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Study on Behavioral Intention and Actual Usage of OTT video streaming platforms in North-East India

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Abstract

India is witnessing a continuous growth of OTT (Over-the-top) video streaming platforms particularly after the Covid-19 pandemic. Many new players have entered the market recently with their offers and created an aggressive competitive situation in the market. This necessitate a detailed understanding of behavior of OTT video streaming platform consumer's so that service providers can a better customer satisfaction and achieve competitive advantage. With this in background, this study tries to utilize the proven model of Unified Technology Acceptance and Use of Technology (UTAUT2) proposed by Venkatesh et al. (2012) and extended factors to understand the OTT video streaming platform user behavior in North-East India. For the study a model is proposed having formative and reflective structures. The measurement model (reflective model) has 36 indicators relating to 7 latent variables defining behavioral intentions, 15 indicators relating to 3 latent variable defining actual usage of OTT. The structural model (formative model) tried to define the relationship of latent variables with behavioral intention and actual usage and the effect of behavioral intention over actual usage. The adapted version of UTAUT2 questionnaire was used to collect sample data from 564 OTT users to assess the proposed model using variance based SmartPLS v.4.0.

The structural model assessment founds the proposed model to be moderate in predicting actual usage and strong in predicting the behavioral intention of OTT use through Q-square predictive relevance calculations. The explanatory power of the structural model is found to be moderate obtained through R-square. The outcome of analysis also verified that amongst gender, age, occupation and use experience, only age is playing a moderator role in the relationship between behavioral intention and actual usage. It was also observed that behavioral intention played a mediating role between the exogenous variables and actual usage of OTT video streaming platforms. With various statistical analysis and parameters into consideration, it is concluded that the proposed model is fit, reliable and valid, and can be considered as an addition to the existing literature on OTT and UTAUT2 extended models.

Keywords: OTT video streaming platform, Extended UTAUT2, PLS-SEM, Predictive relevance, R-Square

1. Introduction

With telecommunication industry offering highly affordable internet packages, accessibility to internet has become quite affordable in today's time (Mairaru et al., 2019). Specifically, in India, with the entry Reliance Jio in the telecommunication market, the cost of accessing internet data has reduced by a high margin leading to substantial increase in daily data usage (Joy and Bahl, 2018). With this consumers can now consume the video content anyplace, anytime on their phones (Bentley et al., 2019). With upgraded technology, internet networks and video content digitization, consumers can now consumer huge collection of video content. After the successful adoption of YouTube by the market, many similar players including Netflix, Amazon Prime, Zee5, Hotstar, etc. entered the market with huge collection of video content to target the Indian consumers (Singh, 2019)

OTT video streaming platforms have been studied in various frameworks. Some of the studies have compared OTT performance with traditional televisions (Chen, 2019), whereas some have considered the OTT consumer adoption behavior through strategic management (Shin et al., 2016).

Considering the growth of OTT video streaming platforms and importance of understanding the consumer perspectives, the author has undertaken this study on behavioral intention and actual usage of OTT video streaming platforms. This study utilizes the extended Unified Theory of Acceptance and Use of Technology, known as UTAUT 2 proposed by Venkatesh et al, (2012). The basic objective is to understand the factors influencing the behavioral intention to use OTT video streaming platforms and the actual usage of the same. This study addresses a significant literature gap as no such study referencing North-East India and OTT was found during the literature review, and the outcomes of the study will definitely be an addition to the existing literature on UTAUT2 and OTT video streaming platforms.

In order to achieve the objective of understanding the behavior of OTT video streaming platform consumers, the researchers has followed the Partial least square - structural equation modeling framework. A study model is proposed after the literature review along with researchers own interpretations. The literature review is utilized to create a questionnaire for data collection. The sample survey is done using the questionnaire and sufficient data is collected for further analysis. The data is used to analyze the proposed structural model using the SmartPLS 4.0. The outcome of the data analysis and structural model assessment are then discussed and conclusion are drawn as part of the study.

2. Literature Review

Many of the factors like accessible internet data, infrastructure support by telecommunication companies, compatibility of mobile phones with video streaming etc. have led to Indian consumers using phones to consume video content. Moreover most of the content is now available in regional languages. These factors are popularity of OTT platforms leading to subscriber base in Indian market (Sundaravel and Elangovan, 2020).

In order to understand the adoption of OTT video streaming platform by consumers, UTAUT2 model was chosen. UTAUT2 model is being used by many researchers as a base model to study the adoption of technology in various fields for example, health and fitness apps in U.S. by Yuan et al., 2015; M-learning in China by Yang, 2013; Travel apps in India by Gupta et al., 2018; Smartphone fitness apps in India by Dhiman et al., 2019; Mobile food ordering apps in Jordan by Alalwan, 2020; Mobile health adoption in Portugal by Duarte and Pinho, 2019).

Venkatesh, Morris, Davis and Davis (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT) after studying eight prominent models. These included: Theory of Reasoned Action, Technology Acceptance model 2, Motivational model, Theory of Planned Behavior, Combined TAM and TPB, Model of PC Utilization, Innovation Diffusion and Social Cognitive Theory (Venkatesh et al., 2003). The model was proposed to describe and explain the user acceptance of new technology in a unified view. UTAUT model proposed that four construct, performance expectancy, effort expectancy, social influence and facilitating conditions influences the use behavior and behavioral intentions (Venkatesh et al., 2003). In a modification to this model, Venkatesh et al.(2012) suggested a new model UTAUT 2 with three new constructs, hedonic motivation, price value and habit. The model also included age, gender and experience as moderating variable.

