Adoption of OTT platforms: Analyzing User Behavior through the UTAUT2 Model

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ABSTRACT

Purpose: This study applied the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) to examine factors influencing the adoption of OTT platforms among youth in Navsari city, India. With the growing popularity of OTT platforms, understanding their key adoption determinants can help service providers enhance user engagement and satisfaction.

Design/methodology/approach: A quantitative research approach was employed, using a structured questionnaire to collect data from 211 youth respondents. Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to analyze relationships among constructs and assess the model's predictive power.

Findings: Results indicate that Facilitating Conditions (FC), Habit (H), and Price Value (PV) significantly influence behavioral intention and actual OTT usage. Facilitating Conditions (FC) emerged as the strongest predictor, emphasizing the role of accessibility and resources. However, Effort Expectancy (EE), Performance Expectancy (PE), Social Influence (SI), and Hedonic Motivation (HM) did not significantly affect behavioral intention. The Q^2predict values for Behavior (0.479) and Behavioral Intention (0.449) confirm good predictive relevance.

Practical implications: OTT providers should enhance accessibility, affordability, and user engagement. Personalized recommendations, seamless user experience, and cost-effective subscription models can further boost adoption among youth.

Originality/value: This study applies UTAUT2 in OTT adoption research, contributing to technology acceptance literature. The finding that EE, PE, SI, and HM do not significantly influence behavioral intention contrasts with previous studies, opening avenues for further research.

Keywords: OTT platforms, UTAUT2 model, Youth, Behavioral Intention, Price Value, Facilitating Conditions, Habit.

INTRODUCTION

The advent of Internet and smartphones in 21st century has made information technologies an indispensable part of human life, that were mostly available only to organisational users during the late 20th century. Technology adoption and diffusion research is a mature stream of exploration within the contemporary information systems (IS) literature and IS researchers are in continuous quest to understand various factors influencing individual acceptance and use of emerging information technology (IT) (Hughes et al., 2016, 2017, 2020). This widespread research stream has witnessed assortment of research methodologies examining multitude of technologies in range of countries with the extant literature revealing numerous theories, contexts, units of analysis and research

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methods (Dwivedi & Williams, 2008; Choudrie & Dwivedi, 2005; Williams et al., 2009). The varying research contexts based on technology, user type, location, adoption time and task performed gave rise to many competing theories and models. For instance, Technology Acceptance Model (TAM), Diffusion of Innovation (DoI), Theory of Planned Behaviour (TPB), and Task Technology Fit (TTF) Theory that were mostly deployed to examine assortment of adoption and diffusion-related issues (Dwivedi et al., 2006, 2007; Dwivedi and Weerakkody, 2007; Kapoor et al., 2014). Based on exhaustive review of eight dominant technology adoption models, Venkatesh et al. (2003) developed unified theory of acceptance and use of technology (UTAUT) in the organisational context emphasising on the utilitarian value (extrinsic motivation) of organisational users after elimination of similar/redundant constructs (see Venkatesh et al., 2003 for review). The rise of consumer technologies necessitated the extension of UTAUT model to consumer context emphasising on hedonic value (intrinsic motivation) of technology users. This led to incorporation of three new constructs such as hedonic motivation, price value, and habit to original UTAUT, the new extended version is popularly refereed as UTAUT2. However, in UTAUT2, voluntariness of use was dropped as moderator since consumers have no organisational mandate and in many situations, consumer behaviour is voluntary (Venkatesh et al., 2012). The predictive ability of UTAUT2 theory is much higher in comparison to UTAUT; explaining about 74 percent of the variance on consumers' behavioural intention to and 52 percent of the variance in consumers' technology usage of focal technology (Venkatesh et al., 2016).

OTT platforms provides wide range of content, including movies, TV shows, documentaries, and original programming, is a significant factor. Exclusive or popular content can attract viewers to a specific platform. (Kumari, T. 2020). OTT Platforms provides opportunity to viewers to compare subscription fees, free trials, and bundling options to determine the best value for their money. (Kumari, T. 2020). OTT platforms that offer superior video and audio quality tend to attract more viewers. High-quality video streaming, including 4K and HDR content, can enhance the viewing experience. (Kumari, T. 2020). OTT platforms has user friendly interfaces. Viewers prefer platforms that are easy to use on various devices, such as smartphones, tablets, smart TVs, and computers. (Kumari, T. (2020). Viewers want to watch content on their preferred devices without compatibility issues. (Vahoniya, D. R., Darji, D. R.,Baruri, S., & Halpati, J. R. (2022).Offline Viewing) OTT platforms provides opportunity to download content for offline viewing. This feature adds value for viewers who want to watch content without an internet connection. (Dasgupta, D. S., & Grover, D. P. 2019). Development of technology that enables machine learning provides better viewing experience. As System sends you notifications and recommendations which suggest you shows with genres you've seen before. (Vahoniya, D. R., Darji, D. R., Baruri, S., & Halpati, J. R. (2022). Word-of-mouth recommendations, reviews, and ratings from friends, family, or online communities can influence a viewer's decision to try a particular OTT platform. (Dasgupta, D. S., & Grover, D. P. 2019).Multi-User Profiles: OTT platforms provides multiple user profiles within a single subscription can be appealing for families or households with different viewing preferences. (Vahoniya, D. R., Darji, D. R., Baruri, S., & Halpati, J. R. 2022). OTT platforms that offer accessibility features like subtitles, closed captions, and multiple language options can attract a more diverse audience. (Vahoniya, D. R., Darji, D. R., Baruri, S., & Halpati, J. R. 2022).

