0,597	0,402
PE3	0,528	0,431	**0,885**	0,471	0,562	0,406
PU1	0,370	0,405	0,423	**0,870**	0,331	0,273
PU2	0,436	0,410	0,541	**0,903**	0,440	0,302
SA1	0,743	0,671	0,575	0,445	**0,875**	0,341
SA2	0,704	0,606	0,587	0,387	**0,913**	0,407
SA3	0,725	0,529	0,555	0,331	**0,871**	0,318
SO1	0,347	0,360	0,451	0,289	0,376	**0,879**
SO2	0,297	0,356	0,435	0,228	0,337	**0,895**
SO3	0,347	0,402	0,389	0,348	0,359	**0,902**

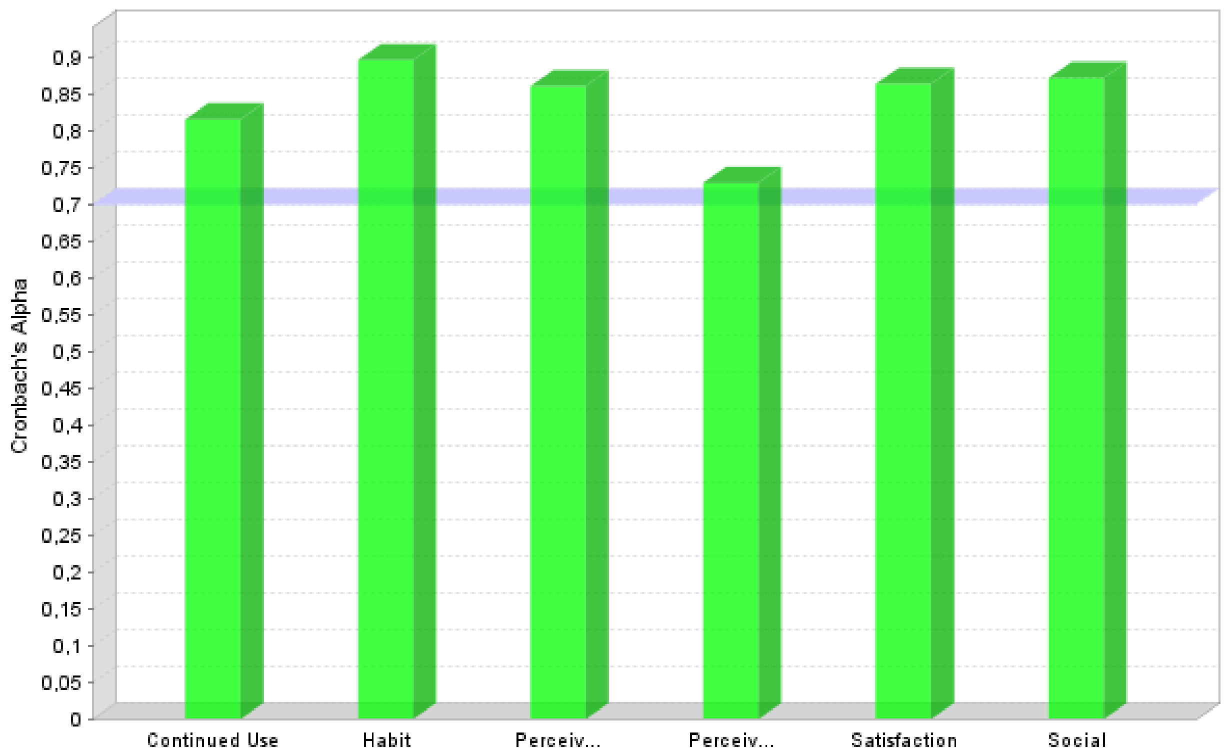
5.5 Reliability

Using Cronbach's Alpha with a cut-off criteria of greater than 0,7 according to Hair et al. (2012), we checked the reliability of the measurement model to ensure consistency over time, retest reliability, internal consistency across items examined, and replicability across various studies (Fornell & Larcker, 1981). All Cronbach’s reliability scores obtained via SPSS in Table 5 were above the cut-off point of 0,7. Furthermore, the CR scores of all seven constructs being measure exceeded the 0,7 level with the scores ranging from 0,730 to 0,896. We, therefore, confirmed the reliability of the measurement model.

Table 5 - Cronbach's Alpha

	Cronbach's Alpha
Continued Use	**0,816**
Habit	**0,896**
Perceived Enjoyment	**0,861**
Perceived Usefulness	**0,730**
Satisfaction	**0,864**
Social	**0,872**

Figure 12 – Cronbach's Alpha



5.6 Structural model

After establishing the measurement model, the research study proceeded to review the structural model and utilised SmartPLS software to assess the strength of the SEM. The results of the PLS-SEM results indicated a good fit. The table below depicts the results of the model fit analysis.

Table 6 – Structural model

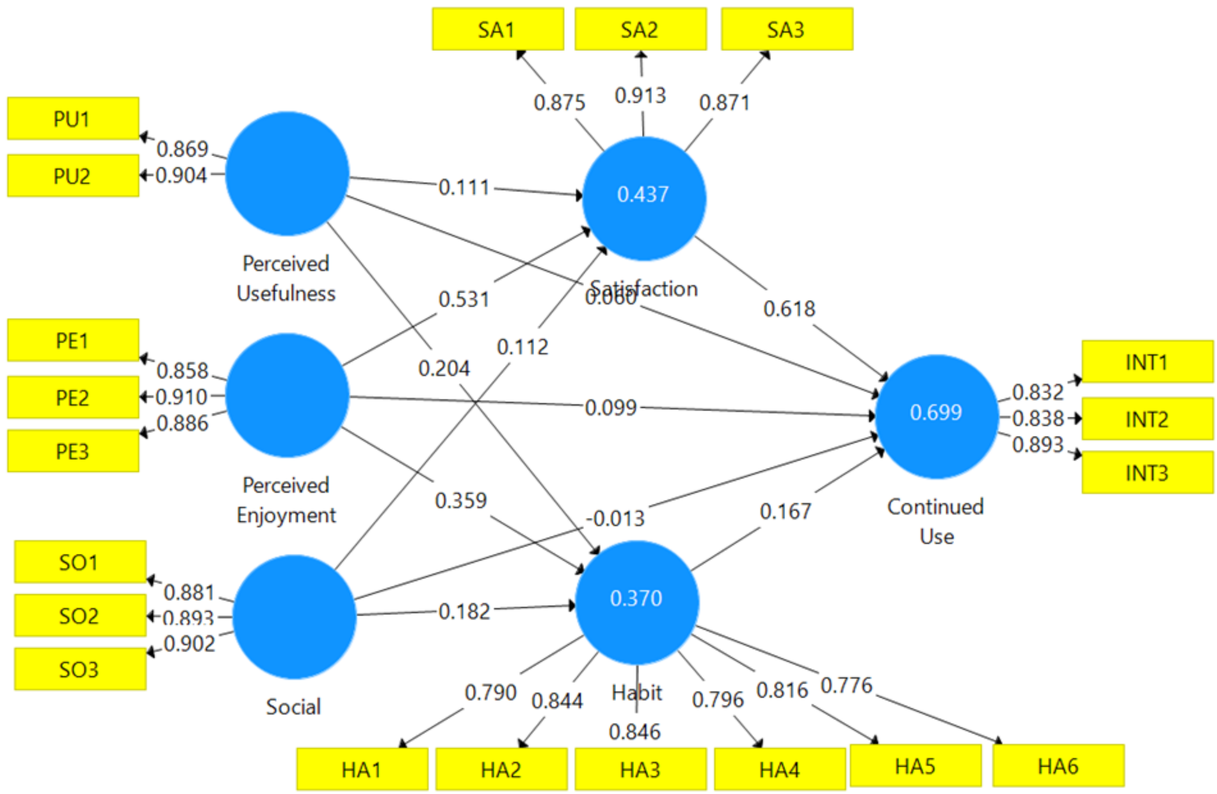


Table 7 - Model fit

	Saturated Model
SRMR	0,063
NFI	0,781

The model fit results from Table 6 highlighted model fit using SRMR (Hsiao et al., 2016a). NFI was below the recommended cut-off of 0,95 for a well-fitting model (Byrne, 2010). However, most of the standardised path coefficients between the constructs were found to be significant with p-values less than 0,05, as depicted in Table 7 below, except for the direct relationship between continued use intention with both ST and PU. Additionally, the R-squared coefficient results of the model were significant at 0,70 (Hair et al., 2012).