Observations from few research studies undertaken with UTAUT2 as a based model are being discussed here:

In a study of application of UTAUT 2 model in m-learning in China, Yang (2013) found effort expectancy, habit as insignificant of using mobiles phone while all other factors where significant. The model was extended with self-management of learning. In a study of health and fitness apps by Yuan et al.(2015) in United States, social influence, effort expectancy, facilitating conditions were found insignificant while others were significant. Oliveira et al. (2016) in their study on mobile payment in Portugal found performance expectancy, social influence and other extended factors as significant in influencing behavioral intentions. The model was extended with perceived securities, diffusion of innovations and intention to recommend technology. Gupta et al. (2018) in their study on travel apps in India, found hedonic motivation, facilitating conditions and effort expectancy as insignificant in influencing behavioral intention or usage. They included perceived risk and perceived trust as additional factors. Alalwan (2020) found performance expectancy, habit and hedonic motivation as significant factors while studying usage of mobile food ordering apps in Jordan. The study used online rating, online review and online tracking as additional factors. Duarte and Pinho (2019) study usage of mobile health adoption in Portugal and found facilitating conditions, habit and performance expectancy as significant factors. Tak and Panwar (2017) found hedonic motivation and habit as strongly influencing behavioral intention and facilitating conditions influencing usage in case of mobile based shopping in India. They extended the UTAUT 2 model with deal proneness as additional factor. Farooq et al. (2017) in their study on adoption of lecture capture system in Malaysia, found all constructs of UTAUT2 as significant and positive in influencing behavior. They included personal innovativeness as additional factor. Kwateng et al. (2018) in their study usage of mobile banking in Ghana found only habit and price value as significant. They included trust as an additional variable which was found significant. They also found age, gender, education and user experience moderating the relationship between behavioral intention and usage. Shaw and Sergueeva (2019) found hedonic motivation and perceived value.as significant in their study on usage of mobile commerce in Canada. They extended the study with perceived value and perceived privacy concerns. The price value is replaced with perceived value.

The above observation from the literature suggests that all constructs undertaken as significant in the UTAUT 2 model, may not be significant in all cases and may depend on the item being evaluated and other factors. Many researchers also extended the model and found additional factors as significant. Thus, researcher also intends to add additional factors to the UTAUT2 model based on specific relevance to OTT video streaming platform and check its relevance.

The constructs undertaken for the study are

i) Performance Expectancy (PE) – It is the user's perception that technology will improve their performance (Venkatesh et al., 2012). Performance expectancy was found to be significantly influencing behavioral intention in many studies (Oliveira et al., 2016; Jambulingam, 2013; Nair et al., 2015, Chua et al., 2018, Sair & Danish, 2018). For this study, PE is considered as the user perception that usage of OTT video streaming platform will lead to improvement in performing his /her activities. However, some studies found influence of PE on behavioral intention as insignificant as in case of smartphone fitness app in India by Dhiman et al. (2019).

ii) Effort Expectancy (EE) – It is about the effort that is required to use any technology or the easiness in using a technology (Venkatesh et al., 2011, Janbulingam, 2013). Effort expectancy is found to be influencing behavioral intention in case of using information technology by trainee teachers in Singapore (Teo and Noyes, 2012), m-learning in university students of Malaysia (Tan, Sim, Ooi and Phusavat, 2011). However, effort expectancy was found insignificant in influencing behavioral intention in technology adoption as in case of 3G mobile telecommunication services in Taiwan (Wu, Tao and Yang, 2008), block chain technology by Malaysian public sector officers (Latif & Zakaria, 2020).

iii) Social Influence – The perception of an individual people close to him/her such as friends, relatives, peers believe that individual should use the technology (Venkatesh et al., 2003)
Social influence has significant influence on consumer's behavioral intention as in block chain technology by Malaysian public sector officers (Latif & Zakaria, 2020); friends influence in adoption of mobile apps by students in U.S. Midwest universities (Taylor et al., 2011) and mobile payment in Portugal (Oliveira et al., 2016); lecture capture system in Malaysia (Farooq et al., 2017). Some studies found social influence as insignificant in influence behavioral intentions as in use of mobile apps by students of Southeast America (Yang, 2013); health and fitness app in U.S. (Yuan et al., 2015).

iv) Facilitating Conditions (FC) – The perception of an individual that organizational infrastructure and technical infrastructure exists to support the use of technology (Venkatesh et al., 2003). Facilitating conditions was found to be positively influencing the behavioral intentions as in case of users' adoption of internet banking in Malaysia (Foon & Fah, 2011); adoption of 3G services (Wu et al., 2008). However, few studies found this influence as insignificant as in case of adoption of m-learning (Jamulingam, 2013; Teo & Noyes, 2012).

v) Hedonic Motivation (HM) – It is pleasure derived from using a technology (Brown & Venkatesh, 2005). Many studies found hedonic motivation as an influence factor of behavioral intentions as in case of mobile food ordering app in Jordan (Alalwan, 2020); mobile app based shopping in India (Tak & Panwar, 2017); lecture capture system in Malaysia (Farooq et al., 2017). However, some studies concluded that hedonic motivation do not positively influence behavioral intentions as in case of smartphone fitness app in India (Dhiman et al., 2019); use of travel apps in India (Gupta et al., 2018).

vi) Price Value – It is the perception of the benefit received from using a technology against the cost incurred to obtain the technology (Dodds, Monroe, and Grewal, 1991). Price value was found as a significant factor in influencing behavioral intention m-banking in Ghana by Kwateng et al., (2018), and lecture capture system in Malaysia (Farooq et al., 2017). Interestingly, Tamilmani et al. (2018) in their studies mentioned that around 59% of 79 empirical studies based on UTAUT2 excluded price value from their research model. It was mainly because the technology these research papers included was mostly free of cost, however, in case of OTT video streaming it is not the case, hence makes price value an important construct. Hence the effect of price value on actual usage becomes important in case of OTT video streaming platforms.

vii) Habit (HT) – Habit is the automatic behavior of an individual due to learning (Limayem et al., 2007) and can be a natural behavior (Kim and Malhotra, 2005). Habit was found significant in many studies including mobile food ordering apps in Jordan (Alalwan, 2020), mobile app based shopping in India (Tak & Panwar, 2017), mobile health adoption in Portugal (Duarte & Pinho, 2017). Habit was found as insignificant in study of health & fitness apps use in U.S. (Yang, 2013). Tamilmani et al. (2019) in their studies mentioned that around 65% of 66 empirical studies based on UTAUT2 excluded habit their research model citing mostly that in case of adoption of new technology, habit is not an issue. OTT video streaming is not a very new technology and is already in market for last 4 – 5 years, hence habit influence on actual usage is also need to be explored.

