

A STUDY OF THE FACTORS AFFECTING THE INTENTION TO SUBSCRIBE OTT SERVICES IN GUJARAT

A Thesis submitted to Gujarat Technological University

For the Award of

Doctor of Philosophy

In

Management

By

VAGHELA NILRAJSINH JAYENDRASINH
209999903015

under supervision of

Dr. Kerav Pandya



GUJARAT TECHNOLOGICAL UNIVERSITY
AHMEDABAD

[September – 2026]

A STUDY OF THE FACTORS AFFECTING THE INTENTION TO SUBSCRIBE OTT SERVICES IN GUJARAT

A Thesis submitted to Gujarat Technological University

For the Award of

Doctor of Philosophy

In

Management

By

VAGHELA NILRAJSINH JAYENDRASINH
209999903015

under supervision of

Dr. Kerav Pandya



GUJARAT TECHNOLOGICAL UNIVERSITY
AHMEDABAD

[September – 2026]

© [VAGHELA NILRAJSINH JAYENDRASINH]

DECLARATION

I declare that the thesis entitled “**A study of the factors affecting the intention to subscribe OTT services in Gujarat**” submitted by me for the degree of Doctor of Philosophy is the record of research work carried out by me during the period from **2021** to **2026** under the supervision of **Dr. Kerav Pandya** and this has not formed the basis for the award of any degree, diploma, associateship, fellowship, titles in this or any other University or other institution of higher learning.

I further declare that the material obtained from other sources has been duly acknowledged in the thesis. I shall be solely responsible for any plagiarism or other irregularities, if noticed in the thesis.

Signature of the Research Scholar:..... Date: 19-09-2026

Name of Research Scholar: VAGHELA NILRAJSINH JAYENDRASINH

Place: Ahmedabad

CERTIFICATE

I certify that the work incorporated in the thesis “**A study of the factors affecting the intention to subscribe OTT services in Gujarat**” submitted by **VAGHELA NILRAJSINH JAYENDRASINH** was carried out by the candidate under my supervision/guidance. To the best of my knowledge: (i) the candidate has not submitted the same research work to any other institution for any degree/diploma, Associateship, Fellowship or other similar titles (ii) the thesis submitted is a record of original research work done by the Research Scholar during the period of study under my supervision, and (iii) the thesis represents independent research work on the part of the Research Scholar.

Signature of the Research Supervisor _____



Date: 19-09-2026

Name of Supervisor: Dr. Kerav Pandya

Place: Ahmedabad

Course-work Completion Certificate

This is to certify that **VAGHELA NILRAJSINH JAYENDRASINH** enrolment no.**209999903015** is enrolled for PhD program in the branch management of the Gujarat Technological University, **Ahmedabad.**

(Please tick the relevant option(s))

☐ He/She has been exempted from the course-work (successfully completed during M.Phil Course)

☐ He/She has been exempted from Research Methodology Course only (successfully completed during M.Phil Course)

☒ He/She has successfully completed the PhD course work for the partial requirement for the award of PhD Degree. His/ Her performance in the course work is as follows-

Grade Obtained in Research Methodology [PHD2001]	Grade Obtained in Research and Publication Ethics [PHD2002]	Grade Obtained in Self-Study Course/ Contact Program [PHD2003]
BC	AB	AB



Supervisor's Sign
Dr.Kerav Pandya
(Name of Supervisor)

Originality Report Certificate

It is certified that PhD Thesis titled “**A study of the factors affecting the intention to subscribe OTT services in Gujarat**” by VAGHELA NILRAJSINH JAYENDRASINH has been examined by us.

We undertake the following:

- a. Thesis has significant new work / knowledge as compared already published or are under consideration to be published elsewhere. No sentence, equation, diagram, table, paragraph or section has been copied verbatim from previous work unless it is placed under quotation marks and duly referenced.
- b. The work presented is original and own work of the author (i.e. there is no plagiarism). No ideas, processes, results or words of others have been presented as Author own work.
- c. There is no fabrication of data or results which have been compiled / analyzed.
- d. There is no falsification by manipulating research materials, equipment or processes, or changing or omitting data or results such that the research is not accurately represented in the research record.
- e. The thesis has been checked using **TURNITIN plagiarism check software** (copy of originality report attached) and found within limits as per GTU Plagiarism Policy and instructions issued from time to time (i.e. permitted similarity index $\leq 10\%$).

Signature of the Research Scholar:  Date: 19-09-2026

Name of the Research Scholar: Nilrajsinh Jayendrasinh Vaghela

Signature of the Research Supervisor:  Date: 19-09-2026

Name of the Research Supervisor: Dr. Kerav Pandya

Place: Ahmedabad

Nilrajsinh Vaghela

Nilrajsinh Vaghela - "A Study of the Factors Affecting the Intention to Subscribe OTT Services in Gujarat"



Phd thesis



Nilraj PhD



Gujarat Technological University

Document Details

Submission ID

trnoid::1:3545280003

Submission Date

Apr 21, 2026, 12:47 PM GMT+5:30

Download Date

Apr 21, 2026, 6:10 PM GMT+5:30

File Name

Nilrajsinh_Vaghela_PhD_Thesis.docx

File Size

4.8 MB

156 Pages

47,579 Words

277,931 Characters

4% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

Filtered from the Report

- Bibliography
- Quoted Text

Match Groups

-  **47** Not Cited or Quoted 4%
Matches with neither in-text citation nor quotation marks
 -  **3** Missing Quotations 0%
Matches that are still very similar to source material
 -  **0** Missing Citation 0%
Matches that have quotation marks, but no in-text citation
-
-  **0** Cited and Quoted 0%
Matches with in-text citation present, but no quotation marks

Top Sources

The sources with the highest number of matches within the submission. Overlapping sources will not be displayed.

1	Publication	Subramanian, Arvin. "Adoption of Over the Top Streaming Services by Youth in Se...	<1%
2	Publication	Murali Srividya Iyengar, Rajagopalan Venkatesh. "A study on the factors impactin...	<1%
3	Internet	www.dacast.com	<1%
4	Publication	T.S. Sujith. "chapter 3 Users' Adoption of Over-the-Top (OTT) Streaming Platforms...	<1%
5	Internet	www.giiresearch.com	<1%
6	Publication		
8	Student papers		

Ph.D. Thesis Non-Exclusive License to

GUJARAT TECHNOLOGICAL

UNIVERSITY

In consideration of being a Research Scholar at Gujarat Technological University, and in the interests of the facilitation of research at the University and elsewhere, I, **VAGHELA NILRAJSINH JAYENDRASINH** having (Enrollment No.**209999903015**) hereby grant a non- exclusive, royalty free and perpetual license to the University on the following terms:

- a. The University is permitted to archive, reproduce and distribute my thesis, in whole or in part, and/or my abstract, in whole or in part (referred to collectively as the “Work”) anywhere in the world, for non-commercial purposes, in all forms of media;
- b. The University is permitted to authorize, sub-lease, sub-contract or procure any of the acts mentioned in paragraph (a);
- c. The University is authorized to submit the Work at any National / International Library, under the authority of their “Thesis Non-Exclusive License”;
- d. The Universal Copyright Notice (©) shall appear on all copies made under the authority of this license;
- e. I undertake to submit my thesis, through my University, to any Library and Archives. Any abstract submitted with the thesis will be considered to form part of the thesis.
- f. I represent that my thesis is my original work, does not infringe any rights of others, including privacy rights, and that I have the right to make the grant conferred by this non-exclusive license.
- g. If third party copyrighted material was included in my thesis for which, under the terms of the Copyright Act, written permission from the copyright owners is required, I have obtained such permission from the copyright owners to do the acts mentioned in paragraph (a) above for the full term of copyright protection.
- h. I understand that the responsibility for the matter as mentioned in the paragraph (g) rests with the authors / me solely. In no case shall GTU have any liability for any acts / Omissions / errors / copyright infringement from the publication of the said thesis or otherwise.
- i. I retain copyright ownership and moral rights in my thesis, and may deal with the copyright in my thesis, in any way consistent with rights granted by me to my University in this non-exclusive license.
- j. GTU logo shall not be used /printed in the book (in any manner whatsoever) being published or any promotional or marketing materials or any such similar documents.

- k. The following statement shall be included appropriately and displayed prominently in the book or any material being published anywhere: “The content of the published work is part of the thesis submitted in partial fulfilment for the award of the degree of Ph.D. in **Management** of the Gujarat Technological University”.
- l. I further promise to inform any person to whom I may hereafter assign or license my copyright in my thesis of the rights granted by me to my University in this nonexclusive license. I shall keep GTU indemnified from any and all claims from the Publisher(s) or any third parties at all times resulting or arising from the publishing or use or intended use of the book / such similar document or its contents.
- m. I am aware of and agree to accept the conditions and regulations of Ph.D. including all policy matters related to authorship and plagiarism.

Date: 19-09-2026

Place: Ahmedabad



Signature of the Research Scholar

Recommendation of the Research Supervisor: - Recommended

Recommendation of the Co-Supervisor (if any):



Signature of the Research Supervisor

Signature of the Co-Supervisor (if any)

Thesis Approval Form

The viva-voce of the PhD Thesis submitted by Shri. **VAGHELA NILRAJSINH JAYENDRASINH** (Enrollment No. 209999903015) entitled "**A STUDY OF THE FACTORS AFFECTING THE INTENTION TO SUBSCRIBE OTT SERVICES IN GUJARAT**" was conducted on 19th September 2026 (Saturday) at Gujarat Technological University.

(Please tick any one of the following options)

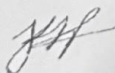
☒ The performance of the candidate was satisfactory. We recommend that he/she be awarded the PhD degree.

☐ Any further modifications in research work recommended by the panel after 3 months from the date of first viva-voce upon request of the Supervisor or request of Independent Research Scholar after which viva-voce can be re-conducted by the same panel again.

(briefly specify the modifications suggested by the panel)

☐ The performance of the candidate was unsatisfactory. We recommend that he/she should not be awarded the PhD degree.

(The panel must give justifications for rejecting the research work)



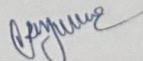
Dr. Kerav Pandya

Name and Signature of Supervisor with Seal



Dr. Charul Jain

1) (External Examiner 1) Name and Signature



Dr. Vinod Malkar

2) (External Examiner 2) Name and Signature

ABSTRACT

This research investigates the determinants influencing consumers' intention to subscribe to Over-the-Top (OTT) services, with a particular focus on Gujarat, India. The expansion of digital infrastructure, coupled with low-cost internet and rising smartphone usage, has significantly reshaped media consumption behavior, making OTT platforms a leading source of entertainment. Although substantial global research exists, there is a lack of region-specific empirical evidence, especially within the Gujarat context. To address this gap, the study proposes and validates an extended version of the Unified Theory of Acceptance and Use of Technology (UTAUT3), incorporating OTT-relevant variables such as content quality and perceived value.

The study aims to evaluate the impact of technological, experiential, and perceptual factors on users' behavioral intention to adopt OTT platforms. It further assesses the relative importance of these determinants and examines whether demographic variables, including gender and generational cohorts, moderate these relationships. A quantitative methodology was employed using a descriptive and cross-sectional research design. Data were collected through a structured questionnaire based on a seven-point Likert scale, targeting OTT users and potential users across major urban regions of Gujarat. A total of 998 valid responses were analysed, obtained through non-probability convenience sampling.

Partial Least Squares Structural Equation Modelling (PLS-SEM) was applied to test the conceptual model and associated hypotheses. The measurement model demonstrated strong reliability and validity, with all constructs meeting acceptable thresholds for Cronbach's alpha, composite reliability, as well as convergent and discriminant validity. The structural model showed substantial explanatory capability, with an R^2 value of 0.730, indicating that 73% of the variation in users' adoption intention is accounted for by the proposed model.

The results indicate that eight out of the nine proposed hypotheses are supported. Performance expectancy ($\beta = 0.221$) and perceived value ($\beta = 0.200$) emerge as the most significant drivers of adoption intention, highlighting the importance of functional efficiency and perceived cost-benefit advantages. Social influence ($\beta = 0.168$) and content quality ($\beta = 0.143$) also exhibit a strong positive impact, reflecting the role of peer influence and high-quality, engaging content in shaping user behavior. Other variables, including facilitating conditions, hedonic motivation, habit, and price

value, show positive but comparatively smaller effects. However, personal innovativeness does not have a significant impact, suggesting that OTT adoption is no longer driven by novelty but has become a mainstream consumption activity.

Multi-Group Analysis (MGA) findings reveal that gender and generational differences (Generation Y and Generation Z) do not significantly influence the relationships within the model, indicating consistent behavioral patterns across user segments. Additionally, the Importance–Performance Map Analysis (IPMA) highlights performance expectancy and perceived value as critical areas for managerial focus, providing practical insights to enhance user satisfaction and increase subscription rates.

The study makes a significant contribution by extending the UTAUT3 framework within the OTT domain and validating it in an emerging market environment. It emphasizes the growing relevance of value-oriented and experience-based factors over innovation-related aspects in determining technology adoption. From a managerial standpoint, the findings offer actionable recommendations for OTT service providers, content developers, and marketers to improve platform performance, strengthen content strategies, and optimize pricing models.

In summary, the study concludes that OTT adoption in Gujarat is primarily influenced by perceived usefulness, value perception, and social factors, rather than individual innovativeness. While offering important theoretical and practical implications, the study is limited by its regional scope and cross-sectional design. Future research may focus on longitudinal analyses, comparative regional studies, and the inclusion of emerging variables such as artificial intelligence-based personalization and trust in algorithmic systems to gain deeper insights into OTT consumption behavior.

Keywords

OTT Platforms, Technology Adoption, UTAUT3 Model, Performance Expectancy, Perceived Value, Content Quality, Social Influence, Digital Media Consumption

Acknowledgement

The successful completion of this PhD research has been a long and challenging journey, much like running a marathon. This journey would not have been possible without the support, encouragement, and guidance of many individuals who stood by me throughout. I feel truly fortunate and blessed to have had such wonderful people beside me during this important phase of my life. I extend my heartfelt gratitude to each one of them.

First and foremost, I would like to express my sincere gratitude to my supervisor, Dr. Kerav Pandya, for his unwavering support, valuable guidance, and continuous encouragement throughout my PhD journey. His mentorship played a crucial role in shaping my academic abilities and professional growth. His constant motivation, insightful suggestions, and intellectual challenges inspired me to achieve my goals. I feel privileged to have worked under his supervision.

I would also like to extend my sincere thanks to my PhD Progress Committee members, Dr. Kunjal Sinha, Pro.V.C at Parul University, and Dr. Krishnaba Vaghela, Asst.Prof of GSMS-GTU, for their continuous encouragement, valuable feedback, and constructive suggestions throughout my research. Their guidance significantly contributed to the successful completion of this work. I am also thankful to Dr. Viral Bhatt for his expert suggestions during my PhD journey. I am thankful to all my colleagues, friends, and the staff of Gujarat Technological University, especially the PhD Department, for their continuous support and cooperation.

I express my deepest gratitude to my parents, Mr. Jayendrasinh Vaghela and Mrs. Kamlaba Vaghela, for their unconditional love, encouragement, and sacrifices. They taught me the value of hard work, perseverance, and dedication, which helped me overcome challenges throughout my academic journey.

A special note of appreciation goes to my wife, Mrs. Alpaba Vaghela, for her unwavering support, patience, and encouragement. Her constant motivation, belief in my abilities, and emotional support gave me the strength to complete this journey successfully. Words are not enough to express my gratitude for her encouragement and faith in me.

I would like to extend my heartfelt gratitude to my dear friend and former colleague, Dr. Animesh Banker, for his constant support and encouragement throughout my PhD journey. His guidance, valuable suggestions, and willingness to help at every stage of my research played a significant role

in the successful completion of this work. He was always there to motivate me during challenging times and provided the confidence I needed to move forward. I am truly grateful for his support, encouragement, and friendship during this important phase of my academic journey.

I would also like to extend my sincere thanks to my friends Dr. Margi Choksi, Ms. Hiral Vora, for their constant motivation, encouragement, and support throughout my PhD journey. Their presence and support made this journey smoother and more enjoyable.

I would like to express my thanks to Dr. Rakesh Sarvaiya, who began this PhD journey alongside me. His constant support, encouragement, and shared experiences throughout this journey were truly valuable. We motivated each other during challenging times and celebrated milestones together.

Above all, I thank the Almighty God for His blessings, guidance, and strength that helped me successfully complete this challenging yet rewarding journey.

Table of Contents

Chapter No.	Sub-Points	Title	Page No.
1		Introduction to the study – OTT Adoption	1 – 32
	1.1	Brief history of OTT Adoption	1
	1.1.1	Technological and Infrastructure Factors	2
	1.1.2	Content and Service Factors	3
	1.1.3	User Motivation and Behavioral Factors	4
	1.1.4	Economic and Market Factors	4
	1.1.5	Environmental and Contextual Factors	5
	1.1.6	Adoption Process Stages	6
	1.2	Types of Over-the-Top (OTT) Services	6
	1.2.1	Subscription Video on Demand (SVOD)	7
	1.2.2	Advertising-Based Video on Demand (AVOD)	7
	1.2.3	Transactional Video on Demand (TVOD)	8
	1.2.4	Hybrid or Freemium Models	8
	1.2.5	Live Streaming OTT Services	8
	1.2.6	Classification Based on Content and Service Focus	9
	1.3	OTT Service history and Evolution	11
	1.3.1	The Modern OTT Landscape (2022–Present)	13
	1.4	The Emergence of Metaverse and Immersive OTT Experiences	15
	1.5	Global Scenario of OTT Services	17
	1.6	Indian Scenario of OTT Services	24
	1.7	SWOT analysis of Indian OTT sector	28
	1.8	Problem Discussion & Rational of Study	30
2		Literature of Review	33–64
	2.1	OTT Adoption	33
	2.1.1	Evolution of UTAUT Models: From UTAUT to UTAUT 3	34
	2.2	Core Constructs of UTAUT 3 Model	37
	2.3	Moderating Variables	41

	2.4	Theoretical Mechanisms and Relationships in UTAUT 3	43
	2.5	Empirical Applications of UTATUT3	45
	2.6	Hypothesis Development	47
	2.7	Multigroup Analysis and OTT	60
	2.8	IPMA analysis and OTT	61
	2.9	Research Gap	63
3		Research Methodology	65-85
	3.1	Introduction to Research	65
	3.2	Research Problem Statement	65
	3.3	Research Questions	66
	3.4	Research Objective	67
	3.5	Research Approach	69
	3.6	Research Design	70
	3.7	Population and Sampling Selection	72
	3.7.1	Target Population	72
	3.7.2	Sampling Techniques	73
	3.7.3	Sample size justification	75
	3.8	Research Instrument Development	76
	3.9	Data collection tools	81
	3.10	Preliminary Data analysis	83
4		Data Analysis	86-152
	4.1	Demographic Analysis	86
	4.2	Cross Tabulation	96
	4.3	Non normality of data	111
	4.4	Reliability and Validity Analysis	124
	4.5	Factor Loading	125
	4.6	Reliability	127
	4.7	Composite Reliability	128
	4.8	Convergent Validity	129
	4.9	Discriminant Validity	131
	4.10	Fornell–Larcker Criterion	131
	4.11	HTMT Test	133
	4.12	Path Analysis	134
	4.13	Multigroup Analysis	139
	4.14	MGA – Gen Z and Gen Y	142
	4.15	IPMA Analysis	145
	4.16	R Square and Adjusted R Square	149
	4.17	Model Fit Summary	151
5		Findings, Suggestions, Conclusion, Future Scope	153-199
	5.1	Findings	153
	5.2	Recommendations	161
	5.3	Variable wise Recommendation	163
	5.4	Theoretical Implications	166
	5.5	Practical and Managerial Implication	168
	5.6	Social Implication	171

	5.7	Conclusion	174
	5.8	Future scope and Limitation	176
	*	Reference	180
	*	Appendix A – Survey Questionnaire	194
	*	List of Publication	199

List of Abbreviation

OTT	Over The Top
VR	Virtual Reality
UHD	Ultra High Definition
CDN	Content Delivery Network
AI	Artificial Intelligence
UGT	Uses and Gratification Theory
SVOD	Subscription Video on Demand
AVOD	Advertising-Based Video on Demand
TVOD	Transactional Video on Demand
PPV	PayPer View
CAGR	Compound Annual Growth Rate
DVD	Digital Video Disk
ML	Machine Learning
NLP	Natural Language Processing
AR	Augmented Reality
ARPU	Average Revenue Per User
SEM	Structural Equation Modeling
MGA	Multi-group analysis
GB	Gigabyte
IPMA	Importance-Performance Matrix Analysis
VAM	Value Based Adoption Model
IT	Information technology
IS	Information system
UTAUT	Unified Theory of Acceptance and Use of Technology
TAM	Technology Acceptance Model
IRT	Innovation Resistance Theory
ANOVA	Analysis of Variance
APP	Application
IPMA	Importance- Performance Map Analysis
NCA	Necessary Condition Analysis
ANN	Artificial Neural Networks
CNQ	Content Quality
FCO	Facilitating Condition

HAB	Habit
HEM	Hedonic Motivation
INO	Innovativeness
PEX	Performance Expectancy
PRV	Perceived Value
PVL	Price Value
SOI	Social Influence
UIA	User intention to Adopt
AVE	Average Variance Extracted
CR	Composite Reliability
SEM	Structural Equation Modeling
d_ULS	Squared Euclidean Distance
d_G	Geodesic Distance
NFI	Normed Fit Index
FOMO	Fear Of Missing Out

List of Figures

Figure Number	Figure Description	Page Number
1.1	Video streaming revenue data	18
1.2	OTT growth revenue prediction	20
1.3	OTT Revenue distribution OTT/SVOD/PPV	22
1.4	Indian OTT Services 2024 vs 2027E	25
1.5	SWOT analysis of Digital media	27
2.1	UTAUT Model	34
2.2	UTAUT 2 Model	35
2.3	UTAUT 3 Model	36
4.1	Age Classification	86
4.2	Gender Classification	87
4.3	Educational Qualification	88
4.4	Occupation of Respondent	90
4.5	Income Classification	91
4.6	Device Used for OTT	92
4.7	Weekly Time Spend	93
4.8	Using OTT since	95
4.9	Normal Q-Q plot of Innovativeness	112
4.10	Normal Q-Q plot of Price Value	113
4.11	Normal Q-Q plot of Performance Expectancy	113
4.12	Normal Q-Q plot of Facilitating Condition	114
4.13	Normal Q-Q plot of Social Influence	114
4.14	Normal Q-Q plot of Hedonic Motivation	115
4.15	Normal Q-Q plot of Habit	115
4.16	Normal Q-Q plot of Content Quality	116
4.17	Normal Q-Q plot of Perceived Value	116
4.18	Normal Q-Q plot of User Intention to adopt	117
5.1	OTT Ecosystem	168

List of Tables

Table Number	Table Description	Page Number
1.1	Types of OTT Platforms	10
1.2	OTT growth drivers	26
2.1	Empirical support for each proposed predictor	46
2.2	Hypothesis and Supporting references	58
3.1	Variable wise Measurement statements	77
3.2	Internal Consistency	81
4.1	Age Classification	87
4.2	Gender Classification	88
4.3	Educational Qualification	89
4.4	Occupation of Respondent	90
4.5	Income Classification	91
4.6	Device Used for OTT	92
4.7	Weekly Time Spend	93
4.8	Using OTT since	95
4.9	Cross Tabulation – Income * Device used for OTT	96
4.10	Chi-Square Tests – Income * Device used for OTT	97
4.11	Income * Weekly time spend	98
4.12	Chi-Square Tests – Income * Weekly Time Spent on OTT	99
4.13	Income * Using OTT since	100
4.14	Chi Square Test – Income * Duration of OTT	101
4.15	Age * Device used for OTT	101
4.16	Chi Square Test – Age * Device used for OTT	102
4.17	Age * Using OTT since	103
4.18	Age * Duration of OTT	104
4.19	Education * Device used for OTT	105
4.20	Chi-Square Tests – Education * Device used for OTT	106
4.21	Education * Weekly time spend	106
4.22	Chi-Square Tests- Education * Weekly Time Spent on OTT	107
4.23	Occupation * Device used for OTT	108
4.24	Chi-Square Tests – Occupation * Device Used for OTT	109
4.25	Occupation * Weekly time spend	110
4.26	Chi-Square Tests – Occupation * Weekly Time Spent on OTT	111
4.27	Test of Normality	118
4.28	Descriptive Statistic	119
4.29	ANOVA table	120
4.30	Model Summary	122
4.31	Coefficients	123

4.32	Reliability and Validity	124
4.33	Fornell-Larcker criterion	132
4.34	HTMT	133
4.35	Path Analysis	136
4.36	MGA – Male & Female	140
4.37	MGA – GEN Y & GEN Z	143
4.38	IPMA – Importance	146
4.39	IPMA – Performance	147
4.40	R Square	149
4.41	F Square	150
4.42	Model Fit summary	151
5.1	Summary of Findings from Hypothesis	156
5.2	Summary of Objective wise findings	159

List of Appendices

Appendix A : Survey Questionnaire

Thesis Body (Chapters)

- Chapter 1: The content on the first chapter of research topic offers the summary of the research subject, Digital Media industry and how OTT applications usage initiated.
- Chapter 2: The second chapter discusses the key literature and theories for OTT use. It relates to the heterogeneous situations and factors that may influence a subscriber's decision for using OTT applications. It provides a systematic review of previous scholars' work of OTT and Digital Media. The chapter ends with an address about the gap in the literature and the theoretical Orientation for the future study.
- Chapter 3: The third chapter is a variety of methods that the current study employed are presented. It gives a report on the sampling technique, research methodology, size of the selected sample, and the different kinds of Analytical devices and methods used in this study.
- Chapter 4: This chapter throws light on a comprehensive understanding by Analyzing data with statistics which are obtained from a primary survey of respondents.
- Chapter 5: The last chapter of the report goes into further detail on the study's key outcomes and the primary analysis's results. It contains the main findings, theoretical contributions, methodological contributions to research, practical consequences, implications for future research, and the limits of the current study. This chapter gives a short summary of the most Important results of the study.

CHAPTER 1 – INTRODUCTION

1.1 - Brief History of OTT Adoption

Over-the-top, also abbreviated as OTT, means the direct transmission of video, audio, and other media content using the Internet, thus eliminating the use of the traditional broadcast, cable, or satellite television systems. OTT services are a notion that came into existence in the late 2000s, and it coincided with the spread of broadband Internet and digital streaming technologies. Netflix and Hulu are early entrants in the media industry, and they changed the industry by allowing users to access movies and TV shows on demand using subscription services. There is significant growth in the OTT ecosystem over the years in developing countries and this is due to the increase in the quantity of people with access to mobile phones and the Internet.

The usage of the OTT services grew faster in the 2010s owing to the progress in technology and the decline in the price of smartphones and the introduction of high-speed mobile Internet technologies (including 4G and 5G). The development of local content and cheap subscription services became the key trends of impressive advance in markets in India, Southeast Asia, and Africa. According to recent studies, the OTT industry in India has been flourishing significantly due to the low cost of mobile data, the presence of multiple languages, and culturally oriented content (TIJER, 2024).

The COVID-19 pandemic further enhanced the adoption of OTTs in the world in 2020. The effect of quarantine was the increased demand of the digital entertainment due to the constriction. With lockdowns, OTT services became key contributors to entertainment and education and social connectivity (Agize, 2016). At the start of the 2020s, the consumption of OTTs has stopped being a niche phenomenon and turned into a ubiquitous habit of all age groups. International research has found that the major long-term determinants of OTT use continuity and customer loyalty are user habits, social influence, and content satisfaction (GJEIS, 2022).

The OTT revolution in India started in 2015 with the introduction of local platforms such as Hotstar, SonyLIV, and Zee5, subsequently joined by foreign entities like Netflix and Amazon Prime Video. The cost-effectiveness of data plans-especially following Reliance Jio's market debut in 2016-significantly enhanced Internet accessibility and spurred widespread OTT usage. Elements include

Bilingual material, regional storytelling, and culturally relevant storylines substantially facilitated the sector's swift expansion (TIJER, 2024). The COVID-19 epidemic expedited worldwide and Indian adoption as lockdowns restricted individuals to their residences, heightening the desire for online entertainment, education, and social interaction (M. S. Kim et al., 2017). By the early 2020s, OTT consumption evolved from a niche activity to a ubiquitous mode of media consumption across all demographics (GJEIS, 2022).

1.1.1 - Technological and Infrastructure Factors

The willingness of technology and infrastructure is the foundation of the adoption of OTT globally. Penetration of the broadband systems, the speed of the Internet, the price of the device, and the stability of the platform play a significant role in terms of user experience. In the rich states like the United States, Japan, and Korea, advanced internet connection and the use of smart devices have allowed unbroken streaming and encouraged multi-platform watching (Maslowska et al., 2017). Additionally, technologies like cloud-based content delivery networks (CDNs), artificial intelligence (AI)-based recommendation engines, and adaptive bitrate streaming have enhanced the quality of playback and minimized buffering to increase the satisfaction of users (Katherine Chen, 2019).

Technical quality has a significant impact on the level of customer satisfaction, and it includes such properties as availability of nonstop streaming, low buffering, and compatibility with a variety of devices (Kou et al., 2024). Based on the empirical evidence, the usage of over-the-top (OTT) services and the advancement of Internet access and pricing, especially in the context of mobile data and 4G networks, is significantly correlated, as is reported in the studies that were done in emerging economies.

Technological changes, in the Indian case, have played a central role in bringing about the democratization of OTT access. Due to the development of 4G telecommunication networks, the number of Internet users has increased more than ever before, thanks to the affordability of mobile devices. India is considered to be one of the major leading countries in terms of mobile data utilization where urban and rural populations are also involved in digital media utilization. The current deployment of 5G networks will result in a significant improvement of streaming quality, allowing the creation of new streaming content like VR (virtual reality) and high-quality streaming in ultra-high definition (UHD). Geographic disparities have been lessened due to technological advancements enabling access to OTT content in the areas that had been underserved (TIJER, 2024). As a result,

Infrastructure building has been a key factor to the success and scalability of OTT platform on a global and national level.

1.1.2 - Content and Service Factors

The basic value proposition of OTT services is the quality and diversity of the content. Customers all over the world take interest in services that feature exclusive, high-quality, and culturally relevant content. Originality, a wide variety of genres and availability in a variety of languages are influential determinants of customer engagement and retention. Netflix and Disney+ are the two platforms that have become popular all over the world thanks to substantial investment in original content that appeals to both local and international audiences.

As an example, the regional originals of Netflix like *Squid Game* (South Korea) and *Money Heist* (Spain) can highlight the way localized stories may acquire a global appeal with the help of localization. Further, the material quality such as visual fidelity, narrative integrity and the production values are paramount factors in the perceived satisfaction and trust that the users have towards a platform. Empirical research revealed that material quality, as well as the diversity of content, is an important factor in determining user engagement and retention (Journal IJAR, 2025). Another way to increase the perceived value is by means of flexible price structures including freemium access, ad-supported streaming, and cheap subscriptions.

OTT platforms have found content localization critical in the Indian scenario. The linguistic diversity and the traditions of narratives of the regions of the country require the vernacular material. The Zee5, Aha, and SonyLIV platforms have anticipated the localized content in Tamil, Telugu, Bengali and Marathi to serve the interests of diverse viewers. Also, the Authenticity and cultural relevance in storytelling is also becoming a significant priority because consumers in India are growing more interested in the authenticity and cultural relevance of the content they consume. Material accessibility has been increased by pricing models, such as freemium models, ad-based levels, and mobile-only subscriptions (Journal IJAR, 2025). These versatile approaches give a sense of value and easy consumption by the price-sensitive population.

1.1.3 - User Motivation and Behavioral Factors

Behavioral and psychological factors constitute a fundamental foundation for the acceptance of OTT. The Uses and Gratifications Theory (UGT) posits that individuals proactively pursue media material to fulfil their desires for amusement, diversion, information, and social interaction, rather than merely absorbing what is available. Worldwide, individuals prefer OTT platforms to conventional broadcast television mostly because of the ease, customization, and autonomy they provide. Hedonic motivations - the pleasure and contentment gained from usage- predominantly influence initial adoption, but the establishment of habits and general happiness emerge as more significant indicators of long-term retention. Dasgupta (2019) discovered that hedonic and habitual motivations are more predictive of sustained OTT usage than utilitarian elements like performance expectations.

Social impact fortifies these behavioral tendencies. A person's initial encounter with an OTT platform is often influenced by friends, relatives, and wider social circles, and as engagement becomes habitual, OTT viewing is further integrated into everyday existence. In India, this phenomenon assumes a unique form: the amalgamation of social media and streaming has cultivated an interactive viewing culture where people engage in discussions, share, and critique material, hence enhancing community involvement. Indian audiences often engage with OTT material in a communal manner - alongside family or social circles - mirroring traditional watching practices adapted to a digital environment. Consequently, emotional and social incentives are crucial in maintaining audience allegiance, both locally and globally.

1.1.4 - Economic and Market Factors

Economic factors significantly influence the adoption of OTT services, both worldwide and inside India. Consumer price sensitivity, disposable income levels, and the presence of adaptable payment options significantly affect an individual's propensity to subscribe to and maintain OTT services. Worldwide, platforms have transitioned to hybrid monetization strategies that integrate Subscription Video on Demand (SVOD), Advertising Video on Demand (AVOD), and freemium options to cater to diverse purchasing capabilities across different regions (Habib et al., 2022). This variety enables platforms to attract both high-paying, ad-free audiences and cost-conscious consumers who choose ad-supported or complimentary access.

Market rivalry serves as another essential economic catalyst. In India, over fifty OTT platforms vie for attention, resulting in customers encountering regular options and little switching expenses, as the majority of subscriptions are available on a month-to-month basis without extended commitments. This heightens price sensitivity and leads to "subscription fatigue," causing customers to restrict themselves to one or two paying services instead of several concurrent memberships. As a result, platforms are progressively utilizing bundling tactics - collaborating with telecom companies like Jio and Airtel to include OTT access in mobile or broadband packages - to diminish the apparent cost obstacle and enhance affordability.

Trends in Average income Per User (ARPU) further elucidate the financial aspect of adoption: as platforms refine pricing structures and advertising resources, user income is anticipated to increase despite competitive subscription rates. In India, the low cost of mobile data, one of the most economical worldwide, has significantly facilitated the expansion of OTT services, reducing overall access expenses and rendering streaming feasible for economically disadvantaged and rural communities. Nonetheless, the commercialization of regional and vernacular material is still relatively nascent, indicating that although the economic accessibility of OTT has significantly advanced, the financial viability of catering to smaller, non-metropolitan audiences is still in development.

1.1.5 - Environmental and Contextual Factors

In addition to technology and economics, the adoption of OTT platforms is influenced by the wider legislative, infrastructural, and cultural contexts in which they function. Regulatory structures affect the speed and character of adoption: in India, OTT content is presently governed by self-regulation thru the Digital Media Ethics Code (2021), yet enforcement is erratic, leading to ambiguity regarding content standards, censorship anticipations, and platform responsibility. As international platforms expand into new territories, varying data privacy standards, content rules, and demands for algorithmic transparency increasingly influence the configuration and promotion of services in each area.

The infrastructural landscape differs dramatically inside nations, as well as between them. In India, the enduring digital divide between urban and rural areas is particularly evident: urban locales enjoy robust 4G/5G connectivity and reliable bandwidth, whereas rural areas suffer from inadequate infrastructure, sporadic connectivity, and diminished digital literacy, all of which hinder fair access to OTT services despite decreasing data prices. This contextual void indicates that national adoption figures may

obscure significant variations in real user experiences across different regions.

Cultural and societal contexts further influence the consumption and regulation of OTT material. Material deemed appropriate in one cultural or political setting may attract regulatory examination in another, especially with issues of religion, politics, or sexuality – a trend that has been more pronounced in the Indian market. Simultaneously, environmental sustainability is becoming a pertinent issue for the industry worldwide, as apprehensions over the energy usage and carbon emissions of data centers and high-definition streaming systems intensify, prompting platforms to adopt more energy-efficient delivery methods. Collectively, these legislative, infrastructural, and cultural influences create the contextual framework within which technical and economic adoption elements function.

1.1.6 - Adoption Process Stages

The phases of adopting over-the-top (OTT) platforms are usually four phases including awareness, evaluation, acceptance and retention. The major activities, which the potential users learn about OTT platforms at the awareness stage, are marketing campaigns, word of mouth, and social media. The evaluation phase is a mechanism of evaluating various variables such as cost, usability, and the quality of information. Perceived accessibility and satisfaction play a big role in the perception of acceptance since users promise the service or start to use it on a regular basis. Information consumption, the sense of a consistent value, and constant innovation of content make the retention stage last.

Following the maturation of OTT market places and the escalating competition, scholars have pointed out that retention is more decisive than initial adoption. As a result, the academic investigation and business strategy must have a thorough knowledge of the adoption lifecycle (ScienceDirect, 2022).

1.2 - Types of Over-the-Top (OTT) Services

Over-the-Top (OTT) services represent a fundamental revolution in how media and communication material are transmitted and consumed. These services function over the Internet, circumventing conventional distribution methods such as cable television, satellite broadcasting, or physical media. The worldwide expansion of OTT platforms is propelled by improvements in internet access, increased smartphone use, and customers' inclination towards tailored, on-demand entertainment. OTT services may be classified into many unique sorts based on their business structures, content strategy, and distribution techniques.

1.2.1 - Subscription Video on Demand (SVOD)

One of the best business models in the over-the-top (OTT) industry is the subscription video on demand (SVOD) paradigm. This model allows the users' unlimited access to a library of digital media in exchange to a recurrent membership charge, usually a monthly or yearly one. With a heterogeneous catalogue that includes feature movies and web series, as well as documentary productions, leading SVOD services have gained extensive recognition on the international level, such as Netflix, Amazon Prime Video, Hulu, and Disney+ Hotstar.

The fact that an advertisement-free viewing experience is provided is the main feature of the SVOD services which increases consumer satisfaction and retention.

To maintain competitive advantage, these services devote significant resources to content curation based on data and the creation of original content. It is estimated that Netflix relates to spend approximately US\$ 8.5 billion on original content in the fiscal year 2024 25, but this time with a significant focus on international ideas. As a result of this trend, the SVOD models focus on the constant content renewal, division of the audience, and constant interaction with the customers to maintain the long-term customer loyalty.

1.2.2 - Advertising-Based Video on Demand (AVOD)

The Advertising-Based Video on Demand (AVOD) services work on the basis of a free access model, allowing users to stream the content free of charge, but in the middle of their viewing, advertisements are being delivered. This type of monetization enables platforms to increase the reach of their audience as well as receiving income by placing advertisements. Popular AVOD platforms, such as YouTube, MX player, Pluto TV, and Tubi have garnered large followings, especially in places where the price sensitivity is extreme.

AVOD model has been successful to the emerging market like India where free access is a stimulating factor to adoption. Users will need to look at adverts at intervals; nevertheless, these sites use algorithmic ad-targeting to match adverts to the interests of users. The targeted advertisement activities show the most pertinent advertisements to users based on the areas of interest, location, and behavior, which increases the effectiveness of advertising. AVOD, therefore, balances access and profits by using the attention of the audience instead of asking individuals to pay.

1.2.3 - Transactional Video on Demand (TVOD)

Transactional Video on Demand (TVOD) also known as Pay-Per-View (PPV) is a system that allows customers to purchase or rent certain content on a per-use basis. TVOD customers pay individually per movie, documentary, or live event that they decide to watch, which not the case with subscription arrangements is. There are such prominent examples as Apple iTunes, Google Play Movies, and Amazon Prime Rentals. The model is specifically applicable to material of high value, exclusive, or fresh material, and the standard cost of renting is between 3.99 & 6.99, and buying costs are not above 29.99. Both the consumers and the suppliers gain the freedom to receive content without entering into long-term subscriptions and better prices on new or exclusive releases respectively. TVOD generally covers two types of pricing such as the rental (temporary access), and ownership (permanent access). Transactional Characteristics of TVOD attracts the customers who want to have flexibility and control over their spending making it a major part of the digital content economy.

1.2.4 - Hybrid or Freemium Models

Hybrid models also known as Freemium systems are a combination of subscription-based and advertising-based models. These services offer free access to a small collection of content, which is usually funded by advertisements, with exclusivity or ad-free content being offered to subscribers. The examples of this paradigm are platforms like Disney+ Hotstar, SonyLIV, Hulu, and Zee5. MX player can be seen to implement this strategy by combining advertising-based and subscription video-on-demand solutions, as it thus draws in a wide range of viewer groups. The hybrid is best where there are variations in economic demographics of the region as the willingness to pay of customers in diverse regions differs significantly. The presence of premium and free options maximizes the interaction of the audience and provides the means of turning free members to paying ones. The freemium model ensures revenue diversification and brand awareness through better accessibility. Hybrid OTT models are therefore a strategic evolutionary development meant to appeal to mass-market customers and high-end content viewers.

1.2.5 - Live Streaming OTT Services

OTT Live streaming services provide instantaneous broadcasting of events like sporting events, concerts, news and interactive programming. These services are different in that they focus on immediacy and user interaction as opposed to the on-demand services. Examples of these are Twitch,

ESPN +, DAZN, and SonyLIV Live Sports. The fast-growing live OTT sector can be explained by the predisposition of the interactive capabilities of this type of platform, which frequently includes chat-related services, polling systems, and live commentary, thus contributing to the increased engagement of the audience.

The co-interactive behavior, which is described as interaction in real time and simultaneous consumption of content, has been reported to have a significant impact on the intention of subscribers to join the live streaming services.

The sports broadcasting, especially, has become one of the most prominent contributors to the phenomenon, as the DAZN has acquired the biggest portfolio of sports broadcasting rights all over the world, including boxing, mixed-martial arts, soccer, and many global tournaments. Moreover, this has broadened the scope of live OTT by incorporating live news and entertainment events, not just the traditional sporting arena.

Twitch, a leading crowdsourced platform of live streaming, has allowed people to stream content to large audiences and, thus, significantly enhanced content creation and viewer interaction opportunities. The hybrid funding system that these services use (subscription fees and advertising revenues), thus illustrates a merging of live broadcasting and digital interactivity.

1.2.6 - Classification Based on Content and Service Focus

Besides financial means, the OTT services are also distinguished by the content type and focus on the offered service. Video OTT applications are focused on movies, series, and TV shows, and such platforms include Netflix, Disney+, and Amazon Prime Video. Spotify and Apple Music represent audio OTT services that offer musical and podcast streaming services. OTT messaging and communication applications like WhatsApp and Telegram provide real-time message exchange and multimedia sharing over the internet networks. WhatsApp, a mobile based application that allows instant messaging, replaces the traditional text messaging services that were being provided by the mobile network operators. Skype, Zoom, and Google Meet are voice and video communication technologies that can be used to hold meetings and calls through IP networks.

These communication tools have been particularly valuable in the educational context, where the real-time captioning, breakout rooms, and communication with the learning management systems features

allow fostering participatory and accessible learning experiences. Emerging categories include Gaming OTT services, such as Twitch and Google Stadia, which focus on live games streaming and passive viewer interactions, allowing viewers to directly impact the gameplay process by voting and interacting in a chat. Educational OTT/ EdTech platforms, including Coursera and Unacademy, offer educational material in digital form through on-demand video collections and through interactive course content. Such classifications show that OTT services do not solely involve entertainment but also communication, education, and interactivity.