Thus, the model fit was deemed adequate to assess the structural model, and therefore, the structural model was confirmed.

Table 8 - Results of Beta and p-values

	Beta	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics	P Values
Habit -> Continued Use	0,167	0,167	0,054	3,104	**0,002**
Perceived Enjoyment -> Continued Use	0,099	0,099	0,047	2,094	**0,037**
Perceived Enjoyment -> Habit	0,359	0,359	0,068	5,276	**0,000**
Perceived Enjoyment -> Satisfaction	0,531	0,532	0,063	8,399	**0,000**
Perceived Usefulness -> Continued Use	0,060	0,060	0,046	1,297	**0,195**
Perceived Usefulness -> Habit	0,204	0,204	0,062	3,270	**0,001**
Perceived Usefulness -> Satisfaction	0,111	0,110	0,051	2,166	**0,031**
Satisfaction -> Continued Use	0,618	0,617	0,050	12,463	**0,000**
Social -> Continued Use	-0,013	-0,012	0,035	0,385	**0,700**
Social -> Habit	0,182	0,182	0,053	3,460	**0,001**
Social -> Satisfaction	0,112	0,112	0,057	1,986	**0,048**

5.7 Hypothesis testing

Hypothesis 1: Individual habit will have a positive influence on continuance intention

Table 9 – Habit -> Continued Use

	Beta	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Habit -> Continued Use	0,167	0,203	0,049	4,148	**0,000**

The proposed model hypothesis that habit will have a direct positive relationship impact on continued use intentions (null hypothesis). The results show a beta of 0,20 at 95 %

confidence level and p-value of 0.00. Thus, we fail to reject the null hypothesis as the p-value is below 0,05.

Hypothesis 2: Satisfaction has a positive influence on continuance intention

Table 10 – Satisfaction -> Continued Use

	Beta	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Satisfaction -> Continued Use	0,618	0,677	0,041	16,387	**0,000**

Hypothesis 2 predicted that satisfaction would have a direct positive effect on continued use intentions. The results of the test depicted in the table above show a beta of 0,68 between satisfaction and habit with a p-value of 0,00, indicating that the relationship between satisfaction and habit is significant. Thus, the null hypothesis is not rejected.

Hypothesis 3: Perceived Enjoyment directly and positively impacts continuance intention

Table 11 - Perceived Enjoyment -> Continued Use

	Beta	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics	P Values
Perceived Enjoyment -> Continued Use	0,099	0,099	0,047	2,094	**0,037**

The model theorises that PE has a direct positive impact on continued use intentions. The correlation coefficient of intentions to use and PE is 0,10. The relationship is significant, with a p-value of 0,04, which is less than 0,05 and significant at a 95% confidence level. We fail to reject the null hypothesis and reject the alternate hypothesis.

Hypothesis 4: Perceived Enjoyment will positively influence consumer satisfaction

Table 12 - Perceived Enjoyment -> Satisfaction

	Beta	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Perceived Enjoyment -> Satisfaction	0,531	0,526	0,068	7,834	**0,000**

Similar to the above, the model hypothesis that PE will have a positive correlation with satisfaction. The beta between PE and satisfaction highlighted in the table above shows a beta of 0,53. The relationship between the two is significant, with a p-value of 0,00 at 95% confidence level. We thus fail to reject the null hypothesis and reject the alternative hypothesis.

Hypothesis 5: Perceived Enjoyment will positively influence habit formation

Table 13 - Perceived Enjoyment -> Habit

	Beta	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Perceived Enjoyment -> Habit	0,359	0,351	0,068	5,273	**0,000**

Similar to the relationship between PE and satisfaction above, the relationship between PE and habit is also significant, with a p-value of 0,000. The correlation coefficient is 0,36, highlighting that PE explains 36% of the variation in habit at a 95% confidence level. The table above highlights the results of the statistical test. Thus, we fail to reject the null hypothesis and reject the alternative hypothesis.

Hypothesis 6: Perceived Usefulness will positively impact consumer continuance of use intention

Table 14 - Perceived Usefulness -> Continued Use

	Beta	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics	P Values
Perceived Usefulness -> Continued Use	0,060	0,060	0,046	1,297	**0,195**

PU was defined in Chapter 2 as the relative advantage of the technology and the advantage the consumer gains from using the technology. The table above highlights the beta between PU and intentions to continued use intentions of OTT technology. Six per cent of the variation in intentions can be explained by a consumer's PU of OTT technology. The relationship is insignificant, with a p-value of 0,195 at a 95% confidence level. Thus, we reject the null hypothesis.

Hypothesis 7: Perceived Usefulness will positively impact consumer satisfaction

Table 15 - Perceived Usefulness -> Satisfaction

	Beta	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Perceived Usefulness -> Satisfaction	0,111	0,109	0,052	2,113	**0,035**

Similarly, the relationship between PU and satisfaction is significant at a 95% confidence level with a p-value of 0,035. The beta coefficient 0,11. Thus, the PU explains 11% of the variation in satisfaction. We, therefore, fail to reject the null hypothesis and reject the alternate hypothesis.

Hypothesis 8: Perceived Usefulness will positively impact consumer habit

Table 16 - Perceived Usefulness -> Habit

	Beta	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Perceived Usefulness -> Habit	0,204	0,209	0,063	3,219	**0,001**

As highlighted in this table, PU correlated positively with consumer habit. PU explains 20% of the variation in consumer habit. The relationship between the two constructs is significant, with a p-value of 0,00 at a 95% confidence level. We, thus, fail to reject the null hypothesis.

Hypothesis 9: Social influence has a positive effect on behavioural intentions

Table 17 - Social -> Continued Use

	Beta	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics	P Values
Social -> Continued Use	-0,013	-0,012	0,035	0,385	**0,700**

The model hypothesises that social influence has a positive correlation with continued use intentions. The beta of ST is -0,01 at a 95% confidence level. The relationship is not significant as the p-value is greater than 0,05, and thus, we reject the null hypothesis.

Hypothesis 10: Social influence has a positive effect on consumer satisfaction

Table 18 - Social -> Satisfaction

	Beta	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Social -> Satisfaction	0,112	0,117	0,056	2,014	**0,045**

ST has a direct positive effect on consumer satisfaction. The study found a positive correlation between ST and satisfaction with ST explaining 11% of the variation in satisfaction. Similar to other constructs, the relationship is significant with a p-value of 0,045, which is less than 0,05. We, thus, fail to reject the null hypothesis.

Hypothesis 11: Social Ties and interactions have a positive influence on consumer habit

Table 19 - Social -> Habit

	Beta	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Social -> Habit	0,181	0,184	0,053	3,444	**0,001**

Similar to satisfaction, ST impact OTT user habits. Thus, ST will positively impact OTT consumer habits. The results show that ST accounts for 18% of the variation in OTT user satisfaction, and the relationship is significant at a 95% confidence level. Thus, we fail to reject the null hypothesis and reject the alternate hypothesis.