viii) Content Availability (CA) – It is the different types of content provided by the OTT service providers in terms of language, genre, quality etc. (Indrawati and Haryoto, 2015). Sundaravel and Elangovan (2020) found that original content on OTT platforms influences user intention and intention to purchase and use an OTT video streaming platform.

ix) Behavioral Intention (BI) - Behavioral intention is considering the fact the intention to consume influences behavior (Ajzen, 1991). It is the extent to which an individual is likely to use technology services for a long time. It suggests how much an individual has planned consciously to perform or not to perform some predefined future behavior (Huang & Kao, 2015).

The following hypotheses are framed

H1: PE influences BI for using OTT video streaming platforms.

H2: EE influences BI for using OTT video streaming platforms.

H3: SI influences BI for using OTT video streaming platforms.

H4: FC influences BI for using OTT video streaming platforms.

H5: HM influences BI for using OTT video streaming platforms.

H6: PV influences BI for using OTT video streaming platforms.

H7: HT influences BI for using OTT video streaming platforms.

x) Actual Usage (AU) - Whether it use intention of behavioral intention actually converts to consumer using the service is actual usage. Many empirical studies have concluded that intention to use a technology significantly predict the actual use behavior (Tao, D., 2009; Febrianto et al., 2018).

The following hypotheses are framed

H8: PV influences AU for using OTT video streaming platforms.

H9: HT influences AU for using OTT video streaming platforms.

H10: CA influences AU for using OTT video streaming platforms.

Venkatesh et al. (2012) also included the moderating effect of age, gender and use experience in adopting a new technology. It is important to study the moderating effect of variables in a relationship as they strengthen or weaken a relationship depending on whether they have significant effect or not. And these variables explain variance in relationship because of different situations or different populations (Du Plessis & De Witte, 2020). And for this reason in this research study, age, gender, use experience and occupation is considered as variable under study for moderation effect in the relationship between behavioral intention and actual usage. The occupation is considered as an additional factor than what is proposed in UTATU 2 model by Venkatesh et al. (2012). Hence, the hypotheses are proposed as

H11a: Gender has a moderating effect on the relationship between BI and AU

H11b: Age has a moderating effect on the relationship between BI and AU

H11c: Use experience has a moderating effect on the relationship between BI and AU

H11d: Occupation has a moderating effect on the relationship between BI and AU.

3. Research Methodology

3.1 Research Objective

- Propose an extended UTAUT2 model and test the model to define the variables influencing behavioral intention and actual usage of OTT video streaming platforms.
- Validate the influence of UTAUT2 defined exogenous variables on the endogenous variables (behavioral intention and actual usage)
- Test the influence of extended variable (content availability) on the actual usage of OTT video streaming platforms.
- Check the explanatory and predicting power of the user behavior by the proposed model.

3.2 Research Design

Based on the comprehensive review of the literature, a multidimensional behavioral intentional conceptual model was developed with UTAUT 2 model as a baseline model. This model, which is modification to UTAUT 2 model is extended with a variable named content availability as it is relevant for the OTT video streaming platform. The study of moderating effect of Gender, Age, Occupation and Use experience in the relationship between behavioral intention and actual usage is also proposed. The proposed model diagrammatic representation is shown below.

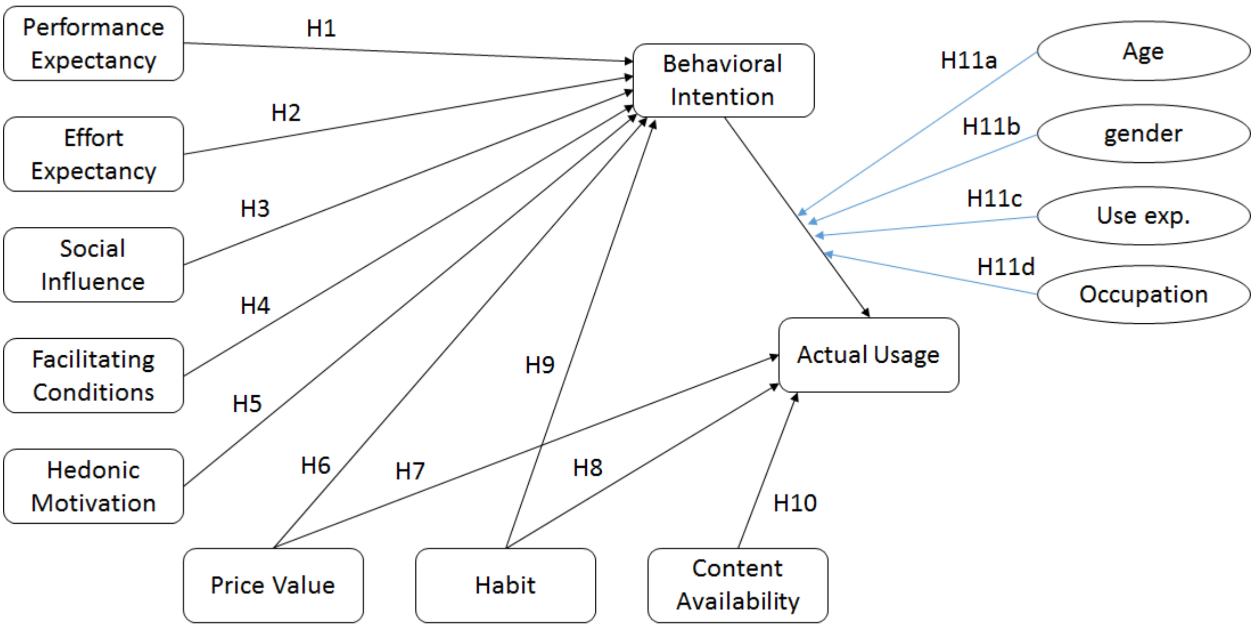

Figure 1: Proposed Conceptual model for the study

3.3 Measurement Instrument

The questionnaire is considered fit as a measurement instrument for collection of data for analysis. Depending on the data requirement, the questionnaire was divided into two section. Section – I to collect the demographic profile of the respondents including age, gender, occupation and years of using OTT platforms (experience). Section – II consisted of questions relating to the different constructs pertaining to this study.