Table 1.1 – Types of OTT platforms		
Type	Description	Examples
Video OTT	Provides on-demand or live video entertainment including films, series, and TV programs.	Netflix, Disney+, Hotstar
Audio OTT	Focuses on music, podcasts, and radio streaming.	Spotify, Apple Music
Messaging OTT	Offers text, multimedia, and group communication services over the internet.	WhatsApp, Telegram
Voice/Video Call OTT	Facilitates audio and video communication using internet protocols.	Skype, Zoom, Google Meet
Gaming OTT	Enables live game streaming and cloud gaming experiences.	Twitch, Google Stadia
Educational OTT (Ed-Tech)	Delivers academic and skill-based learning content.	Coursera, Unacademy

Essentially, the range of content distribution modalities included in OTT services is a heterogeneous set, which is influenced by the technological advancement and new consumer behavior. Five key models of business, including SVOD, AVOD, TVOD, Hybrid (Freemium) and Live Streaming, exemplify the different ways to monetise and with which ways audiences can be engaged. It is estimated that the global OTT market will grow to reach up to 616.42\$ billion dollars in 2032, with a compound annual growth rate (CAGR) of 21.50%.

At the same time, the growing use of OTT into video, audio, communication, gaming, and education industries highlights its growing impact on a variety of aspects of the digital economy. As the world of broadband becomes more and more widely spread due to the development of high-speed networks and the deployment of 5G technology, the OTT industry is transforming the traditional media paradigm and represents a flexible and user-driven content consumption model that best exemplifies the convergence of technology, entertainment, and interactive experience.

1.3 - OTT Service history and Evolution.

The Over-the-Top (OTT) history is exemplary of the future trend of convergence of digital communication and media in the digital age of the internet. OTT refers to deliverables that are sent straight to the consumers by the use of the internet by avoiding the traditional media of broadcast through which particular activities like cable television and satellite transmission are employed. Its popularity started in the early 2000s, however, its roots can be traced back to the mid-1990s, when the media delivery through the internet has become a viable option (Mangini et al.2023). The history of the OTT services development has followed through the specific stages of technological and behavioral development, influenced by the spread of broadband systems, the evolution of smartphones, and the preferences of media consumption.

Early Beginnings (1990s–2005)

The beginning of over-the-top (OTT) streaming is traced to the dot-com boom of the late 1990s, which saw much innovation in the digital broadcasting and video-sharing technologies. The first reception was hampered by technical factors, such as narrow bandwidth and slow Internet connectivity. The release of YouTube in 2005 came as a turning point in the history of OTT services as it offered the first service that could provide the opportunities to stream user-created videos to a large audience. As Malewar and Bajaj (2020) argue, the acquisition of YouTube in 2006 brought the company to the position of the most rated, advertising-supported video service in the world. At the same time, Netflix, which started its operations as a DVD-renting company in 1997, also took the plunge into the sphere of digital distribution technologies that ultimately instigated an avalanche of change in the entertainment sector. These technological innovations caused the end of the linear broadcast models in favor of on-demand content consumption.

Emergence of Subscription Streaming Models (2006)

The earliest types of OTT services to be made public were offered in 2006-2010 based on subscription models. The concept of Subscription Video on Demand (SVOD) was predetermined by the launch of an Internet streaming service by Netflix in 2007. According to Mangini et al. (2023), this innovation has provided consumers with access to a large library of films and TV programs without having to use physical media or make individual downloads. At the same time, Hulu, which was formed in 2007 as a result of a business alliance between NBC Universal and Disney, focused on the provision of on-demand television programs. The era is also marked by technological advancement in broadband Internet, data compression and imminent spread of personal computing equipment. The period saw the appearance of the cord cutting movement, when it had been passed by the customers, who have ditched the traditional type of cable subscriptions in favor of the Internet streaming. It is a trend that had a significant impact on the landscape of the world of entertainment (Shin et al., 2016; as cited in Malewar and Bajaj, 2020).

The Expansion Era (2010–2015)

There was a significant growth in the over-the-top (OTT) sector between 2010 and 2015. This is possible due to the high rate at which smartphones are spreading, the launch of 4G mobile networks, and the accessibility of cheap plans of Internet data transmissions. It was a period when cinematography OTTs (Netflix, Amazon Prime Video, and Hulu) expanded their operations to the international market (Malewar and Bajaj, 2020). The Indian ecosystem started growing with the release of Hotstar in 2015 that was followed by the release of Zee5 and Voot in 2016, thus covering the regions and language variety. Writing about the revolution in the field of data accessibility, Joy and Bahl (2018) claim that the entry of Reliance Jio into the Indian telecom market in 2016 resulted in the creation of low-cost Internet plans (as cited in Malewar and Bajaj, 2020). This evolution triggered a major launch of OTT service penetration.

With the introduction of Netflix Originals, the global release of which started with the first episode of House of Cards in 2013, a new age of the development of platform-owned content has begun. By using the innovative content as the strategy, the streaming companies could stand out among the competition, been able to manage the intellectual property rights and receive the unique audience. At this time, OTT platforms have become an essential part of the digital entertainment value chain.

Consolidation and Technological Integration (2016–2019)

The period of the over-the-top (OTT) industry consolidation and technological integration lasted

between 2016 and 2019. To boost user activity, platforms have invested significantly in data analytics and personalized recommendation systems (Mangini et al., 2023). The growing popularity of smart TVs, streaming devices such as Roku and Amazon Fire Stick, and mobile applications has further integrated OTT services into daily life. Through the use of exclusive franchises and material backed by the studio, new players, i.e., Disney+, Apple TV+, and HBO Max, have further competitive pressure in the content-streaming market.

This era was marked by a shift to advertising-driven models (AVOD) and locally-created content, which had increased access to the less-income earning population groups (Habib et al., 2022). These advancements cemented the OTT as a source of entertainment delivery and digital marketing platform. (AL-Nahdi et al., 2015) argued that digital marketing, promoting through social-media, and influencer marketing have become indispensable in customer acquisition and retention.

Pandemic-driven Acceleration (2020–2021)

Additionally, the COVID-19 epidemic served as a significant turning point in the development of over-the-top (OTT) services. Consumers are increasingly turning to online streaming as a source of entertainment and information as a result of global lockdowns and the closing of conventional cinemas. Viewership of over-the-top (OTT) content increased by 34% in India in March 2020, which is an almost five-year acceleration of the growth that was expected (Malewar & Bajaj, 2020). Film studios started distributing movies directly on over-the-top (OTT) platforms, which marked the beginning of the trend known as "direct-to-digital release". Without a doubt, the pandemic was responsible for the transformation of over-the-top (OTT) services from alternative entertainment channels into indispensable components of everyday life. Consumers' behaviors toward subscription-based and hybrid streaming services were irrevocably transformed as a result of the crisis, which highlighted the endurance of digital media ecosystems (G. Gupta & Singharia, 2021).

1.3.1 - The Modern OTT Landscape (2022–Present)

The characteristics of the current over-the-top (OTT) media sector in particular are the integration of technological modalities, the diversification of competitive policies, and monetization hybridization. Machine learning algorithms and artificial intelligence (AI) are quickly being implemented by platforms to make recommendations more personalized, stream quality better, and anticipate the user preferences. (Abbasi et al., 2021) note that a trend has emerged of hybrid models combining advertising

and subscription revenues to allow services to appeal to a large range of consumer groups. As a result, the line between traditional OTT entertainment and social-media entertainment has become even more unclear, especially with the emergence of short-form content platforms like Tik Tok, Instagram Reels and YouTube Shorts.

The recent empirical studies (Mangini et al., 2023; Habib et al., 2022) have helped to understand the increased relevance of brand image, online interactions, and customer satisfaction in determining the loyalty of OTT consumers. In addition, Liu et al. (2023) refer to the so-called Generation Z a.k.a. digital natives who are used to personalized and interactive media and, therefore, are the most powerful generation that fosters the uptake of OTT services. These results highlight the fact that OTT platforms have not only served as expounders of passive material; they have become fundamental platforms of entertainment, personal interaction, and social interaction to their users.

Future Trends of OTT Services (2025–2030)

The Over-the-Top (OTT) media industry is predicted to experience ten years of radical transformation, which are defined by the invention of new technologies, hybrid ways of monetization, and consumer's behavior changes. It is predicted that the over Loose-over-the-top (OTT) ecosystem will be changed in 2025-2030 as a medium that is currently oriented towards entertainment into a systemic digital infrastructure, which includes entertainment, education, business, and interactive communications. Statista (2025) predicts the global OTT industry (which is projected to reach about 400 billion US dollars in 2025) to grow even higher than 600 billion US dollars in 2030. This is going to be fuelled by the fast introduction of 5G networks, Artificial Intelligence (AI), and personalised digital ecosystems.

Predictive Personalization and Artificial Intelligence

In 2030, the user experience of OTT websites will be altered by the emergence of Artificial Intelligence (AI) and Machine Learning (ML). The following generation of the recommendation algorithm is going to utilize predictive analytics to not only suggest material but also predict mood, time preferences, and emotional states (Mangini et al., 2023). Such customization will shift towards a more predictive than reactive, therefore facilitating hyper-individualization of viewing experiences by the platform. AI will improve automated content production and real-time placement of adverts, which will result in greater relevance and efficiency in the interaction with users (Habib et al., 2022). By the introduction of Natural Language Processing (NLP) and voice-enabled interfaces, OTT navigation will be more accessible, especially in multicultural and multilingual areas like India.

Abbas and Rehman (2024) state that the key element in consumer loyalty is personalization, where behavioral data can be used to enhance brand communication and build stronger engagement on the platform.

Integration of 5G and Edge Computing

The 5G networks with the introduction to the edge computing are likely to result in significant enhancements in the quality, speed, and reliability of the over-the-top (OTT) services due to their ultra-low latency and broadened bandwidth (Mangini et al., 2023). The edge computing mitigates the content-delivery latency, and it uses data that is processed as close to the end user as possible, therefore, improving the stability of the streams and reducing buffering events. Such an intersection of technologies will help with immersive kinds of media, which include 360-degree video, holograph TV, and live virtual concerts. Music-streaming websites can develop into audio-visual platforms that include live performances in an online environment. Liu et al. (2023) point out that the need to provide high-quality mobile experiences that are seamless, particularly within the framework of Generation Z, will only increase the adoption of 5G-based OTT services in the entertainment sectors as well as in e-learning.

1.4 - The Emergence of Metaverse and Immersive OTT Experiences

It can be projected that future trends in OTT will be realized in the metaverse, where virtual and augmented reality (VR/AR) solutions will be integrated to form immersive content platforms. Interactive, multisensory experiences are expected to be involved in OTT service by 2030, when it becomes integrated with metaverse platforms. Not merely watching but actually participating in content: people will visit concerts, movie releases, or sporting events in three dimensional spaces. Currently, the most popular streaming services are examining VR-based storytelling and interactive cinema where viewers can affect the storylines by taking part in them in real-time (Abbas & Rehman, 2024). The streaming aspect of gamification fits the needs of the younger consumers to the interactive media. The combination of OTT with metaverse technology could make it possible to facilitate new economic formats, including virtual products placement, avatars-based advertisement, and NFT-based collectibles correlated with the exclusivity of the content.

Expansion of Hybrid Monetization Models

The over-the-top (OTT) economy in the future will be more and more based on hybrid monetization models, comprising elements of subscription, advertising, and micro-transactions. Traditional

Subscription Video on Demand (SVOD) platforms like Netflix are also introducing ad-based packages to reduce subscription fatigue and expand their customer base (Habib et al., 2022). Similarly, the Advertising Video on Demand (AVOD) platforms are becoming more ad customization so that they can remain relevant in a highly saturated industry. Freemium ecosystems with free basic content, premium upgrades are likely to become the thriving model of the emerging economies, especially in Asia and Africa by 2030 (Mangini et al., 2023). OTT platforms are expected to integrate influencer marketing, brand affiliation, and affiliate e-commerce within their business, resulting in entertainment and consumer engagement with each other. This overlap is expected to enhance the interdependence of digital marketing, brand image and purchase intention hence supporting the results of Habib et al. (2022) that digital interaction plays a fundamental role in OTT purchase behavior as a hub.

Growth of Regional and Multilingual Content

Localization will continue to be a fundamental component of OTT growth till 2030. Platforms are significantly investing in regional narratives and multilingual content production to access varied cultural markets. Abbas and Rehman (2024) assert that consumers in emerging economies are progressively inclined towards localized material that embodies their cultural values, languages, and social situations. The OTT market in India is anticipated to exceed INR 300 billion by 2030, with regional-language content comprising around 60% of overall consumption (Habib et al., 2022). Comparable trends are manifesting throughout Latin America, Southeast Asia, and Africa, where local productions are successfully competing with international franchises. AI-assisted dubbing and real-time translation will augment accessibility, facilitating cross-border content exchange and promoting cultural globalization.

Emergence of Sustainable and Ethical Streaming

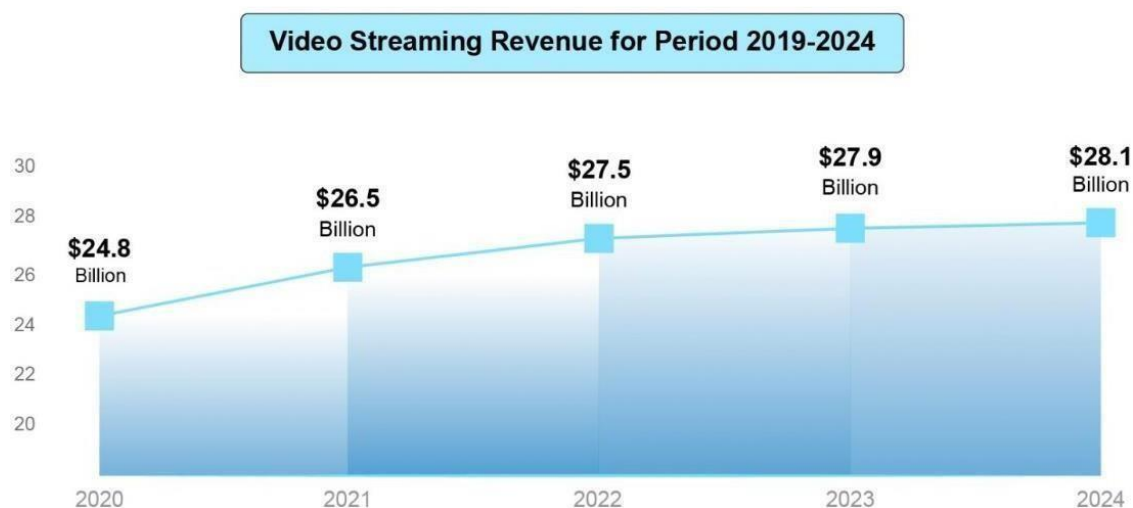
Sustainability is anticipated to emerge as a pivotal factor in the forthcoming stage of OTT advancement. The rapid expansion of digital streaming has raised apprehensions over energy usage, carbon emissions, and electronic waste linked to data centres and high-definition streaming (Mangini et al., 2023). Future OTT infrastructure will emphasize eco-friendly data centres, energy-efficient compression methods, and streaming networks powered by renewable energy. Ethical concerns, including data privacy, algorithmic transparency, and content regulation, will become increasingly significant. By 2030, regulatory frameworks are anticipated to enforce more stringent compliance mandates for OTT platforms, safeguarding user protection while preserving creative autonomy. Ethical AI governance and privacy-by-design methodologies will emerge as competitive differentiators in the worldwide streaming sector.

1.5 - Global Scenario of OTT Services

The Over-the-Top (OTT) services industry in the world has become a critical player in the media and entertainment industry, which has radically introduced new content creation, distribution, and consumption trends on the global platform. Unlike the traditional broadcast / cable television models, OTT systems provide video content directly to the end-users through internet-enabled devices thus bypassing the existing intermediaries. In the last ten years, the model has undergone enhanced adoption, which is due to the advancement in technology, changing tastes and preferences of consumers, and the proliferation of high-speed internet connectivity. The global OTT market is estimated to grow to nearly USD 150.5\$ billion in 2021 and reach about USD 241.6\$ billion in 2030, and its compound annual growth rate (CAGR) is 26.4\$ billion in 2023 to 2030. The trend is an indication of a certain world transition out of the regular television watching towards on-demand and customised consumption of digital media. This breakneck growth also suggests a significant consumer readiness to spend on the high-quality content experience, the sophisticated user interface, and access to it without references to the device used.

International User Base Growth and Infiltration

The increase in the number of users of the OTT services has surged to an unprecedented level. The number of OTT users in the world was estimated at about 1.1 billion in 2020. As of the end of 2022, the number of user base had reached almost 2 billion people, which translates to 82 percent growth in two years. It is estimated that the world will have 4.22 billion OTT users in 2027 and that there will be an increase in the overall user penetration beside 45.7% in 2023 to 53.0% in 2027. The adoption of this technology has been vigorous especially in the emerging economies, which are typified by the use of mobile-first internet. The decrease in the entry barriers to the consumption of digital video may be explained by the spread of inexpensive smartphones, the presence of competitive prices in the telecommunications industry, and the growth of 4G and 5G networks. As a result, OTT platforms have not only become accessible to not just urban and high-income populations but also more and more rural and semi-urban populations throughout the Asia-Pacific region, Latin America, and Africa.



(Figure 1.1 – Video Streaming Revenue Data)

As shown in the chart, this is a drastic and stable rise in OTT revenue globally between the years 2020 and 2024; thus, indicating the ongoing growth and consolidation of the digital streaming space. Market entry was at USD 24.8 billion in 2020; it recorded a significant growth to USD 26.5 billion in 2021, which shows that the market has an excellent growth per year. This first surge can be explained by the fact that the OTT platforms were quickly assimilated during the COVID-19 pandemic where mobility was limited, cinemas closed, and the need to significantly increase the use of digital entertainment drastically changed the consumer viewing behavior. The crisis acted as a booster giving both new and existing users impetus towards ad-based and subscription-based streaming platforms, eventually adding to the revenue base of the sector.

This trend continued into 2022, as the revenues increased to USD 27.5 b billion, indicating that the pandemic-driven growth was not a one-off event but created permanent interest of the consumers towards the OTT services. This phase is an indicator that OTT services have become established as a main channel of consumption of content and not a temporary substitute in exceptional situations. Further development also highlights wise investments by streaming companies in original content, regional language content and international distribution systems, which would boost user retention and monetization opportunities.

However, the figures indicate a progressive slowdown in the growth rate of the years which followed the same period under review. In 2023 and 2024, revenue slightly increased to USD 27.9 bn and USD

28.1 bn, respectively, which shows that the OTT industry is in the next stage of its development, i.e., a more mature stage. As the growth continues, dampened incremental gains indicate increasing market saturation in established markets, increased inter-platform competition and sensitivity to the price of subscriptions. The transition to this phase signifies a shift in structure whereby the rapid subscriber acquisition approach will be replaced by a stabilization of revenue where platforms will seek to depend on differentiated content strategies, hybrid monetization models, and operational efficiencies to continue making profits.

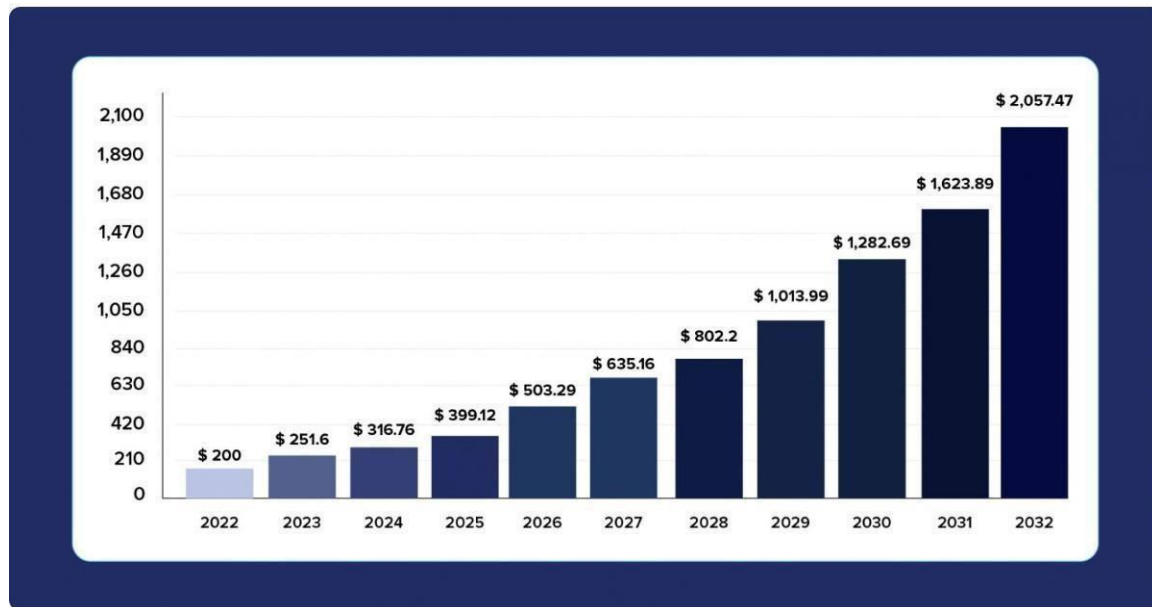
The revenue trend from 2020 to 2024 highlights the robustness and enduring viability of the OTT business. The persistent upward trend, notwithstanding a deceleration in growth rate, signifies a fundamentally robust industry bolstered by changing consumer choices, technical innovations, and the worldwide transition towards on-demand digital entertainment. From a comprehensive analytical viewpoint, the identified trend indicates that forthcoming growth in the OTT sector will likely be propelled less by volume increase and more by strategic innovation, regional market penetration, and improved value extraction per user, signifying a shift from an expansion-driven phase to a consolidation-focused growth model conducive to long-term industry stability.

Regional Distribution of OTT Growth

North America is the biggest market in terms of the over-the-top (OTT) services in the world. This can be explained by the fact that it adopted such services early enough, has a large pool of internet users, and has a high consumer purchasing power. Embarkation of multinational OTT companies, development of standardized advertising models have helped in the collection of a steady revenue in the region. However, current statistics show that growth rates in North America are returning back to the historic levels with indications that the industry is at a maturation stage.

India, China, South East Asia and South Korea are the major growth drivers of the OTT market in the Asia-Pacific region. These are the territories that contain high populations with discretionary spending that is being channelled more towards digital media. In addition, the demand of content that is specific to the major languages that are spoken in these localities is high. There is an increased adoption of OTT services in Latin America, which is also occurring in certain areas of the Middle East and Africa. The growth is based on the proliferation of mobile broadband access, as well as the strategic efforts to localize content.

OTT Statistics 2026 – User Statistics



(Figure 1.2 – OTT Growth Revenue Prediction)

The illustration of the OTT user data up to the year 2026 and later on shows that there is a healthy and accelerating growth curve in the international OTT ecosystem, which highlights the fact that streaming services are expanding with time by increasing size and more penetration. The data reflects a consistent and considerable increase in user-related economic value per annum since 2022 when the figure began with a rate of approximately USD 200. The values increase to USD 251.6 and USD 316.76 in 2023 and 2024, respectively, which indicates an early period of rapid adoption due to improved internet connectivity, lowering smartphone prices, and the general acceptance of the on-demand consumption of video content among different demographics. This era marks the transformation of OTT platforms as platforms of specialized digital options into leading providers of entertainment.

The further growth is steepest in 2025, where the values get USD 399.12 and USD 503.29 suggesting that it is a qualitative change in the trends of user engagement and monetization. This step shows an increase in user base and increment in the income generated per user through subscription improvement, premium content offering and implementation of hybrid monetization approaches combining subscriptions and advertisement. The steady growth to 2027 and 2028, reaching USD 635.16 and USD 802.2 respectively, illustrates the solidified platform ecosystems, supported by the investments in original content, regional and multilingual television as well as personalized recommendation systems that enhance user retention and watching activity.

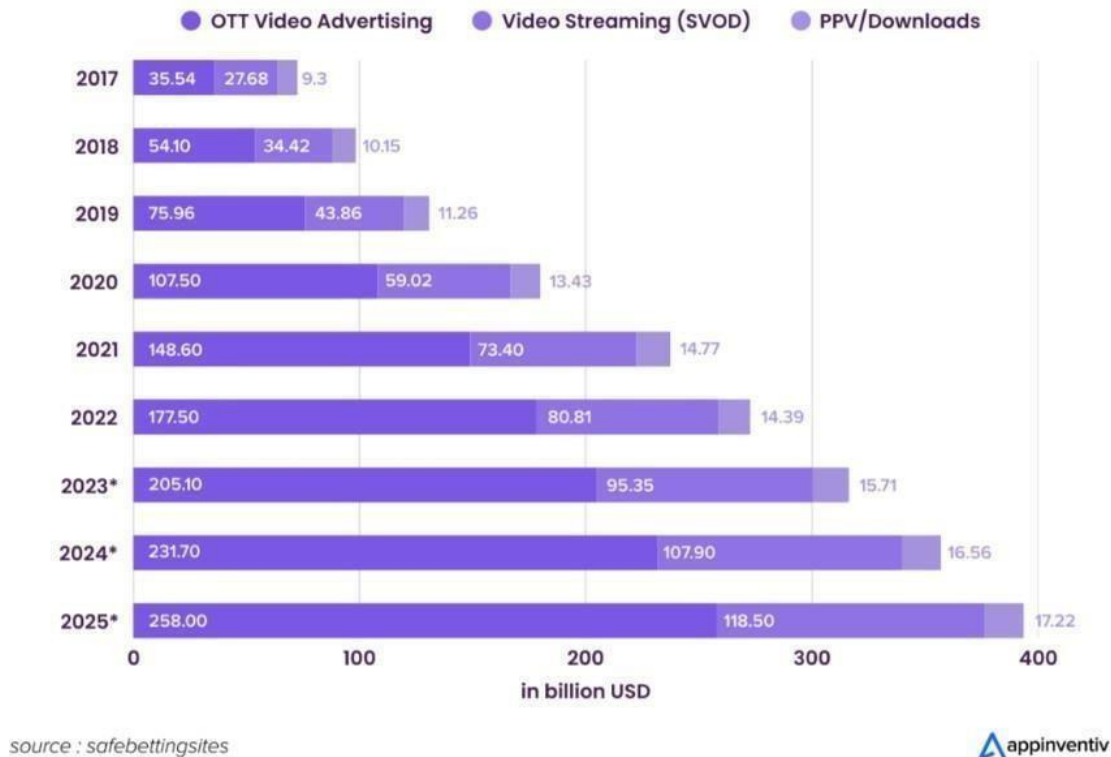
The growth will be significantly higher starting in 2029 with the values related to users exceeding USD 1,000 in 2029 and reaching USD 1,623.89 in 2031 and USD 2,057.47 in 2032. This sharp uptrend is a symptom of a compounding effect caused by an expansion of the market in developing economies, accumulation of household subscriptions, and the transformation of OTT platforms into full-service digital entertainment hubs, which also include films, series, live sports, and interactive content. The level of growth in this decade is an indicator of a growing consumer willingness to allocate money towards high-quality, differentiated, platform-specific content, and the growing role of data-based advertising incomes in ad-based OTT packages.

The statistics tell a unique narrative of relentless and quickened growth in the number of OTT users, signifying quantitative and qualitative improvement of the user engagement. According to the trend, the OTT industry is entering a phase of stable acceptance and consolidation into a maturity phase of cyclical growth characterized by scalability, revenue diversification, and increased economic significance. The trend suggests that the future competitiveness of the OTT industry will rely not only on the user acquisition but also on the ability of platforms to increase the lifetime user value by introducing content innovations, integrating technologies, and using adaptive monetization tactics, which will entrench the critical role that OTT services will play in the evolving global media and entertainment market.

Revenue Models and Monetization Trends

The economic system of the global ecosystem of over-the-top (OTT) services is supported by numerous revenue systems. Substance Video on Demand (SVOD) continues to dominate the monetization model of the well-developed economies, with Advertisement Video on Demand (AVOD) and freemium models increasingly becoming popular in the price-sensitive markets. According to projections, it is expected that the average revenue per user (ARPU) of the OTT video industry will reach about USD \$90.14 in 2027. This positive trend in ARPU is indicative of the increase in monetization effectiveness and the development of hybrid pricing mechanisms. The trend of ever-increasing popular platforms now uses subscription schemes that are supported by advertisements to achieve a balance between the cost-efficiency and commercial sustainability. The importance of this change has been further compounded by the fact that customers are growing more dissatisfied with subscriptions and are in need of cheaper options to entertain themselves.

OTT Video - Revenue Distribution



(Figure 1.3 – OTT Revenue Distribution OTT/SVOD/PPV-Downloads)

Over three hundred million people in India have seen videos on the internet by the time the 2019 fiscal year came to a close. There was a significant shift in the manner in which individuals viewed digital videos. It is anticipated that this number would draw close to 500 million viewers by the time the fiscal year 2023 rolls around. The result would be that India would become the second-largest market for internet video in the world, behind only China. It is anticipated that by the year 2022, the amount of video traffic on India's internet would have increased from 1.5 Exabyte per month to 13.5 Exabyte per month. This growth occurred since 2017. Video content accounts for more than 77 percent of all traffic on the internet. The significant expansion of video content inside India's digital ecosystem is evidence of the significance of this medium

The forecasts of OTT video revenue between 2017 and 2025 suggest a structural shift in the revenue framework of the world-OTT ecosystem, as advertising-based and subscription-based business models showed faster growth as compared to the pay-per-view and download revenue. In 2017, the video advertising sales were USD 35.54billion, Subscription Video on Demand (SVOD) USD 27.68billion

and pay-per-view/download USD 9.30billion. At this stage, OTT business was still in its infancy; in the early days of its monetization, the platforms largely depended on advertisement and subscription as the main business model with transactional models playing a secondary role. The sales of advertising improved USD54.10billion to USD75.96billion and the SVOD revenues improved USD34.42billion to USD43.86billion in the period of 2018-2019. The OTT services are increasingly becoming popular among the customers and advertisers, due to the development of internet infrastructure, increased smartphone penetration and the shift of advertising money out of the traditional media to the digital video platforms. The pay-per-view and download revenues also showed slight growth, but their role was limited, which indicates that the consumers are switching to subscription-based access, government to transactional content.

The COVID-19 pandemic resulted in the global change in the media consumption patterns, specifically in increasing the rate of change since 2020. In 2020, advertising revenues amounted to USD 107.50 billion and then to USD 148.60 billion and USD 177.50 billion in 2021 and 2022, respectively. This fast growth explains the increased popularity of OTT platforms as an advertisement channel, supported by advanced data analytics and personalized content delivery. With the adoption of binge-watching and on-demand viewing by consumers, revenues of the SVOD were USD 59.02billion in 2020 and USD 73.40billion in 2021 and USD 80.81billion in 2022.

After 2023, the OTT market is consolidating and expanding. In 2023, the advertising revenues will amount to USD 205.10billion with potential of reaching USD 258.00billion in 2025 thus being the main source of income of OTT operators. This leadership is indicative of a calculated move to mixed types of monetization, where platforms combine ad-supported and subscription levels to capture maximum reach and profitability. The projections show that in 2023, the SVOD revenues will be USD 95.35billion whereas in 2025, the revenues will be USD 118.50billion, which means that the concept of subscription-based consumption remains relevant to OTT monetization events despite consumer price sensitivity. Nevertheless, the revenue of pay-per-view and download is expected to increase by USD 13.43billion in 2020 to USD 17.22billion in 2025.

Due to the growing popularity of subscriptions or the free access that is ad-supported, ownership-based or transactional content models are also in a decline in relevance. The trend in revenue distributions shows that OTT business is embracing scalable, recurrent, and data-driven revenue models. The simultaneous increase of advertisements and SVOD revenue is an indicator of market maturity, changing tastes, and repositioning of the platform to guarantee its survival in the long term by

diversifying and complementing income streams of monetization.

Content Investment and Competitive Dynamics

The global over-the-top (OTT) platforms are also dedicating a lot of resources to the creation of original content, which has made them stand out in an increasingly crowded market. Large platforms spend tens of billions of dollars a year on content, and they give much importance to original series, feature films, live sporting events and local programming. This investment is mostly budgeted to the establishment of proprietary media assets. The content localization remains one of the most important competitive strategies as it allows platforms to enter culturally different markets and improves user interaction, thus, becoming one of the crucial elements of the current competitive environment. Playing with platform consolidation, mergers, and strategic alliances also contribute to the competitive forces of this industry.

OTT aggregators and bundled packages are on the rise and as customers are becoming more and more demanding to access a wide range of streaming services, they are seeking them and bundling them in an easy way.

Technological Enablers

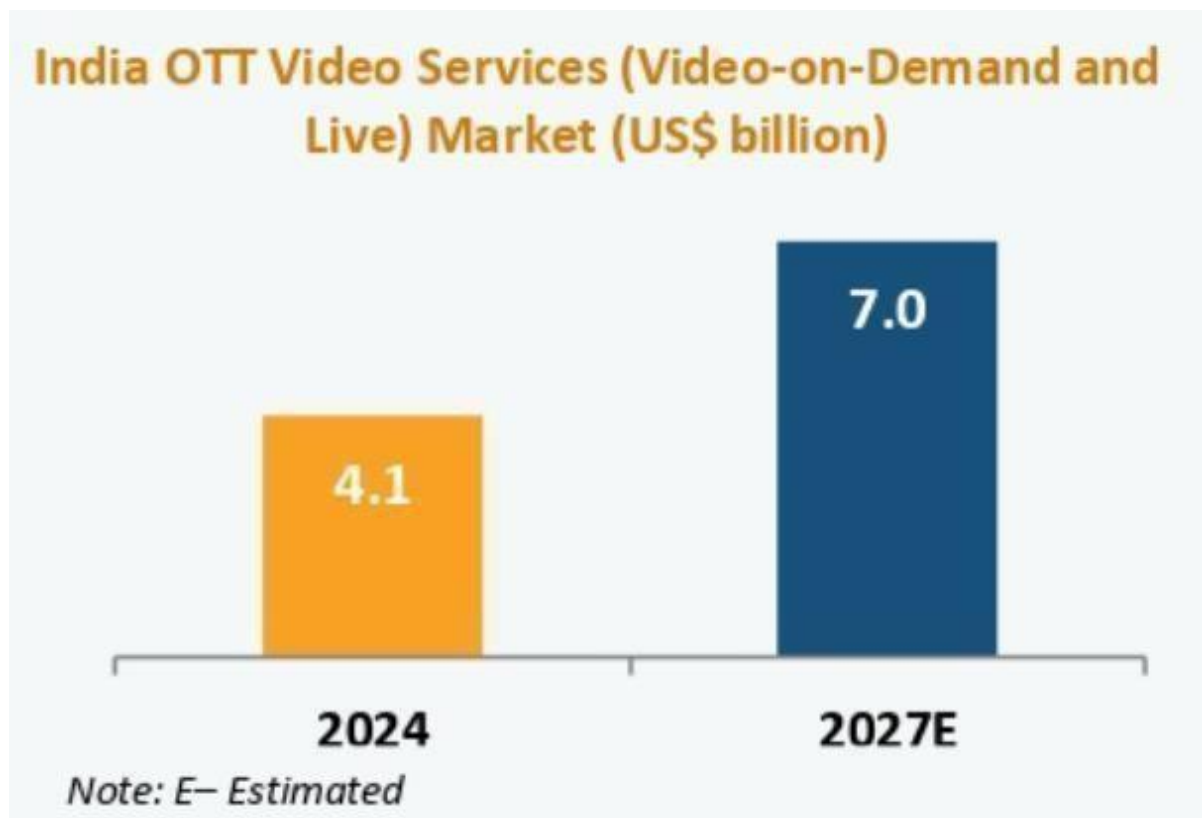
The user experience has been considerably improved as a result of technological breakthroughs such as artificial intelligence (AI), machine learning (ML), and advanced data analytics. These advancements have enabled personalized suggestions, predictive watching behavior analysis, and targeted advertising. In addition, it is anticipated that the introduction of 5G networks would hasten the adoption of ultra-high-definition streaming in both 4K and 8K resolutions, as well as interactive content and immersive watching experiences.

1.6 - Indian Scenario of OTT Services

Market Size and Viewer Base

India had more than 300 million online video viewers by the end of the fiscal year 2019. There was a significant change in the modes in which people were able to consume digital video content. It is

estimated that this figure would reach half a billion viewers by the end of fiscal year 2023. India would therefore become the second largest internet video market in the world, only second only to china. By 2022, the monthly video traffic on the internet in India is estimated to increase by 13.5 Exabyte compared to its 1.5 Exabyte in 2017, with a similar tendency. In the amount of over 77 percent of all internet traffic, video content takes up. The intensive growth of the video content within Indian digital



environment has been empirical proof of the importance of the medium.

Source: ibef.org (Figure 1.4 – OTT Growth Prediction)

There is an impressive trend in growth of video-on-demand and live-streaming services in India as demonstrated by the growth of the Indian OTT video services market. By the year 2024, the valuation of the industry had reached USD 4.1 billion when these platforms grew to be a legitimate source of entertainment. This number can be explained by the increased penetration of smartphones, the affordability of mobile data, and a young, digitally active audience that can absorb the consumption of on-demand and live-streaming entertainment, sports, and infotainment content.

It is estimated that the market will reach USD 7.0 billion by 2027, which is an indication of a faster growth. The almost twofold increase in market worth is a growth in compound owing to the growth of the user base and increased monetization approaches. The projected growth is reflective of increased

usage of paid subscriptions, ad-supported OTT versions, and expansion of regional and vernacular content, therefore, making it easier to reach a wide range of audiences beyond the urban centres. Live streaming especially in sports, news and programmers focusing on events has increased the user interaction and frequency of viewing which have then increased revenue streams.

Analytically, the increasing disparity between the 2024 and the 2027 forecast depicts how India has evolved since 2020 as an emerging market in terms of OTTs to a high-growth digital media ecosystem. That the expected growth is also an indicator of increased confidence on the long-term scalability of Indian OTT industry among investors and operators of the platform. The statistics suggest that India is on the verge of being among the most rapidly expanding OTT markets in the globe, due to the current changes in the digital infrastructure, transforming consumer preferences, and aligning the content, technology, and monetization structures to suit the Indian context.

Drivers of OTT Growth in India

The cost-effectiveness of mobile data has been the primary driver of OTT expansion in India. The cost of mobile data decreased from around INR 313 per GB in 2015 to INR 18.5 per GB, establishing India as the most affordable mobile data market worldwide. The average monthly data consumption per user increased from 0.88 GB in 2016 to 8.7 GB in 2018, facilitating continuous long-form video viewing. Moreover, smartphone penetration surged swiftly, with hundreds of millions of video-capable devices utilised throughout urban and rural India. Rural internet penetration rose from 13% in 2016 to 24% in 2018, introducing new groups of first-time digital customers into the OTT ecosystem.

Table 1.2 – OTT Growth Drivers	
Factor / Key Metric	Details & Statistics
Per Capita Consumption	Second highest consumption of online video in the world
Mobile Data Cost	Cheapest mobile data in the world (INR 18.5/GB). In 2015, it was INR 313/GB.
Rural Internet Penetration	Growth to 24% in 2018 (up from 13% in 2016)
Smartphone Users	Growth to ~340 Million in 2018 (up from 200 Million in 2015). 11% growth in feature phones shipments, which was higher than smartphones growth in 2018.

Average Data Usage per	Growth to 8.7 GB per month in 2018 (up from 0.88 GB
Subscriber	in 2016)
Average Mobile Data Download Speed	Growth to 9.93 Mbps in Nov'18 (up from 8.88 Mbps in Nov'17)

Source: KPMG report

1.7 - SWOT ANALYSIS OF INDIAN OTT SECTOR

SWOT Analysis: Indian Digital Media Landscape	
STRENGTHS	WEAKNESSES
- Massive Mobile-First Audience - Localized and Multilingual Content Strategy - Strong Domestic and International Investment - Youth-Centric Demographics - Policy Push for Digital India.	- Price Sensitivity and Subscription Fatigue - Rural-Urban Digital Divide - Limited Monetization in Regional Content - Piracy and Content Duplication - Fragmented Regulatory Environment
OPPORTUNITIES	THREATS
- Regional Market Expansion; - Hybrid Monetization Models; - Original Indian and Vernacular Productions - Integration with Telecom and Smart Device Ecosystems; - Emergence of Sports and Interactive Entertainment;	- Intensifying Competition and Consolidation; - Regulatory and Political Interventions; - Cultural and Ethical Challenges - Economic Pressures and Ad Revenue Fluctuations - Technological Risks

(Figure 1.5 – SWOT Analysis of Digital Media)

STRENGTHS:

- Massive Mobile-First Audience:** India has more than 700 million smartphone users and some of the lowest mobile data charges in the world. This makes OTT content very easy to get for a lot of people.
- Localized and Multilingual Content Strategy:** Disney+ Hotstar, Zee5, SonyLIV, and regional players like Aha, Hoichoi, and Sun NXT do well by offering material in a variety of Indian languages and genres that appeal to a wide range of cultural tastes.
- Strong Domestic and International Investment:** Both big companies from across the world (like Netflix and Amazon Prime Video) and Indian producers have put a lot of money into making original Indian content. This has led to new ideas and jobs in the creative field.
- Youth-Centric Demographics:** More than 60% of India's population is under 35, and OTT services cater to a tech-savvy, digitally native audience that likes personalized, mobile-based, and on-demand entertainment.
- Policy Push for Digital India:** Digital India programs and more people in Tier-II and Tier-III cities getting online are both helping more people use digital material.

WEAKNESSES:

- Price Sensitivity and Subscription Fatigue:** Indian audiences are very aware of how much things cost, thus they don't want to pay for more than one subscription. A lot of people choose free or ad-supported content (AVOD) models.

- ✚ **Rural-Urban Digital Divide:** Even though digitization is happening quickly, there are still gaps in infrastructure in rural regions that make it hard to stream HD video because of bandwidth limits.
- ✚ **Limited Monetization in Regional Content:** People want regional material, but monetization strategies are still changing, and smaller language markets don't make much money.
- ✚ **Piracy and Content Duplication:** Unauthorized streaming and torrenting are common, which hurts profits and makes it less likely that companies would invest in high-budget productions.
- ✚ **Fragmented Regulatory Environment:** India doesn't have a clear, unified set of rules for OTT content right now. There is self-regulation under the Digital Media Ethics Code (2021), but enforcement is still not consistent.

OPPORTUNITIES:

- ✚ **Regional Market Expansion:** The next step in growth is in Bharat (Tier-II and III cities), where more people are using smartphones and the internet is getting cheaper. This is making new OTT viewers.
- ✚ **Hybrid Monetization Models:** In a market that cares about value, combining freemium, subscription, and ad-based models can help keep costs down while still making money.
- ✚ **Original Indian and Vernacular Productions:** OTT platforms may set themselves apart by investing in culturally relevant stories, local web series, and regional movies.
- ✚ **Integration with Telecom and Smart Device Ecosystems:** Working with Jio, Airtel, and Vi to offer bundled OTT subscriptions with mobile or broadband plans makes it easier for people to access and keep using the service.
- ✚ **Emergence of Sports and Interactive Entertainment:** Live streaming of sports events (like IPL and Pro Kabaddi) and gamified viewing experiences are quickly increasing engagement and advertising revenue.