Hypothesis 12: Multihoming bias will negatively impact continuance intention, satisfaction, and habit for users who do not identify an OTT platform as their primary system

Hypothesis 13: Multihoming will positively impact continuance intention, satisfaction, and habit for users who identify an OTT platform as their primary system.

Hypothesis 12 and 13 were tested together. Both hypotheses imply that there is a difference in user satisfaction and habit for users who identify OTT platforms as their primary platform, and those who identify linear as their primary platform**.** The group statistics depicted in the table below show the results of the independent t-test, and after that, we calculated the effect size.

Table 20 - Group statistics

	Primary Platform	N	Mean	Std. Deviation	Std. Error Mean
Perceived Usefulness	0 (Linear)	99	3,8131	,93292	,09376
	1 (OTT)	213	4,1542	,87052	,05951
Perceived Enjoyment	0 (Linear)	99	4,2795	,77913	,07831
	1 (OTT)	213	4,4766	,62484	,04271
Social	0 (Linear)	99	3,8889	,98630	,09913
	1 (OTT)	213	4,2336	,86213	,05893
Satisfaction	0 (Linear)	99	4,1953	,88450	,08890
	1 (OTT)	213	4,5156	,60902	,04163
Habit	0 (Linear)	99	3,6364	,90738	,09119
	1 (OTT)	213	4,3621	,61716	,04219
Continued Use	0 (Linear)	99	4,1717	,88751	,08920
	1 (OTT)	213	4,4579	,65645	,04487

Table 21 - Test for equality

Independent Samples Test										
		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Perceived_Usefulness	Equal variances assumed	0.057	0.811	-3.151	311	0.002	-0.34107	0.10826	-0.55408	-0.12807
	Equal variances not assumed			-3.071	179.453	0.002	-0.34107	0.11105	-0.56021	-0.12194
Perceived_Enjoyment	Equal variances assumed	3.587	0.059	-2.395	311	0.017	-0.19717	0.08232	-0.35915	-0.03520
	Equal variances not assumed			-2.211	158.536	0.029	-0.19717	0.08920	-0.37334	-0.02101
Social	Equal variances assumed	4.011	0.046	-3.141	311	0.002	-0.34476	0.10977	-0.56074	-0.12877
	Equal variances not assumed			-2.989	169.765	0.003	-0.34476	0.11532	-0.57241	-0.11710
Satisfaction	Equal variances assumed	12.599	0.000	-3.725	311	0.000	-0.32029	0.08600	-0.48950	-0.15108
	Equal variances not assumed			-3.263	142.548	0.001	-0.32029	0.09816	-0.51433	-0.12625
Habit	Equal variances assumed	26.740	0.000	-8.278	311	0.000	-0.72579	0.08768	-0.89830	-0.55327
	Equal variances not assumed			-7.223	141.454	0.000	-0.72579	0.10048	-0.92442	-0.52715
Continued_Use	Equal variances assumed	3.950	0.048	-3.195	311	0.002	-0.28623	0.08960	-0.46252	-0.10994
	Equal variances not assumed			-2.867	149.479	0.005	-0.28623	0.09985	-0.48353	-0.08893

Using Levene's Test for differences, the PU and PE are above the recommended cut-off of 0,05 for the p-value (highlighted in yellow in the table above).

Hypothesis 0: The variances are equal

Hypothesis 1: The variances are not equal

As the p-value is above the cut-off for PU and PE, we fail to reject the null hypothesis. There is no significant difference between the group that identifies OTT as their primary platform and the group that identifies linear as their primary platform when it comes to PE and PU (Pallant, 2013).

For ST, satisfaction, habit, and intention, we fail to reject the null hypothesis, thus meaning that there is a difference between the group that identifies OTT as their primary platform and the group that identifies linear as their primary platform. According to Pallant (2013), the next step would be to test for equality of means. To test if there is a difference based on the primary platform, we must identify the null hypothesis.

Hypothesis 0: There is no difference between the groups (null hypothesis)

Hypothesis 1: There is a difference between the groups (alternate hypothesis)

Using the 5% level of significance and using the equality means table and the p-value (sig. (2 tailed))= 0 which is less than the recommended 0,05, we reject the null hypothesis, and there is a difference between OTT primary users and primary and linear users (Pallant, 2013).

Table 22 - Group statistics for social, satisfaction, habit, and continued use intentions

	Primary Platform	N	Mean	Std. Deviation	Std. Error Mean
Social	0 (Linear)	99	3,8889	,98630	,09913
	1 (OTT)	213	4,2336	,86213	,05893
Satisfaction	0 (Linear)	99	4,1953	,88450	,08890
	1 (OTT)	213	4,5156	,60902	,04163
Habit	0 (Linear)	99	3,6364	,90738	,09119
	1 (OTT)	213	4,3621	,61716	,04219
Continued Use	0 (Linear)	99	4,1717	,88751	,08920
	1 (OTT)	213	4,4579	,65645	,04487

After identifying the differences in the means in the table above, the next step was to identify if the difference in the means was significant by calculating the effect size. Using the ETA Test, we calculated the effect of the difference. The ETA size effect ranges from 0 to 1. According to Pallant (2013), 0,01 equals a small effect, while 0,06 indicates a moderate effect, and lastly, 0,14 represents a large effect. The table below depicts the results of the ETA Squared Test.

Table 23 - ETA Squared (N^2)

	Social	**Satisfaction**	**Habit**	**Intention**
ETA Squared (N^2)	0,03	0,03	0,14	0,03

The effect size on habit is large. Thus, we fail to reject the null hypothesis.

Table 24 - Summary of hypothesis testing

Hypothesis	Accepted/Rejected	Significant/Non-significant
H1: Individual habit will have a positive influence on continuance intention	**Yes**	**Yes**
H2: Satisfaction has a positive influence on continuance intention	**Yes**	**Yes**
H3: Perceived Enjoyment directly and positively impacts continuance intention	**Yes**	**Yes**
H4: Perceived Enjoyment will positively influence consumer satisfaction	**Yes**	**Yes**
H5: Perceived Enjoyment will positively influence habit formation	**Yes**	**Yes**
H6: Perceived Usefulness will positively impact consumer continuance of use intention	**Rejected**	**No**
H7: Perceived Usefulness will positively impact consumer satisfaction	**Yes**	**Yes**
H8: Perceived usefulness will positively impact consumer habit.	**Yes**	**Yes**
H9: Social influence has a positive effect on behavioural intentions.	**Rejected**	**No**
H10: Social influence has a positive effect on consumer satisfaction.	**Yes**	**Yes**
H11: Social connections and interactions have a positive influence on consumer habit	**Yes**	**Yes**
H12: Multihoming bias will negatively impact continuance intention, satisfaction, and habit	**No**	**No**

for users who do not identify an OTT platform as their primary system		
H13: Multihoming bias will positively impact continuance intention, satisfaction, and habit for users who identify an OTT platform as their primary system	**No**	**No**

CHAPTER 6: DISCUSSION

6.1 Introduction

As highlighted in Chapter 1, the study aimed to understand continued use intentions for OTT platforms. Chapter 2 reviewed existing literature, describing the existing literature from both the marketing and IS fields. The proliferation of OTT platforms has increased competition in the market and shifted focus away from adoption to continued use as platforms look to retain customers. In recent years, OTT platforms have increased their share of the market, and as a result, the TV and video market has become increasingly fragmented. Traditional broadcasters and pay-TV providers have seen their share of the market decline, and this has coincided with the increased popularity of OTT platforms (Tao, Zhumin, Yujie & Jun 2018; Schweidel & Moe, 2016; Chow & Van Eeden, 2019). The popularity of these platforms has led to the rise in new market entrants and rapidly altering the industry structure, value chain, and ecosystem. These changes have resulted in business and academia, asking which model and factors can explain the continued use of OTT platforms.