LITERATURE REVIEW

Technology Acceptance and Behavioral Intentions

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) is widely used to explain consumer and organizational adoption of digital technologies (Yuliani et al., 2024). The model extends the original UTAUT framework by incorporating additional constructs such as hedonic motivation, price value, and habits, making it more comprehensive for understanding user behavior in the digital era (Venkatesh et al., 2012).

Studies confirm that performance expectancy and effort expectancy significantly influence behavioral intentions, with users prioritizing perceived benefits and ease of use when adopting new technology (Enriquez et al., 2024). Social influence also plays a pivotal role, especially in environments where peer recommendations and societal trends impact decision-making (Hakimi et al., 2024).

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Factors Influcencing Technology Adopiton

Several studies emphasize the role of psychological and behavioral factors in technology adoption. Matt et al. (2015) employed the Push-Pull-Mooring (PPM) framework to analyze switching behaviors in technology use. Stock and Schulz (2015) investigated the role of consumer predispositions in adoption speed, indicating that early adopters are influenced by cognitive biases. Choi (2016) explored the impact of social presence and privacy concerns on smartphone-based social networking site (SNS) usage, finding that enjoyment significantly moderates adoption intention. Furthermore, Limayem et al. (2007) demonstrated that habit plays a crucial role in continued information system (IS) usage.

Use of Technology in different sector

he adoption of mobile banking and FinTech services has been extensively studied through TAM and UTAUT models. Shaikh and Karjaluoto (2016) identified key factors influencing mobile banking adoption in Finland, highlighting trust and perceived risk as major determinants. Alalwan et al. (2016) extended TAM to analyze mobile banking adoption in Jordan, finding that social influence and performance expectancy significantly impact user intention. The IoT adoption framework by Gao and Bai (2014) integrates TAM and social trust factors, emphasizing the need for security assurances in IoT applications. Similarly, Cimperman et al. (2016) applied UTAUT to study older adults' acceptance of home telehealth services, concluding that effort expectancy and social influence are critical factors. Alazzam et al. (2016) further extended UTAUT2 to analyze electronic health record (EHR) system adoption in Jordanian hospitals, reinforcing the importance of facilitating conditions and performance expectancy.

UTAUT2 Application in various sector

The application of UTAUT2 in higher education highlights key factors affecting technology adoption among students and faculty. Research indicates that performance expectancy is the strongest predictor of technology acceptance, as students perceive digital tools as enablers of academic success (Hakimi et al., 2024). Social influence, particularly from peers and instructors, further shapes students' willingness to adopt learning management systems and digital resources (Enriquez et al., 2024). Perceived ease of use, an extension of effort expectancy, also affects adoption rates, demonstrating the necessity for user-friendly digital interfaces in educational settings (Sembiring et al., 2024).

In the business sector, UTAUT2 is frequently employed to assess the adoption of digital tools, including e-accounting and e-commerce platforms. Research on MSMEs (Micro, Small, and Medium Enterprises) suggests that facilitating conditions, such as digital infrastructure and government support, significantly impact adoption rates (Sembiring et al., 2024). Furthermore, hedonic motivation and price value contribute to adoption decisions, particularly among businesses evaluating cost-effectiveness and perceived enjoyment in technology use (Yuliani et al., 2024). The integration of user experience studies within the UTAUT2 framework highlights the importance of intuitive and accessible technology solutions in driving successful digital transformation in small businesses (Hakimi et al., 2024).

Challenges in UTAUT2 Application and Contextual Adaptation

Despite its effectiveness, UTAUT2 faces challenges related to contextual adaptation across different industries and user demographics (Yuliani et al., 2024). Studies argue that while the model comprehensively explains behavioral intentions, its applicability varies based on cultural, technological, and economic factors (Sembiring et al., 2024).

Some researchers emphasize the need for empirical refinements, including the incorporation of external factors such as privacy concerns, regulatory policies, and user trust in AI-driven technologies (Hakimi et al., 2024). Additionally, studies suggest extending the model to incorporate dynamic factors like evolving consumer preferences and emerging technologies (Enriquez et al., 2024).

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Evolution and Global Expansion of OTT platforms

The development of Over-the-Top (OTT) platforms has transformed the global media landscape, enabling content distribution that bypasses traditional cable and satellite providers (Khanna et al., 2024). Initially restricted to specific markets, these services have expanded worldwide, driven by increased internet penetration and the growing demand for on-demand content (Vaidya et al., 2023). The COVID-19 pandemic further accelerated this shift, with significant growth in subscription-based and ad-supported streaming services, as consumers sought alternative entertainment options during lockdowns (Patni & Ansari, 2024).

Technology Advancements in OTT Services

Innovation in digital technology has played a crucial role in the rise of OTT platforms, improving content accessibility and streaming quality. High-speed internet, 5G deployment, and AI-powered recommendation algorithms have enhanced user experience and engagement (Khanna et al., 2024). Additionally, cloud computing and content delivery networks (CDNs) have facilitated seamless streaming across multiple devices, reducing buffering and enhancing video quality (Vaidya et al., 2023). These technological improvements have positioned OTT services as dominant players in the entertainment industry, competing directly with traditional media.

