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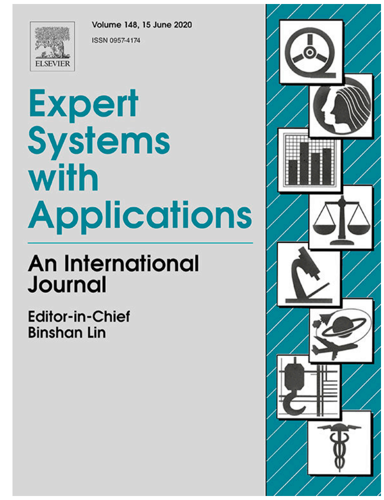

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Abstract:

Streaming services are becoming very popular among people and are considered as an entertainment alternative to the traditional model of broadcasting services due to its exclusiveness as well as better quality and variety of contents. The present article examines various factors influencing the continued intention to use live streaming services in India. To this end, the study fills the research gaps and extends perceived value theory by including a few important determinants, namely effort expectancy, performance expectancy, perceived innovativeness, perceived risk, perceived enjoyment and addiction to heavy viewing. The *study contributes to the existing literature on streaming services addiction and extends its association with heavy viewing. Existing studies on addiction were found insufficient in explaining users' heavy viewing of live streaming content, which has the potential to become a serious social problem in the future. The study's findings suggest that the convenience value has the highest impact on users' continued intention to use streaming services, followed by perceived enjoyment. The addiction to heavy viewing due to the use of streaming services by users has new social implications. The findings suggest that managers of streaming apps should promote their apps to consumers by highlighting various consumption values and make sure that their apps are attractive and provide personalized experience to the users. Moreover, the study discusses the growing addictive behaviour with regard to streaming services.*

Keywords:

Perceived value, Addiction to heavy viewing, Perceived innovativeness, Continued Intention, India, Live streaming services

1. Introduction

In recent years, live streaming services have gained acceptance among users and have been considered as a cheap and entertaining alternative to the traditional model of broadcasting media services (Marketsandmarkets.com, 2016). Streaming media services are the platform that enable users to watch various live-streaming music, TV, news, movies, etc. (Yang & Lee, 2018). Several studies confirmed that users prefer these services over TV due to convenience, better content, low or no cost, exclusiveness, appointment viewing, innovative shows, latest premieres, break-free shows, etc. (Lee et al. 2016; Yang & Lee, 2018). The same trend is also observed among Indian users. Data shows that the value of OTT (Over the Top) media-streaming services (also known as internet streaming services) has increased from 21.5 billion to 35 billion in 2019 in India. This may be due to high growth in the internet consumption of users in India, with more than 850 million mobile subscriptions expected till 2020 (livemint.com, 2018). Moreover, 48 per cent of Indian users who are involved in watching online entertainment are millennials (aged between 22 and 37 years) or the young population (livemint.com, 2018).

There has been a significant rise in the viewing frequency of streaming services by Indian users while commuting from one place to another: they start streaming at 9 a.m., reach a peak at 5 p.m. and continue until late night (home.kpmg, 2016). The report confirms that on average, Indian users spend eight hours on various live streaming platforms, which is far more than the average six-hour trend globally (Ganjoo, 2018). These trends are visible on a regular basis. Recently, an incident was reported in India regarding a 26-year-old man who sought medical help to control his heavy viewing of streaming videos. He admitted that he used to watch streaming videos on an average 12 hours a day to avoid his unemployment issue and family pressure (Ganjoo, 2018). This hints at a growing addictive behaviour and raises a serious question about the link between addiction to heavy viewing and live streaming services. The present study explores this context further.

Despite the increasing popularity of streaming services, very little discussion of the subject is present in previous literature, although some prior research has employed gratification theory, flow theory, self-identity theory and perceived value theory to measure users' perceptions of streaming services (Mäntymäki & Islam, 2015; Tseng, 2015; Oyedele &

Simpson, 2018; Yang & Lee, 2018; Rubio et al. 2019). Many studies posit that specific values derived from streaming services are very relevant to understanding the consumer value perspective, and therefore perceived value theory and its dimensions are widely used in this context (Mäntymäki & Islam, 2015; Bründl et al., 2017; Oyedele & Simpson, 2018). Existing literature related to streaming services largely discuss the technological and system aspects of streaming services (Oyedele & Simpson, 2018; Yang & Lee, 2018). These studies, however, were rather generic and limited to initial acceptance and perception, regardless of heavy use of streaming services (Pal & Triyason, 2017). Thus, there is a clear need to examine the antecedents of continued usage behaviour of the viewers, which has been discussed in a limited fashion among academics (Mäntymäki & Islam, 2015; Ali, 2018; Yang & Lee, 2018). Recently, Mäntymäki and Islam (2015) and Bründl et al. (2017) measured the continued adoption behaviour of consumers of live streaming services. Their findings, however, were limited to perceived value theory as well as gratifications and experiences of such services that are based on the traditional technology acceptance model (TAM). But streaming services are different than other technologies due to their great convenience and exclusiveness (Yang & Lee 2018). Therefore, considering only TAM or a single theory is not sufficient for understanding the continued behaviour of users. Unlike existing studies, the present study not only proposes the influence of product-related attributes and specific values derived from streaming services on users' continued intention to use streaming services but also highlights the effect of streaming services addiction in relation to heavy viewing.

Addictive behaviour has been discussed extensively in the context of gaming disorders (Jeon et al. 2019), computer addiction (Cho, 2010), internet addiction (Kuss & Lopez-Fernandez, 2016), social media addiction (Brand et al., 2014), addiction to heavy viewing (Horvath, 2004), etc. There are a few studies that have considered the addiction among users to entertainment devices such as the TV (Kubey et al., 2001; Kuss & Lopez-Fernandez, 2016; Vijayalakshmi et al., 2019). These studies measured the dependency on entertainment devices based on the number of hours spent in order to differentiate between heavy and normal viewing. These studies confirmed that viewers used these services heavily (more than four hours) (Horvath, 2004; Hui, 2019; Engberg et al., 2019) as an escape from real issues, society, work pressure, family issues, etc. (Ganjoo, 2018). This heavy viewing is further defined as problem viewing and prominent addictive behaviour in the future (Sidhardhan, 2018). The existing studies are insufficient in explaining addiction to live streaming services; therefore, we consider that the present study fills this gap.

The present study considers three main research questions: Which component of perceived value is significant in analysing users' continued intention to use streaming services? What are the possible product-related behavioural attributes of users' continued intention? What is the significant impact of addiction to heavy viewing on continued intention? The study contributes theoretically to the literature on streaming services and the role of perceived value theory with regard to users' continued intention by answering these research questions. To this end, the present study included perceived value theory along with a few product-related attributes, namely effort expectancy and performance expectancy, perceived risk, perceived innovativeness, perceived enjoyment and addiction to heavy viewing to measure users' continued intention to use streaming services. The findings of the study should provide rich insights for developing marketing campaigns and promoting shows or videos available on streaming apps to the users. The study discusses social implications in relation to streaming services addiction.

The article's remaining sections are as follows. Section 2 discuss the existing literature on media-streaming services. Section 3 talks about the theoretical model and hypotheses development. Section 4 explains the research methodology. Section 5 includes results, discussion and implications of the study.

2. Literature Review

Live streaming is a way to obtain access to mass media through the internet. In the history of live streaming, the first video that was live streamed containing the performance of the music band "Severe Tire Damage" on 24 June 1993, although its history goes way back to "Muzak" in the 1910s (Meisfjord, 2018). In contrast to the early years, where videos had to be downloaded before watching, streaming allows the video to be played as soon as the platform starts receiving the data (Bucknall, 2012). Live streaming services are becoming popular as there is no waste of time in downloading videos, and the user also has the ability to rewind or forward the video. Digital insurgency is the major reason behind the popularity of streaming services (IFPI, 2015). The following sub-sections will attempt to identify a few relevant theories, along with some product-related and consumer-related attributes from literature.

2.1. Perceived value theory

Perceived value is the overall utility value of a product or service that a consumer perceives based on a cost-benefit trade-off (Zeithmal 1988). Success and the adoption of a technology or service is based on specific values that a consumer perceives or desires from a service. These values can be related to functional, product, or technical aspects of a technology or service. Several studies aimed to measure these values from a consumer's perspective (Praveena & Thomas, 2014; Pal & Triyason, 2017). However, determining the impact of specific values derived from the use of technologies, streaming services, etc., will be more beneficial from a consumer's viewpoint. Perceived value as a concept is discussed in a number of previous studies in relation to information systems (Singh et al., 2020), mobile services (Singh et al., 2017), streaming services (Shin et al., 2015), brand behaviour (Peng et al., 2014), etc. These studies discussed either perceived value as a whole, for example, the unidimensional price-based value theory (Marchand & Hennig-Thurau, 2013) or multidimensional perceived value theory based on effects, namely consumption value theory, means-end theory, etc. (Sheth et al., 1991). Originally, five broad aspects of perceived value (social, emotional, conditional, epistemic and functional) were included by Sheth et al. (1991) in their study. In later years, functional value was improved with two categories – monetary and convenience values – that make it more appropriate to online services. These aspects were found most suitable and relevant in a number of studies as they considered value as 'experience' and measured the cognitive aspects of value resulting from continuous use of online services (Gummerus, 2013; Chen et al., 2017; Ali, 2018).

Various aspects of perceived value theory are applicable in the context of live streaming services due to the following reasons: At first, streaming media services provide personalized streaming experiences that include personal, situational, and relative choices for each viewer through video or music content. Hence, they should be perceived as 'experience' (Oyedele & Simpson, 2018). Next, multidimensional aspects of perceived value are likely to be significant to streaming services. For example, convenience value is important due to the fact that streaming services allow ease, speed and accessibility in listening or downloading videos anywhere on multiple devices (Sheth et al., 1991). Monetary value is also important as it measures or compares the cost aspects of streaming services with traditional media devices such as DTH (Direct to Home) or TVs (Praveena & Thomas, 2014). Next, emotional value is crucial to streaming services because it provides fun or an enjoyable service experience to viewers. This is also measured in a number of studies as perceived enjoyment (Davis et al., 1992; Chang et al., 2017). However, social value is not directly important to streaming services, but it may influence or enhance a viewer's social identity as a music or video lover (Oyedele & Simpson, 2018). Third, perceived value theory is relevant in the Indian context because India is a low middle-income country where consumers compare the values they derive after using various products or services and express their preferred choices (Singh et al., 2020). In recent years, a few researchers tried to include values to measure perceptions towards online media services but with limited efforts to identify the various dimensions of perceived value (Borja et al., 2015; Lee et al., 2016; Chen et al., 2017; Pal & Triyason, 2017; Cai et al., 2018, Yang & Lee, 2018). Still, to our understanding, no study in the Indian context has used multi-dimensional aspects of value theory related to viewer's continued intention to use streaming services.