The questionnaire was designed for collection of information keeping the UTAUT 2 model questionnaire as its baseline. The items are designed and adapted based on the extensive literature review. The questionnaire was then subjected to pilot survey for framing of the wording and to understand the relevance and suitability of each question. The pilot survey involved 50 samples of OTT users. The construction of the instrument is mentioned in table 2 through authors own judgment and understanding. The answering options used Likert-type Scale representing "strongly agree" to "strongly disagree", with scores varying from 5 to 1 respectively.

Table 1: Scale and Construct

Construct	Number of Items	Source (s)
Performance Expectancy	5	Venkatesh et al. (2012) (4 item); Authors own wording verified through pilot survey (1 item)
Effort Expectancy	5	Venkatesh et al. (2012) (4 item); Venkatesh et al. (2003) (1 item)
Social Influence	5	Venkatesh et al. (2012) (3 item); Yang (2013) (1 item); Authors own wording verified through pilot survey (1 item)
Facilitating Conditions	5	Venkatesh et al. (2012) (4 item); Venkatesh et al. (2003) (1 item)
Hedonic Motivation	7	Venkatesh et al. (2012)(3 item); Yang (2013) (2 item); Authors own wording verified through pilot survey (2 item)
Price Value	4	Venkatesh et al. (2012) (3 item) ; Authors own wording verified through pilot survey (1 item)
Habit	5	Venkatesh et al. (2012) (4 item); Authors own wording verified through pilot survey (1 item)
Content Availability	6	Indrawati & Haryoto (2015) (5 item); Authors own wording verified through pilot survey (1 item)
Behavioral Intention	5	Venkatesh et al. (2012) (3 item); Authors own wording verified through pilot survey (2 item)
Actual usage	3	Authors own wording verified through pilot survey

3.4 Data Collection

The questionnaire was distributed to around 650 individuals through online method and face-to-face survey method. The respondents were selected using non-probability, purposive sampling and snowballing was involved to have adequate responses are received within the stipulated time. It was also done to ensure that only those respondents who are actively using or used OTT services are used for responses (Kwateng et al., 2019). The data was collected over a period of four months stretching from June 2022 to October 2022 in North-eastern states of India, namely, Assam, Meghalaya, Nagaland and Tripura.

53 individuals didn't respond to the request, 21 questionnaire responses were rejected because of missing answers, and 12 questionnaire responses were found to be ineligible because of double and triple responses to some questions. Hence, in total 564 responses were found to be suitable enough for further analysis.

3.5 Data Analysis Technique

Once sufficient data is collected and its correctness is verified, it is used for data analysis. The Smart PLS v4.0 is used for analysis of the data in order to understand the various aspects of the proposed structural model. SmartPLS v.4.0 is utilized to perform PLS- Structural Equation Modelling as it is based on variance and is suitable when study is exploratory in nature than a covariance based SEM.

Multivariate statistics technique (Structural Equation Modelling) is used to estimate the relationship between the measured variable and latent constructs. Sarstedt et al. (2017) posits that partial least square SEM, i.e. a variance based SEM has greater statistical power at all sample size and uses all kinds of variance (Specific and error) from the independent variable to predict the variance in dependent variable. Two stage procedure is followed for assessing the measurement model and structural model (Anderson and Gerbin, 1988) using SmartPLS v.4.0. The reflective model (measurement model) is evaluated using indicator reliability (factor loading), internal consistency reliability, convergent reliability and discriminant validity. The formative (inner model) model is evaluated using collinearity, predictive relevance, explanatory powers and significance and relevance of path through path coefficient (Ringle et al. 2020, Benitez et al., 2020). Moderating and mediating role of the variables are being assessed through β value, t-statistics and p-values.

3.6 Descriptive analysis

The demographic profile of the respondents is presented below. Attempt is made to ensure that no bias is generated due to saturation of respondents in any single category.

Table 2: Descriptive Analysis

Demographic Variable	Category	No. of respondents	Percentage
Gender	Male	377	66.8%
	Female	187	33.2%
Age (in years)	Below 25	262	46.4%
	25 – 35	97	17.2%
	35 – 45	108	19.2%
	Above 45	97	17.2%
OTT user experience	Less than 2 years	270	47.8%
	2 years and above	294	52.2%
Occupation	Student	256	45.4%
	Working Professional	96	17.1%
	Business	112	19.8%
	Not employed	100	17.7%

Source: Author's calculation

4 Analysis and Results

4.1 Measurement Model

4.1.1 Common Method Bias

While measuring behaviors, answers of respondents may vary because of opinions and perceptions depending on context, situation or the way the questions are framed. Harman's single –factor test resulted conducted through SPSS v.20 as shown in Table 2, reports that variance explained by single components is 36.136% which is well below the threshold value of 50% (Podsakoff & Organ, 1986). Thus, the study can be considered as free of common method bias.

Table 3: Total Variance explained (partial output from SPSS v.20)

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	18.673	37.347	37.347	18.068	36.136	36.136
2	6.049	12.097	49.444			
3	3.821	7.642	57.086			
4	2.560	5.119	62.205			

4.1.2 Item reliability, Composite reliability and Convergent validity

In order to check the item reliability of the items in the measurement model, first the factor loading was analyzed. Since the item loadings are more than 0.70, hence the item reliability is achieved (Hair et al., 2011). The table shows the Dillion – Goldstein's rho (rho_a) is above 0.70. The composite reliability, CR values are >0.70. Suggesting internal consistency reliability of the measures. The Cronbach's alpha value was also checked for the reliability of the construct, and as per benchmark set ($\alpha > 0.70$), the instrument is considered reliability (Hair et al., 2011). All the average variance extracted (AVE) meets the minimum criteria of 0.50 (Hair et al. 2011).