Changing Consumer Behaviors and Engagement with OTT

Consumer preferences have shifted significantly in response to the accessibility and convenience of OTT platforms. Personalized recommendations, interactive content, and subscription-based models have increased user retention and engagement (Patni & Ansari, 2024). Studies highlight that younger demographics, particularly Gen Z and millennials, prefer streaming services over traditional TV due to the flexibility of on-demand content and multi-device compatibility (Vaidya et al., 2023). Furthermore, social and cultural influences, such as peer recommendations and regional content preferences, continue to shape adoption patterns (Khanna et al., 2024).

Regulatory and Policy Challenges in OTT Streaming

As OTT platforms disrupt conventional broadcasting norms, regulatory bodies worldwide are addressing concerns related to content moderation, data privacy, and digital rights management (Khanna et al., 2024). Countries have introduced policies to ensure compliance with local content regulations and fair competition among streaming services (Vaidya et al., 2023). Additionally, issues related to subscription pricing, advertising transparency, and consumer data protection remain critical areas for future research and policy intervention (Patni & Ansari, 2024).

Historical Narratives and Their Influence on Media Trends

Although the historical context of the Ottoman Empire is not directly related to OTT platforms, historical narratives play an essential role in shaping contemporary media discourses (Başkan, 2023). Many streaming services incorporate historical dramas and documentaries, leveraging historical storytelling to engage global audiences. This highlights the interconnectedness between past and present in shaping content preferences and media consumption trends.

Theoretical Framework and Hypothesis development

Performance Expectancy

Venkatesh et al. (2003) defined performance expectancy as “the degree to which an individual believes that using the system will help a person to attain gains in job performance”. Previous research reports that performance expectancy was a significant forecaster of behavioral intention (Venkatesh et al., 2003).

H1: Performance Expectancy has a significant effect on behavioral intention to use OTT platform.

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Effort Expectancy

Effort expectancy is defined as "the degree of ease associated with the use of the system". Previous research supports that latent variables related to effort expectancy that was significant in determining a person's intention to adopt new technology (Zhou et al., 2010; Venkatesh et al., 2012)

H2: Effort Expectancy has a significant effect on behavioral intention to use OTT platform.

Social Influence

Social influence means the extent to which a person perceives how vital others believe he or she should use the technology. Previous research supports that social influence was significant in determining an individual's intention to use new technology (Moore and Benbasat, 1991; Venkatesh et al., 1996; Thompson et al., 1991).

H3: Social Influence has a significant effect on behaviroal intention to use OTT platform.

Facilitating Conditions

Facilitating conditions means the extent of availability of technical support for using the new technology (Venkatesh et al., 2003).

H4: Facilitating conditions has a significant effect on behaviroal intention to use OTT platform.

H5: Facilitating conditions has a significant effect on use behavior to OTT platforms.

Hedonic Motivation

Brown and Venkatesh (2005) defined hedonic motivation as an enjoyment or happiness resultant from using a technology and play significant part in determining new technology adoption.

H6: Hedonic Motivation has a significant effect on behavioral intention to use OTT platforms.

Habit

Habit is differentiated in two distinct ways. The first habit viewed as prior behaviour (Kim and Malhotra, 2005) and second, habit is where an individual believes the behaviour to be automatic (Lamayem et al., 2007). Venkatesh et al. (2012) modeled habit as having direct and indirect effect through behavioural intention.

H7: Habit has a significant effect on behaviroal intention to use OTT platform.

H8: Habit has a significant effect on use behavior of OTT platform.

Price Value

Price value is defined as the level of an individual's understanding of the monetary costs and benefits of using a system, PV is one of the factors affecting behavioural intentions of individuals to accept something (Moorthy et al., 2019; Venkatesh et al., 2012).

H9: Price value has a significant effect on behavioral intention to use OTT platform.

Behavioural Intention

Based on primary theory for all of the intention models discussed above we expect that behavioral intention would be best forecaster of actual behavior.

H10: Behavioral Intention has significant effect on use behavior of OTT platform.

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H11: Behaviroal Intention mediates the relationship between facilitating condition and use behavior of OTT platform.

H12: Behaviroal Intention mediates the relationship between Habit and use behavior.

Use Behavior

The number of times an individual uses information technology is referred to as use behavior (Ramírez-Correa et al., 2019). There is evidence that the cultural dimension, collectivism, and uncertainty avoidance have significant moderating effects on the use behavior of customers engaged in online banking (I. U. Khan, Hameed and Khan, 2017).