2.2. Addiction to heavy viewing

Problematic computer use or viewing may be defined as addiction when a user shows the inability to control the number of hours spent in nonwork-related online activities. Addiction is associated with behavioural mood, withdrawal symptoms, avoidance of social/family issues and conflicts that may have negative consequences in the long run (APA, 2000). A number of studies define such symptoms as addiction that leads to numerous positive motives such as high service usage, acquiring more pleasure, sense of control, virtual achievements, etc., and negative consequences to users such as brain disorder (Shih-Ming & Teng-Ming, 2006), compulsive disorder (Young et al., 2011), social and family withdrawal (Kuss & Lopez-Fernandez, 2016), problem and heavy viewing (Kesici & Tunc, 2018), etc. These negative effects get worse with heavy viewing, which is one of the items on crucial research agendas related to entertainment services addiction (Horvath, 2004). A few studies differentiated between heavy and normal viewing based on the number of hours spent in order to define significant addictive behaviour (Young et al., 2011). Four hours or more of viewing every day is defined as heavy viewing and may interfere with real-life relationships;

hence, it is considered addiction (Horvath, 2004; Hoewe and Sherrill, 2019; Hui, 2019; Engberg et al., 2019). Luckily, a few significant research studies linked addictive behaviour to viewing patterns, and they provide support to the present research (Shih-Ming & Teng-Ming, 2006; Kesici & Tunc, 2018; Sidhardhan, 2018). Addiction to heavy viewing is relevant to online streaming services because these services offer entertaining contents to users that force a prolongation of behaviour or heavy viewing, regardless of adverse effects (Shih-Ming & Teng-Ming, 2006; Young et al., 2011). The behaviour becomes intensified when these contents are mood-stimulating, for example, pornography videos, violent videos that include sexual content, fantasy videos, gaming videos, etc. This may lead to prominent addiction and has an impact on users' continued intention to use such services (Kesici & Tunc, 2018).

2.3. Behavioural attributes

The literature suggests that factors contributing to new technology acceptance and determinants of users' perceptions are closely associated with acceptance of live streaming services and behavioural intentions with regard to these services (Zhao et al., 2018). The Unified Theory of Acceptance and Use of Technology (UTAUT) is an established framework in this sense, but uncertainties arise with respect to its ability to describe the acceptance of particular technology, and hence, it has been extended by many researchers (Chao, 2019). Numerous variables such as personal innovativeness (Chao, 2019), perceived value (Pitchayadejanant, 2011), perceived risk (Dwivedi et al., 2017b), perceived enjoyment (Chang et al., 2017), and effort and performance expectancy (Venkatesh et al., 2012) have been incorporated by different authors into extended UTAUT models. The roles of effort and performance expectancy have been found to be important in a number of studies that measured the usefulness and convenience of a technology (Venkatesh et al., 2012; Kalinic et al., 2019a). However, these variables are not directly important to live streaming services. But as these services are online, users have ease and flexibility in terms of handling, downloading and watching live music and video contents (Lee et al., 2016). Streaming services that are user-friendly, entertaining and offer personalized experience enhance a user's performance in terms of accessing suitable content (Yang & Lee, 2018). It has been confirmed that these features also influence users' innovativeness and willingness to try out new services earlier than others (Ali, 2018; Kizgin et al., 2018). The literature on streaming services suggests that users may likely be at risk of various viruses, financial and personal data fraud, etc., while accessing content, paying monthly charges and downloading videos online (Yang & Lee, 2018; Sidhardhan, 2018). However, these threats are limited and vanish with growing user awareness of how to use live media streaming services, and hence, they are not very important (livemint.com, 2018).

3. Research Hypothesis

Figure 1 explains the conceptual model of the present study.

3.1. Convenience value, monetary value, social value and emotional value

Convenience value involves accomplishing a task efficiently and appropriately in an easy and quick way (Anderson & Srinivasan, 2003). Convenience value has a significant consequence for the perceived task value as it provides immediate and opportune access to live streaming services (Mathwick et al., 2001). Monetary value has to do with task completion. It refers to the larger monetary advantage as compared to other options (Sheth et al., 1991). Monetary value has a significant effect on perceived value as it provides easy access to the services that have good monetary value as compared to other options.

Social value is derived from the function of the product or service capable of enriching the social image of the customer (Rippé et al., 2019) when used in sharing mode with others (Sheth et al., 1991). Nasr (2019) suggests that social value refers to social agreement and enrichment of one’s image in the society. Many researchers have supported the significance of customer status in the form of their self-esteem (Bhat et al., 1998). Leung and Wei (2000) report that gratification theories also discuss status and self-image, which are similar to social value. The use of new technology could be one way to showcase one’s status and personality in society.

Emotional value is about the effectiveness derived from the sentiments generated by the product or service. Emotional value may be attained when a product or service stimulates the feelings or sentiments of the consumer (Sweeney & Soutar, 2001). Further, Leung and Wei (2000) described emotional value as consumers' behavioural intention to use a service. As suggested by Holbrook (1994), emotional value relates to the amount of added excitement and pleasure received after using the service. Many times, it has been observed that positive feelings are aroused after using new technology, irrespective of the amenity used (Bozkurt & Gligor, 2019). This encourages us to hypothesize the following:

H1: Convenience value is positively associated with perceived value linked with streaming services.

H2: Monetary value is positively associated with perceived value linked with streaming services.

H3: Social value is positively associated with perceived value linked with streaming services.

H4: Emotional value is positively associated with perceived value linked with streaming services.

3.2. Perceived value

Originally, Zeithmal (1988) defined perceived value as an evaluation of conflict between the cost and utility of the product. Value observed is a result of this conflict, clues about the intention to use the product/service (Zhuang et al., 2010) and further continued intention to use the service (Praveena & Thomas, 2014). The higher the value observed, the higher would be the continued intention (Jia et al., 2014; Xu & Du, 2018). Perceived value plays an important role in maintaining long-term relationships with customers and also has an emotional impact on their purchase intentions (Zhuang et al., 2010). Alawan (2020) found that perceived value influences consumers' trust, loyalty and satisfaction and hence affects the continued intentions of the customers. Perceived value is labelled as an undying contributing factor of intention, continued intention and loyalty (Yang & Peterson, 2004). Kizgin et al. (2018) established the significant effect of perceived value on the continued intention to use online entertainment services. This encourages us to hypothesize the following:

H5: Perceived value positively affects the continued intention to use streaming services.

3.3. Effort expectancy, performance expectancy and personal innovativeness

Effort expectancy relates to the magnitude of ease in using novel technology, whereas performance expectancy relates to the magnitude to which a user feels that new technology helps in gaining benefits (Davis et al., 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003). Since video streaming services are easy to use and provide full entertainment benefits to users, users may like to be innovative with these services. Praveena and Thomas (2014) explained that all users with high personal innovativeness are similar and ready to use a new technology. They further argued that users' personal innovativeness is not eroded by geographical differences. Kou and Yen (2009) suggest the direct effect of personal innovativeness on users' continued intention and indirect effect through effort expectancy and performance expectancy.

Acceptance of new technology is determined by the element of innovation in it or in its use (Venkatesh et al., 2012). The origin of innovativeness is innovation. Personal innovativeness is defined as a unique idea or an article that is perceived to be different from others (Rogers, 2010). Agrawal and Prasad (1998) suggest that an innovative individual adopts innovation promptly and easily. Innovativeness is a trait of personality (Syendsen et al., 2013) that is defined as one's readiness to adapt (Hurt et al., 1977, p. 220) or as a willingness to experience something novel (Simons, 2013). Agreeing with innovation diffusion theory, Rogers (2003) submits that due to different levels of personal innovativeness in different people, they react in different ways to an innovation. Many researchers have concluded that people with higher levels of personal innovativeness have positive attitudes towards new technology and continue the usage even with limited information (Yi et al., 2006; Xu & Du, 2018). However, the level of personal innovativeness is strongly associated with the type of innovation. It may depend on how fast any technological innovation is being embraced by consumers (Bozkurt & Gligor, 2019). Several past studies have established the positive effect of consumers' personal innovativeness on behavioural intention towards the use of a new technology (Xu & Gupta, 2009; Agarwal & Prasad, 1998) and a few on continued intention (Jia et al., 2014; Xu & Du, 2018). Ko et al. (2009) emphasized the positive relationship between continued intention and personal innovativeness, i.e., users with high personal innovativeness are more intent on continuing the use of innovative technology. Further, Dickinger et al. (2008) suggested personal innovativeness, perceived enjoyment and competence as the indicators of behavioural intention. Alawan et al. (2018) proposed individuals' internet innovativeness as a significant predictor of continued intention to do grocery-related shopping online. Similarly, Xu and Du (2018) identified a significant association between personal innovativeness and continued intention to engage in mobile commerce. Similar results were obtained by Dover and Murthi (2006) in a study conducted on online services. This encourages us to hypothesize the following:

H6: Effort expectancy positively influences personal innovativeness.

H7: Performance expectancy positively influences personal innovativeness.

H8: Personal innovativeness positively affects the continued intention to use streaming services.