Table 4: Construct reliability and validity (Connecting two SmartPLS v.4.0 outputs)

	Items	Factor Loadings	Cronbach's alpha	CR(Rho_a)	CR(Rho_c)	AVE
AU	AU1	0.855	0.859	0.871	0.914	0.779
	AU2	0.917				
	AU3	0.875				
BI	BU1	0.895	0.93	0.932	0.947	0.781
	BU2	0.876				
	BU3	0.867				
	BU4	0.888				
	BU5	0.894				
PE	PE1	0.92	0.927	0.937	0.945	0.775
	PE2	0.923				
	PE3	0.908				
	PE4	0.811				

	PE5	0.833				
EE	EE1	0.833	0.928	0.935	0.945	0.776
	EE2	0.88				
	EE3	0.923				
	EE4	0.846				
	EE5	0.918				
SI	SI1	0.847	0.934	0.947	0.95	0.792
	SI2	0.936				
	SI3	0.843				
	SI4	0.885				
	SI5	0.934				
FC	FC1	0.887	0.934	0.941	0.95	0.792
	FC2	0.907				
	FC3	0.784				
	FC4	0.93				
	FC5	0.934				
HM	HM1	0.896	0.933	0.944	0.945	0.713
	HM2	0.868				
	HM3	0.831				
	HM4	0.834				
	HM5	0.804				
	HM6	0.821				
	HM7	0.852				
HT	HT1	0.874	0.903	0.904	0.928	0.721
	HT2	0.82				
	HT3	0.856				
	HT4	0.848				
	HT5	0.845				
PV	PV1	0.909	0.937	0.942	9.555	0.841
	PV2	0.906				
	PV3	0.928				
	PV4	0.925				
CA	CA1	0.838	0.942	0.954	0.954	0.775
	CA2	0.881				
	CA3	0.89				
	CA4	0.904				
	CA5	0.885				
	CA6	0.882				

4.1.3 Discriminant Validity

In order to ensure that a measure of interest is not a reflection of some other measure undertaken for the study, correlation between the measures is checked. Fornell-Larcker criterion table below shows that the square root of AVE (diagonal values) is greater than the correlation with other constructs, and hence there is discriminant validity (Fornell & Larcker, 1981).

Table 5: Discriminant Validity – Fornell – Larcker criterion (Author's calculation)

Construct	AVE	Square root (AVE)
AU	0.779	0.883
BI	0.781	0.884
PE	0.775	0.88
EE	0.776	0.881
SI	0.792	0.888
FC	0.792	0.888
HM	0.713	0.844
HT	0.721	0.849
PV	0.841	0.917
CA	0.775	0.88

Fornell-Larcker criterion output from SmartPLS v.4.0

	AU	BI	CA	EE	FC	HM	HT	PE	PV	SI
AU	**0.883**									
BI	0.627	**0.884**								
CA	0.19	0.364	**0.88**							
EE	0.302	0.285	0.315	**0.881**						
FC	0.378	0.296	0.317	0.514	**0.89**					
HM	0.228	0.414	0.79	0.291	0.287	**0.844**				
HT	0.305	0.382	0.186	0.403	0.381	0.155	**0.849**			
PE	0.524	0.597	0.584	0.51	0.538	0.528	0.492	**0.88**		
PV	0.514	0.544	0.407	0.383	0.348	0.353	0.5	0.687	**0.917**	
SI	0.445	0.429	0.311	0.56	0.578	0.251	0.415	0.647	0.415	**0.89**

In order to further verify the discriminant validity, Heterortrait – Monotrait ratio (HTMT) test was performed in the SmartPLS. The output of the HTMT matrix is shown below, and it can be seen that the correlation are below 0.85, and hence establishing discriminant validity (Henseler et al., 2015, Hair et al., 2010)

Table 6: Discriminant Validity – Heterotrait monotrait ratio (Matrix) (Output from SmartPLS)

	AU	BI	CA	EE	FC	HM	HT	PE	PV	SI
AU										
BI	0.691									
CA	0.2	0.381								
EE	0.329	0.302	0.337							
FC	0.423	0.317	0.338	0.553						
HM	0.237	0.433	0.844	0.312	0.309					
HT	0.338	0.414	0.194	0.437	0.414	0.166				
PE	0.583	0.639	0.618	0.547	0.583	0.559	0.535			
PV	0.565	0.577	0.429	0.412	0.377	0.374	0.541	0.731		
SI	0.488	0.452	0.319	0.592	0.624	0.26	0.449	0.695	0.436	

As a third criteria, the cross loading of individual items in the construct is checked. The cross loading output from SmartPLS is shown in the Table 4. It can be clearly observed that the items loadings to the construct are within the acceptable range of >0.70. Hence, there is no cross loading and measures are not reflection of any other measures (Hair et al., 2011)

Hence, the measurement model is valid in terms of reliability, convergent and divergent validity and can be used for further analyzing the UTAUT2 extended model for understanding the behavioral intention and actual usage of OTT video streaming platforms.

4.2 Structural Model Assessment

4.2.1 Collinearity Assessment

In order to assess the structural model, first the collinearity issue is checked. The table below shows the Variance Inflation factors (VIF) values from the SmartPLS v.4.0. Since all the VIF values are less than 5, hence there is no collinearity issues in the data (Hair, Ringle & Sarstedt, 2011).

Table 7: VIF inner model values (Output from Smart PLS)

VIF Inner model		
	AU	BI
AU		
BI	3.375	
CA	1.258	
EE		1.682
FC		1.729
HM		1.457
HT	1.384	1.528
PE		3.481
PV	1.822	2.056
SI		2.195

4.2.2 Estimating Path Coefficients

In order to estimate the path coefficients, which represents hypothesized relationship among the constructs, PLS-SEM algorithm is run. The goal is not only to identify significant path coefficients but significant and relevant effects. The table below shows the output from SmartPLS v.4.