THREATS:

- ✚ **Intensifying Competition and Consolidation:** The Indian OTT market has more than 50 sites, including big names like Netflix and Hotstar and smaller ones. This saturation makes it more expensive to get new customers and keeps them from leaving.
- ✚ **Regulatory and Political Interventions:** The government is paying more attention to content about religion, politics, or sex, which can make it harder for creators to follow the rules and limit their freedom of expression.
- ✚ **Cultural and Ethical Challenges:** Finding a balance between free creative expression and

established social and cultural standards is still a big problem, and it often leads to debates about censorship.

- ✚ **Economic Pressures and Ad Revenue Fluctuations:** Smaller platforms that rely on AVOD models might be hurt by economic slowdowns and changes in the way digital ads work.
- ✚ **Technological Risks:** Problems with cybersecurity, data privacy, and algorithmic transparency might make people less trusting and lead to harsher rules.

1.8 - PROBLEM DISCUSSION AND RATIONALE OF STUDY:

The introduction of Over-the-top (OTT) media services has reorganized the entertainment and communication industry all over the world with consumers now having the ability to circumvent the traditional broadcasting structures and procure on-demand and customized content through the Internet. The global OTT has developed at a very fast pace due to the advancement of broadband connectivity, the power of AI, and ubiquitous growth of smartphones; however, adoption, consumption, and customer retention patterns show high regional diversity. The given effect is particularly acute in India with one of the largest mobile-first populations in the world and the most affordable mobile data rates, which can be regarded as a bright example of an active and fast-growing OTT marketplace. However, even in the face of such a solid development, the Indian OTT ecosystem has many structural and behavioral issues that deserve additional academic research.

This issue is connected with the lopsided distribution of the use of OTT and its sustainability in the Indian multifaceted socio-economic and cultural context. Despite the significant market penetration of such platforms as Netflix, Amazon Prime Video, Disney+ Hotstar, and regional ones such as Zee5, Aha, and Hoichoi, there are still visible differences related to accessibility, price, and retention of users in the long term. The sector is under threat by a highly competitive, price-sensitive environment which

is magnified by subscription fatigue and piracy. In addition, traditional adoption models, including the Unified Theory of Acceptance and Use of Technology (UTAUT2) and the Technology Acceptance Model (TAM), do not sufficiently account for OTT-specific factors, like the quality of content and personalization of the algorithm, and regional preferences in storytelling. This conceptual gap explains the importance of context specific models that consider both utilitarian and hedonic motivation that is relevant to the Indian market.

Available literature is mainly focused on first adoption intentions instead of continued use or loyalty towards the platform. Given the current structure of an increasingly divided market that currently accommodates over fifty competing services in India, it is crucial to comprehend the psychological and social forces behind the continued engagement. Such aspects as habit formation, hedonic joy, and social connectedness have proved to be more explanatory of enduring OTT utilization compared to conventional elements like performance expectancy. However, such determinants have not yet been empirically studied in the Indian context, especially in the context of cultural features like communal viewing, linguistic identity, as well as family based consumption behavior.

Although OTT access has already been democratized due to the implementation of 4G connectivity and cheap smartphones, the infrastructural differences between urban and rural settings persist. The rural consumers are still faced with challenges such as poor bandwidth, intermittent streaming signal and lack of digital literacy, which make it difficult to adopt it fairly. The growing adoption of modern technologies, including predictive AI-based recommender systems, streaming 5G, and immersive formats leads to new issues related to the privacy of data, user control, and transparency of algorithms. These dynamic aspects bring the need to constantly review the interaction between technological development, user trust, and perceived value in OTT ecosystems.

The Indian OTT market is currently moving towards the phase of consolidation after the period of expansion, when the further development will depend upon the possibility to innovate the business model and to deepen the ecosystem of the regional content. Mixed monetization approaches involving a combination of subscriptions with advertisements (SVOD and AVOD) have also come out as viable mechanisms to balance accessibility and viability. However, monetization of regional and vernacular content, especially in smaller language markets, remains a weak point, despite its increased demand in the market. This mismatch points to the fact that localization efforts of content and monetization strategies that can be large-scale are not aligned.

This inquiry is impregnable in three aspects. First, it attempts to address a conceptual gap by developing technologies-adoption models to integrate OTT-specific factors, namely, content-quality, flexibility of subscription, and customization through algorithms. Second, it will provide empirical evidence on the behavioral, technological, and socio-cultural predictors of OTT adoption in India, which is an emerging digital economy that is co-present with both traditional and modern consumption of media. Lastly, the research presents a comprehensive addition to scholarly literature and business practice through the initiation of tangible solutions to user retention, content relevance, and sustainability of a platform in a competitive digital entertainment environment.

CHAPTER 2 – LITERATURE REVIEW

2.1 - OTT Adoption:

The international media and entertainment industry is currently experiencing a major paradigm shift: the shift of video distribution to nonlinear terrestrial and satellite delivery systems to internet-based and on-demand delivery models better known as Over-The-Top (OTT) platforms. This shift is often called cord-cutting, but it is not the shift in the technological medium of transmission only, but also a reconfiguration of the relationship between the consumer and the content (Sujata et al., 2015). The passive viewer, who was formerly constrained by programming kits and packaged cable services, has now become an active consumer that has the freedom to create their own program choices based on a widening range of service options provided by more and more companies.

The rapid growth of the OTT business has created a competitive environment that is characterized by a high rivalry rate, high user acquisition rates, and, ironically, easy switching barrier. Unlike older cable subscriptions with their often-lengthy contracts and hardware needs (set-top boxes), the OTT subscriptions are mostly sold on a month-to-month basis, therefore, allowing consumers to change the available services with ease according to the existing content availability or financial factors. Based on this, the need to comprehend the variables that affect User Intention to Adopt and Continuous Usage Behavior has become not only an academic issue but also a strategy to ensure the sustainability of a platform.

Theoretical Explanation

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a holistic and integrative model that aims at explaining the processes that underlies human acceptance and adoption of new information systems and technologies. The UTAUT model has been maintained in a sequence of revisions over the last 20 years, therefore, establishing itself as one of the most significant ones in the sphere of information systems research. The focus of this literature review is to consider the UTAUT3 model, the most recent model that takes personal innovativeness as an extra antecedent of user intention to adopt technology. In the UTAUT 3 model, there are eight core characteristics, used as independent variables, three demographic variables, used as moderators and the intention of users to adopt as a dependent variable.

2.1.1 - Evolution of UTAUT Models: From UTAUT to UTAUT 3

Original UTAUT Model (Venkatesh et al., 2003)

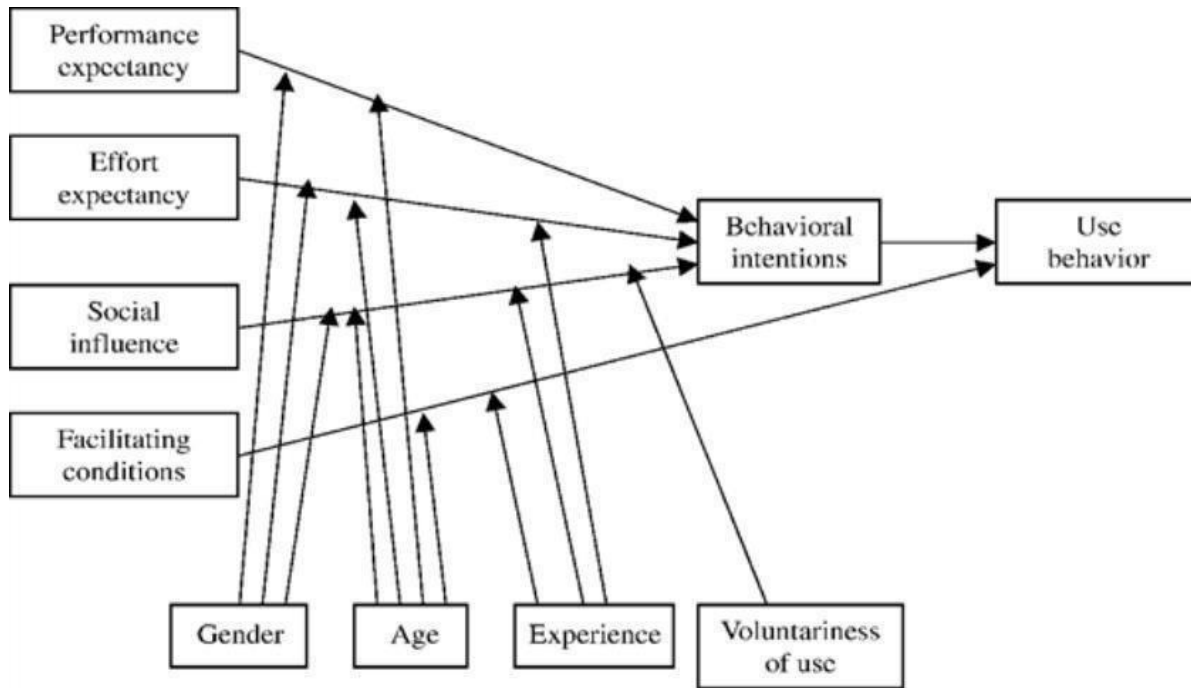


Figure 2.1 – UTAUT Model

(Venkatesh & Morris, 2000) proposed the first UTAUT model in 2003 the model was a conclusion of an extensive synthesis of the eight technology acceptance theories that had been proposed earlier. These theories included the Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), the Motivational Model (MM), the Theory of Planned Behavior (TPB), a TAM-TPB syndrome, the Model of Personal Computer Utilization (MPCU), the Theory of Innovation Diffusion (IDT), and the Social Cognitive Theory (SCT). The authors combined the points of view of these two theoretical perspectives to form a single framework which explains the behavioral intentions to use technology with about 70 percent and the actual use behavior with about 50 percent.

The original UTAUT model identified four major constructs directly affecting the user behavioral intention, namely (1) performance expectancy, (2) effort expectancy, (3) social influence and (4) facilitating conditions. The empirical evidence suggests that these variables are the most consistent predictors of the technology adoption in different organisational settings, and they are based on previous research publications. In addition, the original model had four moderating constants; the gender, age, experience and voluntariness of use assuming that they would moderate the impact of the key constructs on behavioral intention and actual utilization. The fact that these moderators were

included was based on the assumption that they would soothe the effects of the core elements on behavioral intention and actual use behavior (Shankar et al., 2003).

Extended UTAUT Model for Consumer Context (UTAUT 2, Venkatesh et al., 2012)

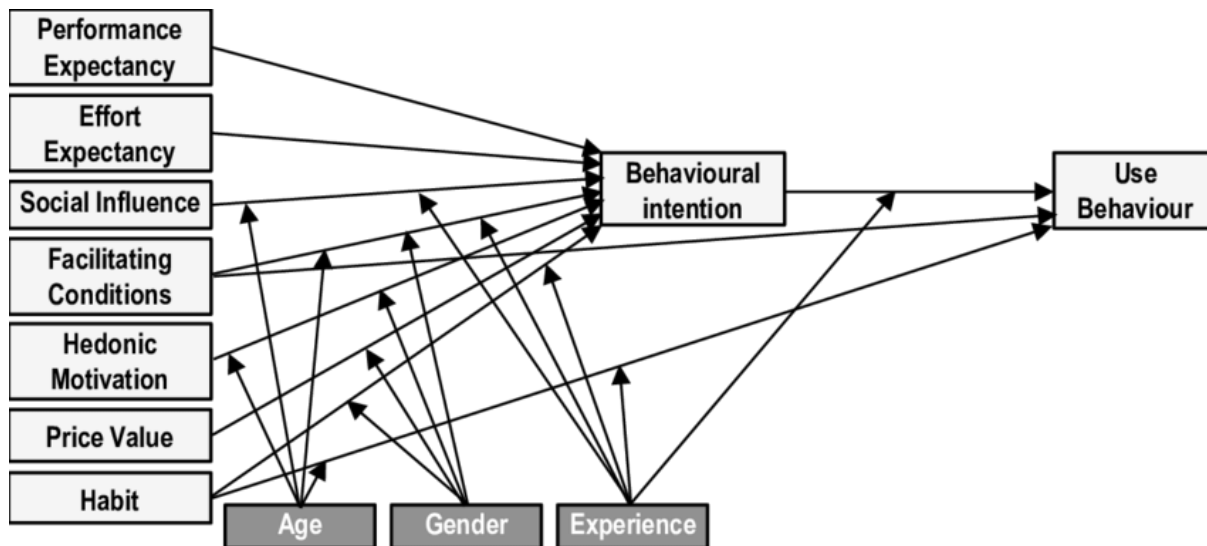


Figure 2.2 – UTAUT2 Model

(Venkatesh et al., 2012), revised the original UTAUT model to come up with UTAUT 2, which was particularly tailored towards consumer technology adoption. This was so in appreciation of the fact that the organizational environments are highly disparate as compared to consumer environments. The three new variables that were included in the extension were Hedonic Motivation, Price Value and Habit. These were considered especially important to the consumer behavior. When it comes to the issues of consumer technology adoption, marketing and consumer behavior empirical evidence indicated that there are variables influencing consumer technology adoption that extend past the utilitarian concerns that are underscored in the organization. This fact was the force behind the inclusion of these elements (Brown et al., 2010).

The model of UTAUT 2 demonstrated better explanatory performances as compared to the former model and explained about 74 percent of the variation in intention to behave and 52 percent of actual behavior in use among consumer demographics. The addition of hedonic motivation emphasizes the importance of pleasure and enjoyment as the factors of technology adoption in the case of entertainment and consumer-focused technologies. It is the price value that brings out the serious cost-benefit evaluation that customers must engage in when it comes to accommodating the usage of

technology since they are directly responsible to the financial impact of their technology purchases. Finally, the notion of habit can be used in conjunction with the automaticity view, in which it is acknowledged that the regular use of technology may lead to automatic and unconscious patterns of behavior that influence technology adoption without having to rely on the intention-making process.(Migliore et al., 2022)

UTAUT 3 Model with Personal Innovativeness (Farooq et al., 2017)

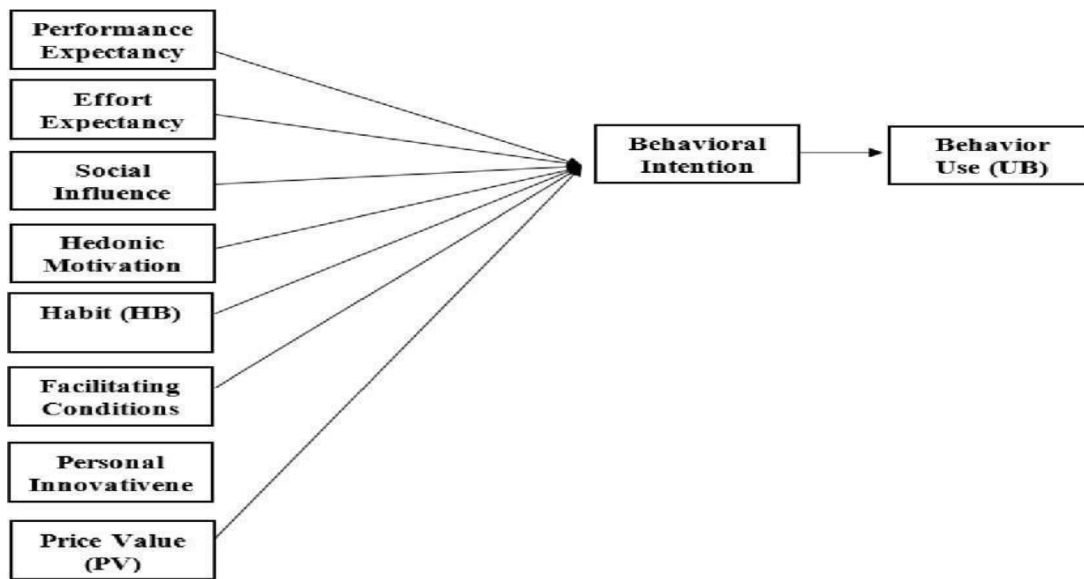


Figure 2.3 – UTAUT3 Model

As a continuation of the theoretic framework introduced by UTAUT and UTAUT 2, Farooq and others came up with UTAUT 3, which incorporates an eighth construct, Personal Innovativeness that can be used as a predictor of behavioral intention. Personal Innovativeness is an attribute of people that is used to demonstrate their readiness to adopt new ideas and technologies before others (Malewar & Bajaj, 2020b). This variable has been incorporated as one of the factors depending on the Innovation Diffusion Theory of Rogers, which states that individual differences in innovation-proneness are very critical determinants of technology adoption decision, regardless of other factors influencing the decisions (Migliore et al., 2022).

The first UTAUT 3 model that was tested on the use of lecture capture systems by business students in Malaysia explained 58.1 percent of the intention to use technology. Later empirical implementations and extensions of UTAUT 3 have demonstrated its greater predictive validity with recent research pointing at R2 values greater than 84 percent which implies that the model can explain a big part of the variation in technology adoption intentions in different settings (Farzin et al., 2021).

2.2. Core Constructs of UTAUT 3 Model

Performance Expectancy

Performance Expectancy refers to the degree to which one considers that the use of a particular technology will help to enhance his/her job performance or help to reach some significant goals. This construct outlines the expected positive outcomes of the usage of technology and summarizes the real advantages that users expect to receive. The prediction of performance expectancy as to behavioral intention has remained a significant predictor in many situations with respect to technology adoption (Wan et al., 2017).

Empirical evidence indicates that the anticipation of improvement in performance contributes greatly towards the willingness of users to adopt technology especially when users are aware of specific improvements in performance (Yadav et al., 2023). In the organizational set-ups, probability of employees adopting new systems is high when employees feel that these systems will either increase productivity, efficiency or total performance. When people in the consumer environment find that the new technology will enhance their capabilities, or provide an addition to them, they are likely to accept the technology (Sujata et al., 2015).

Effort Expectancy

Effort Expectancy is a scale used to estimate the level of comfort when using a specific technology. This construct is the description of the extent to which the user can learn to use and operate the technology with minimal effort or frustration (Arruda Filho et al., 2019). The construct has informed itself on the existing literature touching on technology acceptance in the sense that the more an individual perceives a given technology the easier it is to have an intention of using the technology (Katherine Chen, 2019).

The perceived ease of use of technologies makes the latter far more likely to lead people to develop positive behavioral intentions towards their use. This construct has great applicability to both users who are not necessarily technology savvy and to very complex technologies where learning processes are very intensive and need a lot of investment (Wedlock & Trahan, 2019.). Ease of design, availability of internal friendly interfaces, easy navigation and efficient training and support systems will go a long way when it comes to reducing the effort expectancy which in turn increases the adoption rates (Baki & Amoozegar, 2021).

Social Influence

Social Influence refers to how individuals are aware that significant people, including family members, colleagues, supervisors, peers, and the society at large, have beliefs on the need to use a certain technology (J. Kim et al., 2016). This model summarizes the normative factors and social pressures that shape the decisions made by individuals to adopt. Social influence operates in different ways but they include subjective norms, which are perceptions about what significant other people expect of them; social factors, which are the direct recommendations of peers; and image considerations, which are the implications of technology adoption to the social status of the individual (Poulose, 2020).

Social influence is also especially influential in collectivist cultures and in situations where opinion leaders or other influential people also demonstrate the use of technology (Maslowska et al., 2017). The decisions on technology adoption will likely be influenced by peer influence, organizational approval, and social norms in the reference groups in a significant manner. It has always been demonstrated that social influence has greater effects in situations of compulsory adoption, as well as those people, who are less intrinsically motivated towards the technology adoption (Farzin et al., 2021).

Facilitating Conditions

Facilitating Conditions refer to the degree to which one believes that the organizational and technical infrastructure is in place to make it possible to make use of a particular technology (Escobar-Rodríguez & Carvajal-Trujillo, 2013). The conditions in question cover a range of organizational factors such as: institutional policies, management support and resource allocation, and, a range of technical factors such as: system infrastructure, technical support, training programs and compatibility with existing systems (Cesareo & Pastore, 2014).

The presence of adequate enabling factors takes the edge off barriers to technology adoption and use. These factors include: the availability of technical support personnel, adequate training resources, compatible hardware and software and organizational policies that encourage or mandate the use of technology (Abdul Latiff et al., 2022). When companies put in place comprehensive facilitating conditions, users face reduced obstacles to technology adoption, leading to a huge jump in the rate of technology adoption.

Hedonic Motivation

Hedonic motivation is the fun, pleasure or enjoyment that comes with interacting with a given

technology. This model recognizes that the decisions made regarding how we adopt technology will be influenced not only by pragmatic factors but also by the factors influenced by enjoyment, pleasure, and emotional fulfilment (Brown et al., 2010). Hedonic motivation is a concept that is particularly relevant in the realm of consumer-targeted technologies, such as social media, gaming applications, and other technologies that add an element of experience to what they offer (Madnani et al., 2020).

Findings of empirical studies suggest that hedonic motivation can have significant positive effects on behavioral intentions, which are often as strong as or stronger than the effects of performance expectancy in the consumer context (Madnani et al., 2020). A greater tendency to develop strong adoption intentions and adopt a consistent usage pattern is exhibited by individuals who view technology as fun and entertaining. Its introduction of new design, possibility of gamification, attractive interfaces favourable to the eyes and functions that are entertainment oriented are significant in the enhancement of hedonic motivation thereby making the use of technology easier (Jolley et al., 2006).

Price Value

Price Value may be defined as the psychological evaluation that is done by consumers, where they take the perceived benefits of technology as opposed to the expenditure that is needed to purchase and use the technology (Alalwan et al., 2018). This notion takes into consideration the fact that consumers are engaged in a rational economic process of making decisions, which entails an evaluation of whether the benefits they expect to receive are well justified by the financial cost of the move (Muchlis Gazali et al., 2018). The importance of the price value is considerably increased during the consumer situations when a person directly bears financial responsibility in relation to the purchase of technology (Joshi et al., 2015).

When people are sure that the benefits and advantages prevail over the costs people are likely to look at technology in a better perspective and are more likely to accept it. The price value considerations do not just involve the direct costs incurred in purchasing the product alone, but also the cost incurred in terms of subscriptions, maintenance, and the opportunity cost of the same (de Matos et al., 2018). Competitive pricing, strategic promotions, flexible payment systems, and open communication on the benefits compared to the costs are highly effective in terms of the perception of price value and utilization of technology (Habib et al., 2022).

Habit

Habit may be described as the level to which individual persons display behaviors in an automatic fashion, which are determined by the previous repeated experience of a specific technology (S. Kim et al., 2021). This construct derives its basis on Habit/Automaticity Perspective, which holds that frequent interaction with technology leads to the development of automatic behavioral patterns that are performed without conscious attention. Contrary to other constructs in the UTAUT model that focus on rational decision making processes, habit captures the unconscious and automatic elements of technology based behavior (Abbasi et al., 2021).

It has been shown that habit has direct effects on behavioral intention and usage behavior as well as indirect effects through learned preferences and routines (Singh et al., 2021). As soon as the habitual practices of technology use have been developed through a series of repeated interactions, the further adoption and the further involvement of the user is more likely to become more automatic which reduces the dependence on the influence of conscious evaluation. The habit formation process can be used as a tool to the permanent adoption of technology and creation of regular usage patterns (Arias-Oliva et al., 2019).

Personal Innovativeness

Personal Innovativeness is a personality trait, which depicts the degree to which one is disposed to adopt innovations before others in a particular social setup. This model is based on the Innovation Diffusion Theory developed by Rogers that states that different people have orderly differences in their inclinations to innovations (Venkatesh et al., 2012). The innovative people have the tendency to take risks, they have the keen interest to learn more about their environment and they are welcoming to new experiences and this helps them adapt new technologies before their peers (Cheung & Vogel, 2013).

Members with high scores on personal innovativeness are more likely to find the information about the new technologies, to start using new applications, and to accept the risks and uncertainties that come with early adoption (Nagaraj et al., 2021). These people often become powerful agents and change agents of their social circles and affect how other people make decisions on adoption. The integration of personal innovativeness to the UTAUT 3 model has demonstrated the value of personal personality traits and dispositional characteristics in the formation of technology adoption intentions regardless of contextual factors (Ryu, 2018).

Content Quality

Content Quality concept includes the aspects of accuracy, completeness, reliability and relevance of the information being delivered through a technological system or platform. Provision of quality content greatly enhances users' perception on quality and usefulness of the technology which directly affects their intentions towards adopting the technology (Jariyapan et al., 2022). In information systems, e-learning systems, online service and knowledge-based technologies, particularly in the business sector, content quality matters especially as the level of information quality is directly related to user satisfaction and trust (G. Gupta & Singharia, 2021).

It has been shown that perceived value and intentions to adopt a content can be strongly predicted by its quality. People show increased tendencies to adopt and continue using the technologies which provide accurate, timely, relevant and comprehensive information (Nagaraj et al., 2021). The quality of the content can be improved in the organization by some stringent information validation programs, frequent changes of the content, user control over quality and professional checks of the content (Abbasi et al., 2021).

2.3 - Moderating Variables: Demographic Factors in UTAUT 3

Age

Given that the component of age is the role of a demographic moderator, it influences the strength of the relationships between the basic constructs of UTAUT and behavioral intention (Y. H. Kim et al., 2013). Research indicates that differences in age determine how different people respond to stimuli linked to the use of technology. The younger generations are often more accepting of new technologies, more comfortable with and using new technological interfaces, and more willing to experiment with new functions (Venkatesh et al., 2012).

Conversely, older users might need more comprehensive training, emphasize more heavily on usability over added functionality and require more clearly presented performance benefits before setting up their intentions to adopt (Alalwan et al., 2018). Age disparities in technology adoption can often be attributed to the presence of cohort effects since different groups are exposed to technology at different stages in their lives. Also, cognitive factors including the speed of information processing and the working memory are also important as well as motivational variations that depict the varying priorities and goals existing among various age groups (Aguiar & Waldfogel, 2017). The use of age as a

moderating variable will help organizations tailor the use of technologies to different age groups.

Gender

Gender is a demographic moderator that influences patterns of technology adoption through a variety of processes. Studies indicate that males and females may have varying technology adoption patterns, risk attitudes and worry patterns towards technology use (Ramkumar & Woo, 2018). It has been shown that men are often more welcoming to new innovations and are generally more favourable to technology adoption on the whole. Studies have shown that females tend to be more sensitive to security and privacy issues and dangers related to technology and reliability of computer systems (Evens, 2014).

These gender differences interact with certain UTAUT constructs in complicated and subtle ways. Studies have shown that gender might moderate the relationship between social influence and behavior intention with the results indicating that the social influence of behavioral intentions toward adoption is stronger in females than in males (S. Shin & Park, 2021). Considering that gender may mediate the relationship between performance expectancy and behavioral intention, males might be more responsive to messages conveying the benefits of performance, than females. However, the effects of gender as the moderating factor show variable effects depending on the different technologies and situations (J. Shin et al., 2016).

Experience

Technology use has been a major moderating variable, which determines how individuals respond to the basic constructs of UTAUT model. People who already have a greater amount of previous experience with similar technologies tend to have a lower level of necessity to be trained as a whole, have a faster understanding of new technology specifics, and experience less fear of technology (Moin et al., 2015). People who are well experienced tend to have lower expectations of effort and better facilitating conditions as compared to their less experienced counterparts because they are well equipped with the necessary technical knowledge and skills of operating the technology (Lee et al., 2007).

Experience also plays a significant role in determining the relationship between effort expectancy and behavioral intention because more experienced people will not be deterred by elaborate interfaces or major learning obstacles. Individual experience also plays a large role in the interpretation of the social influence and facilitating conditions, whereby experienced users tend to express more confidence in

their ability to overcome barriers independently (Kwak & Kim, 2020). However, the experience does not necessarily eliminate other barriers to adoption; even experts with considerable skills in the field can face resistance to change or a tendency to cling to existing systems, regardless of their level of technical expertise (Martins et al., 2014).

Dependent Variable: User Intention to Adopt

The desire of users to embrace technology is regarded as the key dependent variable of the UTAUT 3 model. Behavioral intention concept refers to perceived likelihood of the individual to engage in technology use behavior and it captures the motivational effect(s) of different things to actual technology adoption (Migliore et al., 2022). The studies that are based on the Theory of Planned Behavior and the technology acceptance model indicate that behavioral intention is a useful predictor of real usage behavior but there is not a complete deterministic relationship between intention and behaviors (Arun et al., 2021).

Behavioral intention encompasses willingness to use technology, which portrays positive intentions, and likelihood of actual use which portrays behavioral commitment. The results of the research show that the eight antecedent constructs of UTAUT 3 have an impact on user intentions on both the direct and indirect levels, but the latter are mediated by the attitude formation process (Jose, 2020). By looking at the relative role played by each construct on behavioral intention, the organizations may develop more focused interventions to address the most influential barriers or facilitators to adoption (J. Park & Ha, 2016).

2.4 - Theoretical Mechanisms and Relationships in UTAUT 3

Direct Effects on Behavioral Intention

The UTAUT 3 theory assumes that all of the eight independent constructs directly determine the behavioral intention to use technology. Performance expectancy factors, effort expectancy factors, social influence factor, facilitating conditions factor, hedonic motivation factor, price value factor, habit factor, and personal innovativeness are all elements that influence the development of the intentions of people towards the usage of technology (Verhoef et al., 2010). Both the constructs contribute different amounts of variance to predicting behavioral intention, and the contribution of each construct varies with different technologies and user demographics (Baptista & Oliveira, 2015).

When empirical studies of UTAUT 3 are conducted, the eight constructs have significantly large share of behavioral intention variance, often exceeding 70 percent. The remarkably large model of UTAUT 3 proves it to be a synthesis of multiple theoretical insights, which include the use of both utilitarian factors (performance expectancy, effort expectancy, facilitating conditions) and hedonic factors (hedonic motivation, price value, habit), which determine intentions toward the adoption of technology (McCarthy et al., 2017).

Interaction Effects and Mediation Pathways

Besides direct effects, UTAUT 3 acknowledges the considerations that may exist between constructs and which may influence behavioral intention. As an example, high hedonic motivation would counteract high levels of expectation of effort since people may be willing to exert effort in learning when they consider the technology to be interesting or enjoyable (Haritha & Joseph, 2021). Similarly, there is the potential possibility that with enough social influence, those worrying about performance expectancy might reduce their worries and avoid technologies mainly because influential peers suggest adoption (Woo & Ramkumar, 2018).

Recent studies on UTAUT 3 extension studies have delved into the mediation effect, noting the influence of particular constructs on behavioral intention via their impact on other constructs. Indicatively, the performance expectancy and hedonic motivation constructs may contribute to the development of behavioral intention through influence on perceived value, which in turn impacts behavioral intention (Indrawati & Haryoto, 2018). The mediation pathways explain the complexity of psychological processes on which development of technology adoption decisions is based.

Moderating Effects of Demographic Variables

The demographic moderators in UTAUT 3 have no direct effect on the behavioral intention, rather, they act to moderate the relationships between the Core constructs and behavioral intention (Mary Ho et al., 2017). An example is that age has the potential to modulate the relationship between the expectancy of the effort and the behavioral intention meaning that, the effects of the effort expectancy would be much more established in older users than the younger ones. Similarly, gender can be used as a moderator of the relationship between social influence and behavioral intention, which might produce different effects in males and females (Pan & Jordan-Marsh, 2010).

The witnessed trend of mediating influences is often indicative of differences that can be explained by life stage, historical cohort, and socialization differences between two or more demographic cohorts

(Chopdar & Tarafdar, 2021). Organizations can effectively group their users through the identification of the demographic groups that show a high level of influence by certain constructs. This division can enable the adoption of specific strategies that are tailored to specific adoption to the key decision drivers of each segment (Wan et al., 2017).

2.5 - Empirical Applications and Validation of UTAUT 3

Information Technology Contexts

The UTAUT 3 application has been found to be effective in explaining the process of adoption related to different information technologies. A study on the use of electronic health record systems suggests that UTAUT 3 is able to explain 84.5 percent of behavioral intention variance in health professionals, which implies that the model is highly predictive in healthcare technology contexts (Shen et al., 2017). The results also suggest that the personal innovativeness, performance expectancy, and attitude are the strongest predictors of the electronic health record (EHR) adoption. Also, the aspect of gender was identified to mediate the associations between social influence, personal innovativeness and behavioral intention (S. Gupta, 2023).

The use of UTAUT 3 in educational technologies, including lecture capture systems and digital learning platforms, has demonstrated the effectiveness of the model in predicting the intentions of students to use it (Mazambani & Mutambara, 2020). The synergistic combination of the utilitarian aspects of performance expectancy and effort expectancy and hedonic aspect of hedonic motivation has proven to play a major role in the understanding of variables that affect student adoption of learning technologies that integrate learning capabilities with entertainment and engagement (S. Park & Kwon, 2019).

Consumer Technology Adoption

UTAUT 3 framework is actively applied in the domain of consumer-facing technologies, and it includes various domains, including mobile apps, digital payment systems, social commerce ecosystems, and fintech solutions (S. Park & Kwon, 2019). The applications mentioned in the current paper underline the importance of hedonic motivation and price value in consumer settings as these two constructs tend to be some of the strongest predictors of behavioral intention. The research conducted on the adoption of mobile payment system, social commerce platform and ride-sharing applications, shows that the consumer technology acceptance depends not only on hedonic factors but

also on utilitarian performance expectations (S. Park & Kwon, 2019).

Cross-Cultural and Contextual Variations

Empirical studies employing UTAUT 3 in different cultures show there is a vast difference in the relative importance of specific constructs. It has been found that social influence is more eminent within collectivist cultures than individualist cultures with a focus on cultural values related to group harmony and social conformity.(S. Park & Kwon, 2019) Price value consideration can become a much more important factor in price-sensitive markets or in lower-income populations. The identified differences in a given context also highlight the need to implement technology implementation plans, which are specific to a particular market or culture (Dhir et al., 2018).

Table 2.1 Empirical support for each proposed predictor		
Variable	Evidence in OTT / digital services	Key sources
Performance expectancy	Strong positive effect on intention/continuance across OTT, streaming, banking, e-learning	(Malewar & Bajaj, 2020b); Soren & Chakraborty, 2023; Wu et al., 2025; Zheng et al., 2025; (Alalwan et al., 2018)
Social influence	Positive impact on OTT subscription, purchase, continuance, and FinTech adoption	Wu et al., 2025; (Shen et al., 2017)hen, n.d.; Santoso & Ramantoko, 2024; Xie et al., 2021
Facilitating conditions	Significant for intention or use behaviors in OTT, streaming, and e-government	Shah & Mehta, 2022; Dharta et al., 2024; Nasri, 2025
Hedonic motivation	Consistent predictor of OTT intention, satisfaction, and commitment	Wu et al., 2025; (Chakraborty & Ghosh, 2021); (Malewar & Bajaj, 2020b) Saufi et al., 2023
Habit	Often the strongest driver of continuance or intention	Soren & Chakraborty, 2023; (Malewar & Bajaj, 2020b); (S. Kim et al., 2021) Zheng et al., 2025

Price value / cost	Positive effect of price value; negative effect of perceived cost on intention	Malewar & Bajaj, 2020; Dharta et al., 2024; Shen, n.d.; (Alalwan et al., 2017)
Perceived value	Mediates UTAUT effects on OTT and FinTech adoption	Wu et al., 2025; Shen, n.d.; Xie et al., 2021,
Content quality	Strong OTT-specific driver of hedonic motivation, satisfaction, trust, and commitment	Bhattacharyya et al., 2021; Soren & Chakraborty, 2023; Saufi et al., 2023
Personal innovativeness	Significant predictor of intention in OTT, QR-code payments, social commerce, and IVA adoption	Tsai et al., 2024; Shen, n.d.; Suo et al., 2022; (Joshi et al., 2015) (Desirena et al., 2019)

2.6 - Hypothesis Development

With the rise of over-the-top (OTT) streaming services, the application of familiar theory of technology adoption and media consumption in research has grown in an attempt to explain the intentions and actions of users. Recent studies using the Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2), Technology Acceptance Model (TAM) (Venkatesh & Morris, 2000), Value-based Adoption Model (VAM), Uses and Gratifications, and Innovation Resistance Theory (IRT) determine numerous cognitive, affective, and contextual antecedents contributing to the adoption and continued use of Over-The-Top (OTT). Among such factors, there are perceived usefulness, ease of use, hedonic motivation, content quality, perceived value, pricing consideration, habitual use, social influence, and facilitating conditions ((Podsakoff et al., n.d.) The analysis of this body of literature enables developing the hypotheses which can relate the key features of OTT platforms and user attributes to the intention to use and purchase the OTT services (Shankar et al., 2003).

This body of literature provides a detailed explanation of the role of both as functional (e.g., utility, usability) and experiential (e.g., enjoyment, habituation) features in the decision-making process of users in digital media settings. OTT platforms have a notable difference with the traditional technologies in the sense that the content is given the priority and therefore the quality of the content becomes a very important determinant of the satisfaction of the user with the system, their engagement and loyalty towards the system (Venkatesh et al., 2012). The research on the digital media and streaming platforms can also indicate that the richness, relevance, and diversity of the content are the

contributing factors to the perceived value and attention to the users, thereby increasing the adoption and retention intentions (Kim et al., 2017; Soren and Chakraborty, 2023).

However, even with such a strong empirical support, there are certain weaknesses in the present models. Many traditional adoption models like TAM and UTAUT2 were originally developed with utilitarian technology in mind and might be insufficient to account for the content-oriented and experiential nature of OTTs (Venkatesh et al., 2012). Further, content quality is often treated as an extrinsic variable in previous research rather than as a core aspect in the theoretical model. The relationship between the quality of content and other key drivers (e.g. hedonic motivation, perceived value, habit) does not have the required unanimity, which implies a need of further theoretical deepening.

Additionally, the influence of content quality might not be universal across user demographics, cultural conditions, and content options, which means that its impact is not universal (Rogers, 2003). This highlights a great gap in the literature regarding the situational and contingent effect of content quality on OTT adoption behavior.

H1: Content Quality positively influences User Intention to Adopt OTT.

Past studies on OTT confirm again and again that the quality of content and its availability are the key determinants of platform selection and usage intention. The detailed analysis of the adoption of OTTs in 2007 to 2021 revealed content, entertainment value, binge-watching, and cultural inclusiveness to be the key factors that encouraged the adoption of streaming services (Mulla, 2022). Empirical data suggests that the perceived quality of video material and the availability of the latter have a significant impact on satisfaction, trust, commitment, and desire to use OTT platforms further (Soren and Chakraborty, 2023; Yoon and Kim, 2023). Qualitative research highlights content and subscription strategies as the key factors of adoption among the millennial clients (Dasgupta and Grover, 2019). As a result, the more relevant, wealthier, and emotionally appealing content increases the perceived value and strengthens the intention of users to adopt OTT platforms.

These results show that OTT usage is not only determined by technological factors but is also based on content-based value generation. High-quality, relevant and emotionally appealing information increases the level of perceived value and strengthens the inclination of users to adopt and continue using OTT services. This confirms the claim that OTT platforms are hybrid systems, where technology

infrastructure and media content interactively influence user behavior.

Still, even though much attention is paid to content, the contemporary research tends to devote insufficient attention to the facilitating role of technological and infrastructural systems, also known as facilitating conditions. According to the UTAUT model, facilitating factors are availability of resources, technological support, and user understanding, and support systems that enable effective use of technology (Venkatesh et al., 2003; Venkatesh et al., 2012). On the context of OTT platforms, they include reliable internet networks, compatibility of devices, usability of platforms, and customer services.

Notably, despite the excellent quality of the material, a lack of favourable circumstances, such as the slow internet connection, unavailability of devices, or limited technical support, can have a disastrous effect on acceptance and use. It means that the quality of the content by itself does not suffice to support adoption in the absence of a favorable technological system. Furthermore, the impact of favourable conditions could vary across nations particularly in the developed and emerging markets where there are significant disparities in digital infrastructure (Rogers, 2003).

As a result, the facilitating conditions play a supplementary, enabling role, which ensures unhindered access and further use, in contrast to content-related criteria, which are imperative determinants of OTT engagement. This paper informs about the importance of infrastructural and technological readiness in the process of user intention.

H2: Facilitating Conditions positively influences User Intention to Adopt OTT.

In OTT studies involving UTAUT/UTAUT2, favourable conditions (infrastructure, access, skills) have been found to have a positive influence on intention and use. Considering the Indian OTT consumers, facilitating factors, social influence, and attitude have a positive effect on intention to adopt OTT services in UTAUT model (Shah and Mehta, 2022). In holistic UTAUT2 frameworks of OTT video streaming, enabling conditions have a substantial impact on the platform preference of users and have been identified as a key driver of platform improvement (Tsai et al., 2024). The widespread adoption of OTT services suggests that rising internet connectivity and the availability of devices are some of the basic drivers of OTT growth (Nijhawan and Dahiya, 2020; Wang, 2025). Therefore, better facilitating conditions are expected to boost user intention to adopt OTT.

However, despite their importance, facilitating conditions are often thought of as secondary aspects compared to more salient predictors such as hedonic motivation or content quality. This may have the potential to undermine their indirect yet a crucial role in user behavior. When infrastructural limitations, such as limited bandwidth, unstable connection or limited access to devices, characterize the situation, people might not be able to engage in OTT sites to their fullest, regardless of the quality of the content or its perceived worth. Further, the effect of facilitating conditions is highly contingent on the particular context, with a high level of diversity manifested in various geographical regions, socio-economic classes, and technological levels of progress (Rogers, 2003).

Moreover, some studies have suggested that as users become more technologically savvy, the effects of facilitating conditions can decrease since users are more likely to rely on their capabilities, instead of support systems (Venkatesh et al., 2012). This implies that the effect of facilitating conditions can be different across various user groups, and a more in-depth understanding of their role is required.

In spite of these limitations, technology adoption requires enabling conditions, particularly in emerging digital ecosystems such as OTT platforms, where easy access and usability are crucial to user interaction. Therefore, the improved infrastructural infrastructure and technological readiness are expected to have a beneficial impact on user intention to adopt OTT services.

H3: Habit positively influences User Intention to Adopt OTT.

The issue of habit has already become an important part of the study of user behavior, particularly the domain of digital and media consumption, and OTT services, in particular. The UTAUT2 model assumes that habit represents the level to which people follow the behaviors automatically, an effect, which is caused by the prior learning experience and regular use (Venkatesh et al., 2012). As opposed to purely cognitive factors, habit captures the unconscious and routine-based nature of the technology usage, which makes habit especially relevant to entertainment services, such as OTT platforms.

In a positive perspective, empirical studies have always found that the habit is an important determinant of both behavioral intention and the continued use of OTT services. To illustrate, a research study, which integrates UTAUT2 and commitment models, indicates that habit is an important factor that predicts the intention of users to use OTT platforms (Soren and Chakraborty, 2023). Habit has been found in cases of subscription video-on-demand (SVOD) to have a significant impact on continued

usage behavior, often in combination with perceived value and Personalization (Muller-Perez et al., 2025). Moreover, the studies exploring OTT behavior during and after the COVID-19 pandemic have shown that the trend of streaming has become a regular occurrence in the daily lives of users and therefore supports the reinforcement of habitual use of the OTT platforms (Agarwal et al., 2023; Nijhawan and Dahiya, 2020).