3.4. Perceived Enjoyment

Perceived enjoyment is described as an essential spur that defines the degree to which excitement can be derived through using a system (Parveena & Thomas, 2014). A study conducted on US consumers suggests that perceived enjoyment is the significant predictor of perceived values and behavioural intention. Moon and Kim (2001) concluded that if consumers perceive a greater degree of enjoyment, then they intend to use it more. Alalwan et al. (2018) emphasized the role of perceived enjoyment in the continued intention to use information technology (IT) and information system (IS) services. Further, a study conducted by Dickinger et al. (2008) suggested that social norms and perceived enjoyment play ornamental roles in improving continued intentions with regard to IT and IS services. Again, a study conducted in Kuwait found that perceived enjoyment leads to adoption of online payment systems, which further nullifies perceived risk (Rubio et al., 2019). In the context of streaming services, perceived enjoyment plays an important role as it includes the entertaining content that leads to the user's enjoyment. This encourages us to hypothesize the following:

H9: Perceived enjoyment positively affects the continued intention to use streaming services.

3.5. Perceived risk

Ostlund (1974) described perceived risk as the possibility of loss after a consumer uses a service for anticipated outcomes. Many studies have incorporated perceived risk as an external variable of the UTAUT model (Dickinger et al., 2008; Dwivedi et al., 2017a;). Holak and Lehmann (1990) found risk to be a reason for worry for consumers who use innovative products. Alalwan et al. (2018) recommended perceived risk as one of the inhibiting precedents of continued intention. A few researchers have studied the negative impact of perceived risk on the continued intentions of users with e-commerce services (Dickinger et al., 2008). Dwivedi et al. (2017b) found similar results in a study done on mobile payment systems. However, some studies done in the field of mobile banking apps or peer-to-peer mobile payment systems found perceived risk to be an insignificant predictor of continued intention (Kizgin et al., 2018). In streaming services, consumers may perceive risk attached to theft of personal information, any monetary value, compatibility with devices and viruses, etc. (Yang & Lee, 2018; Sidhardhan, 2018). This encourages us to hypothesize the following:

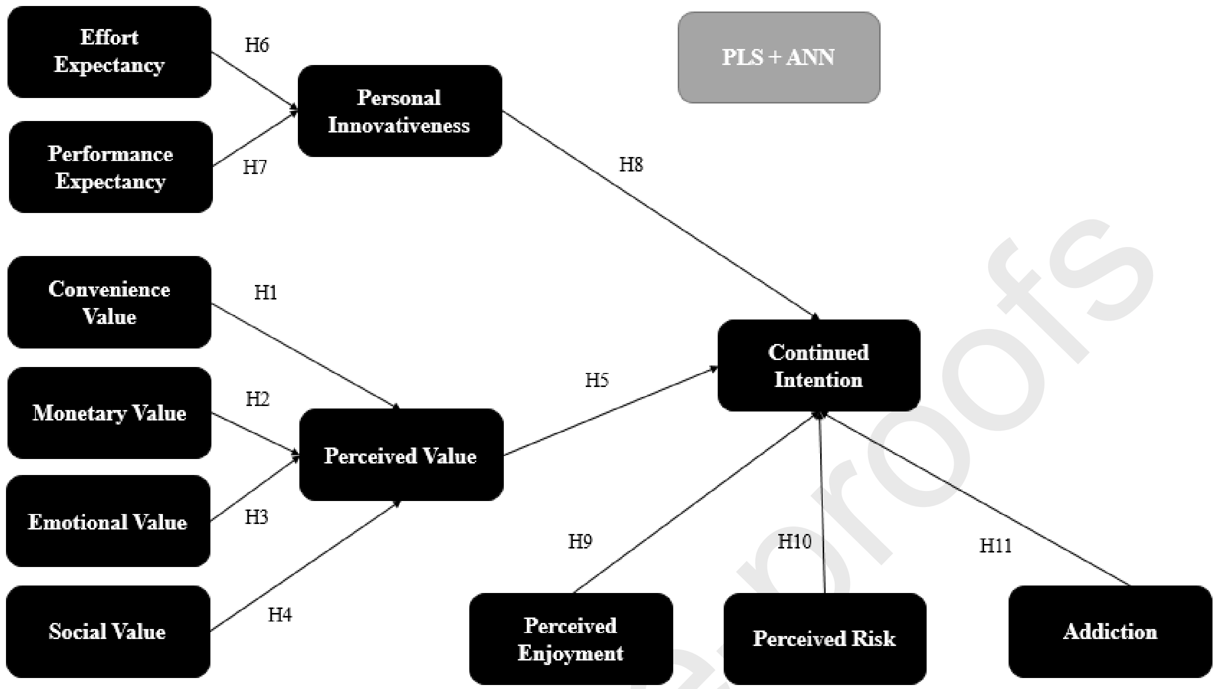
H10: Perceive risk negatively affects the continued intention to use streaming services.

3.6. Addiction to heavy viewing

Sidhardhan (2018) has defined addiction as the habit of spending long hours with a particular product/service. These long hours may result in heavy or problem viewing by users, which may lead to uncontrollable usage of a product/service. Early studies have established both constructive and mostly destructive traits of addiction (Cho, 2010; Kuss & Fernandez, 2016). Yang and Lee (2018) linked addiction to changes in the preferences and habits of consumers in the context of entertainment services. Kesici and Tunc (2018) suggested five sub-dimensions of digital addiction, namely inhibiting the flow of life, non-restraint, emotional state, dependence and overuse. Horvath (2004) was the first to state the direct association between viewing patterns and addictive behaviour; she suggested that heavy viewing (more than four hours) every day with entertainment devices may have negative consequences in real-life situations. This was further supported by Kesici and Tunc (2018) in recent years, who found heavy viewing may lead to prominent addictive behaviour and uncontrollable traits in the future. The association between addiction to heavy viewing and continual use of streaming services may be true because it includes exciting and entertaining content that binds the user for longer hours and forces the continuation of use. The more time users spend with such services, the more addictive they become, and they prolong their use irrespective of its destructive traits (Young et al., 2011). This encourages us to hypothesize the following:

H11: The more users are addicted to heavy viewing of streaming content, the more they continue to use streaming services.

Figure 1: Conceptual Model



4. Research Methodology

In line with the different approaches in the literature, the present study focuses on a descriptive analysis, along with an exploratory examination conducted through a convenience sampling method that enables inexpensive and fast access to pertinent information.

4.1. Data collection and sample design

We developed the questionnaire to collect data. The questionnaire was personally administered through online and offline surveys over six months (July–December 2019). Detailed statements measuring constructs are presented in Appendix 1. Data was collected from Delhi and its National Capital Region (NCR) in India by using a mix of convenience and snowball sampling. This method of sampling is not only convenient, inexpensive and accessible but also very useful for measuring the relationships among different occurrences/situations. The reason for choosing this location to collect data is that people from all over the country come here to study or work, and hence, this region can be considered as the true representative of the entire country. The data collection process included the following steps: The first draft of the questionnaire was designed by reviewing the existing literature, related and tangential studies on information systems, streaming services, consumer behaviour, etc. The draft was then reviewed by a group of ten experts to validate the methodology, measurement scales, content, and appropriateness of the wording of the questions. Next, a pilot test using a convenience sampling procedure was carried out with 50 respondents. Based on the results obtained from the pilot test, one statement concerning addiction to heavy viewing and two concerning personal innovativeness were rephrased. A back-to-back translation system was used for the validation of the scales and retaining the original meaning. The questionnaire was initially prepared in English and was translated into Hindi by a certified translator for the convenience of the respondents. The data collected from pilot testing was not used in the next phase to avoid skewness in the final findings. Finally, the final draft of the questionnaire was prepared and distributed to more than 2,000 smartphone users, customers, students, professionals, etc., via email IDs, social groups or personal sending. They were also asked to forward the survey forms to their personal and professional contacts. Respondents were informed about the objective of the study and told that the time needed to complete the survey was between 10 and 12 minutes. Some survey eligibility questions were added in the study to reduce data filtration, such as: Are you a smartphone user? Are you a streaming services user? Those who answered 'YES' were eligible to fill out the survey form. A total of 869 respondents were used in the present study for analysis (see Table 1). The sample reflects the characteristics of the total population of India in 2019 in terms of gender (the average population of males in India is 51.97% and females is 48.03%), and the majority of the respondents belong to the age group of 18–35 years (the median age of India's population was 27 years in 2019) (United Nations, 2019). The present study satisfies the minimum sample criteria as suggested by Bentler and Chou (1987): the sample size is appropriate when ratio of the total sample to the number of items is greater than 5:1. The study fulfils the minimum sample size criteria with the value 18.89.

The questionnaire is structured into three different thematic segments. The first involves a series of questions intended to test the relevance and uniformity of the proposed research subject. The group of items in the second section of the questionnaire shapes the proposed structure of the study. Lastly, respondents' sociodemographic data are assessed in the third part, along with further statistics (e.g., experience with streaming technologies, gender, age, occupational status, level of education, family background and status, living standards and place of residence, among others).

Table 1: Demographic characteristics of respondents

Demographics	Frequencies	Percentage
Gender		
Male	457	52.6
Female	412	47.4
Age		
Less than 18 years	30	3.5
18–35 years	770	88.6
35–50 years	54	6.2
More than 50 years	15	1.7
Occupation		
Student	569	65.5
Employed	212	24.4
Self-employed	52	6.0
Homemaker	36	4.1
Hours spent on viewing live streaming content (per day)		
Less than 1 hour	258	29.7
1–3 hours	421	48.4
3–5 hours	127	14.6
More than 5 hours	63	7.2
Usage frequency for viewing live streaming content (per week)		
1–2 times	326	37.5
3–5 times	350	40.3
6–10 times	120	13.8
More than 10 times	73	8.4

Source: Author's compilation

4.2. Measurement scales used

The data collection process used the literature in this field of knowledge in order to adapt the most significant and widely used scales. A series of quantitative analyses were conducted with the input of streaming services' professionals to ensure error-free scales and a full understanding of the validity of these measurement tools. The following studies were used as references: research from Horvath (2004) to measure the addiction to heavy viewing; the studies of Collier et al. (2013) for convenience value; Venkatesh et al. (2003) for effort expectancy and performance expectancy; Bhattacherjee et al. (2001) for continued intention**;** Mohd-any et al. (2015) for emotional value and monetary value; Davis et al. (1992) for perceived enjoyment; Alalwan et al. (2018) for perceived risk; Sweeney and Soutar (2001) for perceived value; Whetton and Cameron (2011) for personal innovativeness; and, finally, research from Chen et al. (2008) for social value. The questionnaire design involved the following steps: We used 7-point Likert scales, moving from "strongly disagree" to "strongly agree", to measure the construct items.