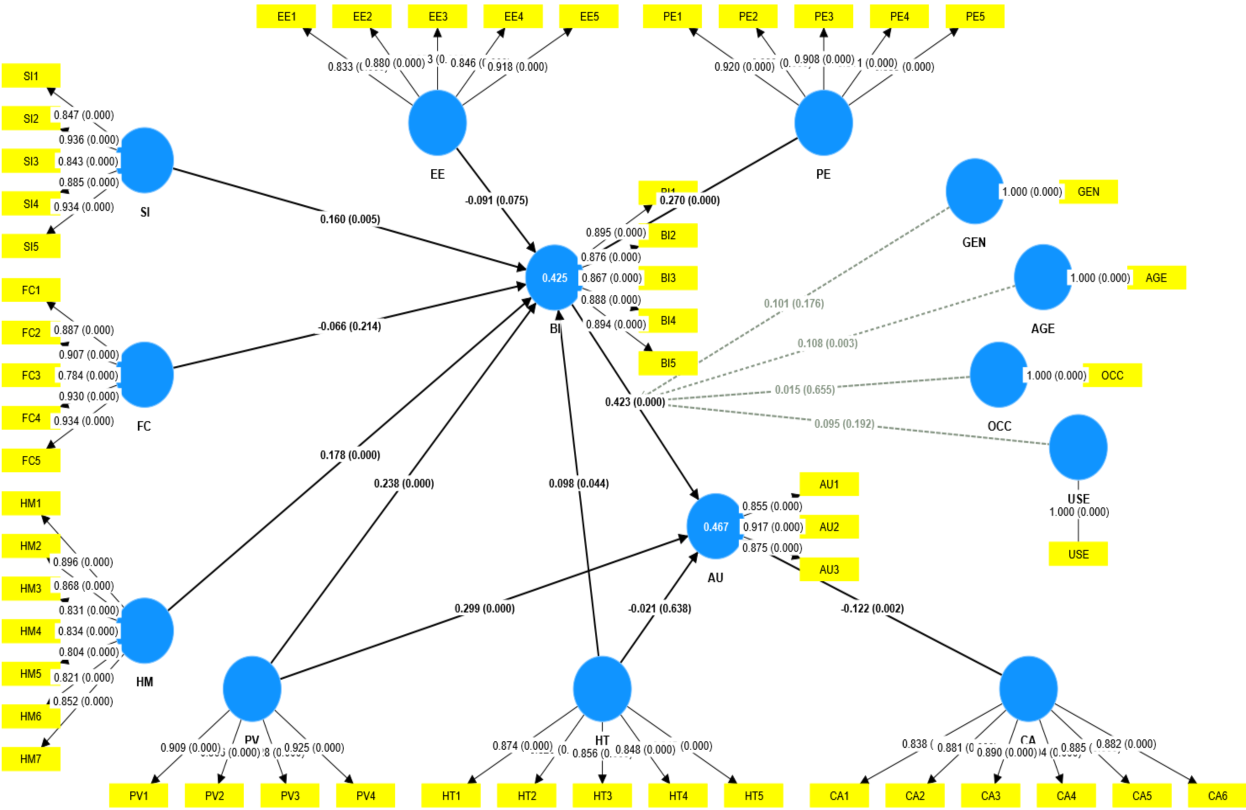

Figure 2: Path analysis of the proposed structural model (Bootstrapping output from SmartPLS)

With T statistics greater than 1.96 and p-value less than 0.05, the path BI – AU, PE – BI, SI – BI, HM – BI, PV – BI, and HT- BI are found significant. The path connecting EE & FC to BI are not significant. In case of Actual Usage (AU), the path CA –AU, and PV – AU are found significant, while HT to AU is found insignificant.

Table 8: Path Coefficients – Mean, STDEV, T values, P values (Output from SmartPLS)

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
BI -> AU	0.423	0.424	0.064	6.625	0
PE -> BI	0.27	0.27	0.072	3.735	0
EE -> BI	-0.091	-0.091	0.051	1.784	0.075
SI -> BI	0.16	0.16	0.057	2.778	0.005
FC -> BI	-0.066	-0.066	0.053	1.242	0.214
HM -> BI	0.178	0.179	0.047	3.755	0
PV -> BI	0.238	0.238	0.055	4.349	0
HT -> BI	0.098	0.1	0.049	2.018	0.044
CA -> AU	-0.122	-0.121	0.039	3.125	0.002
HT -> AU	-0.021	-0.021	0.045	0.471	0.638
PV -> AU	0.299	0.299	0.048	6.172	0

In the path coefficients – confidence interval bias corrected, we try to check whether zero falls into 95%

confidence interval (i.e. between 2.50% and 97.5% CI). From the table 10 data, we observe that the path from EE to BI, FC to BI and HT to AU has zero in between 2.50% to 97.5% confidence interval, making it an insignificant relationship. However, the HT – BI relationship in the confidence interval bias corrected shows a negative value at 2.5% and positive value at 97.5%, indicating presence of zero in between. Thus, the HT – BI path is also not significant.

Table 9: Path Coefficients – Confidence Interval bias corrected (Output from SmartPLS)

	Original sample (O)	Sample mean (M)	Bias	2.50%	97.50%
BI -> AU	0.423	0.424	0.001	0.293	0.543
PE -> BI	0.27	0.27	0	0.123	0.405
EE -> BI	-0.091	-0.091	0	**-0.192**	**0.009**
SI -> BI	0.16	0.16	0	0.048	0.272
FC -> BI	-0.066	-0.066	0	**-0.168**	**0.038**
HM -> BI	0.178	0.179	0.001	0.084	0.27
HT -> BI	0.098	0.1	0.002	-0.003	0.189
PV -> BI	0.238	0.238	-0.001	0.129	0.343
CA -> AU	-0.122	-0.121	0.001	-0.199	-0.044
HT -> AU	-0.021	-0.021	0	**-0.108**	**0.065**
PV -> AU	0.299	0.299	0	0.205	0.393

4.2.3 Mediation Analysis

Mediating variable is an intermediate variable that acts between a dependent variable and an independent variables. Understanding mediating effect helps to understand the nature and strength of the relationship between independent and dependent variable.