The findings suggest that active use of OTT services and such features as personalised recommendations, auto-play, and the opportunity to watch a series of content plays a role in the formation of a habitual usage behavior. These more so ingrained habits result in subsequent people developing the tendency to use OTT platforms more often without thinking of it, thereby increasing their desire to adopt and continue using.

Nevertheless, regardless of its significant predictive power, the role of habit has some limitations. The fact that the strong habitual behavior may potentially overshadow the rational decision-making processes is also a major problem as it causes users to lose sensitivity to the differences in the content quality, prices, or features of the platform. This creates a possibility of inertia where users continue to use a platform despite the declining levels of satisfaction. Moreover, habit formation and impact may vary with different groups of the users, particularly between inexperienced and experienced users as well as between different cultural and demographic contexts (Limayem et al., 2007). In the case of individuals who are just getting familiar with the system, the formation of the habitual use might be in its early developmental phase thus reducing its immediate effect on intention to use the technology.

Moreover, when in a competitive over-the-top (OTT) setting, characterized by low switching costs, the habitual usage of a platform might be affected by an attractive substitute, exclusive content, or promotion strategies offered by a competing service. This implies that habit does not guarantee long-term loyalty in dynamic digital space even though it is a helpful way to sustain behavior. Despite these limitations, habit remains an important behavioral motivator which increases repeated usage and strengthens user engagement during a long-term period. As a result, it is believed that the changes in the intentions of users to implement and continue using OTT platforms will significantly improve.

H4: Hedonic Motivation positively influences User Intention to Adopt OTT.

Hedonic motivation, characterised by the extent of pleasure, enjoyment, and entertainment experienced through technology use, is pivotal in consumer-focused systems, especially within OTT platforms that

are fundamentally centred on entertainment (Venkatesh et al., 2012). In contrast to utilitarian technologies, OTT services are fundamentally structured to deliver experiential value, positioning hedonic motivation as a crucial factor influencing user adoption and engagement.

From an optimistic viewpoint, a significant amount of research underscores hedonic motivation as a key predictor of behavioral intention in OTT contexts. Research utilising the UTAUT2 framework consistently highlights enjoyment and perceived fun as significant factors influencing users' willingness to adopt and persist in using streaming platforms (Bhattacharyya et al., 2021; Soren & Chakraborty, 2023; Tsai et al., 2024). Additionally, extensive analyses of OTT adoption highlight that the perceived entertainment value, user satisfaction, and immersive viewing experiences play a crucial role in shaping users' preferences for streaming services in comparison to traditional media (Mulla, 2022). Evidence from TAM-based studies indicates that perceived enjoyment significantly contributes to user satisfaction and has a favourable impact on behavioral outcomes, including continued usage, willingness to pay, and repurchase intentions (Davis et al., 1992; Kim et al., 2024).

The results indicate that OTT platforms utilise hedonic components-such as captivating content, binge-watching capabilities, tailored experiences, and interactive interfaces-to foster emotionally gratifying experiences. The increased enjoyment users experience from these platforms significantly enhances their intention to adopt and maintain usage, frequently transcending mere functional considerations.

Nonetheless, in spite of its significant predictive capacity, hedonic motivation is accompanied by specific limitations. The excessive dependence on entertainment value could result in transient engagement instead of long-term commitment, particularly in the fiercely competitive OTT markets where users have the ability to effortlessly transition between platforms depending on the availability of content. Furthermore, hedonic motivation is subject to variation influenced by factors such as the novelty of the content, genre preferences, and the mood states of individuals, resulting in a less consistent effect when compared to cognitive factors like perceived usefulness or value.

Furthermore, an overemphasis on hedonic consumption, exemplified by binge-watching, has the potential to result in adverse effects, such as user fatigue or digital burnout, which may subsequently diminish long-term engagement with over-the-top (OTT) platforms. The impact of hedonic motivation is likely to differ among various demographic segments, as younger individuals generally prioritise entertainment value more significantly than their older or more utilitarian-focused counterparts

(Venkatesh et al., 2012).

H5: Innovativeness positively influences User Intention to Adopt OTT.

One of the extensions of UTAUT/UTAUT2 suggested in the absence of research on OTT has been personal innovativeness. Personal innovativeness significantly influences the platform selection and intention to use it in an extended UTAUT2 framework on the OTT video streaming, along with performance expectancy, facilitating conditions, and hedonic incentive (Tsai et al., 2024). The studies focusing on innovation in the adoption of OTT services show that individual innovation characteristics and barriers affect the willingness to adopt and continue using OTT services (Polisetty et al., 2023). Qualitative studies defining OTT users show that the tendency to become an early adopter and technological excitement are the important traits of heavy OTT users (Li, 2020; Dasgupta and Grover, 2019). These findings support the hypothesis according to which more innovative users are more likely to use OTT services.

The positive perspective is that the available literature indicates that individual innovativeness is a key factor affecting the intention to adopt users and their preference in a particular platform. Indicatively, a study that employed unified UTAUT2 models demonstrates that personal innovativeness is an important factor that influences the selection and use intention of OTT platforms alongside other important variables, including performance expectancy, enabling conditions, and hedonic motivation (Tsai et al., 2024). Similarly, the research on the dynamics of innovation resistance and adoption behavior reveals that individuals with higher rates of innovativeness can overcome perceived barriers and adopt OTT services easier (Polisetty et al., 2023). The qualitative data are another source that supports the point of view that heavy users of over-the-top (OTT) services often exhibit the characteristics of early adopters, who are both very interested in technology and highly inclined to explore new types of digital services (Li, 2020; Dasgupta and Grover, 2019).

These findings indicate that people who can be described as innovative have a higher propensity to new OTT capabilities, such as personalised recommendations, content discovery through AI, and the ability to stream on multiple devices. As a result, such people are more likely to adopt OTT at an earlier point and be more proactive, thereby reinforcing the positive relationship between innovativeness and the adoption intention. However, even though it is an important role, the role of personal innovativeness has its limitations. An important factor is that its effects may be more pronounced during the early stages of technology acceptance, but they may decline as the OTT platforms reach mainstream and

become ubiquitous. With evolving technologies, the adoption criterion might start shifting to include aspects more of an innovation orientation but with a more consideration on factors like availability of content, perceived value on price and the existing habits (Venkatesh et al., 2012).

Moreover, individual innovativeness could be intertwined with contextual influences, including socio-economic status, digital literacy, and cultural orientation, and further escalate or constrain its effect on it. As an example, very innovative people can still face barriers to adoption in places with poor internet connectivity or where there is a poor technological infrastructure. In addition, the excessive focus on innovation can overlook the behavior of the late adopters who constitute a significant percentage of the OTT user base, and might be more influenced by social impact and perceived value than novelty (Rogers, 2003).

H6: Performance Expectancy positively influences User Intention to Adopt OTT.

Performance expectancy, often defined as perceived usefulness, denotes the extent to which individuals anticipate that utilising a specific technology will improve their performance or yield significant advantages (Davis, 1989; Venkatesh et al., 2003). In the realm of OTT platforms, performance expectancy denotes users' beliefs of enhanced convenience, flexibility, accessibility, and control over content consumption relative to traditional media.

From a favorable viewpoint, comprehensive research based on UTAUT, UTAUT2, and TAM consistently identifies performance expectancy as a significant predictor of behavioral intention across diverse technological contexts. Research indicates that in OTT contexts, users are more inclined to embrace streaming services when they recognize distinct benefits, including on-demand access, multi-device compatibility, personalized suggestions, and time-shifted viewing (Soren & Chakraborty, 2023; Tsai et al., 2024). Moreover, TAM-based studies indicate that perceived usefulness profoundly affects consumers' attitudes towards OTT platforms, thereby impacting their desire to embrace and persist in using these services (Jeong et al., 2022; Kim et al., 2024).

The swift expansion of OTT usage during and subsequent to the COVID-19 epidemic highlights the significance of performance-related advantages, as consumers increasingly prioritise ease, flexibility, and seamless access to entertainment and information (Nijhawan & Dahiya, 2020). The data indicate that when individuals view OTT platforms as improving their overall media consumption experience, their likelihood of adoption significantly improves.

Nonetheless, despite its robust predictive capacity, the impact of performance expectancy may be contingent upon context and susceptible to certain constraints. As OTT services standardise, the apparent performance advantages among platforms may align, diminishing their impact on user selection. In these instances, elements such as content exclusivity, price schemes, and user experience may play a more significant role in shaping adoption decisions.

Furthermore, performance expectancy is particularly pertinent during the early phases of adoption, as users assess the functional advantages of a technology. Its influence may wane over time when regular usage patterns and hedonic motives become dominant (Venkatesh et al., 2012). Moreover, users with advanced digital literacy may presuppose fundamental performance advantages, consequently diminishing the proportional influence of this factor on their adoption choices.

H7: Perceived Value positively influences User Intention to Adopt OTT.

Perceived value, based on value-based adoption theory, denotes the user's comprehensive assessment of a service's benefits in relation to the expenses associated with acquiring it (Kim et al., 2007). Within the realm of OTT platforms, perceived value involves a balance between financial expenditures (e.g., subscription fees), non-financial expenditures (e.g., time, effort), and perceived advantages such as content quality, convenience, and entertainment experience. Prior research consistently identified perceived value as a crucial factor influencing both uptake and continuing intention in OTT and subscription video-on-demand (SVOD) services. Systematic studies of OTT adoption literature indicate that value for money, price equity, and comprehensive cost–benefit assessments significantly influence consumers' decisions to subscribe to and persist in utilizing streaming services (Mulla, 2022). Empirical research demonstrates that perceived value frequently serves as a predominant predictor of continuance intention, at times exceeding the influence of personalization and habit in specific circumstances (Müller-Pérez et al., 2025).

Furthermore, value-based adoption models indicate that perceived value serves as a mediating construct, connecting cognitive factors (e.g., usefulness, ease of use) and affective factors (e.g., enjoyment) with behavioral outcomes such as purchase intention and subscription renewal (Kim et al., 2007; Polisetty et al., 2023). This underscores its comprehensive function in amalgamating various factors into a unified evaluative assessment that directly impacts user intention. Nonetheless, in spite of its robust explanatory capacity, perceived value remains fundamentally subjective and contingent upon context, thereby presenting specific limitations. The assessment of value by users can differ

Markedly due to a range of factors, including personal preferences, income brackets, cultural backgrounds, and patterns of content consumption. For example, individuals who are sensitive to pricing might assess the value as diminished despite the high quality of the content, whereas others may place greater importance on exclusive content rather than cost factors.

Moreover, in the context of highly competitive OTT markets characterized by numerous platforms providing comparable features and pricing models, the perceived value may diminish as a distinguishing element. In these instances, individuals may place greater emphasis on particular characteristics, including unique content, brand credibility, or the impact of social circles, rather than conducting a comprehensive assessment of costs and benefits. Furthermore, the concept of perceived value is not static; it is subject to fluctuations over time as user expectations develop or as subscription prices rise.

H8: Price Value positively influences User Intention to Adopt OTT.

The notion of price value or the cognitive judgement of the user on the ratio between the perceived benefits of a technology and the financial cost of using the technology is presented in the UTAUT2 framework (Venkatesh et al., 2012). In the context of the OTT platforms, the notion of the price value can be seen in terms of the perceptions of the users with respect to the fairness of the subscription fee, a package, and the flexibility in the price in connection to the quality of the content, features, and the overall viewing experience provided.

Constructively, the available studies all suggest that price-related variables play a significant role in the adoption of the OTT services particularly in markets that are price sensitive. According to research findings, affordability, economic status, and perceived cost-effectiveness are among the factors that influence the tendency of users to subscribe and continue to use OTT services (Bhattacharyya et al., 2021; Nijhawan and Dahiya, 2020). Pricing is one of the most common aspects of the impact of OTT adoption in many literature reviews, along with the content quality and hedonic motivation (Mulla, 2022).

Moreover, more recent cross-country research suggests that pricing flexibility, which includes tiered subscription plans, freemium plans, and promotional discounts, is critical in enhancing user acquisition, retention and willingness to pay, especially in the case of consumers in emerging economies (Sridevi and Sarathy, 2025). The findings reveal that having positive perception of value-

money in OTT services has a major impact on increasing the intentions of the users to adopt and continue using it in the long term.

However, considering its importance, the role of price value is supported by some limitations. The major question to be taken into consideration is the difference in price sensitivity between the separate groups of users that is influenced by income level, habitual aspects of use, and cultural attitudes to spending on the Internet. Indicatively, some users might value affordability more highly than others, thus some users may tend to pay premium prices to access exclusive or quality content hence reducing the overall homogeneity of price value effect.

Moreover, in the context of competitive OTT markets with a significant number of platforms offering similar pricing strategies, the price factor itself might not be a strong differentiating factor. An alternative approach to basing their decisions is through content exclusivity, brand recognition or general user experience. Furthermore, the aggressive pricing and, in particular, extensive discounts can be applied, which can increase the short-term adoption rates. Nonetheless, these strategies may not ensure long-term retention without the support of the steady quality of content and satisfaction of users.

H9: Social Influence positively influences User Intention to Adopt OTT.

Social influence denotes the degree to which individuals recognise that significant others such as family, friends, peers, and society hold the belief that they ought to adopt a specific technology (Venkatesh et al., 2003). Within the framework of OTT platforms, social influence is evident through peer recommendations, prevailing social trends, online reviews, and the overarching cultural dynamics that inform users' perceptions and decisions regarding adoption.

From an optimistic standpoint, existing studies consistently highlight social influence as a crucial factor in the adoption of technology, especially within consumer-focused and socially prominent platforms. Research based on the UTAUT framework indicates that social influence, in conjunction with facilitating conditions and user attitudes, has a positive impact on users' intention to adopt OTT services (Shah & Mehta, 2022; Bhattacharyya et al., 2021). In a similar vein, extended UTAUT2 models underscore the significant impact of social influence on platform preferences and usage intentions, particularly within contexts marked by intense competition and diverse content (Tsai et al., 2024).

Furthermore, studies informed by Uses and Gratifications Theory and qualitative analyses indicate that Word-of-mouth communication, peer recommendations, and discussions on social media play a crucial role in the initial adoption of OTT platforms (Katz et al., 1973; Dasgupta & Grover, 2019; Li, 2020). The impact of this phenomenon is notably pronounced within younger demographics, as factors such as social validation and collective viewing experiences play a significant role in the choice of platforms. Furthermore, recent research highlights the significance of social and psychological influences, particularly the fear of missing out (FOMO), which drives individuals to engage with OTT services to maintain social connections and cultural relevance (Przybylski et al., 2013; Hutapea et al., 2025).

Nonetheless, despite its significance, the effect of social influence is not consistent across various circumstances. A primary restriction is that its impact is more pronounced during the initial phases of adoption but may wane as users acquire expertise and cultivate autonomous preferences (Venkatesh et al., 2012). Furthermore, in highly tailored OTT environments where computers suggest content based on personal watching history the dependence on social cues may diminish over time.

Moreover, the potency of social influence may differ among cultures, as collectivist civilisations generally have more pronounced social conformity effects than individualistic cultures (Rogers, 2003). Excessive dependence on social influence may result in herd behavior, when users select platforms based on trends rather than genuine value or enjoyment.

Table2.2: Hypotheses and Supporting References			
Hypothesis		Brief description	Main supporting references (APA style)
H1	Content Quality positively influences User Intention to Adopt OTT.	Better content, diversity, relevance increase OTT adoption/continuance	Mulla, 2022; Soren & Chakraborty, 2023; Yoon & Kim, 2023; Dasgupta & Grover, 2019

H2	Facilitating Conditions positively influences User Intention to Adopt OTT.	Infrastructure, access, skills enable OTT intention/use	Shah & Mehta, 2022; Tsai et al., 2024; Nijhawan & Dahiya, 2020; Wang, 2025
H3	Habit positively influences User Intention to Adopt OTT.	Repeated OTT use becomes routine, strongly driving intention	Soren & Chakraborty, 2023; Müller-Pérez et al., 2025; Nijhawan & Dahiya, 2020
H4	Hedonic Motivation positively influences User Intention to Adopt OTT.	Enjoyment/fun is a central driver of OTT use	Bhattacharyy a et al., 2021; Kim et al., 2024; Mulla, 2022; Tsai et al., 2024
H5	Innovativeness positively influences User Intention to Adopt OTT.	More innovative users more likely to adopt OTT	Tsai et al., 2024; Polisetty et al., 2023; Li, 2020
H6	Performance Expectancy positively influences User Intention to Adopt OTT.	Perceived usefulness/benefits predict intention to use OTT	Soren & Chakraborty, 2023; Jeong et al., 2022; Kim et al., 2024; Tsai et al., 2024
H7	Perceived Value positively influences User Intention to Adopt OTT.	Higher value for money increases adoption/continued Use	Müller-Pérez et al., 2025; Mulla, 2022; Polisetty et al., 2023

H8	Price Value positively influences User Intention to Adopt OTT.	Positive price– benefit trade-off raises intention	Bhattacharyy a et al., 2021; Mulla, 2022; Sridevi & Sarathy, 2025; Nijhawan & Dahiya, 2020
H9	Social Influence positively influences User Intention to Adopt OTT.	Peers, norms and recommendations support OTT adoption	Shah & Mehta, 2022; Tsai et al., 2024; Dasgupta & Grover, 2019; Hutapea et al., 2025; Li, 2020

2.7 - MULTIGROUP ANALYSIS AND OTT

To find out whether or whether the structural linkages between specific groups differ, a complicated statistical test is applied, and this is referred to as Multigroup analysis. The authors Klesel et al. (2022) explored numerous MGA strategies in the context of PLS path modelling. They discovered that some standard omnibus tests are not as useful in finding small group differences. Cheah et al. (2020) give a series of procedural guidelines to conduct MGA using SmartPLS. These directions stress the necessity of considering the measurement invariance through MICOM method prior to making group comparisons. Cheah, Amaro, and Roldan (2023) then broadened this discussion by proposing solutions to family-wise error rates and fully comparing the model (Cheah et al., 2023). This broadened the discussion to involve MGA with a number of groups.

To investigate the effect of demographic and behavioral variables on user perceptions and satisfaction, many studies that focus on over-the-top (OTT) use statistical methods, including analysis of variance (ANOVA) and regression, which theoretical framework is identical to regression analysis (MGA). As Varalakshmi et al. (2023) results suggest, demographic variables, including age, occupation, and income, affect user satisfaction with over-the-top (OTT) platforms significantly. Conversely, gender and education level do not play a dominant role in influencing the satisfaction levels of the user to OTT

platforms. Through Factor analysis and analysis of variance, Yadav et al. (2023) managed to determine that gender and employment are the key determinants that yield the outcome that follows the use of over-the-top (OTT) services. Formal Multigroup Analysis (MGA) methods may be advantageous to such studies because these techniques provide the possibility to evaluate the structural differences between more than two demographic groups within a common model.

The fact that the various perspectives should be taken into consideration is underscored by studies carried out on the products habits of the youth. A research by Singh (2024) examined the role that young viewers played in watching over-the-top (OTT) services and determined that the factors that influenced the viewing habits and the psychological state were the accessibility, the cost, and the diversity of content. Perhaps the integration of MGA in this study will reveal the variation in these relations among various income level groups and gender.

The recent study has brought about the expansion of over-the-top (OTT) analysis to an array of elements related to technology, including artificial intelligence (AI) and personalization. Chahwala et al. (2025) carried out a study with regard to AI-based recommendation systems and discovered that significant disparities existed between age groups but not between genders in terms of user enjoyment and engagement (Chahwala et al., 2025). Such studies can be advanced with the help of MGA which would enable the researchers to examine whether the effect of artificial intelligence on engagement depends on the user demographics or cultural features.

2.8 - IPMA ANALYSIS AND OTT ADOPTION

Partial Least Squares Structural Equation Modelling (PLS-SEM) has also evolved to become an important development of Importance- Performance Map Analysis (IPMA). This growth enables the researcher to no longer rely on significance testing but to investigate the significance (path coefficient) as well as the performance (mean latent variable scores) of constructs. In this manner, they can end up providing good information to managers that they can apply in their practice. The work by Ringel and Sarstedt (2016) preconditions the IPMA as the means of linking the statistical analysis to strategic decision-making. This paper has highlighted the importance of IPMA in establishing the factors that have the greatest impact on critical outcomes although they demonstrate poor performance in the field (Ringle and Sarstedt, 2016). Later research studies were able to improve the level of methodological rigor of IPMA by creating a stronger framework. Streukens, Leroi-Werelds and Willems (2017) put

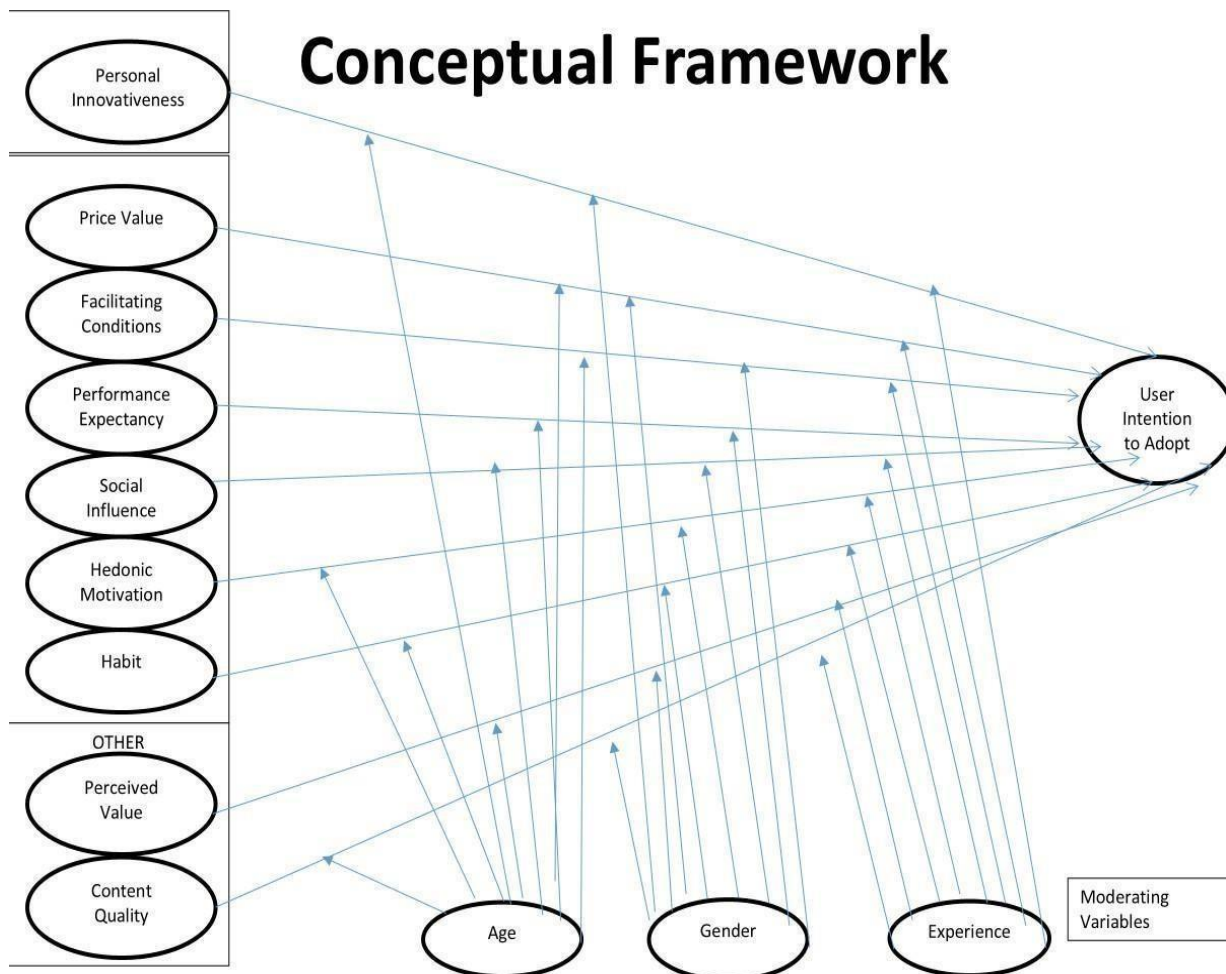
forward structures to resolve nonlinearity in interactions. These models enabled the more accurate determination of the meaning of constructs (Streukens et al., 2017).

The technology has improved through the use of the auxiliary techniques including Necessary Condition Analysis (NCA) and Artificial Neural Networks (ANN). The idea of combined IPMA (cIPMA), where the sufficiency and necessity logics are reconciled to more specifically distinguish between the must-have and should-have performance outcome drivers, was introduced by both Hauff et al. (2024) and Sarstedt et al. (2024) (Hauff et al., 2024; Sarstedt et al., 2024). Zabukovšek et al. (2022) together with ANN and IPMA integrated to shed light on nonlinear and complex relationships. The work under consideration is an illustration of how artificial intelligence can be used to increase the interpretative accuracy of IPMA when it comes to technology adoption.

Other research findings on the usefulness of IPMA in management have been applied in numerous areas of business and service and can be considered as validation of the potential of IPMA. Indicatively, Gim and Cheah (2020) had to use IPMA to establish the dimensions of pay satisfaction that hold the greatest significance to organizational trust (Gim and Cheah, 2020). Equally, Yapp and Yeap (2023) applied IPMA to find out the most influential customer-perceived values in e-hailing services (Yapp & Yeap, 2023)? In a similar way, Haverila et al. (2023) demonstrated how IPMA can be connected with the idea of multigroup segmentation to demonstrate the differences in the perception of service quality among the groups based on marital status (Haverila et al., 2023) The findings are also similar to the presented one. These studies enable researchers to incorporate statistical data into their strategic priorities, and all these studies combine to outline the academic and practical importance of IPMA.

IPMA has not been fully studied in the context of the research on the digital media and over-the-top (OTT) platforms, where it is necessary to understand the multidimensional views of the users, although the scope of its applicability is growing. With the combination of IPMA and Multigroup Analysis (MGA), one would be able to determine both high-impact and underperforming aspects of a service among demographic or regional categories (i.e., quality of content, personalization, and fairness in price, etc.). This would enable multidimensional knowledge concerning user satisfaction. MGA and IPMA usage as a pair is one of the potential analytical frameworks that could be used to bring together data-intensive knowledge and effective actions in the digital consumer experience management. This is especially applicable considering the fact that the scope of the OTT services is widening and the level of competition is getting tougher.

Conceptual Model:



Conceptual model developed from UTAUT 3 theory

2.9 - Research Gap:

Despite the growing body of literature in the field of OTT platform usage, there are still great gaps in the present research. Most of the past research empirically relies on theoretical models on generalized technology adoption, including UTAUT2, TAM, which does not fully cover the specifics of any of the mentioned aspects of OTT, including the quality of its content, its flexibility of subscriptions, customization of its algorithm, and cultural relatability. Current assessment incorporates Content Quality as an additional concept; however, there is not enough empirical evidence of its implementation within UTAUT3 framework at the levels of different OTT.

The existing studies have almost the entire research industry confined to specific areas, such as India, East Asia, and North America, thus limiting the usability of the findings across cultures. Even the effects of such variables as a social influence and pricing value differ significantly in terms of collectivist and individualist civilizations; however, there is few studies on it as a whole. Past research is primarily concerned with the preliminary adoption intention other than persistence or persistence intention. Experts challenging will consider the switch-cost of off-the-top (OTT) ecosystem to be dynamic and low in nature, which makes this narrow-minded view incomplete given that the post-adoption attributes like binge-watching behavior, the need to feel satisfied with the content regardless, the reinforcement of the habit and continued platform payment essential in sense making about the long-term consumer engagement and retention.

Chapter summary:

An extensive literature review of the literature on the usage of OTT platforms was made in the chapter by examining the development of major technological acceptance theories, namely UTAUT, UTAUT2, and UTAUT3, and their relevance in explaining user behavior in the context of digital media. It focused on the fact that, as functional and cognitive factors are sufficiently covered in conventional models, they are not sufficient in order to cover the experience- and content-related aspects of OTT platforms. The chapter discussed the key constructs, including and not limited to performance expectancy, facilitating conditions, hedonic motivation, habit, innovativeness, perceived value, price value, social influence, and content quality, which have a significant but relative influence on user intention to adopt OTT services.

It also marked the moderating effects of the demographic factors that include age, gender and experience and analyzed advanced techniques of analysis like MGA and IPMA to gain deeper insight. Nine hypotheses were developed and included into an integrated conceptual framework founded on the synthesis of existing empirical data. Finally, major research gaps were identified, including the low level of OTT-specific factors inclusion in UTAUT3, the inadequate emphasis on the continuing behavior, and the lack of cross-contextual validation, which, therefore, ensure the need of the present research.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 - Introduction

This chapter presents the methodological framework to be used in the study of the determinants of the adoption and continuance of Over-the-Top (OTT) in Gujarat. The proposed study is rooted in the longstanding Unified Theory of Acceptance and Use of Technology (UTAUT3), with additions of the OTT-specific variable Content Quality. It has described the research design, sampling strategy, data collection process, and statistical procedures used in the study by the methodology. Since the OTT consumption behaviors is multidimensional in nature, the quantitative cross-sectional research design was chosen, and Structural Equation Modelling (PLS-SEM) with Multi-Group Analysis (MGA) were used to test the hypothesized relationships and group differences.

3.2 - Research Problem Statement

The rapid rise of Over-the-Top (OTT) streaming is an event that has transformed the digital entertainment industry making streaming services to be one of the primary sources of communication among various age groups. However, in spite of the continued increase in the use of OTTs, empirical understanding is not clear on the key factors that influence the intentions of users to adopt and continue using OTTs, particularly, in the new digital markets.

The up-to-date studies regarding the adoption of technology have been skewed, to the point of giving generalized models such as UTAUT2 and TAM and yet nothing has been done to address the factors of experience, perception, social, and technological factors in the context of OTT service. Factors such as Content Quality (CNQ), Facilitating Conditions (FCO), Habit (HAB), Hedonic Motivation (HEM), Innovativeness (INO), Performance Expectancy (PEX), Perceived Value (PRV), Price Value (PVL), and Social Influence (SOI) could collectively contribute to User Intention to Adopt (UIA); nevertheless, the relative importance, forecasting ability and their relationship have not been well examined in an overall structural framework.

Also, although demographic factors such as gender and generational group (Gen Y and Gen Z) are often assumed to have an impact on digital adoption behaviors, empirical evidence on such a significant change in structural connection in OTT adoption by demographic factors remains inconclusive. This

creates a theoretical and administrative gap in the understanding of whether adoption drivers are different between the groupings of demographics or are typically applicable.

3.3 - Research questions:

RQ1. How do technological factors such as performance expectancy influence users' intention to adopt OTT platforms?

RQ2. What is the impact of experiential factors (e.g., content quality, entertainment value, user interface experience) on users' intention to adopt OTT platforms?

RQ3. How do perceptual factors such as perceived value and social influence affect users' intention to adopt OTT platforms?

RQ4. Which among the technological, experiential, and perceptual predictors exerts the strongest influence on user adoption intention toward OTT platforms?

RQ5. What is the relative importance of performance expectancy, perceived value, content quality, and social influence in shaping OTT adoption intention?

RQ6. Does gender moderate the relationship between technological, experiential, and perceptual factors and users' intention to adopt OTT platforms?

RQ7. Does generational cohort (e.g., Gen Z, Millennials) moderate the relationship between predictors and user adoption intention?

RQ8. Are there statistically significant differences in adoption intention across demographic groups (gender and generation)?

RQ9. Which constructs demonstrate high importance but low performance in influencing OTT adoption intention based on Importance–Performance Map Analysis (IPMA)?

RQ10. What managerial priorities can be derived from IPMA results to enhance user adoption and

Engagement on OTT platforms?

RQ11. How can OTT service providers strategically allocate resources based on the relative performance and importance of key adoption determinants?

RQ12. To what extent do demographic characteristics strengthen or weaken the predictive relationships within the proposed OTT adoption framework?

3.4 - Research Objectives

- To examine the influence of technological, experiential, and perceptual factors (e.g., performance expectancy, perceived value, content quality, social influence) on users' intention to adopt OTT platforms.
- To analyse the relative significance of individual predictors in shaping user adoption intentions.
- To evaluate the moderating relationships of demographic factors (gender, generation) between predictors and user intention to adopt OTT platforms.
- To identify key managerial implications using Importance–Performance Map Analysis (IPMA) for improving user adoption and engagement on OTT services.

Research Objective	Corresponding Research Question(s)
RO1: To examine the influence of technological, experiential, and perceptual factors (e.g., performance expectancy, perceived value, content quality, social influence) on users' intention to adopt OTT platforms.	RQ1: How do technological factors such as performance expectancy influence users' intention to adopt OTT platforms? RQ2: What is the impact of experiential factors (e.g., content quality, entertainment value, user interface experience) on users' intention to adopt OTT platforms? RQ3: How do perceptual factors such as perceived value and social influence

Research Objective	Corresponding Research Question(s)
	affect users' intention to adopt OTT platforms?
RO2: To analyse the relative significance of individual predictors in shaping user adoption intentions.	RQ4: Which among the technological, experiential, and perceptual predictors exerts the strongest influence on user adoption intention toward OTT platforms? RQ5: What is the relative importance of performance expectancy, perceived value, content quality, and social influence in shaping OTT adoption intention?
RO3: To evaluate the moderating relationships of demographic factors (gender, generation) between predictors and user intention to adopt OTT platforms.	RQ6: Does gender moderate the relationship between technological, experiential, and perceptual factors and users' intention to adopt OTT platforms? RQ7: Does generational cohort (e.g., Gen Z, Millennials) moderate the relationship between predictors and user adoption intention? RQ8: Are there statistically significant differences in adoption intention across demographic groups (gender and generation)? RQ12: To what extent do demographic characteristics strengthen or weaken the predictive relationships within the proposed OTT adoption framework?

Research Objective	Corresponding Research Question(s)
RO4: To identify key managerial implications using Importance–Performance Map Analysis (IPMA) for improving user adoption and engagement on OTT services.	RQ9: Which constructs demonstrate high importance but low performance in influencing OTT adoption intention based on IPMA? RQ10: What managerial priorities can be derived from IPMA results to enhance user adoption and engagement on OTT platforms? RQ11: How can OTT service providers strategically allocate resources based on the relative performance and importance of key adoption determinants?

3.5 - Research Approach

The present study uses the quantitative research methodology to examine factors which determine the desire among consumers to subscribe to the over-the-top (OTT) services with specific reference to the state of Gujarat. Since the aim of the research is to experimentally test hypothesized relationships between latent dimensions including performance expectancy, perceived value, content quality, social impact and user intention, a quantitative research is the best approach to be used.

This research is based on an improved UTAUT3 framework. In this context, various independent variables are put through statistical processing to determine to what extent the variables can offer accurate predictions of the dependent variable, which is User Intention to Adopt OTT. Considering the fact that the goals are as follows (i) to establish the strength of relationships, (ii) to compare the relative importance of predictors, (iii) to analyses the moderating factors of demographic variables, and (iv) To Implement Importance-Performance Map Analysis (IPMA), a quantitative paradigm ensures the objectivity, measurement accuracy, and generalizability.

The study is carried out with the help of a deductive reasoning approach, whereby the hypotheses are taken based on the well-established theories including UTAUT, TAM, and Value-Based Adoption Models and tested experimentally on the basis of primary survey data. The application of Partial Least Squares Structural Equation Modelling (PLS-SEM) can also offer additional aid in selecting a quantitative explanatory framework due to the fact that it allows assessing both measurement and structural models simultaneously. Consequently, the quantitative approach is suitable, as it seeks to give statistical validation of theoretical imaginations, objective testing of hypothesis, and rigor prediction modelling in the environment of the behavior of over-the-top (OTT) uptake in Gujarat.

3.6 - Research Design:

The current investigation makes use of a descriptive, cross-sectional research approach in order to investigate the factors that influence consumers' desire to subscribe to over-the-top (OTT) platforms in the state of Gujarat. According to Creswell and Creswell (2018), research design takes the form of a blueprint that guides the process of data gathering, measurement, and analysis. This blueprint ensures that the research questions are answered in a methodical and scientific manner. In accordance with the goals of testing hypothesized correlations among numerous latent constructs within an expanded UTAUT3 framework, it was determined that a descriptive and explanatory design would be the most suitable approach to use.

Descriptive research design:

A descriptive study design is applied, in the purpose of the systematic description and analysis of the relationships between technical, experiential, and perceptual variables, as outlined by the performance expectancy, perceived value, content quality, social impact, and habit, and user intention to use over-the-top (OTT) services. Descriptive research aims at rendering a realistic description of individuals, events, or situations without trying to control the contextual environment in which the research is carried out (Saunders, Lewis, and Thornhill, 2019).

In the present study, the objective would not be to manipulate independent variables by using experimental means, instead, the researcher would study the perceptions and behavioral intentions of

the respondents in their natural occurring condition. The constructs under investigation do have a psychological and perceptual aspect and the best manner of capturing it is by use of structured survey tools. Descriptive design facilitates the quantification of such impressions and facilitates easier statistical testing of hypothesized structural correlations.

Moreover, this design can also be used to evaluate the relative value of predictors which is one of the main objectives of the study. The study explores the route coefficients, effect sizes, and the explained variance (R^2), which are compatible with the explanatory-descriptive research traditions (Hair, Hult, Ringle, and Sarstedt, 2021). This is achieved with the help of Partial Least Squares Structural Equation Modelling (PLS-SEM). Thus, although it is defined as descriptive, an explanatory orientation also exists in the design, as it focuses on explaining the difference in the adoption intention with referring to the presence of predictors based on theory.

Cross-sectional design:

The cross-sectional design was applied in this research, and the data collected process involved information collection of respondents at a certain time of the year (July 2024 and December 2024). A cross-sectional research is carried out when it is necessary to study the relationships among various variables and collect data about a population or a section of it that is characteristic of the population at a certain moment (Bryman, 2016).

The design is well suited because of a number of reasons. The main aim of the research is to gather the current attitudes and intentions of users in terms of over-the-top (OTT) platforms, as opposed to tracing their temporal evolution. Second, technology adoption studies most often rely on cross-sectional surveys in order to test theoretical models like TAM and UTAUT.

This is so because such surveys facilitate efficient collection of massive data in order to model a structure (Venkatesh et al., 2003). Third, given the highly dynamic and constantly evolving character of the over-the-top (OTT) ecosystem, the study attempts to provide an image of the factors that dictate adoption within a specific time period. Sekaran and Bougie (2016) note that the cross-sectional design will be sufficient to validate the theory and test structural connections. Conversely, longitudinal designs can be applied in looking at the ongoing behavior and habit formation over time. It increases the statistical strength, and the credibility of cross-sectional inferences, due to the large number of cases being studied ($n = 998$).

Justification of the Selected Design

Both theoretical and practical considerations give the decision to select a descriptive, cross-sectional, and non-experimental design support. The empirical hypothesis testing is more suitable than the exploratory qualitative enquiry because the theoretical purpose of the study is to substantiate and generalize UTAUT3 to over-the-top (OTT) services. In practice, the high and geographically spread target population of Gujarat would be in need of a systematic survey methodology providing statistical generalization.

Moreover, the cross-sectional survey methodology resembles the preceding studies in the area of technology adoption (Venkatesh et al., 2003; Williams, Rana, and Dwivedi, 2015), which increases the comparability of the methodology as well as the academic rigour of the study.

The research design, in a short, provides an adequate guideline on how the factors affecting the urge to use over-the-top (OTT) services can be investigated. Through embracing descriptive measurement, cross-sectional data collection, and explanatory structural modelling, the design ensures that all the study objectives, theoretical basis, and methods of analysis are in alignment with each other.

3.7 - Population and sampling selection

3.7.1 - Target Population

The population of interest of the research study consisted of individual consumers who live in Gujarat and are those who have access to internet-enabled devices and have been introduced to or had an experience with at least one over-the-top (OTT) platform. The population was made up of working professionals and students aged 18 years and above up to 55 years old due to the fact that the age groups are the most active users of digital media.

Due to the high level of digital penetration, booming urbanisation and the use of over-the-top (OTT) services in the major cities, such as Ahmedabad, Gandhinagar, Vadodara, Surat, and Rajkot, the choice of Gujarat as the geographical focus can be justified. In this research, the unit of analysis was the individual user or potential user of over-the-top (OTT) services and each respondent was a sample unit. It was only eligible to those respondents who had at least one year of experience in use of digital

services. This was so as to ensure that the comments made by the respondents were well educated and substantial about their behavior towards the consumption of over-the-top (OTT) services.

3.7.2 - Sampling Technique:

Sampling can be described as the process of selecting a few people out of a group of many people in order to make meaningful inferences about that group. Sampling strategies assist researchers to acquire precise and representative data as often it is impossible to investigate a complete population due to time constraints, financial limitations, and access ((Spreng et al., 1960)). Validity, reliability and generalizability of the study results depend on the sampling strategy chosen. Broadly speaking, there are two major categories of sampling methods; probability sampling and non-probability sampling. (Chang & Chen, 2008) state that the methods that belong to the category of probability sampling are those where all members of the population are known to have a non-zero probability of being selected.

Such processes are rigorous statistically and allow generalising the results to the whole population and others (Etemad-sajadi & Ghachem, 2015). Some of the most frequently used forms of sampling include simple random sampling, where all individuals get an equal opportunity of being picked; systematic sampling, where all k th people on a population list are selected; stratified sampling, where the population is subdivided into homogeneous subgroups and the respondents are randomly selected out of such a group; and cluster sampling, where the whole population is subdivided into clusters, and one of them is picked at random. Although probability sampling enhances representativeness and reduces effects of selection bias, it requires a detailed sample frame, and substantial level of resources, which are not always available (Mccarthy et al., 2017).

(Mccarthy et al., 2017) argues that non-probability sampling does not provide a known chance of selection to every member of the population. This is as opposed to that of probability sampling. It is common to find these methodologies being applied in the social science, marketing and technology adoption research, especially where sample frames are inaccessible or in the dynamic population scenario. Convenience sampling is the most general type of sampling, where the respondents are picked based on their availability; purposive sampling also referred to as judgmental sampling, which involves participants being picked using a set of parameters; quota sampling, which means that some features will be represented; and snowball sampling whereby the respondents used will refer other respondents. When the intended use is theory testing and predictive modelling as opposed to estimating correct population parameters, non-probability sampling is widely tolerated ((Hair, Ringle, et al., n.d.)). This

can be done even though it can decrease the statistical generalizability of the results.

The non-probability sampling is often more practical than probability sampling in the context of applied behavioral research. This is particularly the case in the study of digital platforms, including the use of over-the-top (OTT) service usage, since there exist no centralised databases and the number of users is always changing. Consequently, the choice of a sampling method depends on the objectives of the study, the resources, and accessibility of population. There are methodological advantages as well as disadvantages of each methodology (Friedrich et al., 2019).

Given that no easily accessible and comprehensive sampling frame of over-the-top (OTT) consumers is available in Gujarat, the study employed non-probability convenience sampling method. Saunders, Lewis, and Thornhill (2019) argue that convenience sampling is the most appropriate under the circumstances when the population under study is large, immeasurable, and hard to list. This is particularly so in cases of the consumption of digital where there is no centralised database of consumer (Fiedler, 2010). In the case of over-the-top (OTT) services, the personal data of subscribers are not freely available to the population and belong solely to the possession of the streaming services of the private category. Consequently, both probability-based sampling are not feasible or possible.