5. Results

5.1. Common method bias and multicollinearity test

Harman's single factor test was used to examine the effect of common method bias (CMB) (Khayer & Bao, 2019). Should a single factor have total variance above 50%, it is likely that CMB will influence the data and, consequently, the empirical outcomes (Podsakoff et al., 2003). In our study, the total variance for a single factor is 38.31%. This suggests that it is unlikely that common method bias exists (Molinillo et al., 2020). Furthermore, based on the values of the VIF, which were far below the threshold of 10, we can conclude that there is no multicollinearity problem in this study (O'Brien, 2007).

5.2. Reliability and validity

The partial least squares (PLS) regression method was used to analyse the data in a structural equation model (SEM). Collected data was run through the SmartPLS3 suite (Hair et al., 2016) while the reliability and uniformity of the research estimations were tested through a bootstrapping resampling involving 5,000 sub-samples (Roldán & Sánchez-Franco, 2012). The PLS model was examined in two steps: firstly, the validity and reliability of the model were assessed according to the structural model, which was also examined in the second stage (Anderson & Gerbing, 1988).

To gauge the reliability and validity of the measurement model, the following dimensions were also assessed: (a) the consistency of the different measurement items and variables with regard to random, error-free results; and (b) discriminant and convergent validation were conducted to understand the differences between the obtained values and the actual characteristics of the examined items. In addition, the reliability of the items was obtained through the relationships between the dimensions and their items. In this regard, those values exceeding the recommended threshold (0.7) prove that the shared variance between the constructs and their indicators is significantly greater than the error variance (Barclay et al., 1995).

Reliability is instrumental to testing the precision of the different factors through the use of Cronbach's alpha (Cronbach, 1951) while examining the composite reliability of the involved factors (CR) (Nunnally & Bernstein, 1994) in order to test the internal consistency of the model according to the latent variable. In this sense, the literature suggests the abovementioned threshold value of 0.7. However, AVE (average variance extracted) was used to test the convergent validity of the model (Fornell & Larcker, 1981) by guesstimating the variance that each construct would obtain from their indicators, considering the amount of variance related to possible measurement errors. In this regard, the scientific literature suggests a minimum value of 0.5 (see Table 2).

Table 2: Convergent validity and internal consistency reliability

Construct	**Item**	**Standard coefficient**	**Cronbach's alpha**	**CR**	**AVE**
Addiction to heavy viewing	ADD1	0.809	0.882	0.913	0.679
	ADD2	0.816			
	ADD3	0.832			
	ADD4	0.849			
	ADD5	0.812			

Convenience Value	CONV1	0.876	0.923	0.942	0.764
	CONV2	0.881			
	CONV3	0.861			
	CONV4	0.859			
	CONV5	0.891			
Effort Expectancy	EEXP1	0.912	0.902	0.939	0.837
	EEXP2	0.910			
	EEXP3	0.922			
Emotional Value	EMOV1	0.890	0.866	0.918	0.788
	EMOV3	0.888			
	EMOV2	0.884			
Monetary Value	MONV1	0.878	0.866	0.918	0.789
	MONV2	0.899			
	MONV3	0.887			
Perceived Enjoyment	PENJ1	0.908	0.925	0.947	0.817
	PENJ2	0.910			
	PENJ3	0.900			
	PENJ4	0.899			
Perceived Risk	PERR1	0.859	0.795	0.880	0.709
	PERR2	0.831			
	PERR3	0.836			
Perceived Value	PERV1	0.862	0.898	0.929	0.765
	PERV2	0.871			
	PERV3	0.882			
	PERV4	0.883			

Performance Expectancy	PEXP1	0.874	0.906	0.930	0.727
	PEXP2	0.843			
	PEXP3	0.853			
	PEXP4	0.871			
	PEXP5	0.820			
Personal Innovativeness	PINOV1	0.863	0.807	0.874	0.639
	PINOV2	0.822			
	PINOV3	0.845			
	PINOV4	0.842			
Social Value	SOCV1	0.889	0.903	0.932	0.775
	SOCV2	0.879			
	SOCV3	0.871			
	SOCV4	0.883			
Continued Intention	CI1	0.886	0.848	0.908	0.766
	CI2	0.856			
	CI3	0.885			

Source: Author's compilation

Finally, the discriminant validity was analysed to examine the different dimensions measured by each construct. Three methods are used in PLS: (a) a cross-loading analysis comparing whether the average variance shared between a dimension and its items is higher than the variance shared with the other dimensions in the model (Barclay et al., 1995); (b) a Fornell-Larcker criterion analysis analysing whether the correlations between the different dimensions are lower than the value of the square root of the AVE (Fornell & Larcker, 1981); and (c) the HTMT (Heterotrait-Monotrait) ratio analysis measuring whether the correlations between pairs of constructs reach less than 0.9 (Henseler et al., 2014; Leong et al., 2020). Table 4 shows the results of methods b) and c). In the case of the present study, the values are close to the values recommended in the scientific literature. In light of these findings, the discriminant validity in the model is considered moderately satisfactory (Henseler et al., 2015).

Table 3: Discriminant validity. Fornell-Larcker criterion (below the main diagonal) and Heterotrait-Monotrait Ratio (HTMT) (above the main diagonal)

	ADD	BI	CONV	EEXP	EMOV	MONV	PENJ	PERVAL	PEXP	PINOV	Risk	SOCV
ADD	0.824	0.925	0.767	0.714	0.878	0.818	0.772	0.853	0.921	0.903	0.902	0.908
BI	0.801	0.875	0.916	0.880	0.962	0.916	0.918	0.968	0.952	0.985	0.929	0.892
CONV	0.697	0.812	0.874	0.971	0.957	0.887	0.963	0.934	0.823	0.881	0.816	0.729
EEXP	0.643	0.773	0.886	0.915	0.942	0.860	0.982	0.898	0.766	0.842	0.755	0.653
EMOV	0.770	0.825	0.856	0.833	0.888	0.933	0.981	0.974	0.926	0.969	0.889	0.861
MONV	0.717	0.786	0.794	0.761	0.808	0.888	0.895	0.954	0.911	0.930	0.841	0.814
PENJ	0.703	0.816	0.890	0.898	0.878	0.802	0.904	0.932	0.821	0.888	0.808	0.709
PERVAL	0.761	0.846	0.850	0.809	0.859	0.842	0.851	0.875	0.934	0.905	0.896	0.853
PEXP	0.825	0.834	0.753	0.694	0.820	0.808	0.753	0.843	0.853	0.906	0.945	0.962
PINOV	0.842	0.824	0.774	0.737	0.823	0.782	0.785	0.814	0.834	0.799	0.914	0.959
Risk	0.822	0.764	0.703	0.644	0.741	0.701	0.697	0.760	0.803	0.804	0.842	0.901
SOCV	0.836	0.780	0.668	0.592	0.762	0.721	0.651	0.770	0.870	0.816	0.789	0.880

Source: Author's compilation

Note: PINOV = Personal Innovativeness, EEXP = Effort Expectancy, PEXP = Performance Expectancy, PERVAL = Perceived Value, CONV = Convenience Value, MONV = Monetary Value, EMOV = Emotional Value, SOCV = Social Value, CI =Continued intention**,** PENJ = Perceived Enjoyment, ADD = Addiction to heavy viewing.

A bootstrapping method using 5,000 samples was run as a statistical inference procedure to confirm that the structural model follows the recommendations in the literature. In this regard, the present study initially examined R^2 for every analysed construct to detect the amount of variance explained by the model. Falk and Miller (1992) posit that values equal to or greater than 0.1 can be considered adequate. However, standardized regression path weights provide the relative path weights of the different factors with regard to the endogenous variables. In this sense, even if Chin (1998) recommended values greater than 0.3, those values exceeding 0.2 are also accepted. In addition, f^2 (local effect sizes) tests the effect of independent latent variables on dependent latent variables. In this sense, this research obtained values of f^2 ranging from 0.02 to 0.15, 0.15 to 0.35, and even greater than

0.35, indicating a minor, average or significant impact of the exogenous latent variable (Chin, 1998). Lastly, in order to further adjust the model, the SRMR (standardized root mean square residual) (Henseler et al., 2015) identified the variance between the obtained correlation and the projected relationship adjustment measurement for the model. Therefore, values are considered adequate when below the 0.08 threshold. With regard to the NFI (The Normed Fit Index) measure, it can be seen that it is in line with the values proposed by the literature as described in Table 4.

Table 4: Evaluation of structural model (bootstrapping=5,000)

Relationship	**Coefficients**	**R^2**	**f^2**	**SRMR**	**NFI**
Effort Expectancy → Personal Innovativeness	0.305***		0.188		
Performance Expectancy → Personal Innovativeness	0.623***		0.786		
Convenience Value → Perceived Value	0.315***		0.145		
Monetary Value → Perceived Value	0.273***		0.130		
Emotional Value → Perceived Value	0.221***		0.057		
Social Value → Perceived Value	0.194***		0.089		
Personal Innovativeness → Continued Intention	0.153***		0.023		
Perceived Value → Continued Intention	0.302***		0.094		
Perceived Enjoyment → Continued Intention	0.239***		0.072		
Perceived Risk → Continued Intention	0.06 N.S		0.005		
Addiction → Continued Intention	0.225***		0.058		
Personal Innovativeness		0.744			
Perceived Value		0.837			
Continued Intention		0.802			
SRMR				0.044	
NFI					0.910

Source: Author's compilation. Note: *** $p \leq 0.001$; n.s.: not significant

5.3. Hypotheses testing

With regard to the different proposed relationships, the statistical significance of the structural loads was Why do you keep using this word? I don't think it is the most appropriate here. How about estimated to further examine the validity of the structural model. In this regard, results from the SEM analysis are shown in Table 4 and Figure 2, along with the results of the hypotheses. In our research, all hypotheses were significant, with the exception of the hypothesis that related perceived risk to continued intention.