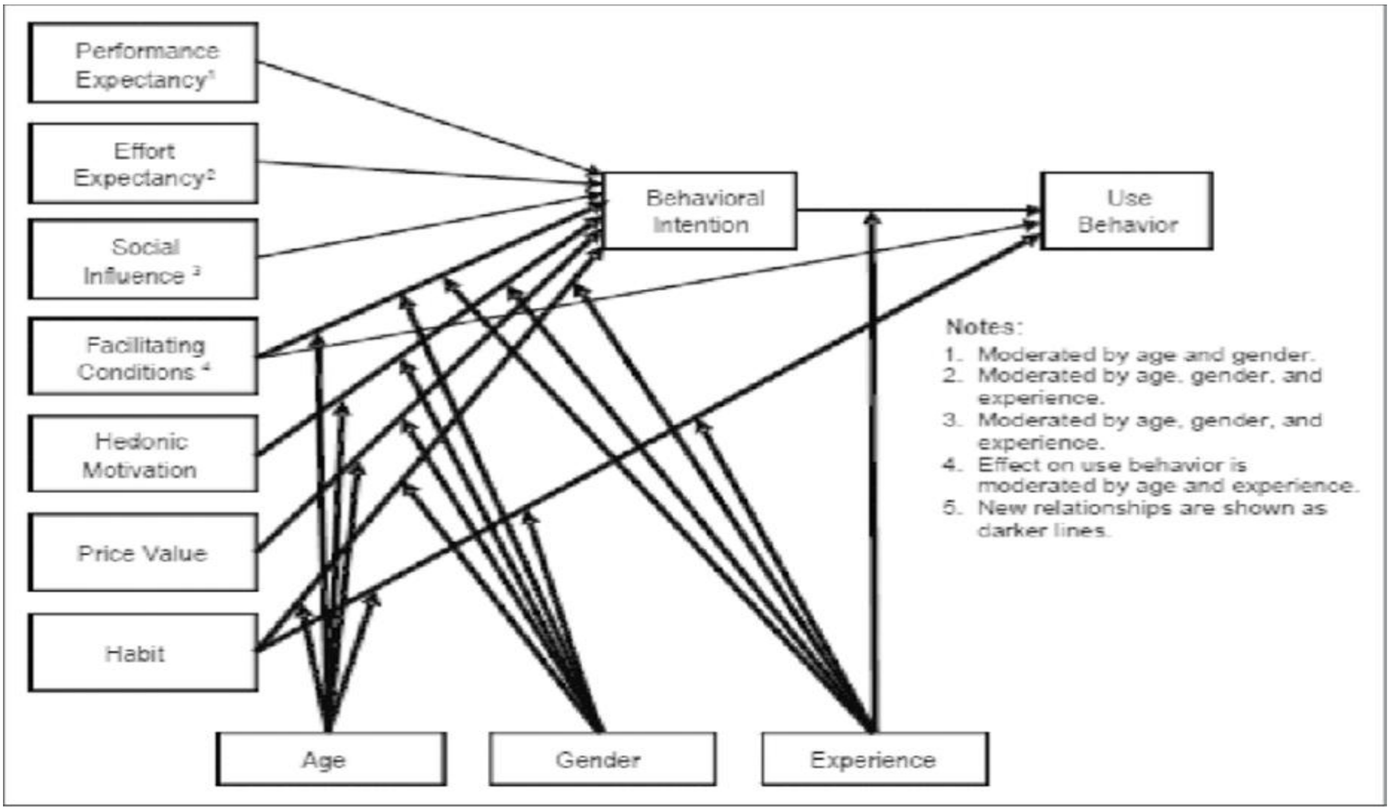

Fig. 1 The UTAUT2 model (Venkatesh et al. 2012)

RESEARCH METHODOLOGY

Research question

The pertinent research question that led to this study forward was: Which factors influence adoption of OTT platform among youths? To answer this question the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) was used (Venkateh et al, 2012).

Figure 2 proposes the final hypothesized structural model for the study. It consist of 7 exogenous variable (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating conditions, Hedonic motivation, Price value, Habit) and 2 endogenous variables (Behavioral intention and Use Beavior). Intention is hypothesized to act as a mediator between all relationships of exogenous and behavior.

Researach design and Sample

A quantitative research design was employed, using a structured questionnaire to collect data from 211 youth respondents of Navsari city. In testing the model, structural equation modelling approach was used (Byrne, 2016; Hair et al; 2019) where assessment of the measurement model and assessment of the structural model was done.

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Items used for the study

The 32 items used in the scale are as below:

Performance Expectancy

1. OTT platforms provide content relevant to my interests.
2. OTT platforms offer features (e.g., recommendations) that enhance my viewing experience.

Effort Expectancy

1. It requires minimal effort to search for content on OTT platforms.
2. The interface of OTT platforms is user-friendly.
3. I find it simple to customize my viewing preferences on OTT platforms.

Social Influence

1. I often discuss OTT shows and movies with people in my social group.
2. I feel motivated to use OTT platforms because others in my group use them.
3. My decision to subscribe to OTT platforms is influenced by popular trends.
4. I often see positive reviews about OTT platforms on social media.

Facilitating Conditions

1. I can easily afford to subscribe to OTT platforms providing content.
2. I have reliable internet access to watch content on OTT platform.
3. Using OTT platforms fits well within my daily routine.

Hedonic Motivation

1. Using OTT platforms is enjoyable.
2. I have fun exploring content on OTT platforms.
3. OTT platforms provide a stress-relieving experience.
4. Watching content on OTT platforms is entertaining.
5. OTT platforms add excitement to my daily routine.

Price Value

1. OTT platforms offer good value for the money I spend.
2. The cost of subscribing to OTT platforms is reasonable.
3. The benefits I get from OTT platforms justify the expense.
4. I feel the subscription fees are worth the content available.