Having established the need for the research and the growing importance of OTT platforms, the study developed research questions defined in Chapter 3. To answer the research questions, a survey questionnaire was distributed to 364 respondents as set out in the methodology as described in Chapter 4. Chapter 5 provided the results of the study. Statistical analysis was conducted on the data using SEM. Chapter 6 will discuss the findings of the research and compare the findings to the literature review in Chapter 2. It will also review the research questions and the research hypothesis.

6.2 Research question 1: Research model

In total, the proposed research model explains 69% of the variation in intention. The direct relationships between PU and intentions, together with ST and intentions, were found to be insignificant and were dropped from the model. The rest of the relationships were significant. The model fit was confirmed, and the reliability and validity of the model were confirmed. We, thus, satisfied that the model is suitable in explaining the continued use intentions of OTT platforms.

6.3 Research question 2: Habit

Hypothesis 1: Individual habit will have a positive influence on continuance intention

The literature review in Chapter 2 highlighted various authors in different fields who have defined habit as the frequency of the act in the behavioural history of the organism (Landis et al., 1978). Habit is the semiautomatic performance of well-learned behaviour (Charng et al., 1988). Tadajewski (2019) defined habit as an action that has become automated as a result of past activities that promote efficiency, avoid cognitive overload, and decision paralysis. The repeated actions result in a decline in consciousness and more automated responses to cues (Tadajewski, 2019). The repeated nature and the automatic responses to cues have been hypothesised to lead to continued use intentions.

Our study found that the relationship between habit and continued use intentions is significant with the p-value being less than 0,05. The habit construct is responsible for 17% of the variation in continued use intentions. Similar to results from Hsiao et al. (2016) and Bhattacherjee (2001), this study also found the relationship between habit and intentions to be significant. Additionally, this study also found variation in habit formation for users who identify OTT platforms as their primary platform and users who identify linear as their primary platform. The effect size in variation in habit formation was found to be significant through the ETA Test. Despite the effect size on habit being significant, this did not translate to a significant effect size for continued use intentions.

This finding supports the theory that multihoming does have an impact on user habit. Multihoming was defined as consumers acquiring and utilising competing products at the same time (Jiang et al., 2019). The utilisation of a competing product as a primary platform was proven to impact habit negatively. The study found that for the 99 users who identified linear as their primary platform, the means for the habit construct was 22% below the mean for the group that identified OTT as their primary platform. SQB could explain the lower percentage for these users as the study did not find any significant differences between these two groups for PE and PU of OTT platforms.

6.4 Research question 3: Satisfaction

Hypothesis 2: Satisfaction has a positive influence on continuance intention

The results of the study indicate that satisfaction has a significant positive impact on continued use intentions of OTT users. The path coefficient between satisfaction and intentions is positive at 0,62, as highlighted in Table 4. In addition to accounting for 62% of the variation in intention, the relationship was significant with a p-value less than 0,05. As highlighted in Table 1, there was general agreement with the satisfaction questions with all three questions having a general agreement above 86%. The means of the responses on the five-point Likert scale averaged 4,4 for all satisfaction questions.

Other research into continued use intentions on other technologies by Hsiao et al. (2016), Piehler et al. (2016), and Limayem et al. (2007) also found satisfaction to play a significant role in users' continued use intentions. Their studies found the path coefficients between satisfaction and intention to be 0,31 in Hsiao et al. (2016), 0,31 in Piehler et al. (2016), and 0,23 in Limayem et al. (2007). The results are above are in line with expectation confirmation theories by Bhattacherjee (2001), Piehler et al. (2016), and Y. Kim & Zhang (2010) that state that satisfaction increases continuance intentions.

OTT companies are more likely to retain their customers if they are satisfied with the service. This finding implies that content curation strategies will play a significant role in customer retention. OTT companies need to ensure that their content libraries have unique and a variety of shows to keep consumers engaged and satisfied. This reasoning is further justified by the fact that of the three variables for satisfaction, PE was found to be the leading determinant of satisfaction with a path coefficient of 0,53 followed by ST at 0,31, and lastly PU at 0,11.

Perceived Enjoyment (PE)

Hypothesis 3: Perceived Enjoyment directly and positively impacts continuance intention

Since OTT platforms are primarily used for entertainment purposes, the hedonic value of the OTT platforms, if hypothesised to impact continued use intentions as highlighted in Prince & Greenstein (2017), video entertainment is the number one use of leisure time. In a consumer context, hedonic factors are a critical determinant of technology use. Thus, it is theorised that hedonic factors will positively impact continuance intentions of OTT platform users.

The study found that hedonic factors are a significant antecedent for continued use intentions. The relationship between enjoyment and use was significant with the p-value being less than 0,05, as highlighted in Table 20 above. PE accounted for 10% of the variation in continued use.

In their study on mobile internet technology in the Hong Kong market, Venkatesh et al. (2012) found hedonic factors to impact continued use intentions directly. PE accounted for 22% of the variation in intentions. The study by Hsiao et al. (2016) on social media technologies also found PE to play a significant positive effect on continued use intentions with PE accounting for 21% of the variation in intentions. The magnitude of the significance at 9% is much less than the results of both Venkatesh et al. (2012) and Hsiao et al. (2016). Given the primary function of the technology, the impact of the enjoyment construct was anticipated to be significantly higher. The lower impact of enjoyment on intentions could be a result of the fact that unlike other technologies, most consumers in the OTT space are using multiple technologies (multihoming) for the same function. The presence of a competing technology could be the possible reason for a lower coefficient compared to other studies.

Hypothesis 4: Perceived Enjoyment will positively influence consumer satisfaction

The study theorised PE to have a significant favourable influence on user satisfaction. The findings indicate that PE accounts for 53% of the variation in satisfaction and found the relationship to be significant. Results from other studies indicate a similar trend with Hsiao et al. (2016) reporting a 48% variation and Limayem et al. (2007) reporting 35%.

Hypothesis 5: Perceived Enjoyment will positively influence habit formation

The study found the relationship between PE and habit to be significant. The study found PE to explain 35% of the variation in the habit. The findings are consistent with the literature that if a consumer evaluates their experience positively, they are likely to repeat the behaviour or action in question. The enjoyment from the use is likely to lead to an inclination to repeat the action subconsciously. Most acceptance and continued use studies like Venkatesh et al. (2012) have mapped PE and habit as parallel constructs in the analysis of continued use intentions. This study agrees with Hsiao et al. (2016) in that PE will directly impact intention and indirectly through its impact on user habit and satisfaction. Our findings are, therefore, consistent with Hsiao et al. (2016) who found the standardised coefficient between PE and habit to be 0,42 and the relationship to be significant.

Similar to satisfaction, PE is a more significant contributor to user habit as compared to PU and ST. The implication from a business perspective is that it highlights the impact of content curation and the need for content that is unique to drive PE on these platforms as compared to other platforms. From an academic perspective, it adds to research on continued use, showing that PE directly impacts habit as opposed to habit and enjoyment being parallel constructs.

Perceived Usefulness (PU)

Hypothesis 6: Perceived Usefulness will positively impact consumer continuance intentions

The study hypothesised that the PU of technology would positively impact continued use intentions of the technology. OTT technologies allow users to consume content on-demand as opposed to linear TV, which relies on appointment viewing (Schweidel & Moe, 2016). With video viewing being the number one use of leisure time, OTT platforms' usefulness relies on its on-demand service that allows viewers to consume content at their convenience.