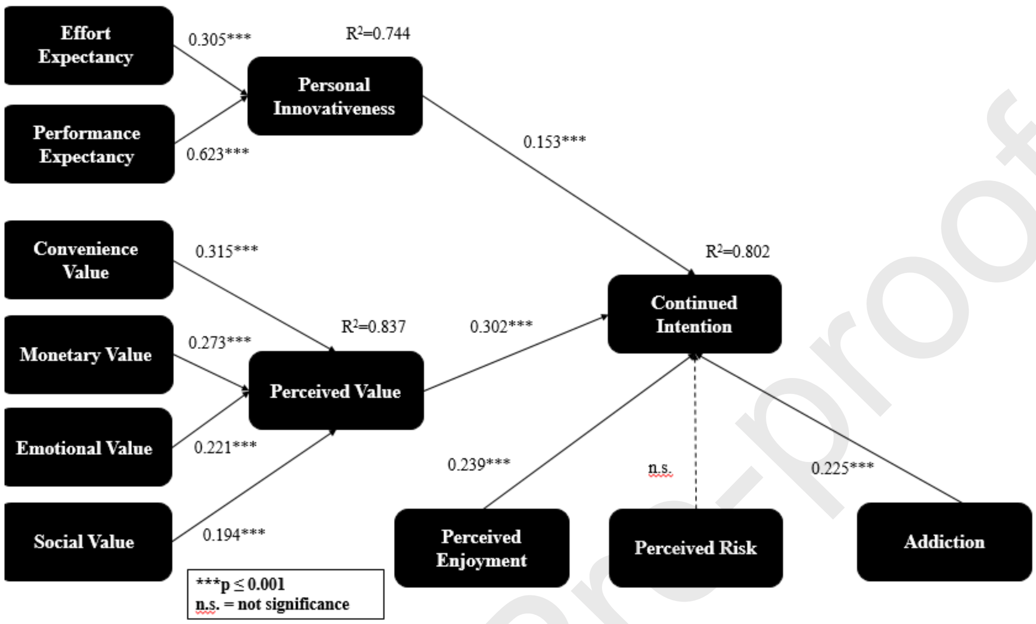
H1, which proposed a positive relationship between effort expectancy and personal innovativeness, was confirmed (β = 0,305; $p \leq 0.001$), which is in line with previous proposals by Singh et al. (2017). H2, which proposed a positive relationship between performance expectancy and personal innovativeness, was confirmed (β = 0,623; $p \leq 0.001$), corroborating the results of Xu and Gupta (2009).

However, the group of hypotheses (H3, H4, H5 and H6) that analysed the antecedents of perceived value were verified in their totality, which is in line with the results of Anderson and Srinivasan (2003) in relation to the convenience value ($\beta = 0.315$; $p \leq 0.001$), Sheth et al. (1991) with regard to monetary value ($\beta = 0.273$; $p \leq 0.001$), Sweeney and Soutar (2001) with regard to emotional value ($\beta = 0.221$; $p \leq 0.001$) and Leung and Wei (2000) with regard to the social value ($\beta = 0.194$; $p \leq 0.001$).

Specifically, H7, proposing a positive and direct relationship between personal innovativeness and continued intention, was confirmed ($\beta = 0.153$; $p \leq 0.001$) according to Xu and Gupta (2009). H8, proposing a direct and positive relationship between perceived value and continued intention, was also confirmed ($\beta = 0.302$; $p \leq 0.001$), which is in line with Kizgin et al. (2018). H9, proposing a direct and positive relationship between perceived enjoyment and continued intention ($\beta = 0.239$; $p \leq 0.001$), was confirmed, which is in line with Moon and Kim (2001). Finally, H11, proposing a direct and positive relationship between addiction to heavy viewing and continued intention ($\beta = 0.225$; $p \leq 0.001$) was also confirmed as Young et al. (2011) proposed.

H10 could not be confirmed ($\beta = 0.006$ $p > 0.001$). We understand that this activity is not perceived by users as a risk activity and therefore will not harm continued intention. In the same vein, it has recently been proven that risk is not a precedent for other innovative technologies or services (Pelaez et al., 2019) such as mobile banking apps (Muñoz-Leiva et al., 2017) or peer-to-peer mobile payment systems (Kalinic et al., 2019).

Figure 2: Results of the structural model analysis.



Source: Author's compilation

5.4. Artificial neural network analysis

The introduction of the artificial neural network (ANN) approach brought two important benefits. Firstly, the results obtained by SEM, with minor differences, were confirmed with another independent data analysis technique. Secondly, it improved the precision and reliability of the final results. In other words, since the existence of three non-linear relationships in the research model was confirmed by the ANOVA test of linearity, it was beneficial to introduce an additional non-linear technique such as ANN, which would take into account these non-linear effects otherwise neglected by SEM. This approach was confirmed as valuable since it produced a much more precise model. The comparison of a goodness-of-fit coefficient R^2 for the ANN analysis, which is similar to the R^2 in the PLS-SEM analysis (Lee et al., 2020), shows that R^2 for the ANN analysis (96.0%, 96.9% and 96.7%, respectively) is considerably higher than R^2 in the PLS-SEM analysis (74.4%, 83.7% and 80.2%, respectively), i.e., variances of the outputs are much better explained by ANN models. Therefore, the final relative rankings of the outputs obtained by ANN models are more precise and reliable than rankings based on beta values obtained by SEM. Higher prediction accuracy and already enlisted minor differences in rankings of significant predictors between the two approaches may be explained by the ability of ANN models to capture non-linear relationships as well. Nevertheless, both SEM and ANN should be seen as complementary rather than competing techniques (Leong et al., 2019) because ANN, although superior, is rarely used alone due to its deficiencies, such as its inability to test hypotheses (Table 5).

The results of the deviation from the linearity test show that for each dependent variable, there is one non-linear predictor, i.e., the relationships between effort expectancy and personal innovativeness, emotional value and perceived value, and personal innovativeness and continued intention all possess statistically significant non-linear components. This finding justifies the necessity of introducing another method that will deal with existing non-linearities, and therefore the artificial neural network (ANN) approach is suggested. ANN is an artificial intelligence technique based on brain operation principles (Negnevitsky, 2011), and it is very efficient in building predictive models of complex problems (Liébana-Cabanillas et al., 2018). In addition, these models are very robust and accurate and do not depend on fulfilment of multivariate assumptions such as normality, linearity or homoscedasticity (Woo et al., 2019). Nevertheless, the "black-box" nature of ANN models limits their applicability in the testing of significance levels of causal relationships (Leong et al., 2019; Woo et al., 2019). Hence, ANNs are used as a complement to PLS analysis, i.e., PLS is used to determine significant determinants of each dependent variable, while ANN models are used to more precisely rank their influence on dependent variables. The suggested two-step approach combining one linear technique (PLS or SEM) and ANNs was successfully implemented in the adoption studies of many modern technologies, including mobile commerce (Chong, 2013; Liébana-Cabanillas et al., 2017), mobile payments (Kalinić et al., 2019; Liébana-Cabanillas et al., 2018; Teo et al., 2015), e-learning (Dwivedi et al., 2017), mobile learning (Dover & Murthi, 2006), mobile social tourism shopping (Hew et al., 2018), blockchain (Wong et al., 2019), Facebook commerce (Leong et al., 2019), mobile government services (Sharma et al., 2018), mobile banking (Sharma & Sharma, 2019), mobile social media (Lee et al., 2019), social media addiction (Leong et al., 2019), etc.

All simulations were performed in SPSS 20. This study employed a multilayer perceptron (MLP), one of the most popular and well-known ANN types (Kalinić et al., 2019). MLP architecture with one input, one hidden layer and one output layer was used, as it can successfully model any continuous function (Negnevitsky, 2011). Based on PLS results, i.e., taking only significant predictors as inputs, it was possible to build three ANN models, which are presented in Figures 3–5.

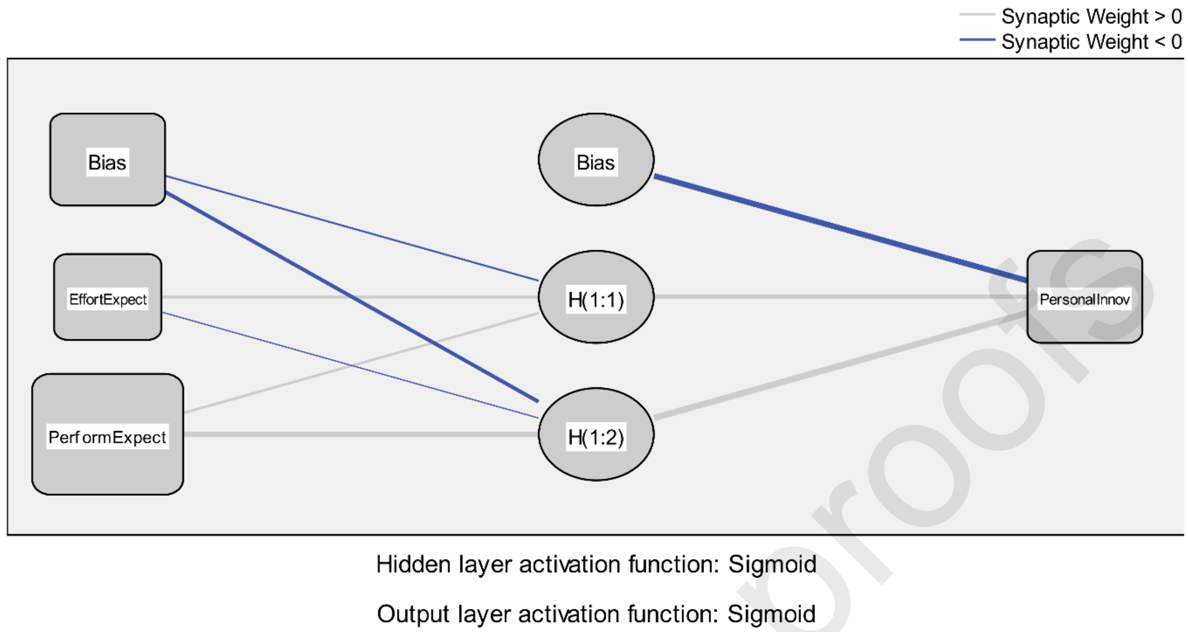
Table 5. ANOVA Test of Linearity

		Sum of Squares	df	Mean Square	F	Sig.	Linear
PINOV * EEXP	Dev. from Linearity	40.831	17	2.402	2.194	0.004	NO
PINOV * PEXP	Dev. from Linearity	21.545	29	0.743	1.054	0.389	YES
PERVAL * CONV	Dev. from Linearity	24.624	29	0.849	1.198	0.218	YES
PERVAL * MONV	Dev. from Linearity	15.242	17	0.897	1.197	0.260	YES
PERVAL * EMOV	Dev. from Linearity	33.665	29	1.161	1.598	0.024	NO
PERVAL * SOCV	Dev. from Linearity	11.307	23	0.492	0.46	0.986	YES
CI * PINOV	Dev. from Linearity	33.948	23	1.476	1.661	0.027	NO
CI * PERVAL	Dev. from Linearity	16.441	23	0.715	0.934	0.553	YES
CI * PENJ	Dev. from Linearity	22.205	23	0.965	1.067	0.377	YES
CI * ADD	Dev. from Linearity	57.833	46	1.257	1.156	0.226	YES