Habit

1. Using OTT platform would become a habit for me.
2. I use OTT platforms as a way to relax without actively deciding to do so.
3. I automatically open an OTT app when I have free time.

Behavioral Intention

1. I intend to use OTT platforms regularly to watch my favorite shows/movie.
2. I plan to increase my time spent on OTT platforms in the near future to watch content.
3. I am willing to pay for premium OTT services to access better content.
4. I am likely to subscribe to additional OTT platforms.

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Behavior

1. I watch content on OTT platforms at least once a week.
2. I have a paid subscription to at least one OTT platform.
3. I frequently switch between different OTT platforms to explore content.
4. I actively participate in online discussions or reviews about content available on OTT platform.

Structural Equation Modeling

Structural Equation Modeling (SEM) is a powerful multivariate statistical technique used to analyze complex relationships between observed and latent variables.

It extends traditional regression and factor analysis by allowing researchers to test theoretical models involving multiple dependent and independent variables simultaneously.

SEM is widely applied in social sciences, psychology, business, education, and healthcare to assess relationships among constructs, validate measurement models, and examine causal pathways.

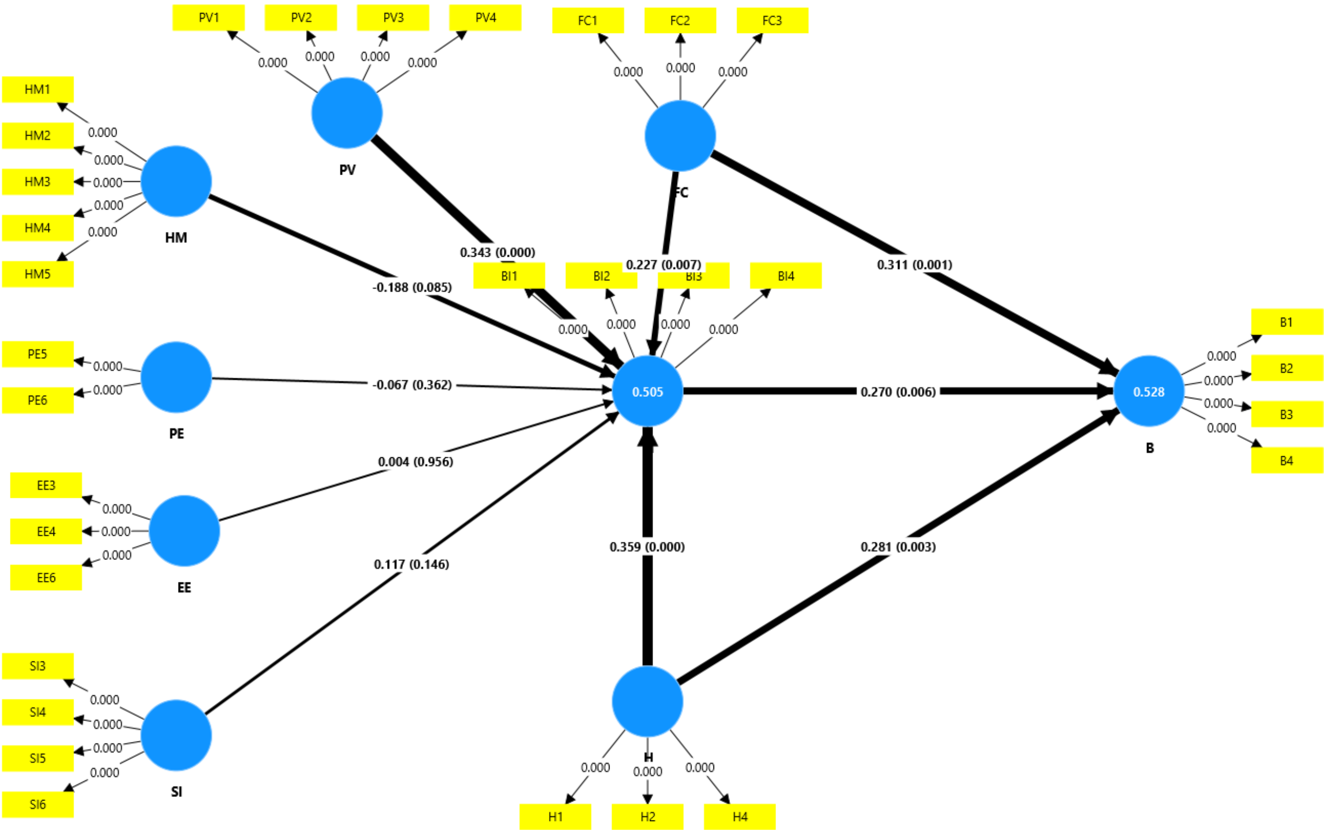

Figure 2 Hypothesized Model

RESULTS OF STRUCTURAL EQUATION MODELLING

Assessing reflective measurement model:

The first step in reflective measurement model assessment involves examining the indicator loadings. Loadings above 0.708 are recommended, as they indicate that the construct explains more than 50 per cent of the indicator's variance, thus providing acceptable item reliability.

The second step is assessing internal consistency reliability, most often using Jöreskog's (1971) composite reliability. Higher values generally indicate higher levels of reliability.