In the study, behavioral intention can be considered as a mediating variable leading to actual usage. Hence, the author has made an attempt to understand the relationship of the exogenous variables with the final output (actual usage). The mediation effect size can also be evaluated to understand the proportion of the total effect mediated by the mediator. Total effect is the overall effect of the independent variable on the dependent variable including both direct effect and indirect effect through the mediator. (Baron and Kenny, 1986; Shrout & Bolger, 2002; Preacher & Hayes, 2008)

Table 10: Specific Indirect effect (Mean, STDEV, T value, P value) (Output from SmartPLS)

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
HM -> BI -> AU	0.075	0.076	0.024	3.192	0.001
HT -> BI -> AU	0.042	0.042	0.021	1.965	0.049
FC -> BI -> AU	-0.028	-0.028	0.023	1.201	0.23
EE -> BI -> AU	-0.039	-0.038	0.022	1.738	0.082
SI -> BI -> AU	0.067	0.067	0.026	2.638	0.008
PV -> BI -> AU	0.101	0.101	0.027	3.763	0
PE -> BI -> AU	0.114	0.115	0.037	3.061	0.002

It can be observed from the table above that except EE and FC, all other constructs (HM, HT, PE, PV, and

SI) have significant indirect effect on the actual usage through behavioral intention. It was observed from the path coefficient all other paths were significant except EE to AU through BI and FC to AU through BI. Interestingly, Habit (HT) which has insignificant direct effect on BI (Baron and Kenny, 1986; Shrout & Bolger, 2002; Preacher & Hayes, 2008).

4.2.4 Estimation of coefficient of determination (R^2)

The R^2, Coefficient of Determination represents the amount of variance in the endogenous construct explained by all the exogenous construct linked to it. The following table shows the output of the PLS-SEM results from SmartPLS v.4.

Table 11 : R-square – Overview (Output from SmartPLS)

	R-square	R-square adjusted
AU	0.467	0.456
BI	0.425	0.418

From the data, it is observed that 41.8% of the variance in behavioral intention (BI) is explained by the exogenous variables connected to it. And 45.6% of the variance in Actual usage (AU) is explained by the exogenous construct linked to it. Thus the R-Square can be considered as moderate values. (Hair et al.(2011) posited values of 0.75, 0.50 and 0.25 as substantial, moderate and weak R-square. Chin (1998) considered 0.67, 0.33 and 0.19 as substantial, moderate and weak R-square values.)

4.2.5 Effect size (f2)

The effect size denotes the strength of each measure in explaining the variance in the dependent variable. The F-square output from SmartPLS is shown below. F-square value of 0.02 to 0.15, 0.15 to 0.35 and greater than 0.35 can be considered to have small, moderate and large effect in the dependent variables (Hair et al., 2011; Cohen, 1992)

Thus, it can be observed that BI has moderate effect on AU. CA and PV have small effect on AU.
CA, HM, PE, PV, and SI have small effect on behavioral intention (BI),

Table 12: f-square matrix (Output from SmartPLS and Author interpretation)

	AU	BI	Effect Size	Significance
AU				
BI	0.1		Medium effect	Significant
CA	0.022		Medium effect	Significant
EE		0.009		
FC		0.004		
HM		0.038	Large effect	Significant
HT	0.001	0.011		
PE		0.036	Large effect	Significant
PV	0.092	0.048	Large effect	Significant
SI		0.02	Medium effect	Significant

4.2.6 Predictive Relevance (Q2)

In the last step of analysis, predictive relevance, Stone-Geisser value (Q2) is calculated using PLS predict feature of SmartPLS v.4. It measures whether a model has predictive relevance of the endogenous construct. A value greater than zero indicates that values are well re-constructed and that the model has predictive relevance. Q-square values are benchmarked at $0.02<Q^2<0.15$, $0.15<Q^2<0.35$ and $Q^2>0.35$ for weak, moderate and strong degree of predictive relevance of each effect (Hair et al., 2019).
Hence predictive relevance on BI is strong and on AU is moderate as represented by the below analysis.

Table 13: Predictive Relevance Q-Square (Output from SmartPLS)

	Q^2predict	RMSE	MAE
AU	0.296	0.842	0.657
BI	0.402	0.775	0.612

4.2.7 Goodness of Fit

For a better model fit, the SRMR (Standardized Root Mean Square Residual), which is an absolute measure of fit, a value of zero is considered as perfect fit. A value less than 0.08 is generally considered as a good fit (Hu & Bentler, 1998). NFI (Normed Fit Index) ranges between 0 to 1 and a value closer to 1 is good fit (Bentler and Bonett, 1980).

From the Model fit data obtained from SmartPLS, it can be observed that the model fit criterion are achieved. And the proposed model can be considered as a good fit.

Table 14 : Model Fit (Output from SmartPLS)

	Saturated model	Estimated model
SRMR	0.047	0.05
d_ULS	3.295	3.763
d_G	1.902	1.937
Chi-square	5895.451	5951.382
NFI	0.803	0.801

4.3 Moderating role of gender, age, occupation and user experience

When relationship between the independent variable and dependent variables is influenced by presence of a third variable, it is termed as moderating effect. Moderating variable affects the strengths or direction of the relationship between dependent and independent variable (Du Plessis & De Witte, 2020, Moradi et al., 2021).

The moderating variables that are considered in this study are age, gender, years of using OTT (Use experience) and occupation to understand their influence over the relationship between the behavioral intention and actual usage of OTT video streaming platforms. In order to determine the moderating roles of the variables in the relationships between behavioral intention and actual usage, the path coefficients are determined using SmartPLS.