Source: Author's compilation

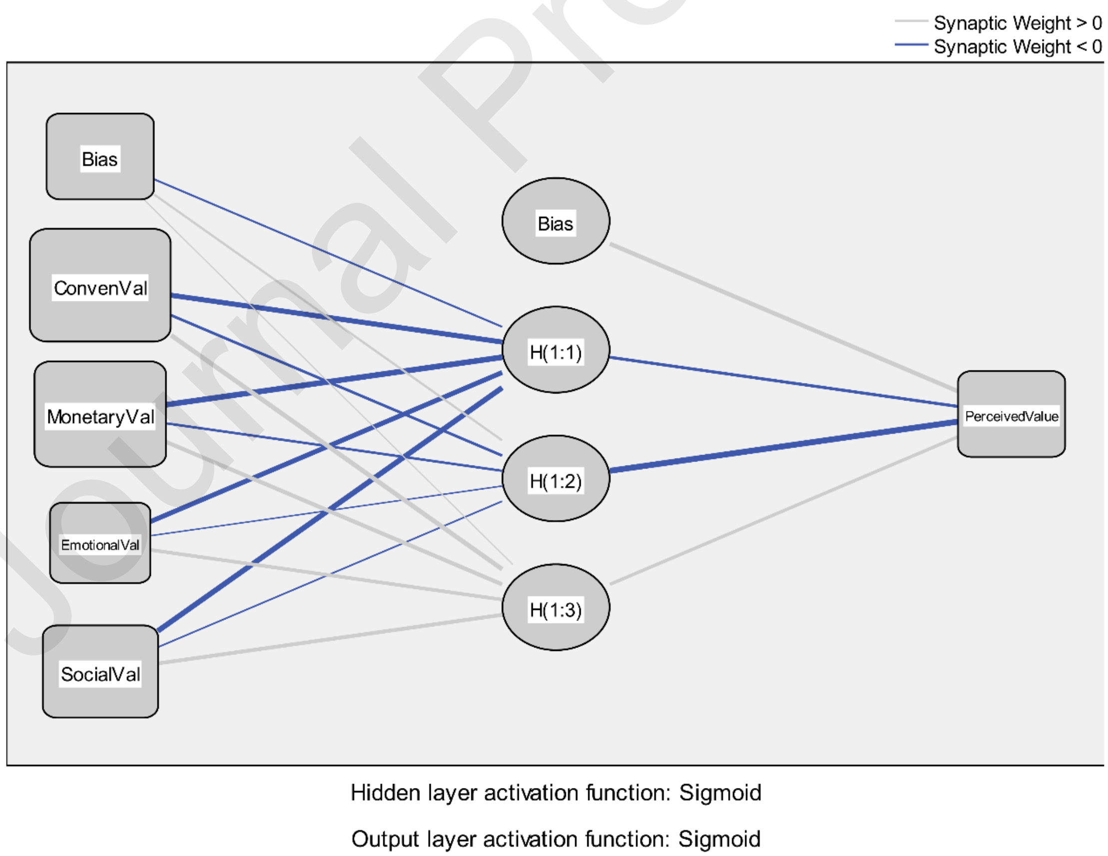
Note: PINOV = Personal Innovativeness, EEXP = Effort Expectancy, PEXP = Performance Expectancy, PERVAL = Perceived Value, CONV = Convenience Value, MONV = Monetary Value, EMOV = Emotional Value, SOCV = Social Value, CI =Continued intention**,** PENJ = Perceived Enjoyment, ADD = Addiction to heavy viewing.

Figure 3: ANN model 1



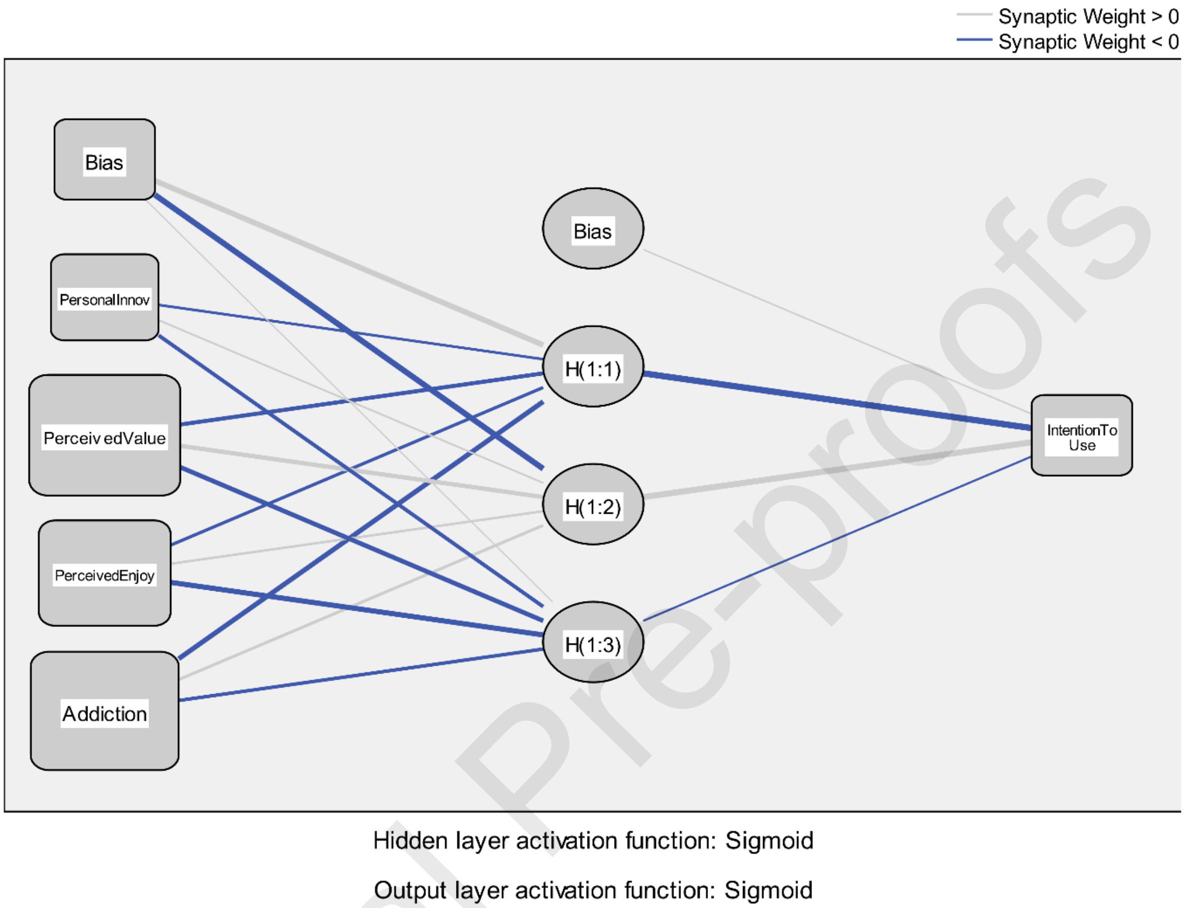
Source: Author's compilation

Figure 4: ANN model 2



Source: Author's compilation

Figure 5: ANN model 3



Source: Author's compilation

The inputs to ANN model 1 are effort expectancy and performance expectancy as significant predictors of personal innovativeness, which is the output of this model. In the same way, ANN model 2 was built (inputs: convenience value, monetary value, emotional value and social value; output: perceived value) as well as ANN model 3 (inputs: personal innovativeness, perceived value, perceived enjoyment and addiction to heavy viewing; output: continued intention). The number of hidden neurons was determined automatically by simulation software (Hew et al., 2018; Liébana-Cabanillas et al., 2018), and it was two for ANN model 1 and three for ANN models 2 and 3. In all three ANN models, in both hidden and output layers, sigmoid was used as the non-linear activation function (Hew et al., 2018; Kalinić et al., 2019; Leong et al., 2019).

To avoid potential problems with over-fitting of ANN models, a ten-fold cross-validation procedure was performed, using 90% of the data sample for network training and the remaining 10% for network testing (Kalinic et al., 2019; Sharma & Sharma, 2019). The predictive accuracy of the models was assessed by the evaluation of Root Mean Square Error (RMSE) values (Li et al., 2019; Liébana-Cabanillas et al., 2018), and these values are presented in Table 6.

Table 6: RMSE values of ANN models

Network	ANN model 1 Inputs: EEXP, PEXP; Output: PINOV		ANN model 2 Inputs: CONV, MONV, EMOV, SCOV; Output: PERVAL		ANN model 3 Inputs: PINOV, PERVAL, PENJ, ADD; Output: CI	
	Training	Testing	Training	Testing	Training	Testing
1	0.0911	0.0983	0.0784	0.0898	0.0893	0.0684
2	0.0900	0.1021	0.0797	0.0756	0.0881	0.0849
3	0.0910	0.0993	0.0819	0.0698	0.0875	0.0821
4	0.0912	0.0898	0.0777	0.0822	0.0858	0.1035
5	0.0917	0.0904	0.0803	0.0720	0.0874	0.0928
6	0.0973	0.0795	0.0775	0.0817	0.0874	0.0861
7	0.0922	0.0814	0.0784	0.0819	0.0867	0.0864
8	0.0948	0.0803	0.0812	0.0749	0.0902	0.0696
9	0.0935	0.0775	0.0780	0.0751	0.0881	0.0996
10	0.0920	0.1053	0.0787	0.0832	0.0872	0.0907
Mean	0.0925	0.0904	0.0792	0.0786	0.0878	0.0864
Standard deviation	0.0022	0.0104	0.0015	0.0061	0.0013	0.0113

Note: PINOV = Personal Innovativeness, EEXP = Effort Expectancy, PEXP = Performance Expectancy, PERVAL = Perceived Value, CONV = Convenience Value, MONV = Monetary Value, EMOV = Emotional Value, SOCV = Social Value, CI = Continued intention, PENJ = Perceived Enjoyment, ADD = Addiction to heavy viewing.