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Table 1: Assessing Reflective Measurement Model:

Construct	Items	Loadings	CR	Rho_a	Rho_c	AVE
Performance Expectancy (PE)	PE5	0.887	0.71	0.712	0.873	0.775
	PE6	0.874				
Effort Expectancy (EE)	EE3	0.719	0.766	0.826	0.861	0.676
	EE4	0.852				
	EE6	0.885				
Social Influence (SI)	SI3	0.739	0.779	0.787	0.857	0.6
	SI4	0.819				
	SI5	0.745				
	SI6	0.793	0.727	0.735	0.845	0.646
Facilitating Conditions (FC)	FC1	0.812				
	FC2	0.765				
	FC3	0.833	0.906	0.944	0.928	0.722
Hedonic Motivation (HM)	HM1	0.795				
	HM2	0.906				
	HM3	0.855				
	HM4	0.853				
	HM5	0.835				
Habit (H)	H1	0.869	0.767	0.769	0.866	0.683
	H2	0.812				
	H4	0.796				
Price Value (PV)	PV1	0.830	0.828	0.829	0.886	0.659
	PV2	0.792				
	PV3	0.802				
	PV4	0.823				
Behavioral Intention (BI)	BI1	0.735	0.812	0.814	0.877	0.64
	BI2	0.795				
	BI3	0.807				
	BI4	0.859				
Behavior (B)	B1	0.727	0.773	0.776	0.855	0.596
	B2	0.748				
	B3	0.820				
	B4	0.791				

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The table provides key measures of construct reliability and validity using Cronbach's alpha, Composite Reliability (rho_a & rho_c), and Average Variance Extracted (AVE).

Assessing Internal Consistency Reliability

Cronbach's Alpha (α): Measures internal consistency (should be **≥ 0.7**). Composite Reliability (rho_a & rho_c): Should be **≥ 0.7** for good reliability. (Hair et al. 2019). All constructs have Cronbach's alpha & Composite Reliability > 0.7, indicating strong internal consistency.

Assessing Convergent Validity

Average Variance Extracted (AVE): Measures how much variance is captured by a construct vs. measurement error. Should be ≥ 0.5 for acceptable validity. (Fornell & Larcker 1981). All constructs have AVE > 0.5, confirming convergent validity (each construct explains at least 50% of its variance).

Discriminant Validity Assessment (Fornell-Larcker Criterion)

The Fornell-Larcker criterion (1981)**,** which checks discriminant validity by ensuring that each construct shares more variance with its indicators than with other constructs. The **diagonal** values (highlited below) represent the square root of AVE for each construct. Discriminant validity is confirmed if the diagonal values are higher than all off-diagonal values in the same row/column. Each highlite diagonal value (√AVE) **is** greater than the correlations in its row/column**.** This confirms that each **construct** has more shared variance with its own indicators than with other constructs**.**

Table 2: Fornell-Larker Criterion

	B	**BI**	**EE**	**FC**	**H**	**HM**	**PE**	**PV**	**SI**
B	0.772								
BI	0.607	0.800							
EE	0.486	0.357	0.822						
FC	0.618	0.557	0.538	0.804					
H	0.611	0.582	0.468	0.556	0.826				
HM	0.611	0.428	0.707	0.644	0.674	0.849			
PE	0.410	0.240	0.654	0.462	0.379	0.619	0.881		
PV	0.637	0.612	0.537	0.654	0.535	0.586	0.393	0.812	
SI	0.519	0.476	0.472	0.478	0.546	0.564	0.385	0.539	0.775

Discriminant Validity Assement – Heterotrait-Monotrait (HTMT) ratio

As a replacement of Fornell-Larcker criterion (1981), Henseler et al. (2015) proposed the heterotrait-monotrait (HTMT) ratio of the correlations (Voorhees et al., 2016). The HTMT is defined as the mean value of the item correlations across constructs relative to the (geometric) mean of the average correlations for the items measuring the same construct. Discriminant validity problems are present when HTMT values are high. Henseler et al. (2015) propose a threshold value of 0.90 for structural models with constructs that are conceptually very similar, for instance cognitive satisfaction, affective satisfaction and loyalty. In such a setting, an HTMT value above 0.90 would suggest that discriminant validity is not present. But when constructs are conceptually more distinct, a lower, more conservative, threshold value is suggested, such as 0.85 (Henseler et al., 2015).

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Table 3: Heterotrait-Monotrait Ratio

	B	BI	EE	FC	H	HM	PE	PV	SI
B									
BI	0.763								
EE	0.609	0.425							
FC	0.820	0.707	0.715						
H	0.789	0.734	0.578	0.750					
HM	0.720	0.462	0.847	0.793	0.783				
PE	0.548	0.306	0.882	0.664	0.514	0.792			
PV	0.799	0.740	0.659	0.838	0.669	0.669	0.513		
SI	0.667	0.586	0.604	0.638	0.707	0.667	0.524	0.676	

Constructs (BI ↔ EE (0.425) , H ↔ EE (0.578), PE ↔ PV (0.513), PE ↔ SI (0.524), SI ↔ PV (0.676) meet the HTMT discriminant validity criteria. As their values do not exceed the 0.85 threshold. For construct (FC ↔ PV (0.838)) these values are below 0.90 but near 0.85.