This study aligns with the earlier studies on technology adoption, which concentrated on testing the theoretical model estimate but not on estimating the population parameters (Hair, Hult, Ringle, and Sarstedt, 2021). Convenience sampling is appropriate in this study and fits the research. Achieving representativeness in the strict probabilistic sense is less important than achieving adequate sample size, construct validity and statistical power (Voss et al., 2003). The reason is that the research aims to confirm and enlarge an already existing theoretical framework (UTAUT3) through the use of Structural Equation Modelling. Moreover, convenient sampling has facilitated the successful collection of data within the limits of time and money allocated, and at the same time ensured that the respondents met the pre-established eligibility criteria that pertained to the behavior of OTT users (Bradley & Lafleur, 2016).

In the field of behavioral and information systems research, non-probability sampling is frequently accepted when theory validation and predictive modelling are the primary aims (Vivek et al., 2012)). This is despite the fact that it may restrict the generalizability of findings to the full population of Gujarat. A further enhancement of the research's external validity is provided by the wide and diversified sample size within the setting of the investigation.

3.7.3 - Sample size justification:

The two methods that were used to calculate whether the sample size was sufficient were the 10-times rule (Hair & others, 2021) and statistical power analysis utilizing G*Power. These two approaches are both known in the Partial Least Squares Structural Equation Modelling (PLS-SEM). According to the 10-times rule, which was promoted by (Hair, Ringle, et al.), the minimum sample size is ten times the number of structural routes directed to every latent construct in the model. According to this rule, the sample size must be not less than 10. In the present study, there is the dependent construct, User Intention to Adopt, which is influenced by eight independent variables.

These variables are performance expectancy, perceived value, content quality, social impact, habit and pricing value among other key determinant variables. Based on the rule of ten times, the minimum size of the sample that could be required is ten times eight, 80 in total, that is, eighty individual respondents. The sample of 998 respondents, which is the final sample and uses, is well beyond this limit and, consequently, meets the minimum requirements that are presented in the analysis of PLS-SEM. Though the 10-times rule is a helpful rule-of-thumb methodology, more recent studies of its methodology suggest that it can be inadequate to estimate the sample sizes required in more complex models or to detect smaller effect sizes, which necessitates a tighter study of statistical power.

To provide a more solid empirical support, statistical power analysis developed under the methodology described by (Cohen et al., 2013) was considered, and the concepts that provide the foundations of G*Power computations were used. As a technique, statistical power analysis calculates the minimum sample size that will be required in order to establish a significant effect given a specific effect size (f^2), significance level (α), statistical power ($1-B$), and a set of predictors. When an accurate knowledge on the previous empirical estimates is unavailable it is conventional in behavioral studies to suppose that the effect size is medium ($f^2 = 0.15$).

Under the assumptions that the significance level was 0.05, the desired statistical power was 0.80 (meaning that there was an 80 per cent chance of finding a real impact), and the number of predictors (in this case, eight) that had an effect on the dependent variable, a linear multiple regression model would need a minimum sample size of about 109 respondents. Due to this, the sample size that was achieved which is equivalent to 998 respondents is considerably large compared to the lowest threshold that is required to detect the medium effects with adequate level of statistical precision. In reality, the power that would have been achieved by such a large sample would be much greater than 0.95 which

would assure a very large probability of finding meaningful correlations in circumstances where such correlations exist (Cohen et al., 2013).

The combination of both the 10-times rule and the statistical power analysis can be used to prove that the sample size the research used in this study is not only statistically reliable, but also methodologically acceptable. Through a large sample size, the consistency of estimating the parameters is maintained, the accuracy of the process of bootstrapping in PLS-SEM is increased, the possibility of Type II error is reduced, and reliability of subgroup comparison implemented by Multi-Group Analysis (MGA) is enhanced. It can be concluded that the 998 respondent's size is more than enough to confirm the proposed structural model and test the hypothesized correlations (Sarstedt et al., 2009).

3.8 - Research Instrument Development

The significant research development technique that was applied in this study was a structured questionnaire. The questionnaire was designed to measure the dimensions which are related with the desire to use over-the-top (OTT) services. Due to its ability to allow systematic data collection, standardisation of responses, and statistical analysis of latent constructs, in most cases, a structured questionnaire is used in a quantitative study (Creswell and Creswell, 2018). This is due to the fact that it enables the consideration of the latent constructs. Given that the study is grounded in the extended UTAUT3 model, the questionnaire was put together on the basis of the previously validated scales of the existing literature. This was to ensure that the questionnaire content was valid and it was in line with the theory.

The instrument was comprised of several different pieces. To make it easy to analyse the subgroups and test moderation, the initial section contained demographic data, including gender, age group, occupation, and generation. The second portion was measurement items which refer to technical dimension, experiential dimension as well as the perceptual dimension. These were performance expectation, perceived value, content quality, social impact, and habit, hedonic motivation, pricing value and user intention to adopt over-the-top (OTT) platforms. To provide the guarantees of construct reliability and comparability, every item was based on the prior empirical works in the domain of technologies acceptance and research of technology acceptance and digital services (Hair, Hult, Ringle, and Sarstedt, 2021; Venkatesh et al., 2003).

The level of assent that the respondents agreed with the statement was measured on a Likert scale with seven points, which were Strongly Disagree (1), Strongly Agree (7). The Likert scale is a perfect tool of obtaining attitudes, perceptions, and behavioral intentions since it provides ordinal data that can be used in multivariate statistical methods, including PLS-SEM (Sekaran and Bougie, 2016). To avoid a biased response and maximize the proportion of individuals who complete the questionnaire, it was designed to be plain, to the point and easily understood.

Before the data were collected in bulk, a pilot test was conducted on the tool to make sure that it was understandable, clearly written, and applied to the subject. Then, reliability and validity were checked consecutively through the use of Cronbach's alpha, composite reliability, Average Variance Extracted (AVE), Fornell-Larcker and HTMT ratio during the measurement model evaluation. The constructs were ensured to be internally consistent, convergent, and discriminant valid because of the techniques that were used.

Table 3.1 Variable wise Measurement Statements			
Variable	Code	Measurement Statement	Source
Performance Expectancy	PEX1	Using OTT platforms improves my entertainment experience.	Venkatesh et al. (2012); Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016)
	PEX2	OTT platforms allow me to watch content more conveniently than traditional media.	
	PEX3	OTT services help me access content anytime and anywhere.	
	PEX4	Using OTT platforms enhances my overall viewing efficiency.	
Content Quality	CNQ1	OTT platforms provide high-quality video and audio content.	Soren & Chakraborty (2023), S Nagaraj, S Singh, VR Yasa, 2021)
	CNQ2	OTT platforms offer diverse and engaging content.	
	CNQ3	The original content available on OTT platforms is appealing.	
Perceived	PRV1	OTT subscriptions provide good value for	Davis, 1989;

Value		Money.	Agarwal & Karahanna, 2000; Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016)
	PRV2	The benefits of OTT services justify the subscription cost.	
	PRV3	OTT platforms provide better value compared to traditional television services.	
Social Influence	SOI1	People important to me encourage me to use OTT platforms.	Venkatesh et al. (2003)
	SOI2	My friends and family influence my decision to subscribe to OTT services.	
	SOI3	Recommendations from others affect my OTT subscription decisions.	
	SOI4	Social media discussions influence my interest in OTT platforms.	
Facilitating Conditions	FCO1	I have the necessary resources (devices and internet) to use OTT platforms.	Venkatesh et al. (2003)
	FCO2	I have the knowledge required to use OTT services.	
	FCO3	OTT platforms are compatible with the devices I use.	
	FCO4	Technical support for OTT services is easily available when needed.	
Hedonic Motivation	HMO1	I find using OTT platforms enjoyable.	Venkatesh et al. (2012)
	HMO2	OTT platforms provide a pleasurable viewing experience.	
	HMO3	I feel excited while exploring new content on OTT platforms.	
Price Value	PVA1	OTT subscription prices are reasonable.	Nijhawan & Dahiya (2020), Agarwal & Prasad (1998)
	PVA2	OTT platforms offer flexible pricing plans.	
	PVA3	The price of OTT subscriptions is acceptable given the content quality.	
Personal	PIN1	I like experimenting with new digital	

Innovativeness		Technologies.	Agarwal & Prasad (1998), Tsai et al. (2024)
	PIN2	I am usually among the first to try new online services.	
	PIN3	I enjoy exploring new streaming platforms and applications.	
	PIN4	I feel confident using new digital technologies.	
User Intention to Adopt	UIA1	I intend to continue using OTT platforms in the future.	Venkatesh et al. (2012)
	UIA3	I plan to increase my usage of OTT platforms.	
	UIA4	I intend to maintain my OTT subscription.	
Habit	HAB1	Watching content on OTT platforms has become a habit for me.	Venkatesh et al. (2012); Soren & Chakraborty (2023)
	HAB2	I use OTT platforms automatically without thinking much about it.	
	HAB3	Using OTT platforms is part of my daily routine.	
	HAB4	I feel uncomfortable if I cannot access OTT platforms regularly.	
	HAB5	I frequently watch content on OTT platforms whenever I have free time.	

Pre-Testing and Pilot Testing

The study instrument was pre-tested and pilot tested before data collection on larger scale was conducted in order to enhance its clarity, reliability and validity. According to Creswell and Creswell (2018), the initial phase of refining the instruments involves the pre-testing. At this phase, evaluation of the questionnaire will be in terms of its clarity in terms of phrasing, logical sequence, its comprehensibility and its applicability to the situation. This is whereby the draft questionnaire was reviewed by subject matter experts in the field of management and information systems, as well as the

Experienced research academics who were conversant with frameworks on adoption of technology. To achieve the goal of making sure every item conveyed its target idea, was not ambiguous or dual-barrelled, and fit the demographic of users of OTT under consideration, the objective was to ensure that every item is appropriate. To align the scale items that had been previously proven in the context of the OTT experience without compromising the conceptual meaning of the items in question, the given endeavour was given special attention. Due to the remarks given by the specialists, slight modifications were carried out to enhance sentence arrangement, eliminate those aspects that were redundant, refine terminology, and make the piece easier to read in general. This process enhanced the content validity of the study and ensured that both the theoretical constructs and the measuring items were harmonized respectively.

After pre-testing, the pilot study was performed with a sample of 98 respondents selected in the target population, which included working professionals and students in Gujarat with a previous experience of exposure to OTT platforms and a year of experience of using digital services. These respondents were individuals who had already experienced digital service usage and were exposed to the over-the-top (OTT) services. The objectives of the pilot testing were to know whether the questionnaire was feasible or not, to get an approximate idea of the time that will be required to respond to the questionnaire, to detect the possible problems during the process, and to get the preliminary reliability test. Strong encouragement was created that the respondents should provide remarks concerning the clarity of the questions, response options, the survey flow, and difficulties they faced when filling out the survey. Cronbach alpha was used to analyse the pilot data to identify the internal consistency reliability.

This was in order to make sure that the constructs met the relevant levels of reliability ($\alpha > 0.70$), which are recommended by Nunnally and Bernstein (1994). The products with low item total correlations or insufficient contribution of reliability were put under thorough review and persuasion without affecting the integrity of the theoretical framework used. The task of pilot testing also helped to verify that the survey could be completed in a reasonable time (approximately 15-20 minutes), which contributed to the minimization of weariness on the side of the respondents and enhanced the quality of the answers provided.

It was assured that the final instrument was conceptually sound, culturally suitable, and statistically reliable by the combination of the pre-testing and pilot testing techniques. During these stages, the robustness, accuracy, and credibility of the empirical enquiry were considerably improved. This was

accomplished by detecting and fixing any potential measurement mistakes that may have occurred prior to the wide-scale administration.

Table 3.2 – Internal Consistency

	Cronbach's alpha	(rho_a)	No of Items
CNQ	0.893	0.895	3
FCO	0.914	0.915	4
HAB	0.891	0.913	5
HEM	0.914	0.915	3
INO	0.919	0.919	4
PEX	0.905	0.906	4
PRV	0.841	0.858	4
PVL	0.931	0.931	3
SOI	0.827	0.827	4
UIA	0.864	0.865	3

3.9 - Data Collection Tools:

To ensure that the proposed research model is theoretically informed as well as empirically confirmed, data collection of the current research was conducted with the help of primary and secondary sources. The inclusion of these two sources of information led to the enhancement of the extent of research, reliability as well as contextual sensitivity.

Secondary Data Collection:

Secondary data were obtained during the initial stages of the research process in an effort to establish the theoretical foundation and conceptual framework of the study. The literature that was reviewed was the relevant literature that contained peer reviewed journal, conference proceedings, doctorate theses, industry reports, government publications, and authorised internet information sources. To find the past empirical research related to the over-the-top (OTT) adoption, digital streaming services, and technology acceptance models (UTAUT, UTAUT2, TAM, and Value-Based Adoption Models),

academic databases (Scopus-indexed journals, Web of Science, and Google Scholar) and available resources of institutional libraries were used.

Also, the market research and industry coverage were researched with the aim of understanding the global and Indian over-the-top (OTT) trends, the rates of digital penetration, pricing patterns, and the consumption patterns among users. These sources were useful because they helped in the identification of research gaps, refining the study objectives, formulating hypotheses, and the choice of validated measuring scales to operationalize the construct. Consequently, secondary data played a vital role in the development of the instrument, setting of theoretical orientation, and offering contextual support of the investigation.

Primary Data Collection:

To carry out the empirical test of the proposed research method, a structured questionnaire survey was used as the tool of obtaining primary data. The reason why Saunders, Lewis, and Thornhill (2019) selected the survey method is that it is appropriate in collecting standardised information that involves many respondents in a short period. This is what made the survey method to be chosen. The questionnaire was designed to help establish how the respondents are impressed with the technological, experiential and perceptual issues that lead to the (Nagaraj et al., 2021a) their inclination to adopt over-the-top (OTT) services (Elagin et al., 2019).

The survey of major urban centres of the state of Gujarat was conducted over a period of one hundred and eighty days and the survey commenced in July 2024 and ended in December 2024. Such centres were Ahmedabad, Gandhinagar, Vadodara, Surat and Rajkot. The target respondents were people aged 18 to 55 and able to use internet-enabled devices and at least one over-the-top (OTT) platform familiar with or experienced with at least one. The scarcity of easily available sampling frame of over-the-top (OTT) users in Gujarat led to the need to use non-probability convenience sampling method.

The number of questionnaires mailed was 1,168 and 1,077 replies were received. Upon examination of the data and discarding 91 incomplete replies, there were 998 valid questionnaires retained with an aim of carrying out the final analysis. The subject of the study was explained to the participants and they were assured of their privacy and confidentiality (G. Gupta & Singharia, 2021b). The potential risk of response bias was minimized because the entire participation process was voluntary, with no monetary and material incentives provided. The structured questionnaire utilized a Likert scale of seven

points to the end of the purpose of measuring latent constructs. It made it possible to statistically analyse it with the help of Partial Least Squares Structural Equation Modelling (PLS-SEM). The large size of the sample was statistically significant and ensured the study hypothesis testing, reliability measurement, and multi-group analysis were conducted with utmost reliability.

Statistical Tools and Techniques:

Descriptive and multivariate statistical analysis was employed in combination with each other to analyse data collected and give the hypotheses that were put forward to test. The SPSS (statistical package of the social sciences) and SmartPLS software packages were used in order to carry out the statistical analysis. This process made sure that the measurement as well as the structural models were evaluated in detail. The nature of the study objectives, the theoretical backbone (expanded UTAUT3), and the complexity of interactions between latent constructs were the main principles that inform the choice of statistical methods (Ringle, n.d.).

3.10 - Preliminary Data Analysis

To start with, SPSS statistical package was used to screen and process the data. Some of the items that were verified through this process were incomplete replies, coding errors, and gaps in data entry. To obtain an insight into general pattern of answers and a general overview of demographic characteristics of the respondents, descriptive statistics were calculated respectively, frequency distribution, mean, and standard deviation. These studies gave a summary of the sample profile and the appropriateness of the data to more advanced modelling was confirmed.

Reliability and Validity Analysis

The assessment of reliability and validity were conducted within the PLS-SEM framework with the help of SmartPLS as a way to test the nature of the measurements of the constructs. Cronbach alpha and Composite Reliability (CR) were applied with the aim of testing the internal consistency reliability of the constructs. (Hair et al., 2019) discussed the values exceeding 0.70 as acceptable ones, which reflected that the internal consistency was rated as satisfactory. Factor loadings as well as the Average Variance Extracted (AVE) method were used to test convergent validity. The fact that the constructs accounted a large percentage of the variance in their indicators was evidenced by the fact that they had

larger indicator loadings (more than 0.70) and had larger AVEs (more than 0.50). To establish the discriminant validity of the test, Fornell-Larker criteria and Heterotrait-Monotrait (HTMT) ratio were used. The lower values of the HTMT below 0.90 indicated satisfactory values of the discriminant validity that guaranteed the difference in the conceptions.

Structural Equation Modeling (PLS-SEM)

The PLS-SEM is the abbreviation of partial least squares structural equation modelling and it was applied to determine whether the correlations between the constructs were true or false as hypothesized. The PLS-SEM was selected as the means of analysis because of its flexibility in making predictive research, complex models that contain several constructs, and non-normal distribution of data (Hair et al., 2019) It is particularly appropriate when the aim of the study is to elaborate on the existing theories and give explanations to variation as opposed to comparing the appropriateness of models in relation to the data. Evaluation of the structural model was carried out with the help of path coefficients (values of the β), t-statistics, and p-values which were evaluated with the help of bootstrapping processes. To test the model in its explanation capacity of the data, the coefficient of determination (R^2) was tested. This value is used to show what percentage of the change in User Intention to Adopt can be explained by the variables that are used as predictors. The effect size (f^2) and predictive relevance (Q^2) were also considered to define the contribution of certain constructs and the extent to which they predict.

Multi-Group Analysis (MGA)

Multi-Group Analysis (MGA) was conducted within the framework of PLS-SEM, to examine the moderating influence of demographic issues like gender and generation (Gen Y- Gen Z). A technique called the permutation test was employed whereby route coefficients were compared across the various groups and it was determined whether or not there were significant differences in the structural linkages between the subgroups. With the use of MGA, the effects of demographic moderation were able to be tested and still retain the statistical analysis reliability (Sarstedt et al., 2009).

Importance Performance Map Analysis (IPMA)

Importance Performance Map Analysis (IPMA) was conducted along with the structural connection test to obtain insight into the management. IPMA is an extension of the results of PLS-SEM that does not only assess the significance (total effects) of each construct on the target variable, but also their

performance (average latent variable scores). This study will enable the managers of OTT platforms to make more informed strategic decisions, which helps identify constructs that are interesting by their high relevance but poor performance.

CHAPTER – 4 - DATA ANALYSIS

The chapter on data analysis is an essential component of any thesis. It offers a comprehensive analysis of the data that was gathered in order to answer the research questions or hypotheses stated in the thesis. The purpose of this chapter is to act as a link between the theoretical framework and the findings, ensuring that the findings are not only reported but also contextualized within the context of the study goals.

The objective of this chapter is to develop meaningful conclusions by methodically presenting, analysing, and interpreting the data that was acquired. This will be accomplished by applying proper procedures. In this chapter, the analysis is aligned with the goals of the research, which guarantees that the results are based on evidence and are scientifically valid.

4.1 - DEMOGRAPHIC ANALYSIS:

Figure 4.1 – Age Classification

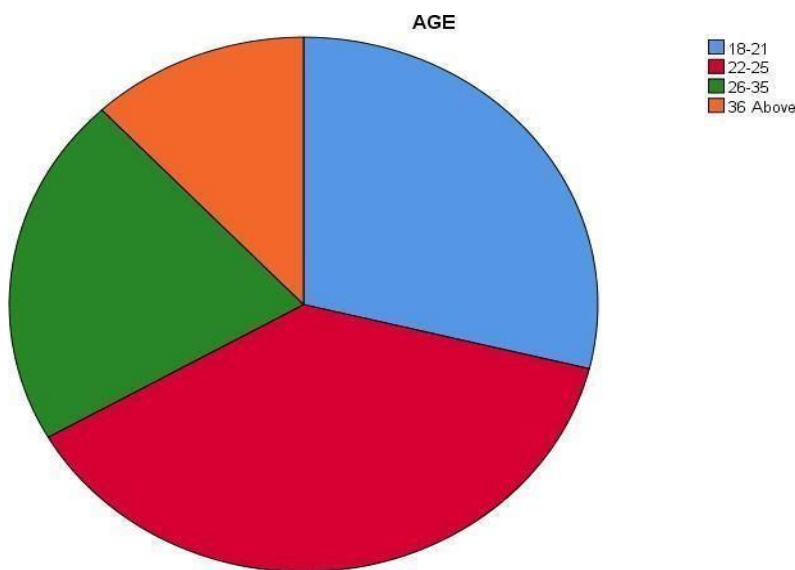


Table 4.1 – Age Classification		
	Frequency	Percent
18-21	288	28.9
22-25	378	37.9
26-35	212	21.2
36 Above	120	12
Total	998	100

The age distribution of the research participants (N = 998) indicates a predominance of younger demographics. The predominant segment of respondents is the 22–25 age bracket, consisting of 378 persons (37.9%) of the sample. The subsequent age group, 18–21, has 288 respondents (28.9%), signifying that over two-thirds of the sample (66.8%) are aged between 18 and 25 years. Individuals aged 26–35 constitute 21.2% (n = 212) of the total, and the group aged 36 and above comprises the smallest segment, with just 12% (n = 120) of the respondents.

Figure 4.2 – Gender Classification

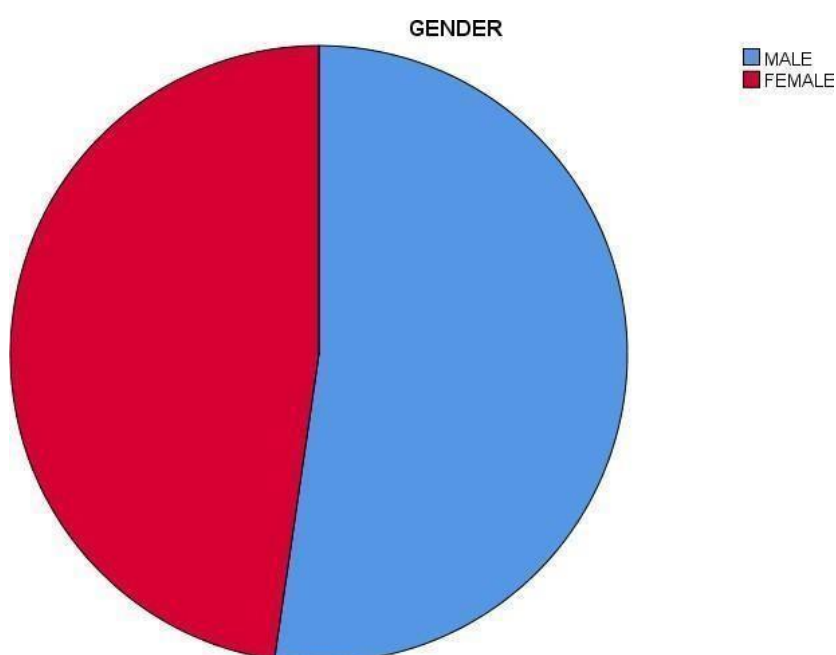


Table 4.2 – Gender Classification		
	Frequency	Percent
MALE	522	52.3
FEMALE	476	47.7
Total	998	100

The sample consists of 998 participants, with 52.3% male (n = 522) and 47.7% female (n = 476), indicating a somewhat greater proportion of males in the dataset. The gender distribution is virtually even, facilitating adequate comparability between the two groups in subsequent gender-focused analyses.

Figure 4.3 – Education Qualification

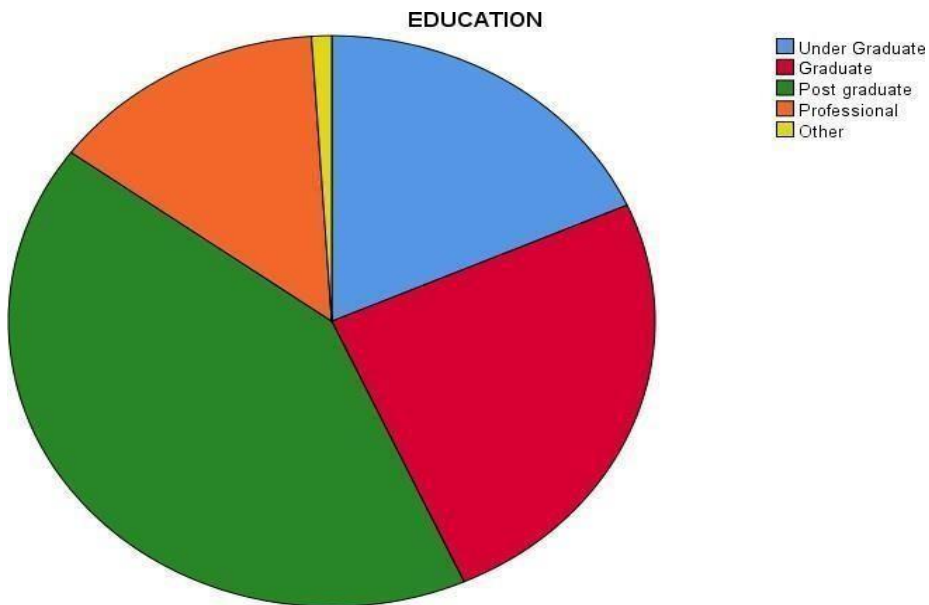


Table 4.3 – Education Qualification		
	Frequency	Percent
Undergraduate	183	18.3
Graduate	249	24.9
Postgraduate	417	41.8
Professional Degree	139	13.9
Other	10	1
Total	998	100

The dataset included responses from 998 individuals, reflecting the distribution of educational attainment across five broad categories. The largest segment of respondents consisted of Postgraduates, representing 41.8% (n = 417) of the whole sample. This indicates a highly educated sample with superior academic qualifications. Subsequently, Graduates constituted the second largest demographic at 24.9% (n = 249), signifying that more than two-thirds (66.7%) of participants possessed at least a graduate-level degree. The Undergraduate group included 18.3% (n = 183), whilst Professional qualifications (e.g., certifications, chartered credentials) represented 13.9% (n = 139), underscoring a cohort of persons possessing specific competence that may not conform to traditional academic trajectories. A negligible 1.0% (n = 10) identified as belonging to the “Other” group, potentially encompassing informal schooling or occupational training, which may not correspond directly with conventional academic classifications.

Figure 4.4 – Occupation Classification

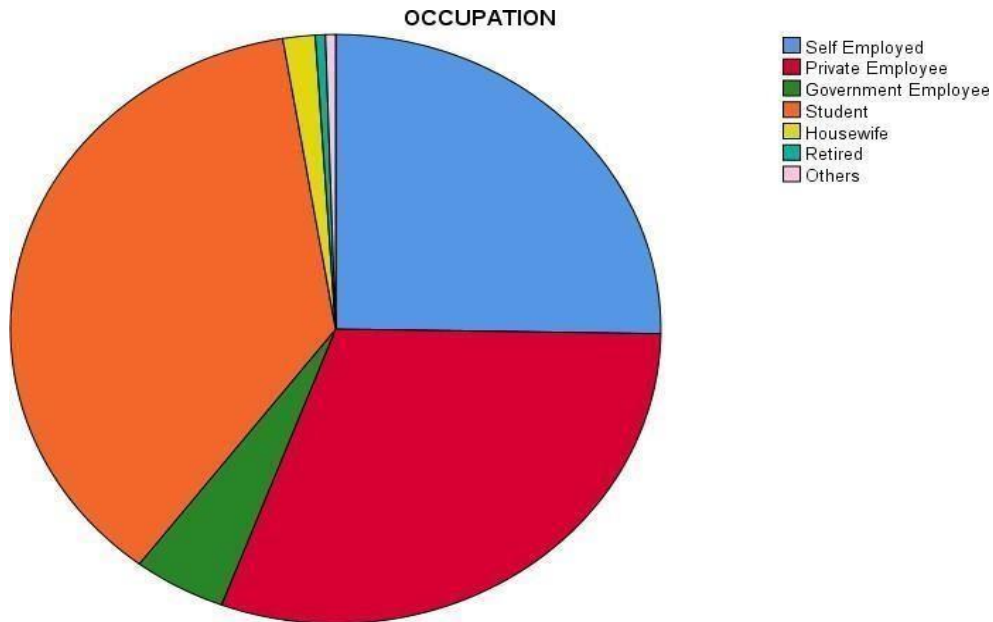


Table 4.4 – Occupation Classification

	Frequency	Percent
Self Employed	252	25.3
Private Employee	304	30.5
Government Employee	46	4.6
Student	370	37.1
Housewife	16	1.6
Retired	5	0.5
Others	5	0.5
Total	998	100

An examination of the occupational distribution among the 998 participants indicates that students comprise 37.1% (n = 370) of the sample. This notable representation may indicate either the academic focus of the study or deliberate sampling tactics aimed at younger or currently enrolled populations. Employees in the private sector constitute the second-largest demographic, accounting for 30.5% (n =

304), while self-employed individuals represent 25.3% (n = 252). Together, these two economically engaged groups comprise over 55% of the respondents, indicating a workforce-oriented sample with diverse experiences in organizational and entrepreneurial sectors. In contrast, government personnel constitute a mere 4.6% (n = 46), possibly reflecting restricted public sector involvement within the sample or demographic-specific trends such as age or area. Housewives, retirees, and other groups represent a negligible fraction, totalling merely 2.6% of the sample (n = 26), with housewives comprising 1.6% (n = 16), and both retirees and other categories at 0.5% (n = 5 each).

Figure 4.5 – Income Classification

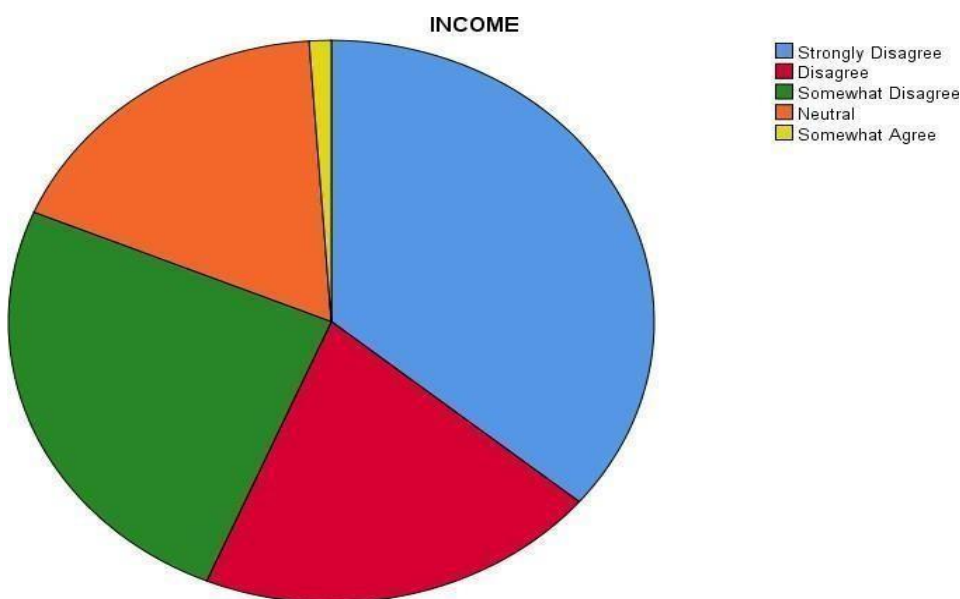


Table 4.5 – Income Classification

INCOME			
		Frequency	Percent
	Below 1,00,000	358	35.87
	1,00,000-3,00,000	202	20.24
	3,00,000- 5,00,000	248	24.85
	5,00,000-7,00,000	174	17.43
	Above 7,00,000	16	1.6
Total		998	

The income distribution of responses reveals that a substantial fraction falls into the lower-income bracket, with the largest number (35.87%) earning less than ₹1,00,000 per annum. Subsequently, 24.85% of respondents belong to the ₹3,00,000–₹5,00,000 income band, while 20.24% fall within the ₹1,00,000–₹3,00,000 category, indicating a significant representation of lower-middle-class persons. Furthermore, 17.43% of respondents belong to the ₹5,00,000–₹7,00,000 income bracket, indicating a moderate-income demographic. Conversely, just 1.6% of respondents earn above ₹7,00,000, signifying a minimal presence of high-income persons. The data indicates that the sample primarily consists of poor and middle-income respondents, potentially affecting the study findings by promoting price-sensitive and budget-conscious behavior habits.

Figure 4.6 – Device Used for OTT

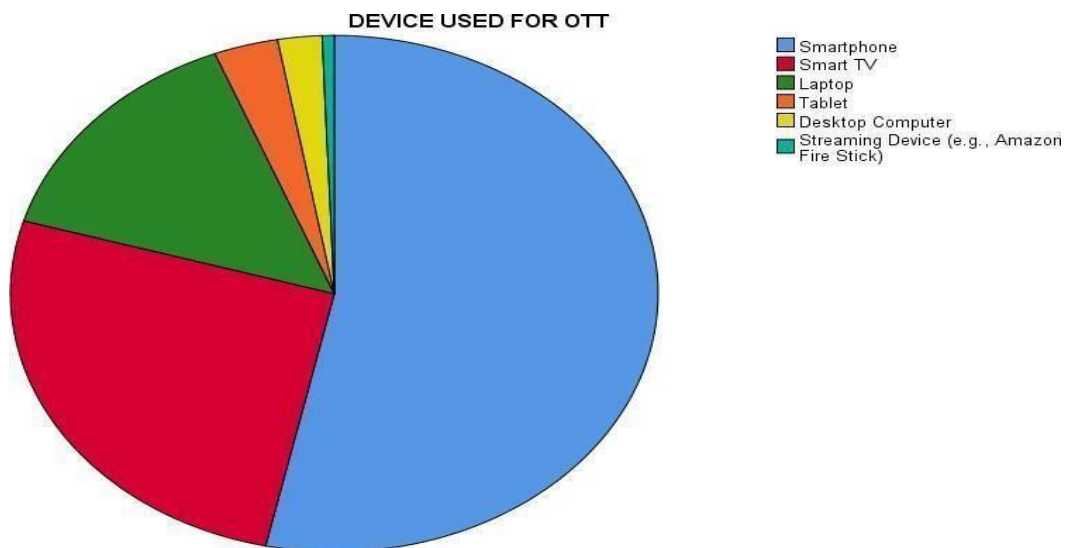


Table 4.6 – DEVICE USED FOR OTT		
	Frequency	Percent
Smartphone	533	53.4
Smart TV	261	26.2
Laptop	144	14.4
Tablet	32	3.2
Desktop Computer	22	2.2

Streaming Device (e.g., Amazon Fire Stick)	6	0.6
Total	998	100

The study indicates that OTT content consumption is mostly mobile-centric, with smartphones being the favoured device (53.4%) owing to their mobility, affordability, and extensive internet accessibility. Smart TVs account for 26.2%, indicating a rising preference among consumers for immersive, large-screen watching experiences facilitated by linked television technologies. Laptops (14.4%) are a secondary option, although tablets (3.2%) and desktop PCs (2.2%) exhibit minimal involvement, presumably due to reduced convenience and mobility. Streaming gadgets like the Amazon Fire Stick represent just 0.6%, signifying limited adoption or awareness. Smartphones and smart TVs collectively account for nearly 80% of OTT usage, highlighting a dual trend of personalised mobile viewing and communal home entertainment. This indicates that OTT platforms and advertisers should focus on optimising content and interfaces for these two primary device categories.

Figure 4.7 – Weekly Time Spend

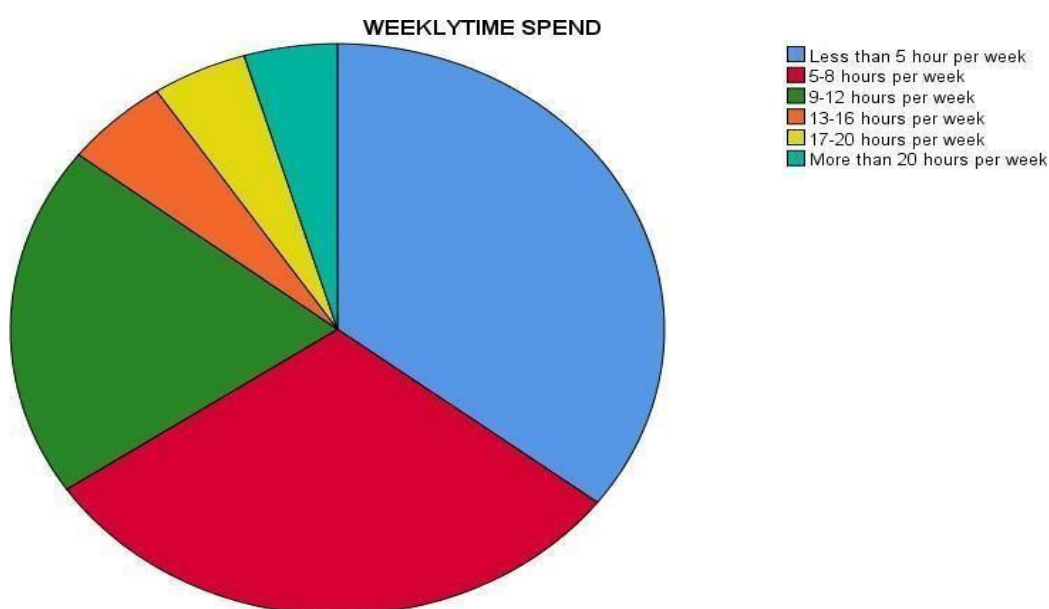


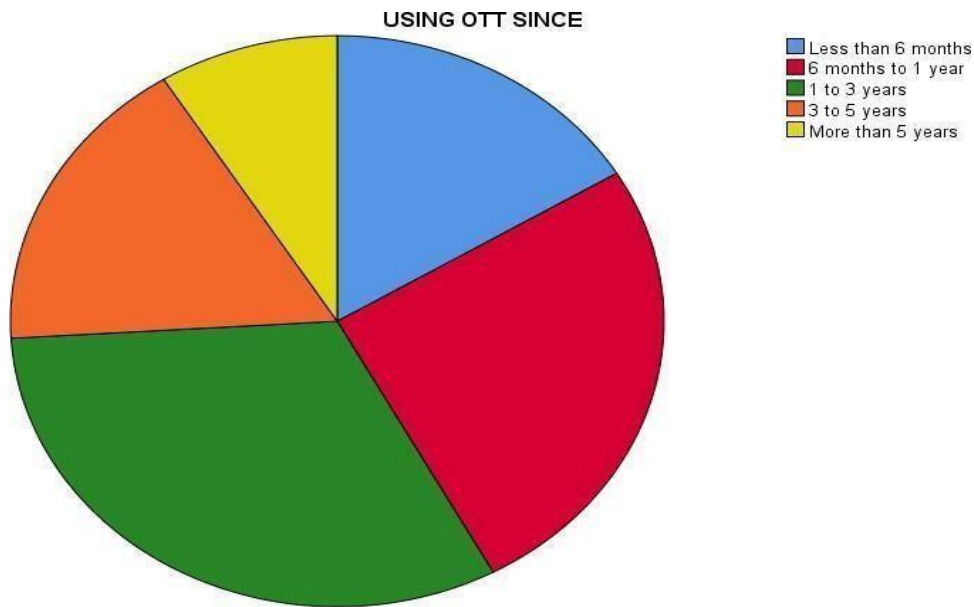
Table 4.7 – WEEKLYTIME SPEND		
	Frequency	Percent
Less than 5 hour per	353	35.4

week		
5-8 hours per week	301	30.2
9-12 hours per week	199	19.9
13-16 hours per week	52	5.2
17-20 hours per week	47	4.7
More than 20 hours per week	46	4.6
Total	998	100

The study reveals that a significant percentage of respondents (35.4%) allocate fewer than five hours weekly to OTT platforms, indicating a casual interaction with limited material, such trending series or short-form entertainment. Another 30.2% of respondents report 5–8 hours of weekly viewing, reflecting moderate usage. Collectively, these two categories account for 65.6% of the sample, indicating that the majority of OTT users allocate fewer than eight hours per week to streaming, underscoring the dominance of moderate consumption over excessive binge-watching.

Approximately 19.9% of respondents fall within the 9–12 hour range, indicating moderate-to-heavy users who consistently engage with serialized content. In contrast, a minor segment-5.2%, 4.7%, and 4.6%-reported viewing for 13–16, 17–20, and over 20 hours per week, respectively, signifying heavy viewers typically linked to binge-watching culture. The research indicates that OTT consumption is modest among the population, with a small percentage of heavy users, suggesting that although OTT platforms are incorporated into users' routines, the majority of viewers balance streaming with other media and offline activities. This trend underscores the opportunity for content producers to augment persistent engagement via techniques such as serial releases, tailored suggestions, and adaptive watching experiences designed to transform moderate users into frequent consumers.

Figure 4.8 – Using OTT Since



	Frequency	Percent
Less than 6 months	163	16.3
6 months to 1 year	257	25.8
1 to 3 years	319	32
3 to 5 years	170	17
More than 5 years	89	8.9
Total	998	100

The analysis reveals that a majority of respondents (57.8%) have been using OTT platforms for one year or less, indicating a strong surge of new adopters driven by factors such as affordable data plans, increased internet accessibility, and the widespread availability of smartphones and smart TVs. The largest single group, representing 32% of respondents, has used OTT services for one to three years, suggesting that a significant proportion of users have integrated streaming platforms into their regular entertainment routines. Meanwhile, 17% of respondents fall within the three to five-year usage bracket, reflecting individuals who likely adopted OTT platforms during their early popularization, particularly around the pandemic period when digital entertainment demand intensified. Only 8.9% of users

reported using OTT services for more than five years, identifying them as early adopters with established viewing habits and potential brand loyalty. Overall, the data indicates a rapidly expanding and maturing user base, where new and moderately experienced users dominate, signifying that OTT consumption has transitioned from an emerging trend to a mainstream mode of entertainment. This pattern highlights the need for OTT service providers to focus on retention strategies-such as personalized recommendations, engaging content libraries, and cost-effective subscription models-to sustain long-term audience engagement and loyalty.

4.2 - CROSS TABULATION:

Cross tabulation, or contingency table, is a statistical method employed to analyze the connection between two or more categorical variables by structuring data into a matrix of rows and columns. Every cell in the table denotes the frequency or proportion of observations within a particular combination of categories, enabling researchers to condense extensive information and visually see patterns, correlations, or disparities across variables. It is extensively utilized as a fundamental instrument in research for the analysis of categorical data and the facilitation of subsequent statistical testing

Table 4.9 - INCOME * DEVICE USED FOR OTT						
		DEVICE USED FOR OTT				
		Smartphone	Smart TV	Laptop	Tablet	Desktop Computer
INCOME	Below 1,00,000	185	107	51	7	8
	1,00,000-3,00,000	117	52	24	7	2
	3,00,000- 5,00,000	122	62	45	11	8
	5,00,000-7,00,000	103	38	23	6	4
	Above 7,00,000	6	2	1	1	0
Total		533	261	144	32	22

A cross-tabulation of income and devices used for over-the-top (OTT) consumption makes it abundantly evident that smartphones are the most popular devices for accessing OTT platforms across all income brackets. This is because smartphones are the primary medium via which users may access OTT platforms regardless of their economic standing. Despite the fact that this choice is most prevalent among those with lower incomes, it continues to be constant even among those with greater incomes.