Previous technology acceptance and continued use studies like Kim & Malhotra (2005), Venkatesh et al. (2003), Davis (1989), Althuizen (2018), and Venkatesh & Davis (2000), have indicated that PU was a significant determinant of continued use intentions. Unlike PEOUS, which has been proven in previous studies to be insignificant (Hsiao et al., 2016). In contrast to previous studies on continued use, our results highlight a correlation coefficient of 0,06. However, the results of the test are insignificant as the p-value was greater than 0,05. We, thus, failed to prove the hypothesis that PU has a direct positive relationship on continued use intentions. Our findings are similar to Hsiao et al. (2016). They also found PU to be insignificant and concluded that this was not in line with conventional marketing and IS literature's view that PU a critical antecedent for continuance intention.

Hypothesis 7: Perceived Usefulness will positively impact consumer satisfaction

In contrast to the relationship between PU and continued use, the relationship between PU and satisfaction is significant, with a p-value less than 0,05. The correlation coefficient between the two constructs is 0,11. PU explains 11% of the variation in satisfaction.

Our findings are consistent with other studies. Hsiao et al. (2016), in their study of social media technology, found that PU contributed 26% in the variation in satisfaction, and similarly, the relationship was significant. The study also found the impact of PU of the technology to be significantly less than PE. This finding is in contrast to previous studies like Kim & Malhotra (2005), Venkatesh et al. (2003), Davis (1989), and Althuizen (2018), who found PU to be a better indicator of satisfaction. This contrast is because these studies were based mainly in a work environment where the usefulness of the technology played a more significant role. In contrast, this study, along with Hsiao et al. (2016), is based on an individual setting with a mostly hedonic focus.

The finding above has implications for management when evaluating long-term investment decisions for improving the customer experience as the functional features of OTT platforms do not lead to increased loyalty and continued use. Furthermore, platforms should track which functions consumers are using, are satisfied with, and are habitually using. Marketing efforts can then be directed, highlighting the potential benefits of the functions and how these benefits can improve efficiency in everyday life and the completion of daily tasks.

Hypothesis 8: Perceived Usefulness will positively impact consumer habit

Similar to the above, the relationship between PU and habit is significant, with PU explaining 20% of the variation in OTT user habit. This finding is consistent with existing theory and literature that states that the more consumers regard a technology to be useful or have great utility towards a particular task, the more users will feel satisfied with the product, and this will positively influence consumer habit. Other studies, like Rey-Moreno et al. (2018), Limayem et al. (2007), and Hsiao et al. (2016), also found utilitarian effects to be a strong antecedent for user habit. Identifying which utility factors users value is crucial in promoting efficiency derived from the use of technology.

Hypothesis 9: Social influence has a positive effect on behavioural intentions

Social influence has consistently proven to be a significant influence on the adoption and continued use of technology products. Social influence refers to the degree to which technology users think that essential people within their social circles, for example, friends and family think they should utilise a particular technology or perform a specific action (Venkatesh et al., 2012). It refers to the perceived pressure to perform a specific action (Venkatesh et al., 2012). This study considered ST to be positively related to continued use. Unlike Althuizen (2018), Sun (2013), Venkatesh et al. (2012), and Hsiao et al. (2016), whom all found the relationship to be significant, this study's findings contradict the findings of these studies. The correlation coefficient between ST and intent was negative 0,01, indicating an inverse correlation.

The findings of our research are inconsistent with previous studies. This study found the relationship between ST and continued use intentions to be insignificant. The variance in question is a result of the technology in question and the context-related factors. OTT technologies are primarily used for entertainment purposes in a consumer setting while Althuizen (2018), for example, was based in an organisational setting. Despite being in a consumer setting, Venkatesh et al.'s (2012) study was based on mobile internet technologies which cover an assortment of digital technologies. Hsiao et al.'s (2016) study was in a consumer context; however, it was based on social media technologies, hence the significant relationship between ST and intention. In the literature review, it was noted that consumers are rejecting pay-TV bundles and creating their own individual bundles using OTT bundles that reflect their tastes and preferences. The fact that consumers are custom-making bundles could explain why the relationship between ST and intentions was insignificant.

Hypothesis 10: Social influence has a positive effect on consumer satisfaction

In contrast to the above, the study found that ST has a significant relationship with satisfaction. As hypothesised in Yang & Wang (2015), sharing of media and the collective experiences for this media consumption can lead to increased consumer satisfaction. This study found the standardised coefficient for ST and satisfaction to be 0,11, explaining 11% of the variation in satisfaction.

Our findings are consistent with the results from Yang & Wang (2015) in their study of consumers' online video sharing attitudes, intent, and behaviour. Their results indicated that consumers derived satisfaction from being able to share online videos with their network on social media platforms. Additionally, they also found the normative pressures of social media use and perceived pleasure to have a significant effect on video-sharing intent.

Hypothesis 11: Social connections and interactions have a positive influence on consumer habit

Habit formation requires a high frequency of subconscious use within a stable context. Herd behaviour theories contend that frequent use within one's social circle is likely to affect individual habit (Sun, 2013).

> *"When people are free to do as they please, they usually imitate each other" (Sun, 2013).*

This study found the relationship between ST and habit to be significant with ST explaining 18% of the variation in habit. Similarly, Hsiao et al. (2016) found the relationship to be significant, with ST explaining 30% of the variation in habit. These findings are consistent with the findings of Yang & Wang (2015), who found that people increased sharing among social media users.

6.6 Research question 4: Primary platform

Hypothesis 12: Multihoming will negatively impact continuance intention, satisfaction, and habit for users who do not identify an OTT platform as their primary system

Hypothesis 13: Multihoming will positively impact continuance intention, satisfaction, and habit for users who identify an OTT platform as their primary system

The review of the literature identified that OTT platform users were using two or more competing products to aggregate their bundles of content. The existing marketing literature is primarily based on the assumption that consumers do not purchase competing products simultaneously (Jiang et al., 2019).

This study theorised that the use of multiple competing products has an impact on the frequency of use and comprehensiveness of use and therefore, will impact user habit, satisfaction, and continued intentions. We noted work by Etworks et al. (2014), which concluded that platform owners risk misspecifying user behaviour by only focusing on consumer behaviour while on their platform.

As part of the survey questionnaire, the study asked users if they were utilising other linear platforms in addition to their OTT platform. Additionally, the study asked the respondents who said “YES” to using additional platforms what their primary platform is. The research identified two groups. Group One comprised of 99 respondents who identified a linear platform as their primary platform, and Group Two had 214 respondents who only use OTT platforms and who identified OTT platforms as their primary platform.

Based on the theory, this study hypothesised that the actions of consumers that consider linear TV to be their primary platform would be impacted by inertia when presented with a choice between pay-TV and OTT. Thus, the incumbent system habit and switching costs will lead to continued use of linear-TV and negatively impact the continued use, habit, and satisfaction for OTT platforms (Karahanna & Polites, 2012). For users who identify OTT platforms as their primary platform, their habit, satisfaction, and continued use intention would be much more significant compared to the other group.

The results of the descriptive statistics highlighted that the majority of the sample (279 respondents) are multihoming and using OTT services in conjunction with their linear platforms as hypothesised by Rich (2019) and Etworks et al. (2014). Only 34 respondents are using OTT services only. Thus, only 10% of the respondents are using OTT services only. This low percentage could be a result of the fact that linear TV and OTT services are not used as substitutes but instead as complementary services to one another (Tao et al., 2018 & Rich, 2019).

The results of the comparisons of the two means indicated the following results: There is no variation between PE and PU between the two groups. The means for the two groups were statistically insignificant. Thus, despite identifying linear as their primary platform, the PE and PU did not vary from primary users of OTT platforms. With 90% of the respondents using both linear and OTT services simultaneously, consumers view these products as complementary rather than substitutes, thus explaining why the means of the two groups do not vary.