Assessing Structural model

Collinearity statistics (VIF) – Outer Model List

Before assessing the structural relationships, collinearity must be examined to make sure it does not basis the regression results. Ideally, the VIF values should be close to 3 and lower. If collinearity is a problem, a frequently used option is to create higher-order models that can be supported by theory (Hair et al., 2017a).

Table 3: Collinearity Statistic (VIF) – Outer Model List

	VIF
B1	1.330
B2	1.486
B3	1.741
B4	1.619
BI1	1.369
BI2	1.773
BI3	1.875
BI4	2.258
EE3	1.429
EE4	1.684
EE6	1.653
FC1	1.379
FC2	1.417
FC3	1.556

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H1	1.815
H2	1.571
H4	1.466
HM1	2.285
HM2	3.833
HM3	2.531
HM4	3.134
HM5	1.872
PE5	1.436
PE6	1.436
PV1	1.917
PV2	1.649
PV3	1.908
PV4	1.901
SI3	1.542
SI4	1.666
SI5	1.356
SI6	1.611

The outer model assesses the relationship between indicators and their latent constructs. Most outer model VIF values are below 3, indicating low multicollinearity among constructs. HM2(3.833), HM4 (3.134) and HM3(2.531) indicates moderate multicollinearity in Hedonic motivation (HM) indicators. Overall the outer model does not exhibit serious multicollinearity issues.

Collinearity statistics (VIF) – Inner Model List

Table 4: Collinearity statistics (BIF) – Inner Model List

	VIF
BI -> B	1.716
EE -> BI	2.486
FC -> B	1.643
FC -> BI	2.200
H -> B	1.713
H -> BI	2.092
HM -> BI	3.402
PE -> BI	1.937
PV -> BI	2.122
SI -> BI	1.717

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The inner model examines relationships between latent variables. Most inner model VIF values are below 3, suggesting that multicollinearity among latent constructs in not severe.

Path Co-efficient and P value results

If collinearity is not an issue, the next step is examining the R square value of endogenous constructs. The R square measures the variance, which is explained in each of the endogenous constructs and is therefore a measure of the model's explanatory power (Shmueli and Koppius, 2011). The R square ranges from 0 to 1, with higher values indicating a greater explanatory power. As a guideline, R square values of 0.75, 0.50, and 0.25 can be considered as substantial, moderate and weak (Henselar et al., 2009; Hair et al., 2012).

Table 5: Path Co-effieicent (R^2 Statistics)

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
B	0.528	0.544	0.064	8.212	0
BI	0.505	0.53	0.062	8.092	0

Both Behavior (B) and Behavior (BI) have significant positive effects, as indicated by path coefficients, low standard deviations, and p-value of 0.000. The model demonstrates stable and precise estimates, with no signs of variability issue.

Path Co-efficient – Confidence interval bias corrected.

Table 6: Path Co-efficient – Confidence interval bias corrected values

	Original sample (O)	**Sample mean (M)**	**Bias**	**2.5%**	**97.5%**
BI -> B	0.270	0.274	0.004	0.082	0.470
EE -> BI	0.004	-0.004	-0.009	-0.134	0.168
FC -> B	0.311	0.303	-0.009	0.136	0.496
FC -> BI	0.227	0.228	0.001	0.062	0.398
H -> B	0.281	0.286	0.006	0.089	0.455
H -> BI	0.359	0.360	0.002	0.151	0.553
HM -> BI	-0.188	-0.184	0.005	-0.422	0.013
PE -> BI	-0.067	-0.064	0.004	-0.220	0.072
PV -> BI	0.343	0.340	-0.003	0.179	0.511
SI -> BI	0.117	0.121	0.004	-0.039	0.275

Significant Relationships (Support for Hypothesis)

- **BI → B (0.270)**: Behavioral intention significantly influences behavior.
- **FC → B (0.311)**: Facilitating conditions positively affect use behavior.
- **FC → BI (0.227)**: Facilitating conditions impact behavioral intention.
- **H → B (0.281)**: Habit influences use behavior.
- **H → BI (0.359)**: Habit affects behavioral intention.
- **PV → BI (0.343)**: Price value strongly influences behavioral intention.

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- **H→BI→B (0.034):** Partial mediation effect of behavioral intention on Habit and use behavior.
- **PV→BI→B (0.04):** Partial mediation effect of behavioral intention on Price value and use behavior.

Non-Significant Relationships (Hypothesis Not Supported)

- **EE → BI (0.004)**: Effort expectancy has no impact on behavioral intention.
- **HM → BI (-0.188)**: Hedonic motivation does not significantly affect behavioral intention.
- **PE → BI (-0.067)**: Performance expectancy has no significant impact on behavioral intention.
- **SI → BI (0.117)**: Social influence does not significantly impact behavioral intention.

F square (Effect size) value

Researchers can also asses how the removal of a certain predictor construct affects an endogenous construct's R square value. This metric is referred to as the **f^2** effect size. The guidelines for assessing **f^2** values of 0.02, 0.15, and 0.35 can be considered as small, medium and large effects (Cohen,1988).

Table 7: f^2 Effect size

	f-square (f^2)
BI -> B	0.090
EE -> BI	0.000
FC -> B	0.125
FC -> BI	0.048
H -> B	0.097
H -> BI	0.124
HM -> BI	0.021
PE -> BI	0.005
PV -> BI	0.112
SI -> BI	0.016

The analysis of f^2 effect sizes reveals that Facilitating Conditions (FC), Habit (H), and Price Value (PV) are the key drivers in the model. Among them, FC → B (0.125), H → BI (0.124), and PV → BI (0.112) demonstrate a moderate impact, indicating that facilitating conditions play a notable role in influencing behavior, habit significantly affects behavioral intention, and price value is an important determinant of behavioral intention.