The use of smart televisions is becoming increasingly visible among respondents with middle-incomes, which suggests that there is a tendency toward greater watching experiences as purchasing power improves. Smart TVs rank as the second most favoured item. Laptops are used by a modest number of people across all demographics, which reflects their secondary role as versatile gadgets rather than only as entertainment tools. Tablet computers and desktop computers, on the other hand, have relatively low usage across all income levels, which indicates that there is a limited desire for over-the-top (OTT) watching on these platforms.

Furthermore, the distribution of respondents is concentrated between the lower and middle-income categories, with just a limited representation from the highest income group; yet, the patterns of choice for devices have remained fairly consistent. The table reveals that, in general, there is a significant dependence on mobile-based over-the-top (OTT) consumption, with only a slow transition toward larger-screen devices accompanying an increase in wealth

Table 4.10 - Chi-Square Tests – Income * Device used for OTT			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	31.556 ^a	20	.048
Likelihood Ratio	23.326	20	.273
Linear-by-Linear Association	.573	1	.449
N of Valid Cases	998		

H0: There is no significant association between income level and the device used for OTT consumption.

H1: There is a significant association between income level and the device used for OTT consumption.

Given that the Pearson Chi-Square value is 31.556 with 20 degrees of freedom and a p-value of 0.048, which is lower than the conventional significance level of 0.05, the results of the chi-square test indicate that there is a statistically significant association between income level and the device used for OTT consumption. This is because the p-value is lower than the conventional significance level. The fact that this is the case shows that the choice of device for over-the-top (OTT) platforms is not independent of the level of wealth, and that fluctuations in income do impact device selection to some degree. The

Likelihood Ratio test, on the other hand, reveals a p-value of 0.273, which is not statistically significant. Furthermore, the Linear-by-Linear Association value ($p = 0.449$) likewise suggests that there is no significant linear trend between income and device usage. In light of this, it may be deduced that although there is a general correlation, it might not adhere to a linear pattern that is constant across all economic categories. An additional factor that contributes to the credibility of the study is the total number of valid instances, which is $N = 998$. A small but statistically significant association between wealth and desire for over-the-top (OTT) devices appears to exist, according to the data as a whole.

Table 4.11 - INCOME * WEEKLYTIME SPEND					
		WEEKLYTIME SPEND			
		Less than 5 hour per week	5-8 hours per week	9-12 hours per week	13-16 hours per week
INCOME	Below 1,00,000	131	109	75	18
	1,00,000-3,00,000	69	69	42	10
	3,00,000- 5,00,000	79	65	53	13
	5,00,000-7,00,000	71	53	29	10
	Above 7,00,000	3	5	0	1
Total		353	301	199	52

The cross-tabulation of income levels and the amount of time spent on over-the-top (OTT) platforms on a weekly basis reveals that the majority of respondents come from all income brackets and spend less than five hours per week on OTT platforms. This is followed by those who spend between five and eight hours per week, indicating a general pattern of moderate OTT consumption. The groups with lower incomes, namely those with less than ₹1,00,000, had the highest frequency across all time categories, particularly in the shorter watching durations.

This indicates that they have limited free time or restricted access. There is a minor trend toward larger watching durations as income grows, particularly among middle-income groups including individuals with incomes ranging from ₹3,00,000 to ₹5,00,000, which indicates significantly more involvement with over-the-top (OTT) platforms. However, the category with the most time spent, which ranges from 13 to 16 hours per week, continues to be the least prevalent across all income levels. This demonstrates that excessive usage is restricted regardless of earnings. Despite the fact that their

viewing duration appears to be relatively low, the highest income category, which is above ₹7,000,000, displays small representation overall, which makes it difficult to build a significant trend. As a whole, the chart indicates that over-the-top (OTT) consumption is typically modest across all income categories. The data also indicates that there is only a gradual increase in watching time as income increases, rather than a significant change toward significant usage.

Table 4.12 - Chi-Square Tests – Income * Weekly Time Spent on OTT			
	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	30.010 ^a	20	.070
Likelihood Ratio	30.999	20	.055
Linear-by-Linear Association	1.172	1	.279
N of Valid Cases	998		

H0: There is no significant association between income level and weekly time spent on OTT platforms.

H2: There is a significant association between income level and weekly time spent on OTT platforms.

The chi-square test results demonstrate no statistically significant correlation between income level and weekly time spent on OTT platforms, as the Pearson Chi-Square value is 30.010 with 20 degrees of freedom and a p-value of 0.070, exceeding the conventional significance threshold of 0.05. This indicates that fluctuations in income do not markedly affect the duration respondents engage with OTT platforms. The Likelihood Ratio test produces a p-value of 0.055, beyond 0.05, hence reinforcing the lack of a statistically meaningful link. The Linear-by-Linear Association test reveals a p-value of 0.279, signifying the absence of a significant linear correlation between income levels and time allocated to OTT consumption. The study is statistically credible, encompassing a total of 998 valid instances. The data indicate that OTT watching time is reasonably uniform across income levels and is not significantly influenced by economic disparities.

Table 4.13 - INCOME * USING OTT SINCE					
		USING OTT SINCE			
		Less than 6 months	6 months to 1 year	1 to 3 years	3 to 5 years
INCOME	Below 1,00,000	54	93	118	64
	1,00,000-3,00,000	34	54	72	27
	3,00,000- 5,00,000	38	61	72	46
	5,00,000-7,00,000	34	48	53	31
	Above 7,00,000	3	1	4	2
Total		163	257	319	170

According to the cross-tabulation that was performed between different income levels and the length of time consumers have been using over-the-top (OTT) platforms, the majority of respondents across all income categories have been using OTT platforms for between one and three years, making this the most prevalent category. It would appear from this that over-the-top (OTT) services had a considerable surge in popularity during this time period across all economic sectors. The second biggest concentration is shown in the category that spans from six months to one year, followed by the group that spans from three to five years, which indicates a steady adoption trend over the course of time. The groups with lower incomes, namely those with less than ₹1,000,000, exhibit the highest frequencies across all duration categories, notably in the segment spanning from 1 to 3 years, which reflects a larger adoption in this particular category.

Additionally, those with a middle-income follow a pattern that is comparable, exhibiting continuous involvement throughout a variety of time periods, which indicates persistent and sustained consumption. There are comparatively fewer users who are new adopters of over-the-top (OTT) platforms, as indicated by the fact that the percentage of respondents that fall into the category of less than six months is the lowest. It is difficult to draw definitive conclusions about this sector due to the fact that the highest income category, which is above ₹7,000,000, has a relatively low representation across all categories. In general, the table demonstrates that the majority of users have not just begun using over-the-top (OTT) services. A sizeable fraction of users have moderate to long-term experience with OTT services, notably within the range of one to three years across all income levels.

Table 4.14 – Chi Square Test – Income * Duration of OTT			
	Value	Df	Asymptotic Significance (2-sided)
Pearson Chi-Square	16.538 ^a	16	.416
Likelihood Ratio	16.738	16	.403
Linear-by-Linear Association	.447	1	.504
N of Valid Cases	998		

H0: There is no significant association between income level and duration of OTT usage.

H3: There is a significant association between income level and duration of OTT usage.

The chi-square test results demonstrate no statistically significant correlation between income level and duration of OTT usage, as the Pearson Chi-Square value is 16.538 with 16 degrees of freedom and a p-value of 0.416, significantly exceeding the conventional significance threshold of 0.05. This indicates that the duration of respondents' usage of OTT platforms is unrelated to their economic level. The Likelihood Ratio test corroborates this conclusion with a p-value of 0.403, suggesting non-significance. The Linear-by-Linear Association test yields a p-value of 0.504, indicating the absence of a significant linear correlation between income and length of OTT usage. The analysis, comprising 998 genuine examples, yields statistically credible results. The data indicate that OTT adoption has progressed uniformly across all income categories, with no substantial variance attributable to economic disparities.

Table 4.15 - AGE * DEVICE USED FOR OTT							
		DEVICE USED FOR OTT					
		Smartphone	Smart TV	Laptop	Tablet	Desktop Computer	Streaming Device (e.g., Amazon Fire Stick)
AGE	18-21	161	68	41	11	5	2
	22-25	193	119	43	9	13	1
	26-35	118	52	35	2	2	3

	36 Above	61	22	25	10	2	0
Total		533	261	144	32	22	6

According to the cross-tabulation that was performed between different age groups and the devices that were used for over-the-top (OTT) consumption, smartphones are the most preferred device across all age categories. The highest usage was observed particularly among individuals aged 22–25 and 18–21, which indicates that younger users have a strong tendency toward mobile-based viewing. Smart televisions have emerged as the second most widely used gadget, particularly among individuals in the age range of 22 to 25 years old, which indicates that in this demographic, there is a rising demand for better watching experiences.

When it comes to over-the-top (OTT) consumption, laptops are used by people of all ages in a modest manner, which reflects their function as secondary devices. Tablet computers and desktop computers, on the other hand, have a low incidence of usage across all categories, which indicates that there is a restricted preference for these devices. According to the results of the survey, streaming gadgets like the Amazon Fire Stick have the lowest total usage, which indicates that respondents have low adoption levels. Furthermore, younger age groups are the most likely to consume over-the-top (OTT) content in terms of overall frequency, whereas older age groups, notably those aged 36 and above, have somewhat lower involvement. In general, the table demonstrates that the consumption of over-the-top (OTT) services is primarily driven by the use of smartphones, with a progressive diversification to include Smart TVs and other devices. There is a significant concentration of OTT use among younger audiences.

Table 4.16 – Chi Square Test – Age * Device used for OTT			
	Value	Df	Asymptotic Significance (2-sided)
Pearson Chi-Square	38.172 ^a	15	.001
Likelihood Ratio	36.697	15	.001
Linear-by-Linear Association	1.066	1	.302
N of Valid Cases	998		

H0: There is no significant association between age and the device used for OTT consumption.

H4: There is a significant association between age and the device used for OTT consumption.

The results of the chi-square test reveal that there is a statistically significant correlation between age and the device used for OTT consumption. This is because the Pearson Chi-Square value is 38.172 with 15 degrees of freedom and a p-value of 0.001, which is significantly lower than the significance level of 0.05. It is evident from this that the desire for devices that are compatible with over-the-top (OTT) platforms differs dramatically across various age groups. A further confirmation of the strength of the link is provided by the Likelihood Ratio test, which demonstrates a p-value of 0.001 and provides additional support for this conclusion. The Linear-by-Linear Association test, on the other hand, produces a p-value of 0.302, which indicates that although there is a link between the two variables, it does not follow a linear trend that is consistent across all age groups. Due to the fact that the research comprised 998 genuine instances, the findings may be considered statistically credible. The data, taken as a whole, indicate that age is a key factor in deciding the choice of device for over-the-top (OTT) usage.

Table 4.17 - AGE * USING OTT SINCE						
		USING OTT SINCE				
		Less than 6 months	6 months to 1 year	1 to 3 years	3 to 5 years	More than 5 years
AGE	18-21	49	77	97	40	25
	22-25	54	101	123	66	34
	26-35	41	53	63	41	14
	36 Above	19	26	36	23	16
Total		163	257	319	170	89

According to the cross-tabulation that was performed between age and the length of time that one has been using over-the-top (OTT) platforms, the majority of respondents across all age groups have been using OTT platforms for one to three years, making this category the leading one. The fact that this tendency is more noticeable among younger respondents between the ages of 22 and 25 and 18 and 21 supports the hypothesis that these age groups constitute the primary user base of over-the-top (OTT) platforms that have sustained engagement over time. A progressive adoption pattern among users is

shown by the fact that the next largest frequencies are recorded in the category ranging from six months to one year, followed by three to five years on average. A relatively lower frequency is shown in the category of less than six months, which indicates that there have been less new adopters in recent period of time. Additionally, longer-term consumption of more than five years is generally restricted across all age categories, although it is significantly more noticeable among those who are younger and those who are middle-aged. Participants aged 36 and older had a lower total involvement across all categories, which indicates that they have a somewhat lower level of interaction with over-the-top (OTT) platforms generally. In general, the chart demonstrates that the majority of over-the-top (OTT) usage is concentrated among younger age groups that have moderate to long-term experience, particularly within the range of one to three years, which reflects sustained and broad acceptance.

Table 4.18 – Age * Duration of OTT usage			
	Value	Df	Asymptotic Significance (2- sided)
Pearson Chi-Square	10.710 ^a	12	.554
Likelihood Ratio	10.585	12	.565
Linear-by-Linear Association	1.190	1	.275
N of Valid Cases	998		

H0: There is no significant association between age and duration of OTT usage.

H5: There is a significant association between age and duration of OTT usage.

Because the Pearson Chi-Square value is 10.710 with 12 degrees of freedom and a p-value of 0.554, which is much greater than the conventional significance level of 0.05, the findings of the chi-square test show that there is no statistically significant correlation between age and the length of time spent using over-the-top (OTT) services. According to this, it appears that the amount of time that users have spent using over-the-top (OTT) platforms does not considerably differ between the various age groups. With a p-value of 0.565, the Likelihood Ratio test provides additional evidence that this conclusion is supported, further showing that there is no significant link between the two variables. As an additional point of interest, the Linear-by-Linear Association test reveals a p-value of 0.275, which indicates that

there is no significant linear trend between age and the duration of time spent using OTT services. Due to the fact that the research comprised 998 genuine instances, the findings may be considered statistically credible. It seems from the data that the adoption of over-the-top (OTT) services throughout the course of time has been pretty consistent across all age groups.

Table 4.19 – EDUCATION * DEVICE USED FOR OTT						
		DEVICE USED FOR OTT				
		Smartphone	Smart TV	Laptop	Tablet	Desktop Computer
EDUCATION	Undergraduate	98	38	24	15	8
	Graduate	135	80	25	0	9
	Postgraduate	217	110	71	9	4
	Professional Degree	74	32	24	8	1
	Other	9	1	0	0	0
Total		533	261	144	32	22

The result of a cross-tabulation between the level of education and the devices used for over-the-top (OTT) consumption is that smartphones are the most favoured device across all educational categories. This is an indication of the fact that smartphones are universally accessible and convenient. This preference is more obvious among postgraduates and graduates, who also demonstrate a somewhat higher usage of smart televisions and computers.

This suggests that there is a predisposition toward more varied and better watching experiences as one's level of education grows. Reflecting a preference for improved screen quality and immersive watching, smart TVs emerge as the second most widely used device across all demographics, particularly among postgraduates. This preference is especially prevalent among televisions. It is possible that the dual functionality of laptops, which allow them to be used for both work and enjoyment, is the reason for the modest and visible usage of laptops among postgraduates and professionals. Tablet computers and desktop computers, on the other hand, have a low utilization rate across all educational levels, which indicates that they have little significance for over-the-top (OTT) consumption. The general level of engagement among respondents who are classed as having "Other" education is quite low. Despite the fact that smartphone usage is prevalent across all educational levels, the table demonstrates that higher levels of educational attainment are connected with a greater utilization of numerous devices for over-

the-top (OTT) consumption.

Table 4.20 - Chi-Square Tests – Education * Device used for OTT			
	Value	df	Asymptotic Significance (2- sided)
Pearson Chi-Square	63.166 ^a	20	.000
Likelihood Ratio	70.698	20	.000
Linear-by-Linear Association	1.118	1	.290
N of Valid Cases	998		

H0: There is no significant association between education level and the device used for OTT consumption.

H6: There is a significant association between education level and the device used for OTT consumption.

The chi-square test findings demonstrate a statistically significant correlation between education level and the device utilized for OTT consumption, as evidenced by a Pearson Chi-Square value of 63.166, 20 degrees of freedom, and a p-value of 0.000, which is substantially lower than the 0.05 significance threshold. This indicates that educational qualifications substantially affect the selection of devices for accessing OTT services. The Likelihood Ratio test corroborates this conclusion, presenting a p-value of 0.000, so affirming the robustness and dependability of the connection. The Linear-by-Linear Association test produces a p-value of 0.290, suggesting that while a link is there, it does not exhibit a consistent linear pattern across educational levels. The analysis includes 998 genuine examples, rendering the conclusions statistically robust. The data indicate that individuals with varying educational backgrounds display markedly distinct preferences for OTT watching devices.

Table 4.21 – EDUCATION * WEEKLYTIME SPEND					
		WEEKLYTIME SPEND			
		Less than 5 hour per week	5-8 hours per week	9-12 hours per week	13-16 hours per week
EDUCATION	Undergraduate	52	51	45	15

	Graduate	82	72	59	7
	Postgraduate	150	137	67	25
	Professional Degree	63	40	25	5
	Other	6	1	3	0
Total		353	301	199	52

The cross-tabulation of education level and weekly time spent on OTT platforms reveals that most respondents in all educational categories allocate less than 5 hours per week, with a significant number spending 5–8 hours per week, indicating a general trend of moderate OTT consumption. Postgraduates exhibit the highest prevalence across all temporal categories, especially in the lower and mid-range watching durations, indicating enhanced involvement with OTT platforms within this demographic. Graduates and professionals display a same pattern, with greater concentrations in the lower time intervals and relatively fewer responses in the higher viewing categories. Undergraduates have a more even distribution across temporal categories, while their engagement diminishes as watching duration escalates. The highest watching group of 13–16 hours per week has the lowest prevalence across all educational levels, suggesting that extensive OTT use is rather rare irrespective of educational attainment. Participants categorized as “Other” education exhibit little overall engagement. The data indicates that OTT use is modest across all educational levels, with only minor variations in watching duration and no significant trend towards excessive usage within any specific category.

Table 4.22- Chi-Square Tests- Education * Weekly Time Spent on OTT			
	Value	Df	Asymptotic Significance (2-sided)
Pearson Chi-Square	41.982 ^a	20	.003
Likelihood Ratio	44.847	20	.001
Linear-by-Linear Association	15.352	1	.000
N of Valid Cases	998		

H0: There is no significant association between education level and weekly time spent on OTT platforms.

H7: There is a significant association between education level and weekly time spent on OTT platforms.

The chi-square test results demonstrate a statistically significant correlation between education level and weekly time spent on OTT platforms, with a Pearson Chi-Square value of 41.982, 20 degrees of freedom, and a p-value of 0.003, which is below the conventional significance threshold of 0.05. This indicates that the duration users engage with OTT platforms differs markedly among various educational cohorts. The Likelihood Ratio test corroborates this conclusion with a p-value of 0.001, so strengthening the strength of the link. The Linear-by-Linear Association test reveals a highly significant p-value of 0.000, signifying a substantial linear correlation between education level and time allocated to OTT platforms. The analysis includes 998 genuine examples, rendering the conclusions statistically credible. The data indicate that educational qualifications significantly influence OTT viewing time.

Table 4.23 - OCCUPATION * DEVICE USED FOR OTT					
		DEVICE USED FOR OTT			
		Smartphone	Smart TV	Laptop	Tablet
OCCUPATION	Self Employed	131	64	39	11
	Private Employee	137	91	50	11
	Government Employee	8	23	5	7
	Student	247	67	50	3
	Housewife	0	16	0	0
	Retired	5	0	0	0
	Others	5	0	0	0
Total		533	261	144	32

The cross-tabulation of occupation and devices utilized for OTT consumption reveals that smartphones are the predominant choice among all occupational categories, with notably elevated usage among students and private employees, highlighting the extensive accessibility and convenience of mobile viewing. Students are the predominant user demographic, exhibiting a pronounced preference for smartphones, accompanied by moderate utilization of Smart TVs and laptops. Private sector employees and self-employed persons exhibit considerable use of Smart TVs and laptops, indicating a propensity for varied viewing experiences in conjunction with mobile usage. Government personnel exhibit diminished smartphone usage yet have a pronounced preference for Smart TVs, suggesting a potential predisposition towards conventional or stationary screen watching. Housewives predominantly utilize

Smart TVs, with no documented use of smartphones or laptops, whilst retired folks exhibit modest participation, restricted solely to smartphone usage. Tablets continue to be the least favoured device among all occupational groups, signifying minimal adoption for OTT consumption. The data indicates that although smartphones prevail in all occupations, device choices exhibit modest variations based on occupational roles, with working professionals and students demonstrating more diverse usage patterns

Table 4.24 - Chi-Square Tests – Occupation * Device Used for OTT			
	Value	df	Asymptotic Significance (2- sided)
Pearson Chi-Square	154.413 ^a	30	.000
Likelihood Ratio	151.004	30	.000
Linear-by-Linear Association	20.396	1	.000
N of Valid Cases	998		

H0: There is no significant association between occupation and the device used for OTT consumption.

H8: There is a significant association between occupation and the device used for OTT consumption.

The results of the chi-square test reveal that there is a highly statistically significant correlation between occupation and the device used for OTT consumption. This is because the Pearson Chi-Square value is 154.413 with 30 degrees of freedom and a p-value of 0.000, which is significantly lower than the significance criterion of 0.05 to indicate that the association is statistically significant. The fact that various occupational groups have dramatically varying preferences for the devices they use to access over-the-top (OTT) services is well demonstrated by this. This discovery is also supported by the Likelihood Ratio test, which showed a p-value of 0.000, indicating the strength and consistency of the association between the two variables. Additionally, the Linear-by-Linear Association test reveals a significant p-value of 0.000, which indicates the existence of a substantial trend in the utilization of devices across all occupational groups. As a consequence of the inclusion of 998 genuine instances in the research, the findings are statistically robust and credible. The data, taken as a whole, indicate that occupation is a significant factor that plays a role in determining the device that is used for over-the-

top (OTT) consumption.

Table 4.25 - OCCUPATION * WEEKLYTIME SPEND				
		WEEKLYTIME SPEND		
		Less than 5 hour per week	5-8 hours per week	9-12 hours per week
OCCUPATION	Self Employed	85	70	54
	Private Employee	95	104	52
	Government Employee	7	16	8
	Student	166	98	72
	Housewife	0	7	9
	Retired	0	5	0
	Others	0	1	4
Total		353	301	199

A cross-tabulation of occupation and the amount of time spent on over-the-top (OTT) platforms on a weekly basis reveals that the majority of respondents across the majority of occupational groups fall within the lower and moderate viewing categories. More specifically, less than five hours per week and five to eight hours per week are the categories that fall into this category. This indicates that the overall pattern of consumption is moderate. Student users make up the largest group of people who use over-the-top (OTT) services.

They have the highest frequency across all time categories, particularly in the shorter watching durations, which indicates that they use the service often but not excessively. The distribution of private employees is well balanced, with a little larger concentration in the category of time spent working between five and eight hours, which indicates moderate participation. Individuals who are self-employed also exhibit consistent engagement across all time ranges, including a noteworthy presence in the higher watching group of 9–12 hours per week, which suggests that they have substantially greater flexibility in viewing time. While housewives have a propensity for moderate to higher watching durations rather than shorter ones, government personnel have a relatively lower participation rate across all categories (compared to other groups). Individuals who are retired or who are employed in other jobs have a low level of comprehensive participation. All things considered, the table indicates that patterns of consumption of over-the-top (OTT) content differ among different professional groups,

although they continue to be mostly focused within moderate viewing durations, with just a modest representation in higher time-spent categories.

Table 4.26 - Chi-Square Tests – Occupation * Weekly Time Spent on OTT			
	Value	Df	Asymptotic Significance (2-sided)
Pearson Chi-Square	94.840 ^a	30	.000
Likelihood Ratio	93.526	30	.000
Linear-by-Linear Association	7.573	1	.006
N of Valid Cases	998		

H0: There is no significant association between occupation and weekly time spent on OTT platforms.

H9: There is a significant association between occupation and weekly time spent on OTT platforms.

The chi-square test findings demonstrate a highly statistically significant correlation between occupation and weekly time spent on OTT platforms, with a Pearson Chi-Square value of 94.840, 30 degrees of freedom, and a p-value of 0.000, well below the 0.05 significance threshold. This illustrates that the duration of time users engage with OTT platforms differs markedly among various job categories. The Likelihood Ratio test corroborates this conclusion with a p-value of 0.000, proving the robustness and constancy of the association. The Linear-by-Linear Association test reveals a p-value of 0.006, which is statistically significant, demonstrating a substantial trend in OTT watching time across various vocations. The study comprises 998 genuine examples, rendering the conclusions statistically robust and dependable. The results indicate that profession significantly influences the duration of time spent on OTT platforms.

4.3 - NON NORMALITY OF DATA:

A Q–Q plot analysis reveals that the data does not precisely follow a normal distribution. This is the conclusion that can be drawn from the normality evaluation. In a typical Q–Q plot, the data points are supposed to lie along a straight diagonal line. However, in this specific instance, numerous points stray

from this line, notably at the ends, which indicates that there is some deviation from normalcy. This pattern demonstrates that the distribution is slightly uneven, with certain values not fully fitting with the trend that was anticipated. In spite of this, the deviations are not exceptionally significant, which indicates that the data, despite the fact that it is not entirely normal, does not exhibit serious anomalies. On the whole, the Q–Q plots indicate that the data have a slight degree of non-normality.

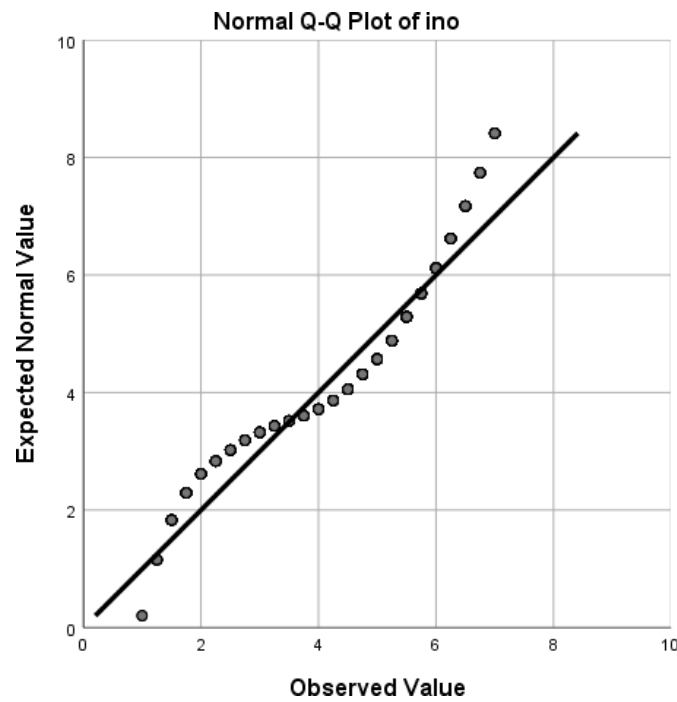


Figure 4.9 – Normal Q-Q plot of Innovativeness

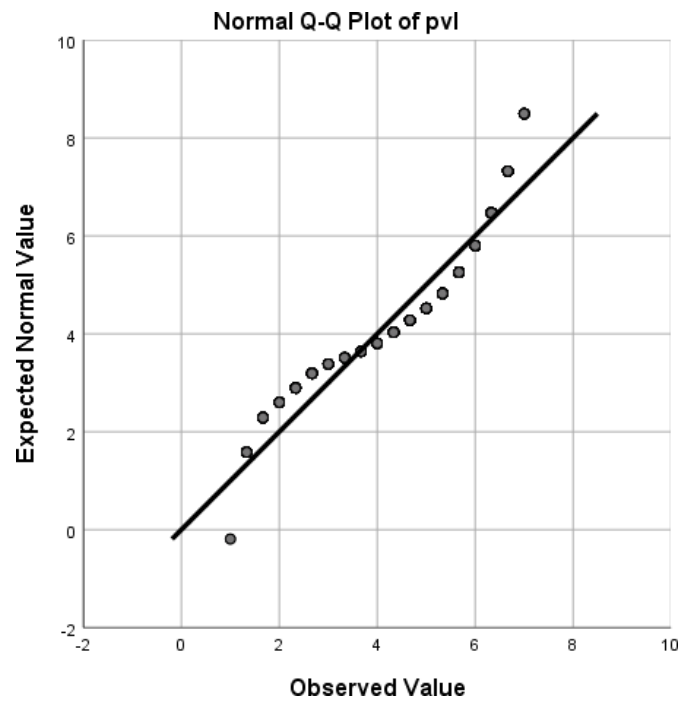


Figure 4.10 – Normal Q-Q plot of Price Value

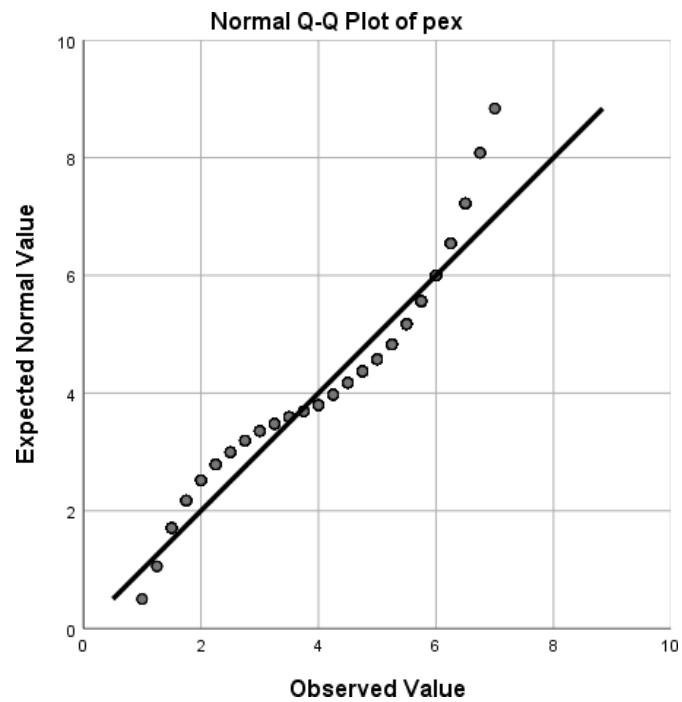


Figure 4.11 – Normal Q-Q plot of Performance Expectancy

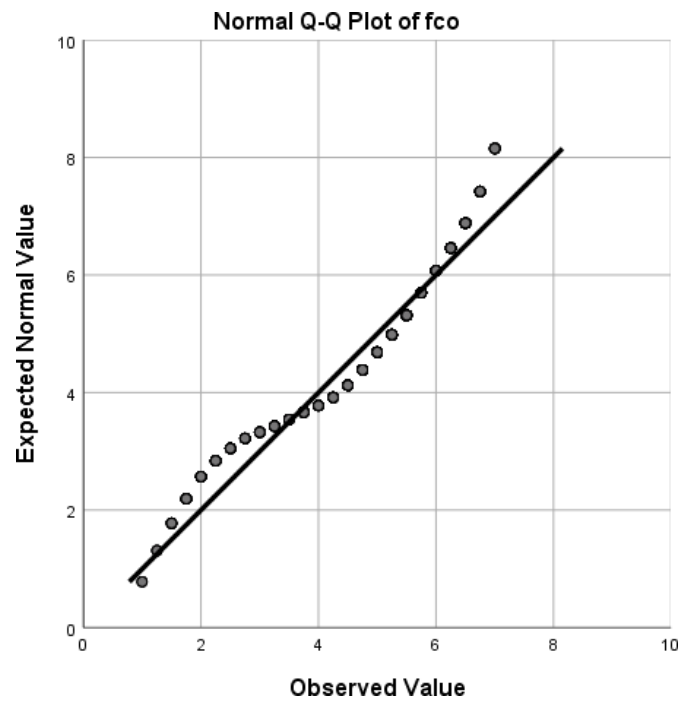


Figure 4.12 – Normal Q-Q plot of Facilitating Conditions

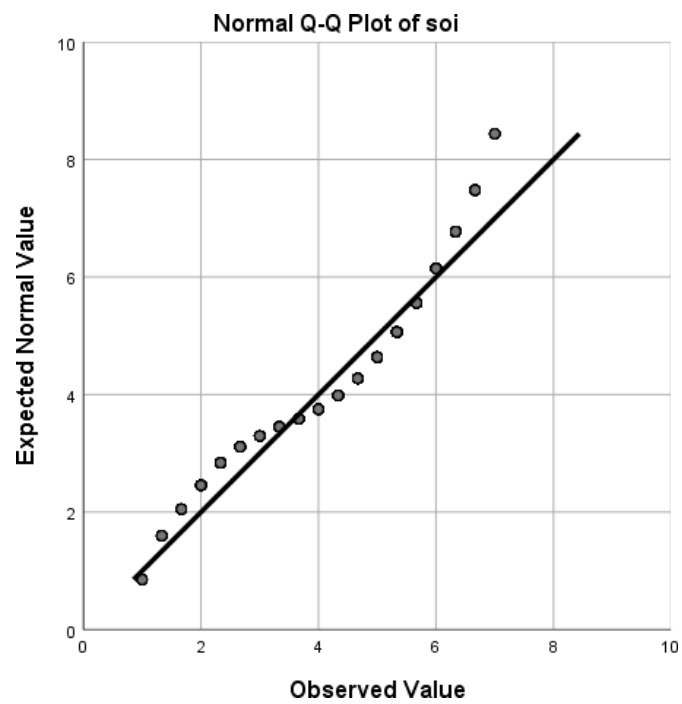


Figure 4.13 – Normal Q-Q plot of Social Influence

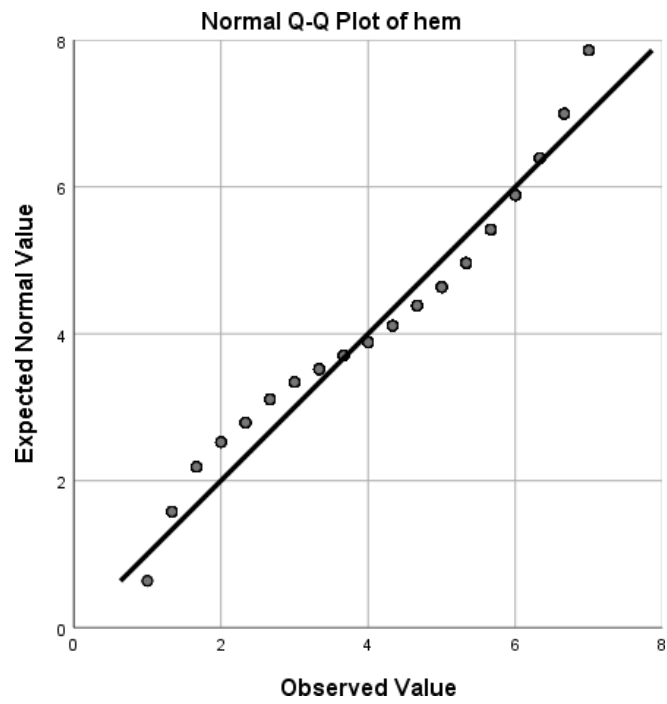


Figure 4.14 – Normal Q-Q plot of Hedonic Motivation

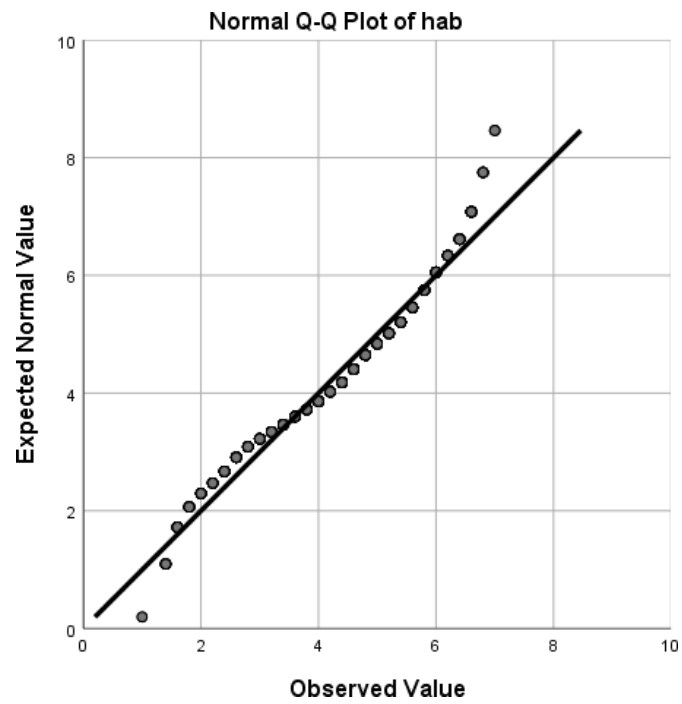


Figure 4.15 – Normal Q-Q plot of Habit

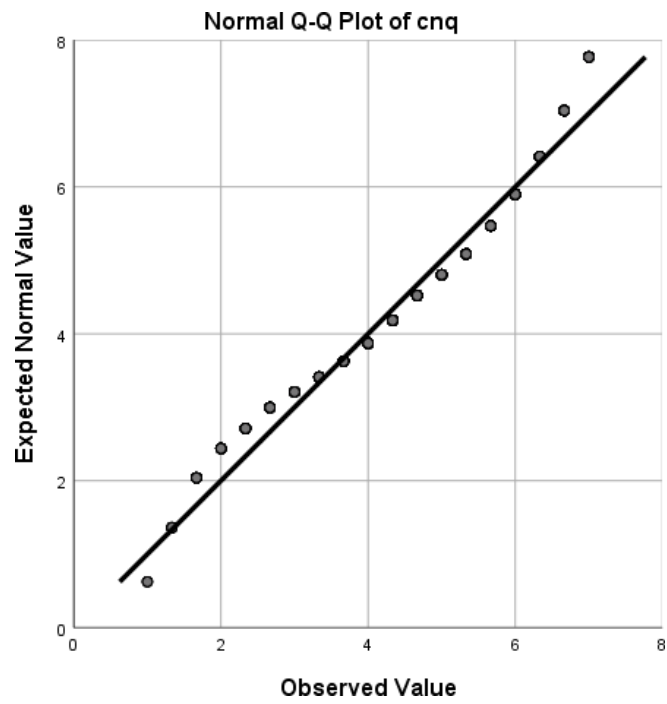


Figure 4.16 – Normal Q-Q plot of Content Quality

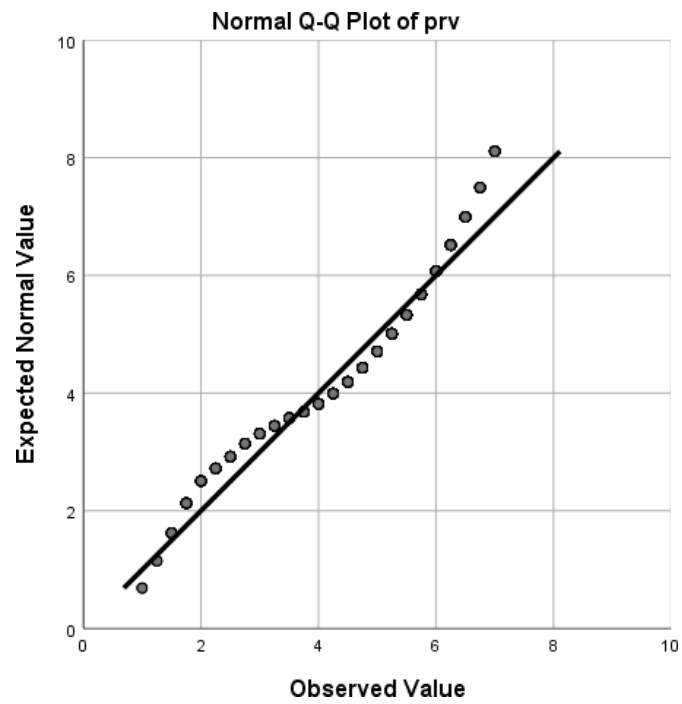


Figure 4.17 – Normal Q-Q plot of Perceived Value

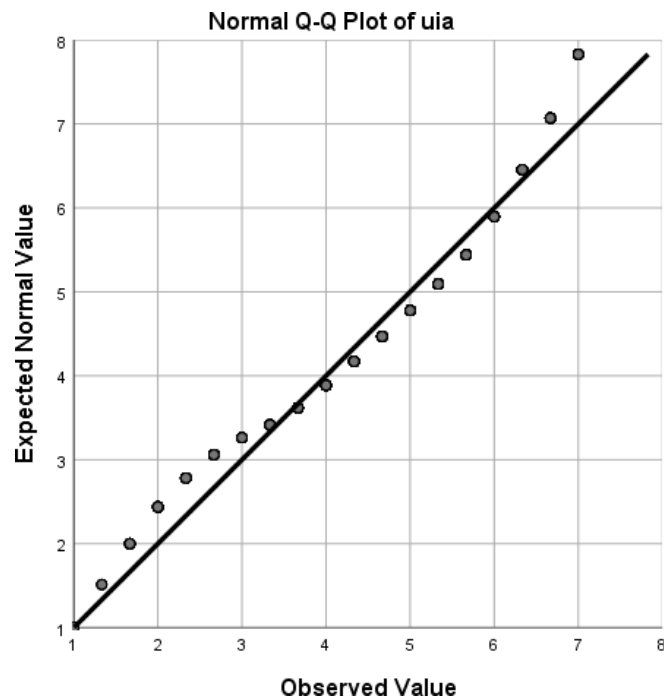


Figure 4.18 – Normal Q-Q plot of Users Intention to Adopt

H0: Performance Expectancy adheres to a normal distribution.

H1: Performance Expectancy does not conform to a normal distribution.

H0: Content Quality adheres to a normal distribution.

H2: Content Quality does not conform to a normal distribution.

H0: Perceived value adheres to a normal distribution.

H3: Perceived value does not conform to a normal distribution.

H0: Social Value adheres to a normal distribution.

H4: Social Value does not conform to a normal distribution.

H0: Facilitating Conditions adheres to a normal distribution.

H5: Facilitating Conditions does not conform to a normal distribution.

H0: Hedonic Motivation adheres to a normal distribution.

H6: Hedonic Motivation does not conform to a normal distribution.

H0: Price Value adheres to a normal distribution.

H7: Price Value does not conform to a normal distribution.

H0: Personal Innovativeness adheres to a normal distribution.

H8: Personal Innovativeness does not conform to a normal distribution.

H0: Habit adheres to a normal distribution.

H9: Habit does not conform to a normal distribution.

H0: User Intention to adopt adheres to a normal distribution.

H10: User Intention to adopt does not conform to a normal distribution.

Table 4.27 - Tests of Normality						
	Kolmogorov-Smirnov ^a			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	df	Sig.
UIA	.109	771	.000	.952	771	.000
INO	.168	771	.000	.901	771	.000
PVL	.193	771	.000	.881	771	.000
PEX	.169	771	.000	.900	771	.000
FCO	.142	771	.000	.933	771	.000
SOI	.173	771	.000	.905	771	.000
HEM	.161	771	.000	.931	771	.000
HAB	.106	771	.000	.965	771	.000
CNQ	.106	771	.000	.961	771	.000
PRV	.140	771	.000	.933	771	.000
a. Lilliefors Significance Correction						

A strong indication that the data does not follow a normal distribution is provided by the findings of the normality tests that were conducted using both the Kolmogorov-Smirnov and Shapiro-Wilk methods. The significance values for each and every variable are 0.000, which is lower than the threshold of 0.05 that is currently considered acceptable. This indicates that the premise of normalcy

is not held true in this situation. To put it another way, the data does not necessarily follow a pattern that is completely balanced or symmetrical. In spite of the fact that the sample size is rather big, which frequently results in these tests being more sensitive, the fact that the findings are consistent across all variables demonstrates that the data exhibits behavior that is not normal. As a result, it is possible to draw the conclusion that the dataset does not follow a normal distribution, and it is recommended that appropriate methodologies be examined for future investigation about this circumstance.