The results for ST indicated that there was a difference between the two groups. However, as highlighted in Table 20, the effect size of the difference was small. Similarly, for satisfaction, the research found a difference between the two groups. This finding was in line with the theory that there would be a difference between the satisfaction levels of both groups. However, despite the difference between the groups, the study noted that the effect size was 0,03, which was not as large as anticipated. Our findings are inconsistent with existing marketing literature, where the presence of two similar products negatively affect the repurchase intentions of the other product (Etworks et al., 2014). Similarly, our finding is in contrast to adoption theories by Venkatesh et al. (2016) and SQB (Karahanna & Polites, 2012) and theories that assume a winner-take-all mentality in their models. Thus, consumers cannot be satisfied with two competing products and will always select one product to adopt or continue using over another and thus can only be satisfied with one product.

Our findings for habit are different from the rest of the constructs. The study found a significant difference in the means of both groups and the effect size of the variance was significant with an ETA score of 0,14, which represents a large effect according to Pallant (2013). The means for both groups shows the linear group with a lower habit mean of 3,63 versus 4,36 for the OTT group. OTT habit is weaker for the groups that identified linear as their primary platform as compared to the group that identifies OTT as their primary platform.

Existing literature states that habit formation requires a stable context (Limayem et al., 2007). In Chapter 2, we theorised that the presence of both linear and OTT platforms would create an unstable environment for habit formation. Our findings indicate that the presence of the two platforms does not create an unstable environment for habit formation, as discussed in Chapter 2. In their study of temporal patterns, Tao et al. (2018) found that OTT usage increased significantly during weekends, school holidays, and public holidays. They concluded that OTT usage increased when consumers had extended leisure time at home (Tao et al., 2018). This result can be explained by binge-watching theories, where consumers watch multiple episodes of the same shows continuously (Schweidel & Moe, 2016). Thus, the presence of both does not create an unstable environment, but instead, consumers are using both platforms to fulfil different tasks. Thus, while the presence of both platforms impact habit of OTT platforms, the presence of both does not create an unstable environment for habit formation.

The study found that there was a difference between the intentions of the two groups for continued use intentions; however, similar to satisfaction, the effect size of the variance was not significant. Thus, for Hypothesis 12 and 13, we confirm that the following SQB will negatively impact continuance intention, satisfaction, and habit for users who do not identify an OTT platform as their primary system. On the other hand, SQB will positively impact continuance intention, satisfaction, and habit for users who identify an OTT platform as their primary system.

CHAPTER 7: CONCLUSIONS AND RECOMMENDATIONS

7.1 Introduction

This chapter will reconcile the findings of this study within the context of the research questions, academic literature, and the business problem. Chapter 1 described the growing importance of OTT platforms in the video entertainment mix. The chapter defined OTT platforms as the delivery of video content via the internet bypassing traditional satellite and cable platforms. The chapter reviewed the effect of OTT platforms in other industries, particularly the music industry. The chapter then proceeded to discuss the business implications for media and entertainment companies and discussed the potential future impact on industry structure and business models. It then reviewed the potential contributions to academic literature and concluded by discussing the scope of the research, research questions, and the structure of the research.

The chapter also highlighted the need to understand the continued use of OTT platforms given the rapid proliferation of OTT platforms in the market. Understanding the continued use of these platforms was identified as being critical for business, academia, and legislators. The future of the video entertainment industry is largely dependent on the continued use patterns of consumers using this technology. Understanding the continued use of these platforms is, therefore, critical in developing competitive strategies to develop sustainable business models.

In Chapter 2, we reviewed the existing literature from the marketing and IS fields on technology adoption and continued use intentions. In this chapter, the study reviewed previous continued use models from Venkatesh & Davis (2000) and expectation confirmation models from Bhattacherjee (2001). The review of the literature identified satisfaction and habit as constructs with a direct association on continued intentions. These constructs, in turn, were determined by the PE, PU, and ST variables (Hsiao et al., 2016). In addition to these variables, our literature review noted that consumers were using multiple platforms (multihoming) at the same time while marketing and IS literature both assume that the consumer will adopt and use one product and reject competing products. Thus, we hypothesised that this would impact habit and satisfaction constructs.

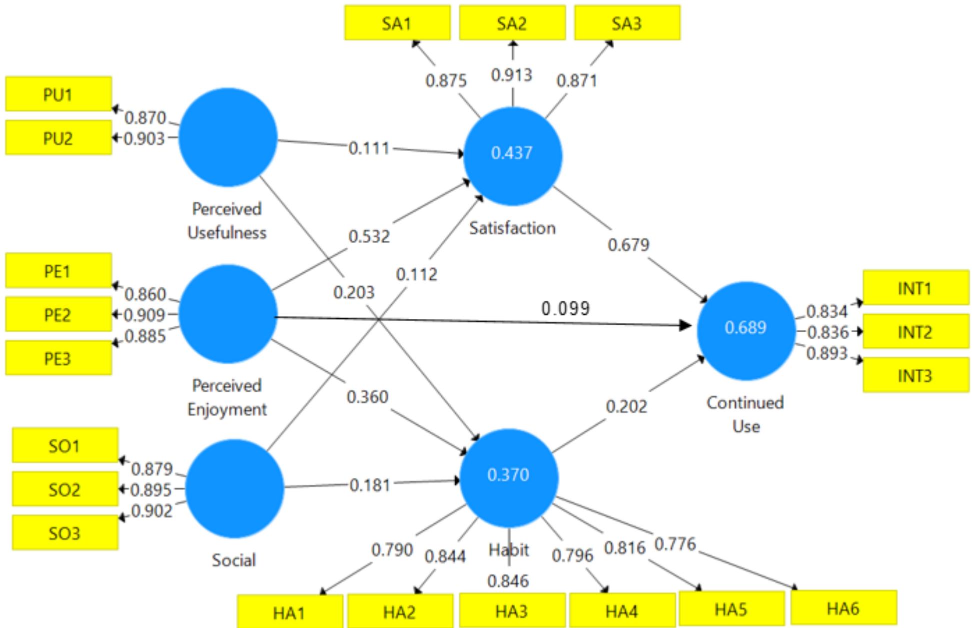
In Chapter 3, the research questions were developed. The questions and the associated hypotheses are highlighted in this chapter. The methodology used in the study can be found in Chapter 4. The study was quantitative, and data were collected from 313 participants who met the criteria set in the research. The methodology was considered appropriate, given the depth of past research into IS technology adoption and continued use.

In Chapter 5, the study provided the descriptive statistics of the sample and the details of the statistical tests conducted. Chapter 6 discussed the results of the tests performed in Chapter 5 and the implications of the results for business and academia. The chapter also reconciled the findings to the literature review to identify if our findings were consistent with previous studies. The remainder of Chapter 7 will summarise the insights from the study and will conclude by discussing the possible limitations of the study.

7.2 Research question 1

The research aimed to identify a model that explained variations in consumers intentions to use OTT platforms. The relationship between PU and continued use together with ST and continued use were removed from the original model. The model below was adopted as the final model. The model explained 69% of the variation in use and was adopted as the final model. Our findings, therefore, confirm that the proposed model is sufficient for explaining continuance intentions variations for OTT platforms.

Figure 13 – The final model



7.3 Research questions 2 and 3

The study aimed to understand if OTT users are satisfied with OTT platforms and if they will habitually use OTT platforms similar to linear TV. Habitual use explained 20% of the variation in continued use intentions for OTT platforms while satisfaction explained 61% of the variation in intention to use. This relationship was statistically significant for both constructs similar to other studies (Hsiao et al., 2016 & Piehler et al., 2016). We, therefore, conclude that habitual use of OTT platforms has a positive effect on continued use intentions. Thus, we are satisfied that Research Question 1 has been answered.