Table 15: Moderating path coefficients (Output from SmartPLS)

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
GEN x BI -> AU	0.101	0.099	0.075	1.354	0.176
AGE x BI -> AU	0.108	0.107	0.036	3.018	0.003
USE x BI -> AU	0.095	0.094	0.073	1.304	0.192
OCC x BI -> AU	0.015	0.016	0.035	0.446	0.655

	Original sample (O)	Sample mean (M)	Bias	2.50%	97.50%
GEN x BI -> AU	0.101	0.099	-0.002	**-0.042**	**0.253**
AGE x BI -> AU	0.108	0.107	0	0.036	0.177
USE x BI -> AU	0.095	0.094	-0.001	**-0.048**	**0.237**
OCC x BI -> AU	0.015	0.016	0.001	**-0.051**	**0.086**

There is only one relationship that is significant i.e. Age has a moderating effect on the relationship between BI and AU. And the effect is positive, thus, age strengthens the relationship between BI and AU (Du Plessis & De Witte, 2020, Moradi et al., 2021)

4.4 Hypotheses testing

To verify the posited hypotheses for the proposed path, bootstrapping method with 5000 samples was run in SmartPLS v.4.0. The following t-statistics and p-value were generated. The significance was tallied at 95% level.

Table 16: Hypotheses testing (SmarPLS output and Author Interpretations)

Hypotheses	Paths	T statistics	P values	Result
H1	Performance expectancy – Behavioral intention	3.735	0**	Supported
H2	Effort expectancy – Behavioral intention	1.784	0.075	Not Supported
H3	Social influence – Behavioral intention	2.778	0.005**	Supported
H4	Facilitating condition – Behavioral intention	1.242	0.214	Not-supported
H5	Hedonic motivation – Behavioral intention	3.755	0**	Supported
H6	Price value – Behavioral intention	4.349	0**	Supported
H7	Habit - Behavioral intention	2.018	0.044**	Supported
H8	Price value – Actual usage	6.172	0**	Supported

H9	Habit – Actual usage	0.471	0.638	Not Supported
H10	Content availability – Actual usage	3.125	0.002**	Supported
H11a	Gen moderates BI -> AU	1.354	0.176	Not supported
H11b	Age moderates BI -> AU	3.018	0.003**	Supported
H11c	Use Experience moderates BI -> AU	1.304	0.192	Not supported
H11d	Occupation moderates BI -> AU	0.446	0.655	Not supported

** Statistically significant with 95 percent confidence

It can be concluded that facilitating condition and effort expectancy has no significant influence over behavioral intention of using OTT video streaming platform. Similarly, habit has no significant influence over actual usage of OTT video streaming platform. It was also observed that only age positively moderates the relationship between BI and AU. Other variable have no significant moderating effects on the relationship between BI and AU.

5. Conclusion

The study was conducted to examine the UTAUT 2 model in the context of behavioral intention and actual usage of OTT video streaming platforms in India. The UTAUT2 model was extended with one construct namely, content validity. The model was assess using structural equation modeling run through SmartPLS v.4.0

After verifying the indicator reliability and internal consistency reliability, the convergent validity between the item within the construct and divergent validity between the constructs were also checked and found to be within prescribed limits and concluded as reliable and valid.

The SEM model is assessed via path coefficients, explanatory power and predictive power obtained from the variance based SmartPLS v.4.0. The path coefficients and p-value indicated that all the path are significant except effort expectancy and facilitating conditions connecting to behavioral intention. The path leading from habit to actual usage was also found insignificant. The effect size as assessed from the f-sqare values shows these relationship having medium to large effects on the dependent variable. The explanatory power of the structural model expressed through R-square was towards moderate level (AU – 0.45 and BI – 0.41). The predictive power assess through the Q-square value shows that model is moderate in predicting actual usage (AU – 0.296) and strong in predicting behavioral intention (BI – 0.402). The structural model also meets the model fit criteria.

The study found a small positive significant moderating effect by age in the relationship between behavioral intention and actual. The other variables gender, occupation and use experience has no significant moderating effect on the relationship between BI and AU. It was also observed that behavioral intention is mediating the relationship between the exogenous variable and the actual usage of the OTT video streaming platforms. It was observed that except FC and EE, all other variables including, PE, SI, PV and HM have significant indirect effect on actual usage through behavioral intention.

6. Theoretical Implications

The analysis of the data collected confirms the correctness of the theoretical model conceptualized to study the behavioral intention and actual usage of the OTT video streaming platform. It also emphasized that the predictive relevance of the model is moderate in predicting actual usage and strong in predicting the behavioral intention. It clearly indicated that the extended UTAUT 2 model is relevant for predicting behavior of the consumers.

The outcome of the study verifies that the UTAUT2 model (Venkatesh et al., 2012) predicts the behavioral intentions in technological adoption. And this study provides enough evidence to consider it to influence the actual usage. It is also in agreement with other studies as of learning in China (EE, HT as insignificant, Yang, 2013), mobile payment in Portugal (PE & SI significant, Oliveira et al., 2016), travel apps in India (EE & FC as insignificant, Gupta et al., 2018), health and fitness app in U.S. (EE & FC as insignificant, Yuan et al., 2015).

This study contributes to the existing knowledge by verifying the influence of extended UTAUT 2 model in understanding OTT consumer behavior and provides a new perspective that may be explored further with other extensions relevant to the OTT platforms.

7. Limitations

In the study the UTAUT 2 model was extended only by one variable – content validity, the scope of the study can be expanded by extending the model by adding of more variable like effect of promotional schemes, DTH connections, effect of regional language etc. Only the path coefficients and significance assessment was done for moderating and mediating effect analysis, further advanced tools and techniques may be utilized for detailed analysis. The sample population was majorly from one part of the country, so there is a scope to extend the study to a larger spread of the population. The researchers has not included the effect of contextual responses in the data. The data was found to be platykurtik (with highest value of -2.00) and the skewness effect is not significant (highest value of 0.753).

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