Table 4.28 – Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
INO	998	1.00	7.00	4.5877	1.49005	-.741	.077	-.521	.155
PVL	998	1.00	7.00	4.7452	1.61597	-.732	.077	-.646	.155
PEX	998	1.00	7.00	4.6688	1.45797	-.736	.077	-.550	.155
FCO	998	1.00	7.00	4.7505	1.38867	-.788	.077	-.174	.155
SOI	998	1.00	7.00	4.5598	1.44460	-.708	.077	-.476	.155
HEM	998	1.00	7.00	4.8681	1.48053	-.723	.077	-.358	.155
HAB	998	1.00	7.00	4.4068	1.37831	-.392	.077	-.723	.155
CNQ	998	1.00	7.00	4.6890	1.42162	-.539	.077	-.472	.155
PRV	998	1.00	7.00	4.6754	1.35502	-.695	.077	-.335	.155
UIA	998	1.00	7.00	4.7709	1.40316	-.628	.077	-.345	.155
Valid N (list wise)	998								

According to the descriptive statistics, all of the variables have the same amount of replies, and the values range from one to seven, which implies that a rating scale was utilized. The ratings, on average, range from around 4.4 to 4.9, indicating that the majority of respondents provided replies that were rather favourable. There is a modest amount of diversity in the replies, which indicates that the reactions are slightly dispersed but not very severe. Taking a look at the distribution, the majority of the values are somewhat skewed toward the upper end, which indicates that a greater number of individuals selected higher ratings. However, this tilt is not particularly powerful, and the data does

not exhibit any patterns that are particularly uncommon or dramatic. From a general standpoint, the data seems to be well-balanced and dispersed, which means that it may be regarded typical and appropriate for future investigation.

Linearity and deviation from linearity:

Table 4.29 - ANOVA Table							
			Sum of Squares	df	Mean Square	F	Sig.
UIA *	Between						
INO	Groups	(Combined)	630.754	23	27.424	27.453	0.000
		Linearity	602.086	1	602.086	602.713	0.000
		Deviation from Linearity	28.668	22	1.303	1.304	0.159
	Within						
	Groups		746.223	747	0.999		
UIA *	Between						
PVL	Groups	(Combined)	722.203	17	42.483	48.856	0.000
		Linearity	658.976	1	658.976	757.832	0.000
		Deviation from Linearity	63.227	16	3.952	4.545	0.000
	Within						
	Groups		654.774	753	0.870		
UIA *	Between						
FCO	Groups	(Combined)	626.881	23	27.256	27.143	0.000
		Linearity	558.135	1	558.135	555.832	0.000
		Deviation from Linearity	68.746	22	3.125	3.112	0.000
	Within						
	Groups		750.096	747	1.004		
UIA *	Between						
SOI	Groups	(Combined)	801.398	17	47.141	61.672	0.000
		Linearity	761.070	1	761.070	995.668	0.000

		Deviation from Linearity	40.328	16	2.521	3.297	0.000
	Within Groups		575.579	753	0.764		
UIA *	Between Groups	(Combined)	515.522	17	30.325	26.507	0.000
HEM		Linearity	452.269	1	452.269	395.329	0.000
		Deviation from Linearity	63.253	16	3.953	3.456	0.000
	Within Groups		861.455	753	1.144		
UIA *	Between Groups	(Combined)	358.824	27	13.290	9.698	0.000
HAB		Linearity	284.964	1	284.964	207.953	0.000
		Deviation from Linearity	73.860	26	2.841	2.073	0.001
	Within Groups		1018.153	743	1.370		
UIA *	Between Groups	(Combined)	669.508	18	37.195	39.536	0.000
CNQ		Linearity	638.836	1	638.836	679.047	0.000
		Deviation from Linearity	30.672	17	1.804	1.918	0.014
	Within Groups		707.469	752	0.941		
UIA *	Between Groups	(Combined)	796.884	22	36.222	46.706	0
PRV		Linearity	783.535	1	783.535	1010.328	0
		Deviation from Linearity	13.348	21	0.636	0.82	0.697
	Within Groups		580.094	748	0.776		
	Total		1376.977	770			

The results of the analysis of variance (ANOVA) linearity demonstrate that all of the independent variables (INO, PVL, FCO, SOI, HEM, HAB, CNQ, and PRV) have a relationship with UIA that is statistically significant. This is because the significance values for linearity are 0.000 in every instance, which confirms the existence of a meaningful correlation. However, when looking at deviation from linearity, only INO ($p = 0.159$) and PRV ($p = 0.697$) exhibit values that are not significant, which indicates that their connections with UIA are linear in the correct sense. In contrast, the variables PVL, FCO, SOI, HEM, HAB, and CNQ display a substantial departure from linearity ($p < 0.05$). This indicates that although these variables are associated with UIA, their interactions are not completely linear and may include some degree of curvature or complexity. Overall, the data indicate that although all factors have a considerable impact on UIA, only INO and PRV exhibit a clear linear pattern. The remaining variables, on the other hand, exhibit partial non-linearity in their connections with one another.

Table 4.30 - Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin - Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.852 ^a	0.726	0.723	0.70349	0.726	224.594	9	761	0.000	1.474
a. Predictors: (Constant), PRV, HAB, HEM, FCO, CNQ, INO, PVL, SOI, PEX										
b. Dependent Variable: UIA										

A high R value of 0.852 indicates that the model reveals a significant association between the independent variables and UIA. This is demonstrated by the existence of the model. Approximately 72.6 percent of the variance in UIA can be attributed to the combined impact of PRV, HAB, HEM, FCO, CNQ, INO, PVL, SOI, and PEX, as indicated by the R Square value of 0.726. This indicates that the combined effect of these variables possesses a high level of explanatory power. An adjusted R Square of 0.723 indicates that this strength has not changed at all, even after the adjustment has been made. The standard error of the estimate is relatively low, which indicates that the values that were predicted are relatively close to the values that were actually observed. The fact that the F change value

is extremely significant and has a p-value of 0.000 demonstrates that the model as a whole is statistically significant and that the predictors have an impact on UIA in conjunction with one another. It should also be noted that the Durbin-Watson score of 1.474 suggests that there are no significant problems associated with autocorrelation. In general, the model is robust and trustworthy, and it provides an explanation for a significant amount of the variation in UIA.

Table 4.31 - Coefficients^a								
Model				Standardized Coefficients	t	Sig.	Collinearity Statistics	
				Beta			Tolerance	VIF
1	(Constant)	-	0.121		-0.559	0.576		
		0.068						
	INO	0.005	0.029	0.005	0.175	0.861	0.366	2.735
	PVL	0.071	0.026	0.084	2.738	0.006	0.378	2.643
	PEX	0.204	0.033	0.217	6.178	0.000	0.291	3.440
	FCO	0.083	0.028	0.082	2.989	0.003	0.482	2.075
	SOI	0.174	0.035	0.170	5.035	0.000	0.315	3.174
	HEM	0.077	0.024	0.080	3.284	0.001	0.608	1.644
	HAB	0.074	0.022	0.074	3.428	0.001	0.765	1.307
	CNQ	0.145	0.028	0.146	5.272	0.000	0.468	2.136
	PRV	0.198	0.036	0.190	5.580	0.000	0.311	3.214
a. Dependent Variable: UIA								

When all of the variables are taken into consideration together, the coefficients table illustrates how each independent variable contributes to the outcome of the experiment. Among all of the predictors, the ones that have the most significant positive effect on UIA are PEX, PRV, CNQ, and SOI. This is demonstrated by the fact that their beta values are greater and their p-values are significant (less than 0.05). In addition, variables such as FCO, HEM, HAB, and PVL have a favourable and statistically significant impact, despite the fact that their influence is rather moderate. INO, on the other hand, does not have a significant influence on UIA since its p-value is large (0.861), which indicates that it does not add to the model in a meaningful way. Moreover, the constant word does not hold any significance. Furthermore, the collinearity statistics demonstrate that all of the VIF values are lower than the permissible threshold, which indicates that there are no significant multicollinearity concerns among

the variables. PEX emerges as the best predictor, whereas INO appears to have no substantial impact on UIA. In general, the majority of factors have a significant and positive influence on UIA.

4.4 - RELIALIBILITY AND VALIDITY ANALYSIS

In the process of assessing the measurement model in Partial Least Squares Structural Equation Modelling (PLS-SEM), the evaluation of reliability and validity is a critical stage. The primary goal of this evaluation is to ascertain if the observed indicators (items) included in the model are consistent, accurate, and valid representations of their respective latent constructs (Hair & others, 2021)

Table 4.32 – Reliability and Validity						
CONSTRUCT	ITEMS	FL	ALPHA	CR	AVE	VIF
CNQ	CNQ1	0.919	0.893	0.895	0.824	2.888
	CNQ2	0.892				2.425
	CNQ3	0.912				2.788
FCO	FCO1	0.881	0.914	0.915	0.796	2.713
	FCO2	0.886				2.666
	FCO3	0.901				3.063
	FCO4	0.900				2.987
HAB	HAB1	0.812	0.891	0.913	0.691	2.879
	HAB2	0.849				2.780
	HAB3	0.849				2.790
	HAB4	0.822				2.982
	HAB5	0.822				3.230
HEM	HEM1	0.914	0.914	0.915	0.854	2.909
	HEM2	0.933				3.499
	HEM3	0.924				3.243
INO	INO1		0.919	0.919	0.804	3.070
	INO2	0.898				3.464
	INO3	0.902				3.233
	INO4	0.878				2.629
PEX	PEX1	0.911	0.905	0.906	0.781	3.542

	PEX2	0.911				3.679
	PEX3	0.795				1.734
	PEX4	0.912				3.596
PRV	PRV1	0.670	0.841	0.858	0.683	1.335
	PRV2	0.869				2.286
	PRV3	0.885				2.643
	PRV4	0.862				2.259
PVL	PVL1	0.936	0.931	0.931	0.879	3.727
	PVL2	0.941				4.022
	PVL3	0.936				3.680
SOI	SOI1	0.873	0.827	0.827	0.743	2.113
	SOI2	0.875				2.162
	SOI3	0.836				1.624
UIA	UIA1	0.896	0.864	0.865	0.786	2.338
	UIA2	0.897				2.425
	UIA3	0.867				2.005

4.5 - FACTOR LOADING

Factor loading denotes the degree of correlation that exists between an observed indicator (item) and the latent construct it is intended to represent. In the context of structural equation modelling (SEM), and more specifically within Partial Least Squares SEM (PLS-SEM), factor loadings serve as a critical metric for evaluating the reliability of indicators. This assessment is essential for understanding the extent to which each observed variable effectively contributes to the measurement of the theoretical construct it is intended to represent. A greater factor loading value suggests that the indicator accounts for a larger share of its variance in relation to the latent construct, thereby offering more substantial support for measurement reliability (Hair & others, 2021)

The squared factor loading (λ^2) quantitatively indicates the extent to which the variance in the indicator is accounted for by the underlying latent construct. For example, a loading of 0.80 indicates that 64% (0.80^2) of the variance in that item can be attributed to the construct, whereas the remaining 36% represents unexplained variance or measurement error. Consequently, items exhibiting high loadings suggest a more robust representation of the construct and a reduction in measurement error.(Hair,

Ringle, et al., n.d.)

Established guidelines indicate that the acceptable threshold for standardized factor loadings is 0.70 or higher, as this signifies that more than 50% of the variance in the observed item is accounted for by the construct (Hair et al., 2021; Chin, 1998). Nonetheless, items exhibiting loadings within the range of 0.40 to 0.70 may be preserved, provided that their exclusion does not lead to a substantial enhancement in composite reliability (CR) or average variance extracted (AVE). Items exhibiting loadings below 0.40 are generally discarded, as they demonstrate insufficient association with the underlying construct.(Hair et al., 2019)

The factor loadings derived from the PLS-SEM analysis varied between 0.67 and 0.94, with all values meeting or surpassing the suggested threshold of 0.70, except for one minor instance. The majority of indicators exhibited loadings significantly exceeding the optimal threshold, suggesting that they serve as robust and dependable measures of their corresponding constructs.(Hair et al., 2010)

The constructs CNQ, FCO, HEM, PEX, and PVL exhibited notably high loadings ranging from 0.88 to 0.94, thereby affirming that the items associated with these constructs possess outstanding measurement reliability. The data pertaining to the items categorized under CNQ (CNQ1 = 0.919, CNQ2 = 0.892, CNQ3 = 0.912) indicate robust correlations with the underlying construct, thereby implying that these indicators are proficient in encapsulating the essence of content quality. In a similar vein, the indicators associated with FCO (spanning from 0.881 to 0.901) and PVL (extending from 0.936 to 0.941) reinforce the reliability of the construct, suggesting a high degree of cohesion and representativeness in the measurement approach.

The construct HAB exhibited loadings that varied from 0.812 to 0.849, suggesting a high level of reliability. Although these loadings are marginally lower than those of the highest-performing constructs, they remain significantly above the acceptable threshold, indicating that each item plays a meaningful role in elucidating the latent construct of habit. Similarly, the PRV values, which ranged from 0.670 to 0.885, encompassed one item that was marginally below the established threshold (PRV1 = 0.67). Nevertheless, given that the overall composite reliability (CR = 0.858) and average variance extracted (AVE = 0.683) fell within acceptable thresholds, the item was retained, as it does not compromise the measurement integrity of the construct.

The constructs SOI (0.836–0.875) and UIA (0.867–0.897) demonstrate robust and consistent factor loadings, suggesting that the items accurately reflect their respective constructs. The indicators associated with INO (0.878–0.919) exhibit a high degree of reliability, thereby supporting the validity of the construct within the model.

In summary, the constructs exhibit robust indicator reliability, with the majority of items achieving or surpassing the suggested threshold of 0.70. Furthermore, the items with slightly lower loadings do not detract from the psychometric integrity of the constructs. The findings suggest that each construct within the measurement model is assessed with precision and reliability via its respective indicators.

4.6 - Reliability:

Cronbach's Alpha (α) serves as a prominent metric for evaluating internal consistency reliability within the realms of psychometric and behavioral research. This analysis evaluates the degree of relatedness among a collection of items as a cohesive unit, thereby examining the consistency of results produced by indicators that measure a latent construct (Cronbach, 1951). This assessment determines if various items intended to measure the same construct produce consistent or coherent responses. A high Cronbach's Alpha value suggests a strong correlation among the items, indicating their reliability in effectively capturing the construct. In the context of PLS-SEM and various structural modelling methodologies, Cronbach's Alpha serves as a crucial metric for validating the internal consistency of the scale items associated with each latent construct.

The calculation relies on the mean inter-item correlation, under the premise that each indicator contributes uniformly to the construct (Hair et al., 2021). Nonetheless, this assumption may prove to be limiting, as empirical data frequently exhibit items with diverse loadings. Consequently, Cronbach's Alpha is frequently analysed alongside additional reliability metrics, including Composite Reliability (CR) and ρ_A , which contribute to a more comprehensive evaluation of reliability.

According to (Nunnally, 1978) and (Hair & others, 2021)), values above 0.70 are considered acceptable for most research contexts, while values above 0.80 indicate good internal reliability.

The reliability table indicates that the Cronbach's Alpha values for all constructs varied between 0.827 and 0.931, which suggests that each construct demonstrates a high level of internal consistency reliability (Cronbach, 1951). In particular, constructs such as PVL ($\alpha = 0.931$), FCO ($\alpha = 0.914$), and

HEM ($\alpha = 0.914$) demonstrate a high degree of reliability, suggesting that the items within these constructs are strongly interrelated and consistently measure the underlying construct. The observed values surpass the established benchmark of 0.80, which is categorized as “good to excellent.” This finding substantiates that the indicators associated with these constructs function cohesively in reflecting their theoretical dimensions.

The constructs CNQ ($\alpha = 0.893$), PEX ($\alpha = 0.905$), and INO ($\alpha = 0.919$) exhibit robust reliability, indicating that the items associated with these constructs consistently contribute to their measurement. In a similar vein, the reliability coefficients for PRV ($\alpha = 0.841$), SOI ($\alpha = 0.827$), and UIA ($\alpha = 0.864$) are all within the acceptable range, indicating that these indicators possess adequate reliability for subsequent analysis. While the Alpha values observed are marginally lower than those of the highest-performing constructs, they nonetheless surpass the minimum threshold of 0.70, thereby satisfying the criteria for internal consistency.

All constructs demonstrated Cronbach’s Alpha values that met or exceeded the recommended threshold, indicating the stability and reliability of the measurement scales employed. This indicates that the survey items were effectively constructed and uniformly understood by participants, leading to consistent response patterns across all constructs.

4.7 - Composite Reliability (CR)

Composite Reliability (CR) serves as a sophisticated and favoured metric for assessing internal consistency reliability in Structural Equation Modelling (SEM), especially within the context of the Partial Least Squares (PLS-SEM) methodology. In contrast to Cronbach’s Alpha, which operates under the assumption that all indicators contribute equally to the measurement of a construct, Composite Reliability takes into consideration the actual loadings of each indicator. This approach yields a more precise and realistic assessment of construct reliability (Hair & others, 2021).

CR assesses the degree to which a collection of items reliably reflects the same underlying latent construct. This assessment evaluates the internal consistency of a construct by analysing the magnitude and relevance of indicator loadings, thereby ensuring that constructs with differing contributions from indicators are accurately evaluated. Essentially, CR assesses the reliability of the observed variables within the model, ensuring they are consistent and not significantly affected by measurement error.

According to (Hair, Ringle, et al., n.d.) And (Fornell & Larcker, 1981b), Values above 0.70 are typically considered acceptable for established constructs, while exploratory studies may tolerate slightly lower values.

The findings indicate that the Composite Reliability (CR) values for all constructs fell within the range of 0.827 to 0.931, thereby affirming that each construct demonstrates robust internal consistency reliability. The constructs PVL (CR = 0.931), FCO (CR = 0.915), and HEM (CR = 0.915) exhibit high reliability, indicating that their measurement items maintain a strong degree of consistency and are significantly correlated with the respective latent variable they represent. The elevated CR values suggest that the indicators linked to these constructs exhibit a significant degree of shared variance, thereby collectively offering a precise depiction of the latent construct (Hair, Hult, et al., n.d.).

In a similar vein, the constructs CNQ (CR = 0.895), INO (CR = 0.919), PEX (CR = 0.906), and PRV (CR = 0.858) demonstrate satisfactory reliability, as indicated by their CR values surpassing the 0.80 benchmark. This indicates that the measurement items associated with these constructs demonstrate stability and possess internal cohesion. The constructs SOI (CR = 0.827) and UIA (CR = 0.865) demonstrate acceptable reliability standards, suggesting their adequacy for incorporation into the measurement model due to their sufficient consistency.

It is noteworthy that all constructs demonstrated CR values that met or surpassed the established threshold of 0.70, indicating that each latent construct fulfils the reliability criteria necessary for confirmatory analysis. The elevated and consistent CR values observed across all constructs serve as evidence indicating that the measurement scales employed in the model exhibit both stability and reliability. The observed consistency indicates that the data collection instrument employed in this study successfully captured the intended theoretical constructs while minimizing measurement error.(Hair et al., 2010)

4.8 - Convergent Validity:

The Average Variance Extracted (AVE) serves as a critical metric for assessing convergent validity within the measurement framework of Structural Equation Modelling (SEM). Convergent validity evaluates the extent to which various indicators intended to measure the same construct indeed converge or exhibit a significant degree of shared variance (Fornell & Larcker, 1981). The AVE value

indicates the mean proportion of variance in the indicators that is accounted for by the latent construct, in relation to the variance that can be ascribed to measurement error. An elevated AVE value signifies that the indicators account for a greater share of the construct's variance, implying that the construct effectively embodies the theoretical concept it aims to represent.(Hair et al., 2019)

The findings indicate that the Average Variance Extracted (AVE) values for all constructs fell within the range of 0.683 to 0.879, significantly exceeding the recommended threshold of 0.50. This indicates that all constructs within the model exhibit robust convergent validity.

The constructs PVL (AVE = 0.879) and HEM (AVE = 0.854) exhibited the highest AVE values, suggesting that approximately 88% and 85% of the variance in their respective indicators is accounted for by their underlying latent constructs. The findings indicate that the items assessing Price Value (PVL) and Hedonic Motivation (HEM) exhibit a strong representation of their respective constructs, accompanied by minimal measurement error.

In a similar vein, CNQ (AVE = 0.824), INO (AVE = 0.804), and PEX (AVE = 0.781) exhibited robust convergent validity, with over three-quarters of the indicator variance accounted for by their corresponding constructs. The constructs FCO (AVE = 0.796) and PRV (AVE = 0.683) surpassed the 0.50 threshold, thereby affirming that their indicators effectively converge in encapsulating their conceptual significance. Despite PRV (0.683) and HAB (0.691) showing lower AVE values in comparison to other constructs, they nonetheless indicate acceptable convergence levels, given that their CR and Cronbach's Alpha values exceed 0.80. This provides additional evidence for the internal validity of the constructs. In conclusion, the constructs SOI (AVE = 0.743) and UIA (AVE = 0.786) demonstrated adequate convergence, suggesting that their measurement items effectively represent these constructs.

The analysis indicates that all constructs exceeded the minimum threshold for Average Variance Extracted (AVE), thereby affirming that the measurement items adequately reflect the theoretical foundations of their respective constructs. This outcome presents compelling evidence of convergent validity.

4.9 - Discriminant Validity:

Discriminant validity pertains to the extent to which a construct is genuinely separate from other constructs in the model, encompassing both conceptual and statistical dimensions. This approach guarantees that each construct within the measurement model accurately represents distinct phenomena that are not captured by other constructs ((Hair, Ringle, et al., n.d.); (Fornell & Larcker, 1981a). Discriminant validity serves to validate that a construct accurately measures its intended concept and maintains a distinct separation from other constructs, minimizing excessive overlap.

Establishing discriminant validity in Partial Least Squares Structural Equation Modelling (PLS-SEM) is essential, as constructs within intricate models frequently exhibit correlations. The absence of established discriminant validity raises questions regarding the authenticity of the observed effects, leaving ambiguity about whether they can be accurately ascribed to a single construct or if they are affected by another variable that is conceptually similar. Consequently, the verification of discriminant validity is essential for establishing the model's conceptual clarity and empirical distinctiveness.

4.10 - Fornell–Larcker Criterion

The Fornell–Larcker criterion represents a foundational and extensively utilized approach for evaluating discriminant validity. The analysis involves a comparison of the square root of the Average Variance Extracted (AVE) for each construct against the correlations observed between that construct and other constructs within the model framework.

(Fornell & Larcker, 1981b) assert that discriminant validity is confirmed when the square root of the Average Variance Extracted (AVE) for each construct exceeds the highest correlation of that construct with any other construct. This indicates that each construct exhibits a greater degree of variance with its respective indicators compared to any other construct within the model.

Within the framework of your model, the constructs exhibited AVE values that spanned from 0.683 to 0.879, leading to square roots of AVE values that ranged from 0.826 to 0.938. Upon analysis of the inter-construct correlation matrix, it was observed that the diagonal values, represented by the square root of the average variance extracted (AVE), exceeded the off-diagonal correlation values for all constructs. This indicates that each construct demonstrates a stronger association with its respective

indicators compared to other constructs, thus fulfilling the Fornell–Larcker criterion and confirming the presence of discriminant validity.

Table 4.33 - Fornell-Larcker criterion										
	CNQ	FCO	HAB	HEM	INO	PEX	PRV	PVL	SOI	UIA
CNQ	0.908									
FCO	0.512	0.892								
HAB	0.359	0.372	0.831							
HEM	0.489	0.447	0.355	0.924						
INO	0.577	0.545	0.364	0.501	0.897					
PEX	0.640	0.618	0.427	0.582	0.754	0.883				
PRV	0.655	0.620	0.440	0.512	0.667	0.718	0.826			
PVL	0.603	0.600	0.473	0.501	0.663	0.692	0.708	0.937		
SOI	0.655	0.675	0.416	0.543	0.669	0.697	0.747	0.645	0.862	
UIA	0.681	0.638	0.472	0.574	0.662	0.757	0.758	0.693	0.746	0.886

Analysis of the table reveals that all diagonal values, representing the square roots of the Average Variance Extracted (AVE), exceed their respective correlations with other constructs. For example, the square root of the Average Variance Extracted (AVE) for CNQ, which is 0.908, exceeds its maximum correlation with UIA, recorded at 0.681. Similarly, PEX, with a square root of AVE of 0.883, surpasses its highest correlation with UIA, which stands at 0.757. The observed pattern is consistent across all constructs, thereby fulfilling the Fornell–Larcker criterion (Fornell & Larcker, 1981a). This suggests that each construct accounts for a greater portion of the variance in its indicators compared to the variance it shares with any other construct. Consequently, the analysis reveals an absence of multicollinearity or conceptual overlap, thereby affirming the uniqueness of each construct within the measurement model.

The findings of this matrix indicate that all constructs demonstrate robust discriminant validity. This indicates that variables such as Content Quality (CNQ), Facilitating Conditions (FCO), Perceived Value (PRV), and User Intention to Adopt (UIA) are statistically differentiated and embody distinct theoretical constructs. The observed inter-construct correlations are notably high, with values such as $r = 0.758$ between PRV and UIA, and $r = 0.757$ between PEX and UIA. However, these correlations remain lower than the respective $\sqrt{\text{AVE}}$ values of 0.826 and 0.883. This indicates that while these

constructs exhibit a relationship, they remain distinct and assess unique dimensions of user perceptions and behavioral intentions.

The observation of significant correlations, such as those between PRV and UIA, as well as PEX and UIA, is theoretically justifiable. These correlations illustrate the logical relationships among user experiences, perceived value, and adoption intent, all the while preserving empirical differentiation. The model exhibits a clear and precisely delineated measurement structure, wherein each latent construct makes a distinct contribution to the overarching conceptual framework.

4.11 - Heterotrait–Monotrait Ratio (HTMT) - Assessment of Discriminant Validity

The Heterotrait–Monotrait ratio of correlations (HTMT) serves as a contemporary and methodologically sound standard for assessing discriminant validity within the measurement model. The HTMT method, as introduced by Henseler, Ringle, and Sarstedt (2015), addresses the shortcomings of conventional measures such as the Fornell–Larcker criterion, which may not effectively identify a lack of discriminant validity in instances where constructs exhibit high correlation.

The HTMT metric evaluates the extent of similarity among constructs by analysing the average correlations between different traits measured by different methods (heterotrait–heteromethod) in comparison to the average correlations within the same trait measured by the same method (monotrait–monomethod). This assessment evaluates the empirical distinctiveness of constructs in relation to one another. In instances where two constructs are conceptually distinct, one would expect the HTMT ratio to exhibit a low value. A high HTMT ratio suggests the possibility of conceptual overlap.

Table 4.34 – HTMT										
	CNQ	FCO	HAB	HEM	INO	PEX	PRV	PVL	SOI	UIA
CNQ										
FCO	0.566									
HAB	0.382	0.390								
HEM	0.541	0.489	0.376							
INO	0.637	0.595	0.376	0.546						

PEX	0.712	0.679	0.448	0.639	0.827					
PRV	0.757	0.703	0.481	0.582	0.764	0.826				
PVL	0.660	0.650	0.478	0.543	0.717	0.753	0.801			
SOI	0.760	0.773	0.464	0.623	0.768	0.805	0.894	0.734		
UIA	0.775	0.717	0.516	0.646	0.743	0.856	0.887	0.772	0.881	

The HTMT analysis corroborates the previous conclusions drawn from the Fornell–Larcker criterion. The findings indicate that no construct pair surpasses the threshold of 0.90, with the majority of values residing well below 0.85, thereby affirming robust discriminant validity.

The highest HTMT ratio is recorded between PRV and SOI (0.894) as well as between PRV and UIA (0.887), indicating a strong conceptual relationship among these constructs. This aligns with existing behavioral research, suggesting a strong correlation between perceived value, social influence, and user adoption intention. Although the correlations are substantial, the HTMT values consistently fall below the 0.90 threshold, indicating that the constructs maintain statistical distinctiveness.

All other pairs - including CNQ–FCO (0.566), HEM–INO (0.546), and HAB–PVL (0.478) -exhibit moderate or low correlations, thereby affirming that the constructs assessing content quality, hedonic motivation, habit, and visual layout are conceptually distinct.

4.12 - PATH ANALYSIS

Upon establishing the reliability and validity of the measurement model, the subsequent phase in the Partial Least Squares Structural Equation Modeling (PLS-SEM) process involves the assessment of the structural model via path analysis. The structural model illustrates the proposed connections between latent constructs, grounded in the theoretical framework established in the research. This phase evaluates the causal connections between exogenous (independent) and endogenous (dependent) variables, aiming to ascertain the strength, direction, and statistical significance of each proposed pathway (Hair, Hult, Ringle, & Sarstedt, 2021).

Path analysis entails the estimation of standardized path coefficients (β values), which serve to indicate both the strength and direction of influence among various constructs. The path coefficient quantifies the expected change in the dependent variable resulting from a one-unit change in the independent

variable, while controlling for other variables. Elevated positive coefficients suggest more robust positive correlations, while negative coefficients denote inverse associations. The evaluation of the statistical significance of these path coefficients is conducted through bootstrapping procedures, which produce T-statistics and p-values for the empirical testing of each hypothesis. A T-value exceeding 1.96 alongside a p-value lower than 0.05, at a 95% confidence level, suggests that the observed relationship holds statistical significance.

The assessment of the structural model encompasses not only the significance of individual paths but also evaluates its predictive accuracy and explanatory power through the analysis of R^2 (coefficient of determination), f^2 (effect size), and Q^2 (predictive relevance) values. Collectively, these indices illustrate the extent to which the model accounts for the variance in the dependent constructs and the significance of each predictor's contribution. The coefficient of determination, R^2 , quantifies the extent to which the variance in the endogenous construct is accounted for by the exogenous variables. In contrast, the effect size measure, f^2 , assesses the influence of specific predictors on the dependent variable. The evaluation of the model's predictive accuracy is conducted through the implementation of blindfolding procedures in Q^2 analysis.

The objective of the path analysis is to assess the extent to which the hypothesized relationships outlined in the conceptual model receive statistical validation from the data collected. This facilitates the assessment of the significance of each independent construct in affecting the dependent construct(s). This research involved the application of path analysis to investigate the influence of various antecedents, including Content Quality (CNQ), Facilitating conditions (FCO), Habit (HAB), Hedonic Motivation (HEM), Innovativeness (INO), Performance Expectancy (PEX), Perceived Value (PRV), Price Value (PVL), and Social Influence (SOI), on the dependent variable User Intention to Adopt (UIA).

The findings of the structural model are detailed through standardized path coefficients (β), T-statistics, and p-values, which were derived using bootstrapping with 5,000 resamples. The results offer empirical support for the acceptance or rejection of each hypothesis and highlight the comparative impact of each predictor on users' intention to adopt the platform. The following section provides a comprehensive analysis of the path coefficients, including their significance levels and interpretations.

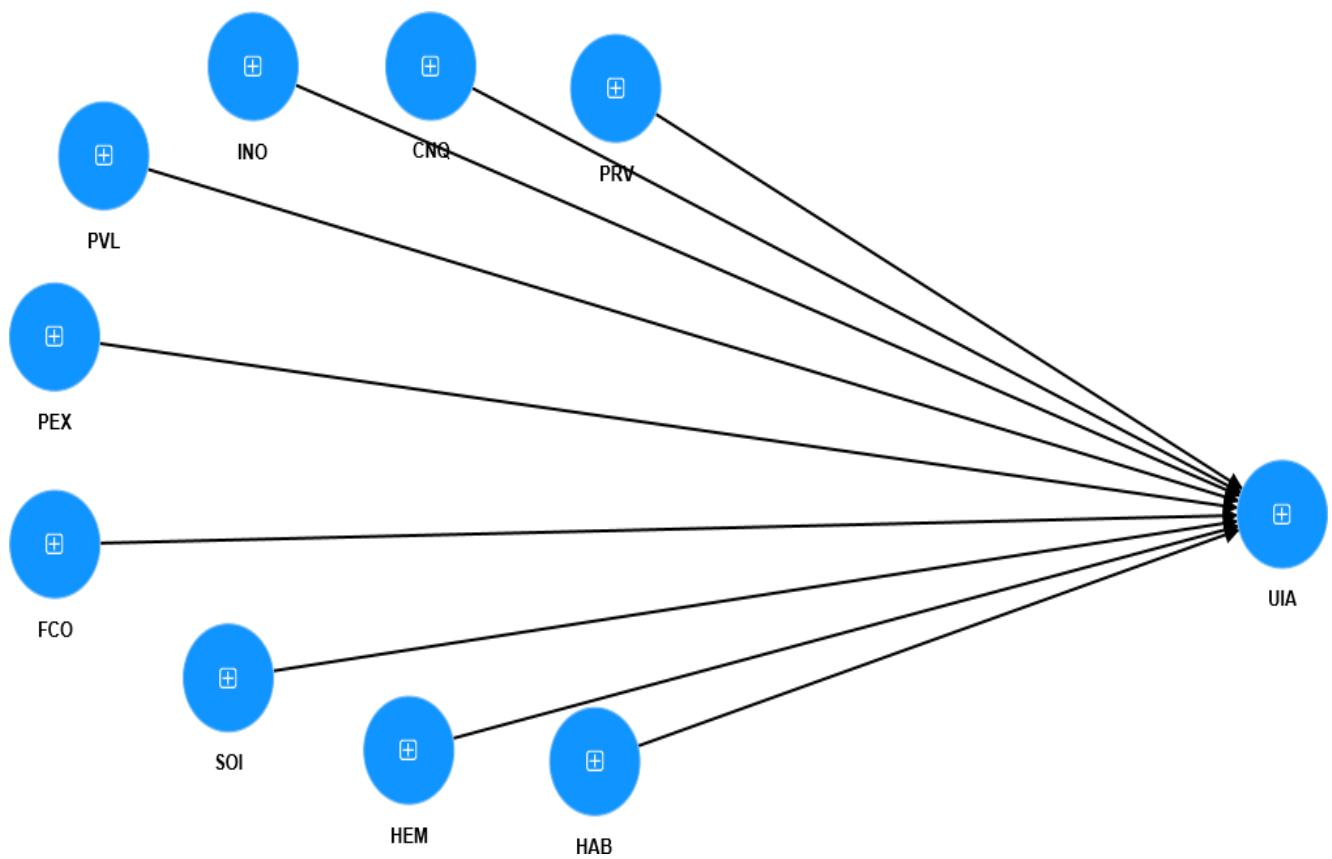


Table 4.35 - Path analysis interpretation

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
CNQ -> UIA	0.143	0.143	0.032	4.433	0.000
FCO -> UIA	0.078	0.078	0.029	2.651	0.008
HAB -> UIA	0.072	0.072	0.021	3.383	0.001
HEM -> UIA	0.079	0.080	0.024	3.360	0.001
INO -> UIA	0.007	0.005	0.041	0.162	0.871
PEX -> UIA	0.221	0.221	0.045	4.958	0.000
PRV -> UIA	0.200	0.202	0.041	4.865	0.000
PVL -> UIA	0.079	0.080	0.034	2.358	0.018
SOI -> UIA	0.168	0.166	0.039	4.254	0.000

H1: Content Quality positively influences User Intention to Adopt OTT.

The path coefficient for CNQ ($\beta = 0.143$, $t = 4.433$, $p = 0.000$) demonstrates a statistically significant positive association with UIA. This indicates that the quality of content (CNQ) significantly impacts users' intentions to engage with OTT platforms. The provision of superior content significantly improves user satisfaction and fosters a greater likelihood of continued engagement or adoption of usage. The observed significance level ($p < 0.001$) and a t-value exceeding 1.96 provide evidence that H1 is supported.

H2: Facilitating Conditions positively influences User Intention to Adopt OTT.

The association between facilitating conditions (FCO) and UIA is noteworthy, with a coefficient of $\beta = 0.078$, a t-value of 2.651, and a p-value of 0.008. This suggests that the navigation simplicity, usability, and functional design of the platform have a favourable impact on users' intentions to adopt it. Despite the coefficient being smaller than certain other factors, the statistically significant result provides support for H2, indicating that functionality plays a meaningful role in influencing user intention.

H3: Habit positively influences User Intention to Adopt OTT.

The relationship between habit (HAB) and UIA is characterized by a positive and statistically significant effect, with a coefficient of $\beta = 0.072$, $t = 3.383$, and $p = 0.001$. This indicates that increased frequency and regularity of user engagement with OTT services correlates with a heightened intention to maintain continued usage. Habitual behavior serves as a reinforcing mechanism for the adoption of technology, thereby validating hypothesis H3.

H4: Hedonic Motivation positively influences User Intention to Adopt OTT.

The association between hedonic motivation (HEM) and UIA is noteworthy, with a coefficient of $\beta = 0.079$, a t-value of 3.360, and a p-value of 0.001. This indicates that the factors of entertainment and enjoyment associated with OTT usage have a positive impact on users' propensity to adopt or persist in utilizing these platforms. HEM serves as a psychological driver that markedly improves perceived user satisfaction, thus providing support for H4.

H5: Innovativeness positively influences User Intention to Adopt OTT.

The relationship between innovativeness (INO) and UIA is not statistically significant, as indicated by the coefficients ($\beta = 0.007$), t-value ($t = 0.162$), and p-value ($p = 0.871$). The findings indicate that individuals' personal innovativeness, or their propensity to experiment with new technologies, does not

have a significant impact on their intention to adopt over-the-top (OTT) services. In this scenario, the adoption process appears to be influenced more by external elements, including content and usability, rather than by an inherent motivation to engage with new technologies. Consequently, H5 lacks support.

H6: Performance Expectancy positively influences User Intention to Adopt OTT.

The relationship between Performance Expectancy (PEX) and UIA is of considerable importance, as indicated by the statistical values ($\beta = 0.221$, $t = 4.958$, $p = 0.000$). This suggests that users' prior positive experiences significantly influence their intention to persist in utilizing OTT platforms. The elevated t-value and diminished p-value indicate the strength of this relationship, thereby substantiating H6. This indicates that platforms that provide seamless, tailored, and interactive experiences may notably enhance the intention to adopt.

H7: Perceived Value positively influences User Intention to Adopt OTT.

The correlation observed between perceived value (PRV) and UIA is both positive and statistically significant, with a coefficient of $\beta = 0.200$, a t-value of 4.865, and a p-value of 0.000. This indicates that individuals who recognize the value of OTT services—be it in relation to cost, time, or entertainment—exhibit a higher propensity for adoption. The robust coefficient and elevated significance level lend support to H7, suggesting that value perception serves as a crucial factor influencing adoption intention.

H8: Price Value positively influences User Intention to Adopt OTT.

The path coefficient associated with perceived visual layout (PVL) demonstrates a positive and statistically significant relationship, with a value of $\beta = 0.079$, $t = 2.358$, and $p = 0.018$. This indicates that aesthetically pleasing and thoughtfully designed platform interfaces contribute to an increased likelihood of users adopting OTT services. An enhanced visual experience contributes significantly to user satisfaction and increases the likelihood of sustained engagement. Consequently, the hypothesis H8 is affirmed.

H9: Social Influence positively influences User Intention to Adopt OTT.

The relationship between social influence (SOI) and UIA is notably significant, with a coefficient of $\beta = 0.168$, a t-value of 4.254, and a p-value of 0.000. This suggests that social influence, recommendations from peers, and prevailing community trends significantly enhance user intention. The adoption of OTT services by users appears to be influenced significantly by the endorsement and

frequent usage of these services within their social circles. The robust t-value and its associated significance provide confirmation for hypothesis H9.

The findings from the path analysis reveal that eight out of the nine proposed relationships between the independent constructs and user intention to adopt (UIA) demonstrate statistical significance. This indicates that the behavior of users in adopting new technologies is predominantly shaped by experiential, social, and perceptual elements, including Performance Expectancy, perceived value, content quality, and social influence. In this analysis, Performance Expectancy ($\beta = 0.221$) and perceived value ($\beta = 0.200$) were identified as the most significant predictors of user intention. This finding underscores the critical importance of positive experiences and perceived benefits in the context of technology adoption. Conversely, the findings suggest that innovativeness (INO) did not have a significant impact on the intention to adopt, implying that the choice to engage with OTT platforms may be primarily influenced by functional and social factors rather than the users' intrinsic innovativeness.

4.13 - Multi-Group Analysis (MGA)

Following the assessment of the comprehensive structural model, the subsequent phase of the analysis involved investigating possible variations among subgroups within the dataset. The accomplishment was realized via Multi-Group Analysis (MGA), a methodological approach that assesses the significance of differences in path relationships across various categorical groups, including gender, age, or experience level (Hair, Hult, Ringle, & Sarstedt, 2021). This research employed MGA to examine the differences between genders (male and female) regarding the structural relationships that exist between the predictor constructs and the dependent variable, User Intention to Adopt (UIA).

MGA demonstrates significant utility in the identification of moderation effects influenced by categorical variables. This analysis evaluates the significance of variations in estimated path coefficients (β values) across different groups, suggesting that the strength of a specific relationship may differ between groups (Henseler, Ringle, & Sinkovics, 2009). In SmartPLS, multiple methodologies can be employed to conduct Multi-Group Analysis (MGA), including the parametric test, the Welch-Satterthwaite test, and the permutation test. The permutation test utilized in this investigation is regarded as the most robust approach, as it facilitates the comparison of group-specific path coefficients without the necessity of assuming equal variances or a normal distribution of the data

(Sarstedt, Henseler, & Ringle, 2011).

The MGA procedure evaluates the importance of differences among groups by utilizing p-values obtained through non-parametric resampling methods. When the permutation p-value is below 0.05, it suggests that the disparity in path coefficients between the two groups is statistically significant, thereby indicating a meaningful variation in the relationship across gender groups. In contrast, a p-value exceeding 0.05 indicates the absence of a statistically significant difference between male and female respondents regarding the strength of that specific relationship.

Table 4.36 – MGA Male & Female					
	Original (MALE)	Original (FEMALE)	Original difference	Permutation mean difference	Permutation p value
CNQ -> UIA	0.097	0.204	-0.107	0.001	0.106
FCO -> UIA	0.037	0.115	-0.078	0.000	0.192
HAB -> UIA	0.046	0.109	-0.064	0.000	0.141
HEM -> UIA	0.083	0.085	-0.002	0.000	0.955
INO -> UIA	-0.023	0.036	-0.059	0.000	0.516
PEX -> UIA	0.270	0.146	0.124	0.001	0.168
PRV -> UIA	0.219	0.202	0.017	0.000	0.842
PVL -> UIA	0.113	0.020	0.093	0.001	0.163
SOI -> UIA	0.208	0.130	0.079	0.000	0.340

Interpretation of results:

The findings from the permutation-based Multi-Group Analysis indicate that there are no significant differences in the structural relationships between male and female respondents, as all p-values are above the 0.05 significance threshold. This suggests that gender does not influence the relationship between the independent constructs and the dependent variable, User Intention to Adopt (UIA).