Similarly, for satisfaction, we find a significant correlation between users who are satisfied and their continued use intention. We conclude that satisfied users are likely to continue using OTT platforms. Our findings for both the habit and satisfaction constructs are in line with existing marketing literature that states that satisfaction and habitual use are likely to lead to continued use (Tadajewski, 2019). It is, therefore, imperative for management and academia to understand the predictors of habit and satisfaction to drive continued use of

OTT platforms. We will address the conclusions of these predictors in the paragraphs below.

Perceived Enjoyment (PE)

Additionally, we found that PU, PE, and ST explained 37% of the variation in habit while explaining 43% for satisfaction. PE accounted for the largest variation in habit at 36%, followed by PU at 20%, and ST at 18%. For satisfaction, PE accounted for 36% of the variation in habit and 53% for the satisfaction construct.

This leads us to conclude that the entertainment value of OTT platforms is the leading determinant of viewer habit and satisfaction. For users to develop habitual use and satisfaction of OTT platforms, these platforms need to curate content that is unique and entertaining. Ensuring that the content is unique will drive consumers to the platform as it is not available elsewhere. If consumers are satisfied with the content, they are likely to stay and continue utilising the platform. Thus, it has implications for the commissioning of new shows and negotiations of rights to existing shows. Thus, platforms must differentiate themselves from existing OTT and linear platforms. From a marketing perspective, marketers can focus on the hedonic factors by using images and communication to remind users or highlight the enjoyment/satisfaction derived from using the platform. Habit is a function of the subconscious state, responding to specific cues; therefore, images should be used as cues for the subconscious to act (Hsiao et al., 2016).

Perceived Usefulness (PU)

PU refers to the utility value of the technology in question (Venkatesh et al., 2016). The utility refers to the efficiency gained from utilising the product. OTT allows consumers to view content on-demand and is thus useful for managing leisure time. Furthermore, it allows viewers to consume multiple episodes continuously, unlike linear TV. Our results indicate that PU explains 11% of the variation in satisfaction and 20,3% in habit. While OTT consumers value the entertainment value, the usefulness of the technology does contribute to the satisfaction and habitual use of the technology. Thus, PU influences intentions through habit and satisfaction as the direct relationship was not statistically significant and thus rejected.

Identifying aspects of the technology that users value for their utility is therefore crucial in communicating the key benefits of OTT platforms to both current users and potential users. Furthermore, significant investments in user interface and backend developments intended to improve user experience need to be carefully analysed as they might not yield the desired return as compared to PE.

Social Ties (ST)

The results of our study indicate that ST and norms do not have an impact on users' continuance use intentions. The study found that the relationship was insignificant and therefore dropped from the final model. ST influence the perception people have that the people around or are important to them want them to use technology. This is a significant finding. ST has long been used as a predictor of continued use intentions. This result can be linked to the fact that consumers are curating their own platforms based on their preferences. Users are rejecting generalised linear TV bundles in favour of individualised/custom bundles. The custom nature of these bundles could explain the insignificance of the relationship between ST and intention. Given the success of Disney's OTT launch, reaching 50 million subscribers in five months, a feat that took Netflix 10 years to achieve (The Market is Open, 2019), future research can be done into the role of herd behaviour in the continued use of OTT platforms as opposed to ST. Herd literature suggests that people tend to discount their beliefs and imitate others when making adoption decisions and that the resulting adoption decisions are fragile and can be easily reversed during the post-adoptive stage (Sun, 2013).

The relationship between ST and satisfaction was significant, and similarly, the relationship between ST and habit was significant. While ST does not have a direct impact on intentions, they do affect intentions through satisfaction and habit. While consumers want to custom-make their bundles, sharing their experiences and having people important to them, sharing the same experiences enhances satisfaction and habitual use.

7.4 Research question 4

Multihoming

Our study found that multihoming does not impact PE and PU of OTT platforms. The study did not find any differences in PE and PU between the two groups, those who identify linear as their primary platform and those who identify OTT as their primary platform. We conclude that the use of both platforms is complementary rather than substitutes. Since both are used primarily for entertainment purposes, consumers do not vary in their PU and PE of both platforms.

The study found variations in the means for ST, satisfaction, habit, and continued use intentions. The effect size of the differences was small for satisfaction, ST, and continued use intentions. Thus, the presence of a competing platform in the form of linear TV has an impact on user satisfaction and continued use intentions of OTT platforms. However, the difference is not significant.

In contrast to habit and intentions, the effect size on the difference between the two groups for habit was significant. The presence of two platforms has a significant impact on OTT user habit. The use of one platform will have an inverse effect on the use of the other platform.

The implications for management are to contextualise that from a business perspective, OTT and linear platforms are competing platforms. However, from a consumer perspective, these products are complimentary. Thus, managers cannot only focus on what consumers are doing while on their platforms, but they need to understand what consumers are using other platforms for. Understanding how consumers are using both platforms will allow OTT platforms to create a better product offering and better competitive strategies.

7.5 Limitations of the research

The limitations of the research are associated with its generalisability and validity. The study recruited respondents from South Africa only, and the study utilised convenience sampling as there was no database of all OTT consumers available to the study. The implication of this is that it limits the generalisability of the study beyond South Africa. With four out of the top five OTT platforms being used by respondents being global platforms, the external validity of the research is limited. Global generalisability is also limited due to the age distribution of the sample. Our sample is skewed towards the younger age groups, with 53% below the age of 34. This is significantly below The Broadcasting Research Council Of South Africa's (2018) 70% for the same age group. It does not represent European or American demographics with a similar age group, only contributing 27%. However, despite this, the research is useful for local broadcasters and platforms with a strategy to launch their own branded platforms to compete with global platforms in the local market.

The use of convenience sampling could impact the results of the study. Studies of this nature are more likely to attract responses from consumers who have a strong affinity to the technology. In addition, 53% of the respondents were male. This gender split might not be the ideal depiction of the South African population distribution. To address this issue, the research was distributed to respondents via multiple methods to drive the diversity of the sample.

Facilitating conditions relate to perceptions of resources and support available to perform a behaviour. In the case of OTT platforms, this relates to internet connections and the speed of the connection. The facilitating condition for the use of OTT platforms is different in South Africa compared to other countries. Firstly, internet fibre penetration rates are low for South Africa compared to European and America markets (PwC, 2019). However, South Africa's fibre penetration rates are the highest in Africa. A similar trend has been noted with internet speeds. In addition to the above, the cost of data or internet connections' affordability remains an issue in South Africa. Understanding how these facilitating conditions impact the adoption of OTT platforms is an area for further research and is not covered by this research (Venkatesh et al., 2016).

As highlighted in the methodology section, the timing of the survey was considered, given that it was conducted after the initial lockdown period in South Africa. The study acknowledges that this extraordinary period could have skewed the results; however, prior research has indicated the use of OTT platforms increased during holiday seasons and public holidays when consumers have more available time at home. This was considered similar to the lockdown period.

Finally, our model measured continuance intentions, not the actual use of OTT platforms. While intentions are a good predictor of actual use, intention to use does not always translate to actual use. Future studies can perform longitudinal studies to include actual use. Furthermore, these studies can track the relationship of the constructs over time.

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ANNEXURES

8.1 Ethical clearance

Gordon Institute of Business Science
University of Pretoria

Ethical Clearance Approved

Dear Ralph Nyarenda,

Please be advised that your application for Ethical Clearance has been approved.
You are therefore allowed to continue collecting your data.
We wish you everything of the best for the rest of the project.