Based on the fact that mean RMSE values are in the range 0.0786–0.0925, i.e., they are all very small, it may be concluded that all three ANN models have very good reliability and prediction accuracy (Ooi et al., 2018; Sharma et al., 2018). High predictive relevance is also confirmed by the fact that each of the input neurons (in all three ANN models, Figures 3–5) is connected to all corresponding hidden neurons through non-zero synaptic weights (Hew et al., 2018, 2019). Finally, to estimate the percentage of the variance explained by the ANN models, following the approach suggested by Leong et al. (2019), R^2 was computed using the following formula:

$$R^2 = 1 - \frac{RMSE}{s_y^2}$$

where s_y^2 is the variance of the desired output. Results show that ANN model 1 explains 96.0% of the variance in personal innovativeness, ANN model 2 explains 96.9% of the variance in perceived value, while ANN model 3 explains 96.7% of the variance in continued intention, which confirms the high suitability of the models (Leong et al., 2019; Wong et al., 2019).

In order to compare the importance of the predictors, the normalized importance of each predictor was computed by dividing its relative importance by the highest relative importance of predictors of the dependent variable in question (Liebana-Cabanillas et al., 2017; Wong et al., 2019), and the results of this sensitivity analysis are presented in Table 7.

Table 7: ANN sensitivity analysis

Network	ANN model 1 Rel. importance		ANN model 2 Relative importance				ANN model 3 Relative importance			
	EEXP	PEXP	CNOV	MNOV	EMOV	SCOV	PINOV	PERVAL	PENJ	ADD
1	0.270	0.730	0.395	0.270	0.109	0.226	0.157	0.356	0.225	0.262
2	0.281	0.719	0.347	0.300	0.138	0.215	0.170	0.298	0.241	0.290
3	0.333	0.667	0.320	0.246	0.237	0.197	0.146	0.344	0.243	0.268
4	0.261	0.739	0.354	0.283	0.186	0.177	0.179	0.307	0.243	0.271
5	0.254	0.746	0.388	0.264	0.126	0.222	0.195	0.319	0.250	0.236
6	0.383	0.617	0.340	0.276	0.199	0.185	0.109	0.362	0.245	0.284
7	0.251	0.749	0.367	0.260	0.187	0.187	0.112	0.364	0.255	0.268
8	0.238	0.762	0.346	0.254	0.225	0.175	0.240	0.312	0.205	0.243
9	0.240	0.760	0.388	0.275	0.135	0.202	0.163	0.310	0.308	0.218
10	0.302	0.698	0.339	0.252	0.154	0.254	0.119	0.345	0.258	0.278
Average importance	0.281	0.719	0.358	0.268	0.170	0.204	0.159	0.332	0.247	0.262
Normalized importance (%)	39.7	100.0	100.0	75.0	48.1	57.1	48.8	100.0	75.0	79.2

Note: PINOV = Personal Innovativeness, EEXP = Effort Expectancy, PEXP = Performance Expectancy, PERVAL = Perceived Value, CONV = Convenience Value, MONV = Monetary Value, EMOV = Emotional Value, SOCV = Social Value, CI = Continued intention, PENJ = Perceived Enjoyment, ADD = Addiction to heavy viewing.

ANN model 1 predicts that performance expectancy has a much stronger influence than effort expectancy, which is in line with the PLS findings. Convenience value is the strongest predictor of perceived value, followed by monetary value, social value and emotional value. Compared to the PLS findings, we may notice some differences. In PLS analysis, emotional value has a stronger influence than social value and almost the same influence as monetary value, while ANN analysis identified monetary value as the least significant determinant.

Finally, the most significant determinant of continued intention is perceived value, followed by addiction to heavy viewing, perceived enjoyment and personal innovativeness. Again, minor differences may be noticed when compared with PLS results. Through PLS analysis, perceived enjoyment had a stronger impact than addiction to heavy viewing, which is contrary to the ANN results. These minor differences between the PLS and ANN findings are the result of higher prediction accuracy and the non-linear nature of ANN models (Kalinic et al., 2019).

6. Discussion, Implications, Limitations, Scope of Future Studies and Conclusions

6.1. Discussion

The study was designed to develop a comprehensive model to measure the impact of perceived value theory, along with a few exogenous variables related to product (i.e., effort expectancy, performance expectancy), attributes of the service provider (perceived risk), behavioural attributes of consumers (i.e., perceived innovativeness, perceived risk) and, finally, addiction to heavy viewing in order to measure users' continued intention to employ live streaming services. At first, the study confirmed the significant direct and indirect relationships between all determinants and users' continued intention, except for perceived risk.

First, among the four main antecedents of perceived value, convenience value was found to be most significant and has the strongest impact on the perceived value of a user, followed by monetary value (Mathwick et al., 2001), emotional value (Pura, 2005) and social value (Oyedele & Simpson, 2018). Similar research done by Praveena and Thomas (2014) stated that convenience and monetary value play major roles in influencing users' continued intention to use self-service technology, for example, mobile entertainment services. Oyedele and Simpson (2018) highlighted the positive significance of both convenience value in terms of accessing streaming contents anywhere easily and emotional value in terms of the pleasure and gratification that consumers derive while using streaming services. The findings were reconfirmed with the positive impact of perceived enjoyment on users' continued intention to use streaming services (Jia et al., 2014). However, Oyedele and Simpson (2018) did not find any significance of monetary value in relation to the benefits of streaming services. They emphasized the fact that the limited impact of monetary value is due to very low and flat monthly fees for such services. Moreover, users generally prefer free streaming apps or services rather than fee-based entertainment services. In contrast to their findings, the present study found monetary value to have a very significant impact on the perceived value of users. This is because most of the live streaming services differ in levels of subscription charges, ranging from free to small monthly charges for limited and unlimited usage. Hence, it plays a significant role in assessing users' choices and continued intention (Mathwick et al., 2001). The present study confirms a small effect of social value. Social value itself, however, is not important but may be important for creating the social identify of the user (Oyedele & Simpson, 2018). A very limited or no effect of social value on users is supported in a few studies. For example, Mohd-any et al. (2015) confirmed that the role of social value is only important when used in the context of establishing a social identity as a music or video lover while using streaming services. Mostly, users are not concerned about their social identity, which is based on social expectations and created with the use of streaming services. This is correct in the Indian context as TV contents are still the most preferred entertainment and common topics for social conversations rather than online streaming programs (Ganjoo, 2018). Moreover, reports show that viewers in India watch streaming content to avoid social interactions, real issues, etc., and enjoy life alone (Ganjoo, 2018), hence giving little significance to social expectations.

Next, the significant positive impact of perceived value on users' continued intention to use streaming services is supported by the findings of various studies (Gummerus, 2013; Ali, 2018; Oyedele & Simpson, 2018). Gummerus (2013) defined perceived value as an experienced outcome that is most applicable to streaming services because they provide technology-based experiences to users while they assess the music and video contents of the service and influence usage positively. Oyedele and Simpson (2018) used perceived value in the context of streaming applications and found its significant impact on users' perceptions, recommendations, etc.; their findings confirmed the need to investigate consumers' perceived value with regard to different apps.

In addition, the study confirmed the positive influence of addiction to heavy viewing on users' continued intention. Online addiction is a widely discussed topic among researchers; various studies have measured its impact and effect on users' perceptions, behaviour, mental health, etc. (Cho, 2010; Kuss & Lopez-Fernandez, 2016). These studies confirmed the positive and mostly negative aspects of online addiction on users. In the context of entertainment services, a few articles have discussed the changes in users' habits and preferences towards streaming services, but none have emphasized the growing addiction to streaming services which may lead to social problems and health-related consequences in the future (Yang & Lee, 2018). This is a new highlight in the present study.

Consistent with previous studies, effort expectancy and performance expectancy had a significant influence on perceived innovativeness. The findings related to perceived innovativeness are consistent with previous works on innovation, which was first conceptualized in innovation diffusion theory (Rogers, 1983). The theory confirmed five main aspects of innovation: effort expectancy, relative advantage, complexity, trialability and observability. A similar study was done by Pal and Triyason, (2017) on online services and it stated that users perceive a service as innovative when it provides high performance and effort expectancy to them. These results support Singh et al.'s (2020) findings that technology with high usability and convenience improves users' perceived innovativeness, and they adopt a new service relatively earlier than others. However, there are studies that confirmed the impact of perceived innovativeness on effort and performance expectancy, in contrast to current findings (Ali, 2018). They found that the perceived innovativeness of a user enhances his performance and effort expectancy while using a new online service or technology.

Finally, the study concluded that there is no impact of perceived risk on users' continued intention due to high awareness and usage information of a service. Perceived risk measures the uncertainty of the outcome that a consumer perceives from the use of a product or service (Dickinger et al., 2008). In relation to online live streaming services, perceived risk measures the insecurity of viewers exposed to viruses, worms, financial and personal data fraud, etc., while paying subscription fees or watching and downloading videos online, which may cause damage to their computer or mobile phones (Yang & Lee, 2018; Sidhardhan, 2018). With advancement in secured and protected operating systems, such fears and threats are disappearing with time. Moreover, the impact of perceived risk is very small as most of the streaming services are free or low in value and easily accessible to users; hence, the significance of perceived risk is very low to viewers of streaming services.