Several factors exhibit a small but meaningful effect on the model. Specifically, Behavioral Intention (BI) impacts Behavior (B) (0.090) with a small effect, while Habit (H) also influences Behavior (B) (0.097) in a similar manner. Additionally, Facilitating Conditions (FC) contribute to Behavioral Intention (BI) (0.048), albeit with a minor effect, and Hedonic Motivation (HM) has a very small effect on Behavioral Intention (0.021).

On the other hand, some factors show negligible or no effect on behavioral intention. Effort Expectancy (EE) (0.000) has no influence, Performance Expectancy (PE) (0.005) has an almost insignificant impact, and Social Influence (SI) (0.016) contributes only marginally.

These results suggest that while facilitating conditions, habit, and perceived value are significant predictors, effort expectancy, performance expectancy, and social influence do not play a major role in shaping behavioral intention.

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Q square value

To assess the PLS path model's predictive accuracy is by calculating the Q square value (Geisser, 1974; Stone, 1974). As a guideline, Q square values should be larger than zero for a specific endogenous construct to indicate predictive accuracy of the structural model for that construct. As a rule of thumb, Q square values higher than 0, 0.25 and 0.50 depict small, medium and large predictive relevance. of the PLS-path model.

Table 8: Predictive accuracy by Q^2 value

	Q^2predict	**RMSE**	**MAE**
B	0.479	0.731	0.554
BI	0.449	0.751	0.536

Q square predict value for Behavior (0.479) and Behavioral Intention (0.449) are above zero indicating good predictive relevance of the model.

CONCLUSION

This study investigated the adoption and usage behavior of OTT platforms among the youth of Navsari city using the UTAUT2 model. A total of 211 respondents participated in the study, providing insights into the key determinants of behavioral intention and actual behavior. The reliability and validity of the measurement model were confirmed through Cronbach's alpha, composite reliability, AVE, and discriminant validity tests (Fornell-Larcker and HTMT criteria). Additionally, the structural model exhibited stable estimates with no severe multicollinearity issues, as reflected by the VIF values.

Key findings indicate that Facilitating Conditions (FC), Habit (H), and Price Value (PV) significantly influence behavioral intention and actual behavior. Behavioral Intention (BI) was found to be a significant predictor of Behavior (B), confirming the core premise of the intention-behavior relationship in technology adoption. Among these factors, Facilitating Conditions (FC) emerged as a crucial driver, significantly influencing both Behavioral Intention and Behavior, highlighting the importance of external support in driving OTT platform usage.

Conversely, Effort Expectancy (EE), Performance Expectancy (PE), Social Influence (SI), and Hedonic Motivation (HM) did not significantly impact Behavioral Intention. This suggests that the youth of Navsari may prioritize practical factors such as Facilitating Conditions and Price Value over ease of use, social influence, or enjoyment when forming their intention to use OTT platforms.

The model exhibited strong predictive relevance, as indicated by the Q^2predict values for Behavior (0.479) and Behavioral Intention (0.449), both above zero. Effect size analysis further revealed that Facilitating Conditions, Habit, and Price Value had a moderate impact on behavioral intention and behavior, while other factors demonstrated small or negligible effects.

These findings provide valuable insights for OTT platform providers and policymakers aiming to enhance adoption and engagement among youth. Strategies should focus on improving facilitating conditions, reinforcing habitual usage, and emphasizing price value to drive continued usage. Future research could explore additional moderating variables or incorporate alternative theoretical frameworks to further refine predictive power.

Limitation and Future Scope of Research

This study has certain limitations that should be considered while interpreting the findings. First, the research was conducted among youth in Navsari city, which may limit the generalizability of the results to other regions or age groups. A broader geographic scope could provide a more comprehensive understanding of OTT platform adoption. Second, while the sample size of 211 respondents offers valuable insights, a larger sample covering different cities or states could enhance the robustness and reliability of the conclusions. Third, the study employed a cross-sectional design, capturing consumer behavior at a single point in time. Since digital consumption habits evolve rapidly, a longitudinal approach could help track changes in user preferences and engagement over time.

For future research, several directions can be explored to build upon these findings. Expanding the study to a larger and more diverse sample across different regions and demographics would enhance generalizability. Conducting longitudinal studies could provide deeper insights into how user behavior changes over time, particularly in response to technological advancements and market trends. A comparative analysis between different age groups, regions, or **cultural** backgrounds could reveal variations in adoption patterns. Additionally, integrating new variables such as content quality, personalized recommendations, and user engagement factors could offer a more comprehensive understanding of OTT platform usage. Researchers could also explore alternative theoretical models, such as TAM, TPB, or hybrid frameworks, to assess OTT platform adoption from different perspectives. Lastly, with the increasing role of AI-driven recommendations, future studies could investigate how personalization impacts consumer behavior and brand loyalty in the OTT industry. These directions could help deepen the understanding of OTT platform adoption and contribute to more effective strategies for service providers and policymakers.

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