Ethical Clearance Form

Kind Regards

This email has been sent from an unmonitored email account. If you have any comments or concerns, please contact the GIBS Research Admin team.

8.2 Project plan

Stage	June	July	August	September	October	November	December
Write a research proposal: Draft 1 to Kerry Chipp	3-Jun						
Ethics clearance workshop	3-Jun						
Write a research proposal	22-Jun						
Ethics clearance		13-17 Jul					
Complete literature review and conduct a pilot study			3- 7 Aug				
Main data collection			24 Aug - 7 Sep				
Analyse data				7 - 14 Sep			
Write the first draft				15-Sep			
Complete first draft					15-Oct		
Discuss draft with supervisor					22-Oct		
Second draft					30-Oct		
Proofing/checking						1-Nov	
Submission							1-Dec

8.3 Survey

Factors driving the continued use of Over-the-Top (OTT) platforms

We are conducting research to explain factors driving variability in consumers' behavioural intent towards the continued use of Over-the-Top (OTT) platforms. To this end, you are kindly asked to look at and complete a survey about OTT platforms. This will help us better understand the continued use of these platforms. The exercise should take no more than 10 minutes of your time. Your participation is voluntary, and you can withdraw at any time. Your participation is anonymous, and only aggregated data will be reported.

By completing the survey, you indicate that you voluntarily participate in this research. If you have any concerns, please use the contact details below:

Email: 19388676@mygibs.co.za

Email: chippk@gibs.co.za

*Required

The study will be conducted to explain variability in consumers' behavioural intent to continue using OTT platforms like Netflix, Showmax, Amazon Prime Video, YouTube, Apple TV, and DEOD.

The study aims to explain variability in consumers' behavioural intent toward the continued use of OTT platforms. It aims to identify factors driving the continued use of OTT platforms.

Over-The-Top (OTT) video streaming services refer to the provision of services via the internet and bypassing the traditional broadcasting services that deliver content via Cable, Satellite and Over-The-Air (OTA). They include platforms such as Netflix, Showmax, Amazon Prime Video, YouTube, Apple TV, and DEOD.

Linear TV refers to traditional television viewing. To watch a show, the viewer must tune in to a specific channel on TV at an appointed time. Viewers access linear TV via OTA or subscription satellite services. They include platforms such as the SABC, e.TV, OVHD, DStv, and StarTimes.

1. Are you currently subscribing to any OTT platforms (Netflix, Showmax, Amazon Prime Video, YouTube, Apple TV, DStv Now (online platform) and DEOD) or part of a household that subscribes to an OTT platform (Yes/No)? *

- Yes *Skip to question 2*
- No

Section 3

2. Which of the following services are you currently subscribing too? (You can select multiple boxes) *

Netflix

Showmax

Amazon prime video

YouTube

Apple TV

DEOD

Other:

3. What is your age? *

- a) 18 to 24
- b) 25 to 34
- c) 35 to 44
- d) 45 to 54
- e) 55 or older

4. In which province do you reside? *

- Eastern Cape
- Free State
- Gauteng
- KwaZulu-Natal
- Limpopo
- Mpumalanga
- Northern Cape
- North West
- Western Cape

5. To make sure all groups are represented in this survey, are you...? *

- a) Black
- b) White
- c) Coloured
- d) Indian
- e) Other

6. Gender? *

- Male
- Female

7. What is the highest degree or level of school you have completed? If currently enrolled, highest degree received to date. *

- a) No schooling completed
- b) High school graduate (matric)
- c) Diploma
- d) Bachelor’s degree
- e) Honours degree
- f) Master’s degree
- g) Doctorate degree

8. Which of the following income categories best describes your gross monthly household income in Rands before tax? *

- R0 – R17 158
- R17 159 – R26 800
- R26 801 – R37 091
- R37 092 – R48 683
- R48 684 – R62 067
- R62 068 – R131 441
- Above R131 442

Section 4

9. Using OTT/Streaming services help me manage my spare time more effectively. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

10. Using OTT/Streaming services is the best use of my leisure time. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

11. I find mobile internet useful in my daily life. Using OTT/Streaming will improve my performance in managing my personal life. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

12. Using OTT/Streaming services is pleasurable for me. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

13. I have fun using OTT/Streaming. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

14. I find using OTT/Streaming services to be enjoyable. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

15. People in my social circle use OTT platforms. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

16. People in my social circle regularly discuss what they have watched on OTT platforms. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

17. People in my social circle recommend that I use OTT platforms. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

Section 5

18. Are you also currently using any of the following linear services? (SABC, e.TV, OVHD, DStv, StarTimes). *

- Yes *Skip to question 19*
- No *Skip to question 25*

Section 6

19. Are you also currently using the following services? (you can select multiple options)

Tick all that apply.

☐ a) SABC1-3 & e.TV

☐ b) Openview HD (OVHD)

☐ c) DStv

☐ d) StarTimes

☐ e) None of the above

20. Primary viewing platform (the one you instinctively select when you want to watch video content). Is OTT your primary viewing preference (Yes) or linear TV as your primary viewing preference (No)?

- Yes (OTT services, i.e. Netflix, Showmax, Amazon Prime Video, YouTube, Apple TV, DStv Now (online platform), and DEOD are my primary viewing preference.) *Skip to question 25*
- No (Linear services, i.e. SABC, e.TV, OVHD, DStv, StarTimes are my primary viewing preference.) *Skip to question 21*

Section 7

21. I will continue using linear TV as my primary viewing channel because I am comfortable doing so. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

22. I will continue using linear TV as my primary viewing channel because I enjoy using these platforms. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

23. I will continue using linear TV as my primary viewing channel because changing would be stressful. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

24. Using linear TV, pay-TV, and satellite TV to watch video content rather than OTT platforms enhances my satisfaction. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

Section 8

25. Using OTT (streaming) to watch video content rather than linear TV, pay-TV, and satellite TV enhances my satisfaction. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

26. I will continue using OTT platforms as my primary viewing platform because changing would be stressful. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

27. I will continue using OTT platforms as my primary viewing platform because I enjoy using these platforms. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

28. I will continue using OTT platforms as my primary viewing platform because I am comfortable doing so. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

Section 9

29. The use of OTT/Streaming services is natural for me. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

30. The use of OTT/Streaming services has become automatic for me. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

31. Choosing OTT (streaming) when I want to watch TV or video content is something I do as a matter of habit. *

	1	2	3	4	5	
Strongly disagree	⬭	⬭	⬭	⬭	⬭	Strongly agree

32. I find using OTT (streaming) for TV or video content the easiest thing to do.*

	1	2	3	4	5	
Strongly disagree	⬭	⬭	⬭	⬭	⬭	Strongly agree

33. I would rather use OTT (streaming) over anything else. *

	1	2	3	4	5	
Strongly disagree	⬭	⬭	⬭	⬭	⬭	Strongly agree

34. When I have alternatives for watching video content, I prefer using OTT platforms. *

	1	2	3	4	5	
Strongly disagree	⬭	⬭	⬭	⬭	⬭	Strongly agree

35. I do not need to devote a lot of mental effort to decide that I will use OTT (streaming) to watch. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

36. Selecting OTT (streaming) to watch video content does not involve much thinking. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

37. Choosing OTT (streaming) to watch video requires very little mental energy. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

Section 10 (Almost done)

38. I think I made the correct decision in using OTT services. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

40. I am satisfied with the OTT services I use. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

Final section

41. I intend to continue using OTT services in the future. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

42. I will always try to use OTT services in my daily life. *

	1	2	3	4	5	
Strongly disagree						Strongly agree

43. I will keep using OTT services as regularly as I do now. *

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