6.2. Theoretical implications

Despite the increasing popularity and adoption of streaming services, very little research exists on how users value and perceive them. The study makes the following significant contributions to the existing literature. First, the study developed a comprehensive model to measure all the linear and non-linear relationships between all the determinants of video streaming services and users' behaviour. The study includes and analyses perceived value theory, along with a few distinct variables, namely addiction to heavy viewing, perceived risk and perceived enjoyment, to measure users' continued intention to use video streaming services. These variables have been discussed in various studies but very few studies have examined the impact of these variables and perceived value theory in the context of streaming services, which is quite unique in the present study (Ali, 2018; Oyedele & Simpson, 2018). For this, the study includes PLS-ANN methods to measure the effectiveness of each endogenous and exogenous variable. Using a combination of PLS, which is a statistical technique to measure the linear relationships among the variables, and ANN, which is relevant for assessing existing non-linearities in the model and complex relationships among the variables, was a new idea and very few studies used the combination in the context of India. The study confirmed the higher predictive accuracy of both methods by showing the minor differences in the results predicted by each PLS and ANN model as desired (Kalinic et al., 2019).

The present study contributes primarily by discussing perceived value theory and various aspects of perceived value theory that are relevant to OTT media streaming services. The study confirms the importance of perceived value theory to the behaviour of streaming services users. There are limited studies available in the Indian context (Ali, 2018). Highly influenced by convenience and monetary values, perceived value was confirmed to have a significant positive impact on users' continued intention. Emotional value was also found to be crucial in influencing users' continued intention through perceived value.

Second, this is the first known study to highlight the growing addictive behaviour of users in relation to streaming services. The findings call for future research in this context and the examination of the various negative effects of addiction to heavy viewing on users. The limited effect of social value in the present study also hints at the changing habits of viewers and their lower inclination towards social interactions. Another contribution of the study is the significant impact of effort expectancy and performance expectancy on the perceived innovativeness of users of streaming services. This contributes to the existing literature on effort and performance expectancy as well as perceived innovativeness and supports the influence of these variables on users' inclination to try out new and innovative services.

6.3. Practical implications

Teenagers and the young population in India are very attracted and inclined to streaming services because they provide the flexibility to watch their shows anytime and anywhere, based on their convenience and preferences. We now have plenty of video streaming services available, so content is available to everyone based on their regional or cultural preferences. Moreover, these services are preferred by users because they are highly affordable, and some of them are actually free to users. In addition, some of these streaming media apps, such as Netflix, Amazon Prime and Hot Star, provide a free trial offer period to users to watch interesting shows and movies before actually paying for streaming content (livemint.com, 2018). This confirms the need to understand the growing trends and to examine the behavioural changes among the viewers in India. The present study provides important practical implications and strategic guidelines for the management of companies and organizations involved in or influenced by the development and implementation of video streaming services

First, managers should focus their marketing strategies on the benefits of the video streaming services. According to Holbrook (1999), perceived value can be first-person oriented (the product/service provides benefits to oneself) or third-person oriented (the product/service provides benefits to others). Perceived value can also be intrinsic (e.g., the songs downloaded) or extrinsic (e.g., a fast and convenient music download service). The perceived value should therefore be understood as the sum of convenience value, monetary value, emotional value and social value.

Second, to increase the consumer's feelings of excitement and enjoyment, the user interfaces should be user-friendly and pleasant. The customization of both the appearance of the user interface and the services offered would surely increase the positive feelings of the consumer. Thanks to technological advances, it is possible to collect large amounts of data on consumer behaviour and habits through different systems (artificial intelligence, Big Data, cookies, etc.) so that streaming companies can personalize each of the services that the customer needs to improve his or her enjoyment.

In addition, the personal innovation of users seems to be a phenomenon to consider in the analysis of video streaming service users' behaviour, so that those users with higher levels of innovation will show greater interest in adopting these services. Finally, it is worth noting that perceived risk does not represent an inhibiting element of streaming services since the majority of the population has overcome the possible problems derived from the use of this type of technology. Moreover, after the advancements of better secured systems and phones, perceived risk plays a minimal role in influencing user behaviour.

6.4. Social implications

The study confirms the trend that users are capable of being addicted to streaming services. Based on their viewing patterns, it is observed that heavy viewing prolongs the use of streaming services by users. This may be beneficial from a marketing and revenue perspective but may hint at negative or social problems in the long run. The findings of the study highlight the addiction trend which should be carefully monitored by medical societies, practitioners, etc. Various user awareness programmes should be designed to sensitize them to the negative consequences associated with heavy viewing or spending long hours on streaming services.

6.5. Limitations and scope of future research

Although the present study provides lots of insights on users' continued intention to use video streaming services, it has certain limitations. The first limitation of the study lies in the cross-sectional design of the study. A longitudinal study design could have provided better results if the period of data collection for behavioural attributes such as personal innovativeness, perceived risk and addiction to heavy viewing had been different from the period of data collection for continued intention to use live streaming services. The second limitation concerns the variables (such as attitude towards streaming services, trust of streaming services and familiarity with streaming services) not included in the study but that otherwise may have significant impacts on the continued intention to use streaming services. In addition, future studies may extend research by discussing a few other relevant technology adoption theories such as the expectancy confirmation model (ECM), flow theory, satisfaction theory and motivation theory to refine the results further. the third limitation of the study is that demographic variables are not involved in the study; however, demographic variables can have significant impacts on the continued intention to use live streaming services. In future studies, the moderating effect of demographic variables could be included. Another probable limitation of the present research lies in limited research on addiction to heavy viewing that has more negative traits. Future research may include negative traits of addiction to heavy viewing in relation to streaming services.

6.6. Conclusions

The stimulus behind the current study was to assess users' continued intention to use online live streaming services. This is the first known study to investigate consumers' continued intention to use streaming services in the Indian context. In order to identify the factors influencing consumers' continued intention to use streaming services, we used perceived value theory, behavioural attributes and addiction to heavy viewing. To our knowledge, our study is the sole attempt to use multi-dimensional perceived value theory to measure continued intention; the convenience value was found to be most impactful in the case of live streaming services. Our study supplemented earlier studies on streaming services by assessing the link between addiction to heavy viewing and streaming services. Many previous studies established a negative and significant relationship between perceived risk and the continued intention to use a technology (Dickinger et al., 2008; Alalwan et al., 2018). In our study, the impact of perceived risk on continued intention was insignificant because technology is now very advanced and fool-proof, so there is no risk to consumers. This result is in line with the studies conducted by Thusi and Maduku (2020). Further, the model proposed in the study was analysed using partial least squares and artificial neural network, which helped us in understanding not only the linear but also non-linear relationships between various constructs.

Appendix 1. Detailed statements used to measure various constructs

Perceived Enjoyment

PENJ1: Using a streaming service is fun.

PENJ2: Using a streaming service is enjoyable.

PENJ3: Using a streaming service is pleasurable.

PENJ4: Using a streaming service is very interesting.

Perceived Risk

PERR1: A streaming service is dangerous to use and access.

PERR2: Using a streaming service would add great uncertainty to my bill paying.

PERR3: Using a streaming service exposes you to an overall risk.

PERR4: It is rare for unexpected threats to occur while using a streaming service.

Perceived Value

PERV1: Overall, the use of a streaming service delivers good value to me.

PERV2: Streaming services are good value for the money and are worthwhile.

PERV3: Considering the efforts I put in using a streaming service, it is worthwhile.

PERV4: Considering the time I put in using a streaming service, it is worthwhile.

Convenience Value

CONV1: Streaming services allow me to watch or listen to whatever I want whenever I choose.

CONV2: Streaming services allow me to watch or listen to whatever I want at a convenient time.

CONV3: I value the ability to use streaming services to watch or listen to what I want while away from home.

CONV4: I like the ability to use streaming services to watch or listen to what I want on multiple devices (e.g., iPads, smartphones).

CONV5: I like the ability to use streaming services to watch or listen to what I want from anywhere.

Monetary Value

MONV1: I feel that the subscription cost of streaming services is not expensive relative to substitute services such as DTH services.

MONV2: I feel that using streaming services offers significant cost savings relative to substitute services such as DTH services.

MONV3: I feel that using streaming services is cost-effective relative to DTH services.

Social Value

SOCV1: I value streaming services because they enhance my peer status.

SOCV2: I value using streaming services because they help increase my connections on social media.

SOCV3: I value using streaming services because they are popular among my peers.

SOCV4: I value streaming services because they improve my image among my friends and family.

Emotional Value

EMOV1: I feel much better after using streaming services.

EMOV2: I feel excited after using streaming services.

EMOV3: Streaming services are those that I enjoyed.

Performance Expectancy

PEXP1: Using streaming services improves my efficiency.

PEXP2: Using streaming services enables me to do my task conveniently.

PEXP3: Using streaming services would enhance my effectiveness in my daily work.

PEXP4: Using streaming services would improve my task productivity.

PEXP5: In general, I believe that streaming services are useful.

Effort Expectancy

EEXP1: Learning to use streaming service is easy for me.

EEXP2: Overall, streaming services are understandable and clear.

EEXP3: Overall, using streaming services is easy.

Personal Innovativeness

PINOV1: When I hear about streaming services, I look for possibilities to try it.

PINOV2: I don't want to try a new streaming service.

PINOV3: I am usually the first to try out new streaming services.

PINOV4: I like to try new streaming services.

Continued Intention

CI1: I plan to use streaming services on a long-term basis.

CI2: I am willing to purchase streaming services, use them and share them with others through social networking websites on a regular basis in the future.

CI3: I will continue to use streaming services.

Addiction to Heavy Viewing

ADD1: I find myself using streaming services longer than I planned to.

ADD2: I would rather spend time watching streaming content than do things around the house.

ADD3: Much of my time I spend watching online streaming videos or music shows.

ADD4: Streaming services take up almost all of my leisure time.

ADD5: I am bothered when people interrupt me while I am watching streaming content.

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Credit author statement

Assessing determinants influencing continued use of live streaming services: an extended perceived value theory with streaming addiction

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Dear Editor,

This is to declare that we have no potential conflict of interest pertaining to this submission.

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Article Title: Assessing determinants influencing continued use of live streaming services: an extended perceived value theory with streaming addiction

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Highlights:

- The study aims to identify determinants of continued intention to use live streaming services in India
- The study extends perceived value theory by including few important determinants.
- The findings suggest that perceived value, perceived enjoyment, addiction and Personal Innovativeness determine continued intention to use streaming services.
- The study suggests about the growing streaming services addiction.
- The study provides important insights and recommendations to streaming companies, viewers, contains social implications etc.