While there exist slight discrepancies in the path coefficients across the two groups, these differences do not reach statistical significance. For example, the relationship between Content Quality (CNQ) and UIA appears to be more pronounced among females ($\beta = 0.204$) compared to males ($\beta = 0.097$). This indicates that female respondents may exhibit a greater susceptibility to the quality and attractiveness of content in their intentions to adopt. In a similar vein, facilitating conditions (FCO $\rightarrow$ UIA) and Habit (HAB $\rightarrow$ UIA) demonstrate more pronounced effects in females, which may indicate an increased sensitivity to usability and habitual influences. Nevertheless, given that the permutation p-values (0.192 and 0.141, respectively) exceed the threshold of 0.05, it can be concluded that these differences lack statistical significance.

In contrast, the effects of Performance Expectancy (PEX $\rightarrow$ UIA) and Perceived Value (PRV $\rightarrow$ UIA) appear to be more pronounced among male respondents ($\beta = 0.270$ and 0.219 , respectively) than their female counterparts ($\beta = 0.146$ and 0.202). This indicates that male participants may be more significantly impacted by practical experiences and perceived advantages in the context of forming adoption intentions. Nonetheless, the results of the permutation test ($p = 0.168$ and $p = 0.842$) suggest that these differences do not reach statistical significance.

The Hedonic Motivation (HEM), Innovativeness (INO), and Social Influence (SOI) pathways exhibited nearly identical relationships across genders, reinforcing the consistency of these constructs across various demographic subgroups.

The findings from the MGA indicate that gender does not play a significant moderating role in any of the proposed relationships within the structural model. This indicates that both male and female participants develop their intentions to adopt OTT platforms influenced by comparable cognitive and experiential elements.

Discussions and Implications:

The results of the MGA suggest that gender does not yield statistically significant differences in the causal relationships among the constructs analysed. This is consistent with existing studies in the field

of technology adoption, specifically the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), which indicates that the impact of gender on technology usage tends to decrease as familiarity and accessibility increase among different user demographics (Williams et al., 2015).

The lack of notable gender disparities suggests that the intention to adopt OTT platforms is influenced by overarching factors such as content quality, perceived value, and user experience rather than by demographic differences. This observation highlights the increasing digital equality between genders, as both male and female users demonstrate similar levels of engagement, motivations, and patterns of adoption.

From a managerial perspective, the findings indicate that OTT service providers could benefit from implementing gender-neutral marketing and engagement strategies, given that both male and female users exhibit comparable responses to functional, experiential, and social factors. Nevertheless, the minor directional differences noted such as increased content sensitivity in females and heightened experience-driven motivation in males may be utilized to enhance micro-targeting or personalization approaches within user retention and recommendation frameworks.

4.14 - MGA – GEN Y AND GEN Z

Subsequent to the evaluation of comprehensive structural relationships, a Multi-Group Analysis (MGA) was performed to examine the potential impact of generational differences on the robustness of the path relationships within the structural model. The analysis focused on comparing respondents from Generation Y (born 1981–1996) and Generation Z (born 1997–2012) to assess whether the predictors of User Intention to Adopt (UIA) exhibit significant differences between these two generational cohorts.

Analysis of Multiple Groups in Partial Least Squares Structural Equation Modeling (PLS-SEM) facilitates the investigation of moderation effects associated with categorical variables, enabling the assessment of whether structural relationships maintain invariance across different subgroups (Hair, Ringle, et al., n.d.). This study utilized the Permutation Test method, as advocated by (Henseler et al., n.d.), owing to its robustness and capacity to accommodate non-normal data distributions. This approach assesses variations in path coefficients across different groups and evaluates statistical significance through non-parametric resampling techniques.

A p-value below 0.05 signifies a statistically significant difference between groups concerning that specific path, indicating that generational cohort plays a moderating role in the relationship. In contrast, a p-value exceeding 0.05 suggests the absence of a statistically significant difference, indicating that the model remains invariant across generations.

Table 4.37 – MGA Generation Y and Generation Z					
	Original (GY)	Original (GZ)	Original difference	Permutation mean difference	Permutation p value
CNQ -> UIA	0.200	0.074	0.127	0.003	0.181
FCO -> UIA	-0.014	0.062	-0.076	-0.002	0.313
HAB -> UIA	0.074	0.058	0.017	-0.002	0.798
HEM -> UIA	0.052	0.073	-0.021	-0.001	0.781
INO -> UIA	0.044	-0.095	0.138	-0.001	0.343
PEX -> UIA	0.179	0.284	-0.105	0.001	0.504
PRV -> UIA	0.168	0.233	-0.065	-0.004	0.608
PVL -> UIA	0.083	0.118	-0.035	0.000	0.712
SOI -> UIA	0.237	0.189	0.048	0.005	0.666

The findings from the MGA reveal that there are no statistically significant differences between respondents from Generation Y and Generation Z across all structural paths, as all permutation p-values exceed 0.05. This finding suggests that generational cohort does not influence the relationships among the independent constructs (CNQ, FCO, HAB, HEM, INO, PEX, PRV, PVL, SOI) and User Intention to Adopt (UIA).

The relationships exhibit slight variations in strength between the two groups; however, these differences lack statistical significance. For example, the relationship between Content Quality (CNQ $\rightarrow$ UIA) demonstrates a more pronounced effect in Generation Y ($\beta = 0.200$) compared to Generation Z ($\beta = 0.074$). This indicates that older users (Gen Y) may exhibit a greater sensitivity to content variety and perceived quality when forming their adoption intentions. Nevertheless, the permutation p-value of 0.181 suggests that this observed difference lacks statistical significance.

In a similar vein, the relationships between Performance Expectancy (PEX $\rightarrow$ UIA) and Perceived Value (PRV $\rightarrow$ UIA) exhibit more pronounced effects for Generation Z ($\beta = 0.284$ and 0.233 , respectively) in contrast to Generation Y ($\beta = 0.179$ and 0.168). This suggests that younger users may exhibit a greater inclination towards experiential satisfaction and value perceptions in their adoption of OTT platforms. Both p-values (0.504 and 0.608) exceed the 0.05 threshold, indicating a lack of significant moderation.

It is noteworthy that Innovativeness (INO $\rightarrow$ UIA) and Social Influence (SOI $\rightarrow$ UIA) exhibit marginally elevated coefficients within Generation Y ($\beta = 0.044$ and 0.237) in comparison to Generation Z ($\beta = -0.095$ and 0.189). The observed pattern indicates that Generation Y users may exhibit a heightened responsiveness to social cues and personal innovativeness in comparison to their younger peers. Nonetheless, the observed effects remain non-significant ($p = 0.343$ and 0.666), thereby reinforcing the conclusion that generational differences are statistically trivial.

Discussions and Implications:

The findings from the MGA, which did not reach significance, indicate that users from both Generation Y and Generation Z exhibit comparable behavioral mechanisms in their intention to adopt OTT platforms. The findings suggest that there is model invariance across different generations, aligning with the perspective that digital streaming services have emerged as a predominant medium that transcends generational boundaries (Dwivedi et al., 2020; Hair et al., 2021).

The absence of notable differences corresponds with existing research on technology acceptance and digital behavior, indicating that generational gaps are narrowing as a result of the extensive proliferation of technology and common experiences within digital environments (Venkatesh et al., 2012). Although there are slight variations in mean path values, such as more pronounced experiential and value-driven influences within the Gen Z demographic, the findings substantiate that the fundamental factors influencing adoption behavior remain stable across different age groups.

From a managerial standpoint, this invariance indicates that OTT service providers have the opportunity to formulate cohesive marketing and engagement strategies aimed at both Generation Y and Z users as a collective demographic. Nonetheless, nuanced distinctions in behavioral focus illustrated by Gen Z's heightened responsiveness to experiential design and value propositions in contrast to Gen Y's inclination towards content quality may be utilized for the purposes of audience segmentation and personalization.

4.15 - Importance–Performance Map Analysis (IPMA)

In addition to the evaluation of the structural model, an Importance–Performance Map Analysis (IPMA) was undertaken to ascertain the constructs that exert the most significant influence on the target variable, User Intention to Adopt (UIA), as well as to assess the effectiveness of each construct in elucidating this variable. The Integrated Performance Measurement Approach (IPMA) transcends conventional path coefficient analysis by incorporating both the significance of total effects and the performance metrics represented by average latent variable scores. This integration provides a more pragmatic viewpoint on the areas where managerial or strategic focus ought to be directed (Hair, Hult, et al., n.d.)).

In PLS-SEM, the concept of importance pertains to the relative strength of the association between an independent variable and the dependent construct, as indicated by the total effect, commonly represented by the path coefficient. Performance, conversely, denotes the mean value or degree of accomplishment of the independent variable measured on a standardized scale ranging from 0 to 100. The integration of IPMA reveals constructs that exhibit significant importance yet demonstrate low performance, thereby pinpointing critical areas for enhancement for decision-makers.

The aim of IPMA is to transcend basic statistical significance and deliver actionable insights-identifying the constructs that have the most substantial impact on behavioral intention and highlighting the areas that need focus to enhance user satisfaction and engagement (Ringle & Sarstedt, 2016).

IMPORTANCE PERFORMANCE MAP TABLE

Table 4.38 – IPMA Analysis	
	UIA
CNQ	0.143
FCO	0.078
HAB	0.072
HEM	0.079
INO	0.007
PEX	0.221
PRV	0.200
PVL	0.079
SOI	0.168

According to the IPMA findings, Performance Expectancy (PEX) exhibits the highest degree of significance (0.221) among all the predictors of User Intention to Adopt (UIA), followed by Perceived Value (PRV = 0.200) and Social Influence (SOI = 0.168). These results imply that the most important factors influencing adoption intention are users' past experiences with OTT platforms, their assessment of the service's value, and the impact of their social surroundings.

The comparatively high relevance of (PEX) suggests that consumers' propensity to continue using or embrace OTT platforms is greatly influenced by their perceptions of usability, general happiness, and previous interactions. This is consistent with other studies showing that among the best indicators of technology adoption and sustained usage behavior are perceived utility and user experience (Alalwan et al., 2018).

Users are highly driven by the perceived trade-off between the advantages obtained and the cost or effort expended, according to Perceived Value (PRV), which also shows up as a key influencer (0.200). This implies that customers' inclination to utilize OTT services is significantly increased by competitive subscription price, a wide variety of content, and platform quality. Adoption intention is further influenced by Social Influence (SOI) (0.168), which highlights. It explores how peer recommendations, social identification, and community involvement influence watching choices. On the other hand, although having a good correlation with UIA, constructs like Content Quality (CNQ

= 0.143), Facilitating conditions (FCO = 0.078), Hedonic Motivation (HEM = 0.079), and Habit (HAB = 0.072) show somewhat lower relevance levels. This suggests that although these elements improve user experience, Performance Expectancy and value have a greater influence on adoption.

Innovativeness has the lowest significance (INO = 0.007), indicating that consumers' OTT adoption behavior is not significantly impacted by their receptiveness to new technologies. This could be because streaming technologies have become so commonplace that most consumers no longer consider them to be innovative breakthroughs.

Performance expectancy (PEX), Perceived Value (PRV), and Social Influence (SOI) were shown to be the most significant factors influencing User Intention to Adopt (UIA) by the Importance–Performance Map Analysis (IPMA). Despite the positive contributions of categories like Content Quality and Functional Convenience, their relative relevance is lower, indicating that consumers place a higher priority on sensory and value-based aspects than on fundamental functional features. These findings show that in order to maintain user uptake and competitive advantage, OTT platforms must concentrate on enhancing perceived value and experience quality.

Table 4.39 – IPMA Analysis - Performance	
	Performance
CNQ	60.216
FCO	62.322
HAB	56.591
HEM	62.704
INO	60.006
PEX	62.579
PRV	59.641
PVL	63.679
SOI	62.263

The IPMA results indicate major differences between the significance and efficacy of the factors affecting User Intention to Adopt (UIA) OTT platforms. The construct Performance Expectancy (PEX) has the greatest significance (0.221), indicating that it has the most substantial impact on user adoption intention. The performance score of 62.579 is above average, suggesting that respondents

often report favorable experiences; nevertheless, additional enhancements might significantly boost overall adoption. This suggests that enhancing platform usability, interface fluidity, and user happiness might substantially increase adoption rates.

Perceived Value (PRV) ranks as the second most significant concept (importance = 0.200; performance = 59.641). Notwithstanding its considerable significance, PRV's performance is rather deficient, indicating a critical area for managerial attention. This research suggests that customers may recognize potential enhancements in the cost–benefit equilibrium, subscription affordability, or perceived equity of pricing and features.

The role of Social Influence (SOI) is significant, with an importance score of 0.168 and a performance metric of 62.263, highlighting the effect of peer behavior and social recommendations on adoption decisions. Improving social engagement features, including community-driven content, watch-party options, and influencer marketing, has the potential to significantly bolster this aspect.

The assessment of Content Quality (CNQ) reveals a moderate significance score of 0.143 alongside a mid-range performance rating of 60.216. This indicates that users place a considerable value on diverse and rich content, while simultaneously suggesting that OTT platforms are currently achieving a satisfactory level of performance in this domain.

The constructs of Facilitating conditions (FCO), Hedonic Motivation (HEM), and Perceived Visual Layout (PVL) exhibit a pattern of low importance coupled with high performance. This indicates that these elements function primarily as foundational drivers of satisfaction, rather than as significant differentiators influencing user adoption behavior.

In contrast, Habit (HAB) demonstrates a low importance score of 0.072 and the lowest performance score of 56.591, suggesting that habitual usage has not yet been firmly established among the respondents. The implementation of personalized recommendations, loyalty features, and reminder notifications has the potential to transform occasional users into habitual consumers. Ultimately, Innovativeness (INO) exhibits the lowest significance (0.007) alongside moderate performance (60.006), suggesting that the inclination towards novelty has minimal influence on the adoption of OTT services—aligning with the perspective that streaming platforms have transitioned into mainstream technologies rather than remaining as innovative novelties.

The analysis conducted through the Importance–Performance Map revealed that Performance expectancy (PEX) and Perceived Value (PRV) emerge as the most significant and performance-

sensitive factors influencing User Intention to Adopt (UIA). While the performance levels observed across various constructs were deemed satisfactory, there exists a significant opportunity to enhance adoption outcomes by focusing on improvements in these high-importance areas. Factors such as Social Influence (SOI) and Content Quality (CNQ) play a role in adoption; however, they are considered secondary in terms of strategic priority. The results highlight the importance of prioritizing user experience and perceived value as fundamental components in the growth strategies of OTT platforms.

4.16 - R square and adjusted R square:

The Coefficient of Determination (R^2) serves as a fundamental metric for evaluating the predictive accuracy and explanatory capacity of the structural model within the framework of Partial Least Squares Structural Equation Modeling (PLS-SEM). This indicates the extent to which the variance in the endogenous (dependent) construct is accounted for by its exogenous (independent) predictors, as noted by Hair, Hult, Ringle, and Sarstedt (2021). The Adjusted R^2 takes into consideration the quantity of predictors incorporated within the model, offering a more cautious assessment by compensating for the complexity of the model.

Established guidelines indicate that R^2 values of 0.75, 0.50, and 0.25 are categorized as substantial, moderate, and weak, respectively (Hair et al., 2021). Elevated R^2 values suggest that the model effectively accounts for a greater share of variance in the dependent variable, indicating a robust model fit and significant explanatory power.

Table 4.40 – R square		
	R-square	R-square adjusted
UIA	0.730	0.726

The findings demonstrate that the aggregate predictors - Content Quality (CNQ), Facilitating Conditions (FCO), Habit (HAB), Hedonic Motivation (HEM), Innovativeness (INO), Performance Expectancy (PEX), Perceived Value (PRV), Price Value (PVL), and Social Influence (SOI) - account for roughly 73.0% of the variance in User Intention to Adopt (UIA). The Adjusted R^2 value of 0.726 indicates that the model has substantial explanatory power, even when considering the number of independent variables.

This degree of explained variation is deemed significant in behavioral and social science research (Hair et al., 2021; Henseler et al., 2009). This indicates that the separate structures together offer a comprehensive account of consumers' intents to embrace OTT platforms. The little decrease from R^2 (0.730) to Adjusted R^2 (0.726) suggests no multicollinearity or overfitting, demonstrating model parsimony and statistical robustness.

Table 4.41 – F Square	
	f-square
CNQ -> UIA	0.035
FCO -> UIA	0.011
HAB -> UIA	0.014
HEM -> UIA	0.014
INO -> UIA	0.000
PEX -> UIA	0.053
PRV -> UIA	0.046
PVL -> UIA	0.009
SOI -> UIA	0.032

The f^2 analysis indicates that among the nine predictors of User Intention to Adopt (UIA), certain dimensions demonstrate tiny yet significant impact sizes, whilst others contribute very minimally to the overall model. The most significant impacts are noted for Performance Expectancy (PEX, $f^2 = 0.053$) and Perceived Value (PRV, $f^2 = 0.046$), both categorized within the small-to-moderate range.

This suggests that eliminating these elements from the model would result in a significant decrease in the R^2 value of UIA. These findings underscore their significance as main determinants of user adoption behavior and correspond with previous path coefficient and IPMA results indicating that experience and value judgments are pivotal to the adoption process.

Content Quality (CNQ) and Social Influence (SOI) have modest effect sizes (0.035 and 0.032, respectively), indicating that although their impact is less significant than that of PEX and PRV, they still contribute meaningfully to the formation of adoption intention. For instance, increased perceived content diversity and social validation both augment user engagement and confidence in OTT platforms.

In contrast, categories like Facilitating conditions (FCO), Habit (HAB), Hedonic Motivation (HEM), and Perceived value (PVL) have low impact sizes (between 0.009 and 0.014), suggesting they provide only slight further insights into understanding UIA. This indicates that people can regard these elements as fundamental expectations rather than distinguishing characteristics. Innovativeness (INO) exhibits no significant impact ($f^2 = 0.000$), indicating that consumers' receptiveness to new technologies does not substantially influence their desire to embrace OTT platforms-presumably due to the ubiquity and familiarity with streaming technologies.

4.17 - MODEL FIT SUMMARY:

The model fit summary offers a statistical assessment of the extent to which the proposed structural model accurately reflects the observed covariance matrix, thereby illustrating the alignment between the theoretical model and the empirical data (Hair, Hult, Ringle, & Sarstedt, 2021). In Partial Least Squares Structural Equation Modelling (PLS-SEM), model fit indices function as approximate measures of fit, contrasting with the absolute criteria utilized in covariance-based SEM. Nonetheless, these indices retain their significance in corroborating the overall fit of the structural model and confirming that the suggested relationships align with the observed data structure.

Table 4.42 – Model Fit Summary		
	Saturated model	Estimated model
SRMR	0.053	0.053
d_ULS	1.903	1.903
d_G	0.657	0.657
Chi-square	3138.001	3138.001
NFI	0.869	0.869

The findings indicate that the Standardized Root Mean Square Residual (SRMR) value for both the saturated and estimated models is 0.053, significantly lower than the suggested threshold of 0.08 (Hu & Bentler, 1999; Henseler et al., 2014). The findings suggest that the model demonstrates a strong overall fit, indicating that the disparity between the observed and predicted correlations is negligible. A reduced SRMR value indicates a diminished difference between the theoretical and empirical models, thereby affirming that the proposed model effectively captures the data structure.

The values of d_ULS (Squared Euclidean Distance) at 1.903 and d_G (Geodesic Distance) at 0.657 provide additional evidence for the adequacy of the model. The indicators evaluate the disparity between the empirical correlation matrices and those implied by the model. Lower values indicate a superior model fit, and given that these values are comparatively small and almost identical for both the saturated and estimated models, they support the conclusion that the model is appropriately specified and devoid of estimation bias.

The Chi-square statistic (3138.001) is presented for reference purposes; however, it is not considered a primary measure in PLS-SEM, as this technique prioritizes variance-based modeling over covariance-based assumptions. In contrast to CB-SEM, which employs chi-square tests to assess absolute model fit, PLS-SEM emphasizes predictive relevance and path relationships. This distinction renders the value more descriptive in nature rather than evaluative.

In conclusion, the Normed Fit Index (NFI) for both models is recorded at 0.869, surpassing the suggested minimum threshold of 0.80. This finding suggests a satisfactory level of model fit, as noted by Hair et al. (2021). The preference for higher NFI values (≥ 0.90) indicates a strong model fitness; however, the value obtained in this study suggests that the hypothesized model accounts for approximately 87% of the covariance among the constructs. This level of fit is deemed acceptable within the context of exploratory and behavioral research models.

The model fit indices collectively indicate that the proposed PLS-SEM model attains an acceptable to good level of overall model fit. The SRMR value suggests the presence of minimal residual correlations, whereas the d_ULS and d_G values reflect the internal consistency of the model. Furthermore, the acceptable NFI value indicates a robust correspondence between the proposed and observed data frameworks. The findings indicate that the constructs and structural paths of the model effectively capture the observed relationships among the variables, thereby affirming the theoretical robustness and empirical validity of the proposed framework. This finding is consistent with the guidance provided by Henseler et al. (2014) and Hair et al. (2021), who emphasize that the values of SRMR, d_ULS, and NFI together offer a robust evaluation of overall model fit in the context of variance-based SEM.

CHAPTER 5 - FINDINGS, CONCLUSION, SUGGESTIONS, IMPLICATIONS & FUTURE SCOPE

5.1 - FINDINGS:

5.1.1 Findings from Demographic Analysis

The results obtained during the demographic analysis demonstrate that the usage of over-the-top (OTT) platforms is largely predominated by younger individuals. A large proportion of the respondents that is equivalent to 66.8 percent of the total respondents fall within the age group of 18-25. This shows that the digital-savvy youth demographics are the major consumers of over-the-top (OTT) content. There is a very equal distribution of genders, of which 52.3% of the respondents were male and 47.7% were female. This makes sure that the conclusions are not biased with regard to either gender based on gender distribution. Concerning education, most of the respondents were either graduate or post graduate, implying that the use of over-the-top (OTT) services is more among the well-educated individuals who are more knowledgeable about digital technology. Judging by the distribution of occupations, it becomes obvious that the largest categories are students and private workers.

This implies that the number of people using over-the-top (OTT) platforms is very high among the academic and working population. The analysis of the device choice shows that Smartphones are the most common gadget, next comes Smart TV. Such a phenomenon of personal and group viewing is manifested in the reality that smartphones are the most widespread device. Based on the weekly use patterns, most of the respondents devote less than eight hours a week on over-the-top (OTT) platforms and this shows that they have moderate consuming behavior. Moreover, the use of over-the-top (OTT) services has been accepted by a considerable proportion of users over the last year, which can be considered the indicator of the rapid growth and the increasing market share of the services. The chi-square analysis is additional support that demographic data including age level, education, and employment have significant influence in the behavior of the over-the-top (OTT) users especially in terms of the devices that they use and the duration that they use it. Conversely, income is not a strong or consistent variable that has a relation with OTT usage behavior.

5.1.2 Findings from Reliability and Validity Analysis

As the outcomes of the reliability and validity analysis show, one can conclude that the measurement model that was used in the research project is both reliable and valid. All of the constructs that were derived out of the questionnaire have a high level of internal consistency. They are: Performance Expectancy, Content Quality, Perceived Value, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Personal Innovativeness, Habit and User Intention to Adopt. The value of Cronbach Alpha is more than the established value of 0.70 in all of the constructs and this value shows a high level of reliability of the measuring scales. Similarly, the Composite Reliability values are well above the allowable values and this served as another indication that the constructs are consistent.

The fact that the factor loading of most of the indicators is above 0.70 is a sign that the items asked in the questionnaires are a good measure of the constructs that they are supposed to be. Based on the definition of convergent validity, convergent validity is indicated when the values of Average Variance Extracted (AVE) of all constructs are greater than 0.50. This implies that the underlying constructs could have contributed a considerable proportion of variance of the indicators. The FornellLarcker criterion as well as the HTMT ratio also suggests the presence of the discriminant validity. Such ratios and criteria indicate that all of the constructs are distinct and measure different aspects of OTT adoption behavior. Overall, the results indicate that the measurement model can be trusted and is suitable in completing further structural analysis.

5.1.3 Findings from Structural Model (Smart PLS Analysis)

The findings of the structural model analysis show that most of the hypothesized relationships are statistically significant and influence the intention to adopt over-the-top (OTT) platforms in a positive way. The ease, accessibility, and efficiency that are provided by over-the-top (OTT) services are the key drivers of users as can be seen in the fact that, Performance Expectancy is the most compelling factor throughout all the constructions. The second most relevant predictor is revealed as Perceived Value which implies that consumers evaluate over-the-top (OTT) platforms according to the benefits received relative to the pricing of the membership. Another important role is played by the social influence that underlines the importance of peer recommendations, the influence of other members of the family and interactions on social media platforms within the process of making user adoption choices.

The quality of the material is another critical aspect that proves that the availability of information of high quality, diversification, and engagement could contribute greatly to the increased chances of users adopting over-the-top (OTT) platforms. Along with it, the impact of the Facilitating Conditions, Hedonic Motivation, Habit, and Price Value factors are also positive and significantly impactful, even though their contribution is quite insignificant. According to these data, it would seem that, though experience and functionality factors may have a role to play in adoption, the impact of these factors is subordinate to the fact of considering perceived utility and value. In its turn, personal innovativeness does not play a significant role in user intention. This implies that the usage of over-the-top (OTT) services is no longer driven by something special or the readiness to experiment with new technologies; instead, it has become a habit. The model has a value of R^2 of 0.730, which means that the model has great explanatory power suggesting that a large proportion of the variation in user intention is accounted by constructs selected.

5.1.4 Findings from Multi-Group Analysis (MGA)

The findings of the Multi-Group Analysis indicate that the associations between the constructs do not have any statistically significant differences, in terms of gender and generational groups. As per the analysis results, no differences exist. Although there are minor alterations in route coefficients between the male and female respondents, Generation Y and Generation Z respondents, these changes are not found to be statistically significant. Moreover, there exist certain inconsistencies between the generations as well.

It would seem out of this that the factors that affect user intentions to adopt over-the-top (OTT) platforms are always in a similar direction regardless of the different groupings of demographics. Using the information, a conclusion can be made that users of both gender, users of different age groups demonstrate similar reactions to most of the factors including performance expectations, perceived value, social impact, and content quality. Consequently, the behavior of taking over-the-top (OTT) services seems to belong to the universal type and is not sensitive to gender or age peculiarities in a significant way.

5.1.5 Findings from Importance–Performance Map Analysis (IPMA)

The findings of the Importance-Performance Map Analysis will show that the most important factor that affects the user intention to adopt over-the-top (OTT) platforms is Performance Expectancy. The

next important factors according to the findings are the Perceived Value and Social Influence. It may exist between the expectation of the user and the perceived benefits as the perceived value factor is rather less performing, although these aspects reveal a high degree of relevance. With this in mind, it is seen that over-the-top (OTT) platforms ought to improve their value propositions, especially as concerns price and services offered. Both Hedonic Motivation and material Quality show a moderate level of significance and an excellent level of performance, and it means that over-the-top (OTT) platforms are already working relatively well in terms of providing engaging and pleasant material.

The performance of Habit, however, is very poor which means that users do not have strong habitual usage patterns as yet. This provides a chance of platforms to generate more user interaction by offering customised features and a constant stream of updated content. Innovativeness at the personal level is of least significance which substantiates the fact that the phenomenon of over-the-top (OTT) platform has become a universally accepted phenomenon and is no longer viewed as a kind of innovation technology. Overall, the results of the IPMA shed light on the fact that improving the user experience and perceived value could significantly result in the increased adoption of over-the-top (OTT) services.

Table 5.1 - Summary table of findings from Hypothesis		
Hypothesis No	Hypothesis Statement	Findings
H1	Content Quality positively influences User Intention to Adopt OTT	The results demonstrate that content quality exerts a favourable and statistically significant influence on users' desire to embrace OTT platforms ($\beta = 0.143$, $p < 0.001$). This indicates that people are more inclined to embrace OTT services when they regard the material as high-quality, diversified, and interesting. Elements such as unique material, exceptional audio-visual quality, and diverse genres significantly contribute to augmenting user engagement. Consequently, H1 is validated, affirming that content is a primary catalyst for OTT uptake.

H2	Facilitating Conditions positively influence User Intention to Adopt OTT	The findings indicate that enabling conditions exert a favourable and substantial influence on user intention ($\beta = 0.078$, $p = 0.008$). This suggests that availability to essential resources, including devices, internet connectivity, technical assistance, and user-friendly platforms, facilitates the adoption of OTT platforms by users. Despite the effect being minor, it underscores the need of a conducive technical environment. Therefore, H2 is endorsed.
H3	Habit positively influences User Intention to Adopt OTT	The research indicates that habit has a substantial impact on user intention ($\beta = 0.072$, $p = 0.001$). This research indicates that users who regularly interact with OTT platforms are likely to establish habitual viewing patterns, hence reinforcing their decision to persist in usage. OTT consumption is progressively integrating into consumers' everyday routines. Consequently, H3 is corroborated.
H4	Hedonic Motivation positively influences User Intention to Adopt OTT	The results indicate that hedonic motivation exerts a favourable and substantial influence on user intention ($\beta = 0.079$, $p = 0.001$). This signifies that pleasure, amusement, and emotional gratification obtained via OTT platforms significantly impact adoption choices. Users have a greater propensity to utilise OTT services when they see them as enjoyable and captivating. Consequently, H4 is substantiated.
H5	Innovativeness positively influences User Intention to Adopt OTT	The findings indicate that personal innovativeness exerts no significant influence on user intention ($\beta = 0.007$, $p = 0.871$). This indicates that the propensity to embrace new technologies does not markedly affect OTT uptake in the present scenario. OTT platforms have attained mainstream status, with adoption no longer reliant on consumers being inventive or early adopters. Consequently, H5 is

		unsupported.
H6	Performance Expectancy positively influences User Intention to Adopt OTT	The results demonstrate that performance expectation exerts the most significant positive effect on user intention ($\beta = 0.221$, $p < 0.001$). This indicates that customers are strongly inclined to embrace OTT platforms when they regard them as beneficial, convenient, and effective in comparison to traditional media. Attributes like ubiquitous availability and an enhanced viewing experience substantially increase adoption. Therefore, H6 is robustly substantiated.
H7	Perceived Value positively influences User Intention to Adopt OTT	The findings indicate that perceived value has a substantial impact on user intention ($\beta = 0.200$, $p < 0.001$). This indicates that consumers assess OTT platforms by weighing the expense against the advantages. Users are more inclined to use OTT services when they believe the membership cost is warranted by the quality of content and features offered. Consequently, H7 is corroborated.
H8	Price Value positively influences User Intention to Adopt OTT	The results indicate that price value exerts a positive and statistically significant influence on user intention ($\beta = 0.079$, $p = 0.018$). This signifies that competitive pricing, adaptable subscription models, and cost-effectiveness significantly impact adoption choices. Despite its small impact, it continues to be a vital element in price-sensitive markets. Consequently, H8 is corroborated.

H9	Social Influence positively influences User Intention to Adopt OTT	The research demonstrates that social influence exerts a substantial and significant effect on user intention ($\beta = 0.168, p < 0.001$). This indicates that endorsements from friends and family, together with social media discourse, substantially influence individuals' choices to embrace OTT services. Social affirmation and social influence are crucial, particularly during the earliest phases of adoption. Therefore, H9 is validated.
----	--	---

Table 5.2 - Summary table of Objective wise Findings

Obj. No	Objectives	Findings
Objective 1	To examine the influence of technological, experiential, and perceptual factors on users' intention to adopt OTT platforms	The results indicate that technological, experiential, and perceptual elements substantially affect consumers' inclination to embrace OTT services. Performance expectation is identified as the most significant predictor, suggesting that customers are greatly impacted by the ease, accessibility, and efficiency provided by OTT services. The perceived value is significant, indicating that consumers meticulously assess the cost-benefit ratio prior to embracing OTT services. The quality of content plays a crucial role in adoption by delivering entertaining, varied, and superior watching experiences, while social impact amplifies user intention through peer endorsements and social media visibility. Moreover, experiential elements like hedonic motivation and habit positively influence adoption, suggesting that pleasure and habitual use enhance user engagement. Nonetheless, personal innovativeness does not substantially affect adoption, indicating that OTT platforms have attained mainstream status and are no longer reliant on users' propensity to explore new technology.

Objective 2	To analyse the relative significance of individual predictors in shaping user adoption intentions	The examination of path coefficients and IPMA outcomes reveals distinct variations in the relative significance of variables affecting user intention. Performance expectation is recognised as the paramount aspect, succeeded by perceived value and social impact, indicating that consumers prioritise functional advantages, cost-effectiveness, and social endorsement while embracing OTT platforms. The quality of content plays a significant although relatively moderate influence, underscoring its value as a supportive element rather than the principal catalyst. Additional factors, including enabling circumstances, hedonic motivation, habit, and price value, exhibit positive albeit comparatively lower impacts, suggesting they augment user experience but do not serve as primary determinants. Innovativeness exhibits minimal impact, further substantiating that OTT uptake is no longer propelled by novelty. The data indicate that adoption decisions are predominantly shaped by perceived utility and value, rather than by emotional or technological curiosity aspects.
Objective 3	To evaluate the moderating relationships of demographic factors (gender, generation) between predictors and user intention to adopt OTT platforms	Multi-Group Analysis results reveal that demographic parameters, including gender and generation, do not significantly influence the associations between independent variables and user desire to embrace OTT platforms. Minor variations in route coefficients are evident among groups; however, these discrepancies lack statistical significance. This indicates that individuals of all genders and generational groups exhibit comparable reactions to critical elements such as performance anticipation, perceived worth, social impact, and content quality. The results demonstrate that OTT adoption behavior is uniform and pervasive across demographic divisions, signifying the extensive acceptance and incorporation of OTT platforms into daily life. Consequently, demographic variables do not significantly modify the impact of primary predictors on adoption intention.

Objective 4	To identify key managerial implications using Importance–Performance Map Analysis (IPMA) for improving user adoption and engagement on OTT services	The IPMA findings offer significant management insights by pinpointing high-impact areas for strategic focus. Performance expectation is identified as the paramount aspect affecting user intention, suggesting that OTT platforms should prioritise enhancements in usability, accessibility, and the entire watching experience. Perceived value is identified as a significant element with comparatively low performance, indicating a necessity to improve price strategies, subscription flexibility, and value propositions. Social influence is essential, underscoring opportunities for platforms to utilise word-of-mouth, influencer marketing, and social engagement functionalities. The quality of content and hedonic motivation exhibit commendable performance, suggesting that platforms are effectively providing compelling material, albeit further enhancement is essential. Habit demonstrates comparatively diminished performance, indicating that platforms must to prioritise the development of user retention tactics, including personalised suggestions and continuous content delivery. The IPMA findings underscore that enhancing user experience and perceived value may substantially increase OTT uptake and sustained engagement.
----------------	---	---

5.2 - RECOMMENDATIONS

5.2.1 - Demographic Profile Based Recommendations.

The results show that the use of OTT is strongly skewed towards the younger generations (18-25 years) and can be assumed that they are the primary adoption agents. In the case of this audience, OTT platforms must be about video production of the most interesting, trendy and shareable content on social media. It can be engaged by such features as short-format content, trending recommendations, interactive aspects, and influencer collaborations. Simultaneously, older age categories (26+) have a relatively low adoption rate, which should not be overlooked by platforms. To these users, the interface design can be simplified, content discoverability can be enhanced and more content with family Oriented and informational content can be provided to encourage adoption.

5.2.2 - Gender-Based Recommendations

The research also found no significant differences among male and female consumers that could be used to create a gender-neutral approach to the platform design and critical functionality. Nevertheless, detailed content customization can be applied. Social platforms can use the history and data on behavior to suggest genre specific content without relying on generalized gender segmentation. This ensures that everybody is included and it does not eliminate individuality.

5.2.3 - Education-Based Recommendations

The findings suggest the presence of an educated audience as a large proportion of users are graduates and postgraduates. The OTT services must focus on the quality of content, high-quality content, substantive content, and diverse content which should include documentaries, foreign series, and education programs. Informed consumers would find it easy to value information that is in depth and unique, hence their investment in mentally-challenging material can enhance memory. In addition, advanced recommendation and algorithms can be utilized to meet special tastes.

5.2.4 - Occupation-Based Recommendations

Considering the fact that the student and working population is the most common user group, OTT platforms have to align their efforts with their lifestyle trends. Cost-effective pricing scheme, material that is mobile friendly, and trendy entertainment are critical elements to the students. To busy employees, less time-consuming content, such as short episodes, personalized playlists and stop watching features may enhance convenience. On demand subscriptions and offline viewing options could also help provide service to busy consumers.

5.2.5 - Income-Based Recommendations

Although the aspect of income was not regarded as a major differentiator, the pricing remains an essential aspect. The OTT platforms must be able to sustain fair and flexible pricing frameworks that will cater to different income groups. The introduction of low-price membership packages, advertising-based schemes, and integrated telecommunication packages will be able to draw low-end customers,

but retain the high-end users with the high-quality services and exclusive content.

5.2.6 - Recommendations on the use of devices.

The use of smartphones and smart TVs also indicates a two-fold consumption pattern. OTT services need to be mobile-first optimized to ensure that they work flawlessly on smartphones with the lowest use of data. At the same time, the enhanced smart TV interfaces to provide the viewers with immersive watching experiences can support the family and group usage. The cross-device synchronization should be easy so that the consumer can switch across the devices without inconvenience.

5.2.7 - Usage Behavior (Spending Time) Recommendation.

Since most users engage in small usage (less than 8 hours a week), OTT platforms can offer an opportunity to increase user interest. Individualized suggestions, periodic content delivery, push notifications, and hand-selected suggestions are some of the techniques that could encourage users to become more active on the site. In order to keep recurring customers interested, platforms can add loyalty programs and offer special early access to content.

5.2.8 - OTT (Usage Duration) Recommendations Experience.

The number of new users (less than one year) is an indication of a growing industry where on boarding is possible. Platforms need to focus on improving user on boarding experiences based on guided interfaces, specific recommendations, and tenure of trials. To reduce churn, unique content, loyalty benefits, and enhanced customization are essential to the retention initiatives of long-term customers.

5.3 - Variable wise Recommendation

5.3.1 - Performance Expectancy (PEX)

Since the performance expectancy has already become the most important predictor of the user intention, OTT platforms must centre the improvement of usability and efficiency. The platforms have to assure buffering-free streaming, minimal buffering, easy navigation, and fast loading of the content. The capabilities such as cross-device syncing, offline viewing and smart search options should be

Continuously improved to add to the perceived utility. Any inconvenience in the user experience will impact negatively on adoption, with speed optimization becoming a key objective.

5.3.2 - Perceived Value (PRV)

Perceived value requires immediate managerial action because of its influential effect and relatively underperformance. OTT platforms should increase the cost benefit equilibrium through flexible pricing models, subscriptions, and freemium models. Adding value, content exclusiveness, device-content compatibility, and customized recommendations can also justify the cost of memberships. Consumer impression of value can be increased through articulate information about the benefits and clear pricing schemes.

5.3.3 - Social Influence (SOI)

Such a significant effect of social influence points to the idea that social ecosystems should be strategically used by OTT platforms. User engagement can be enhanced by the addition of such features as watch parties, social sharing, and recommendation based on community. The marketing approach should be based on collaboration with influencers, user-generated content, and viral campaigns to utilize peer-to-peer adoption. Favourable reviews and ratings would be able to boost trust and social acceptance.

5.3.4 - Content Quality (CNQ)

As much as content quality is a basic requirement, it is a critical component to keeping the users engaged. OTT providers should invest in quality content, distinctive, and diverse content with a focus on regional and culturally relevant content. The continued updating of the contents, genre diversity and exclusivity of releases play important roles in maintaining competition. Platforms need to use data analytics to match content offers to user interests.

5.3.5 - Facilitating Conditions (FCO)

The enabling factors are facilitating circumstances, which should be maintained at all times. OTT systems should ensure the interoperability support on a wide range of devices, contribute to improved performance under low bandwidth, and provide reliable technical support. More adoption can be

Enhanced through the implementation of lightweight applications and adaptive streaming technologies to improve accessibility in rural and semi-urban areas.

5.3.6 - Hedonic Motivation (HEM)

Since fun and amusement are important determinants of adoption, a platform should focus on improving the entire watching experience. These include the elements of immersive interfaces, interactive capabilities, gamification, and engaging information presentation. Personalization of content discovery and attractively designed UI/UX can contribute to the increase in user happiness and emotional engagement.

5.3.7 - Habit (HAB)

The relative weakened effectiveness of the habit implies a possibility to increase user retention. OTT services need to focus on the development of addictive consumption through customized suggestions, auto play settings, content updates, and episode drops. On-demand notifications and tailor-made playlists have the potential to create a long-lasting presence, gradually building into the daily routine of the consumers using OTT.

5.3.8- Price Value (PVL)

Sensitivity to price remains a major issue particularly in the developing nations. Platforms must introduce price flexibility plans, including student plans, family plans, and ad-supported subscriptions. The short-term plans, as well as trial periods, can be used to attract new customers, whereas affordability can be applied to retain them on a long-term basis.

5.3.9 - Personal Innovativeness (INO)

Since innovativeness is insignificant, the OTTs are advised to avoid focusing on complex or experimental features that do not contribute value that can be discerned. The focus must be set on increasing the basic functionality and user experience. An innovation should be user-centric and practical by aiming to make it convenient and interactive instead of being novel.

5.3.10- User Intention to Adopt (UIA) - Strategy in general.

In order to enhance user intent, OTT platforms need to adopt an integrated approach that combines performance effectiveness, value addition, socialization and content quality. Strategies should focus on not only on acquiring the users, but also on the retention of the user engagement by making continued improvements in the user experience.

5.4 - Theoretical Implications

The results of this study contribute to the understanding of the adoption of technology by demonstrating how OTT platforms operate in a semi-autonomous area where traditional technology usage intersects with the pattern of media consumption. Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology -3 have already pointed to the importance of the perceived usefulness; the current research confirms that the given basic construct still possesses a strong explanatory value in the context of entertainment. The high influence of performance expectancy suggests that users do not think about OTT platforms as just a source of leisure; they also consider the services as being both useful and convenient as an alternative to traditional media use, which explains why the perceived usefulness continues to be highly relevant in digital adoption (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012).

The results also show that adoption behavior in OTT settings goes beyond functional attributes and largely depends on the value perception. The great importance of the perceived value reminds us that the users will always make an evaluation of the benefits in comparison to the cost particularly when it comes to the subscription-based services. This has a lot of congruence with the Value-Based Adoption Model, which contextualizes adoption as a trade-off between the benefits perceptions and the costs (Kim et al., 2007). However, the findings show that the value perception in the OTT platforms is not straightforward and it includes variables like pricing, content variety, availability, and overall user experience. This improves the theoretical context of value in digital services, indicating that there is a strong interrelation between the economic and experiential aspects.

The current research is a special contribution as it underlines the significance of content quality as a key construct. Unlike the traditional technology systems, over-the-top (OTT) platforms are content centric in nature. The evidence shows that quality of the content is a very important factor in

Determining user intention. This articulates the perspectives of the media and communication theory, which argues that the content engagement of audience is basically anchored on the quality and relevance of content (Napoli, 2011). The content quality incorporated into the framework of adoption can be identified as the process that links the technology acceptance theories to the media consumption theories and gives it the model that is more applicable to the context of digital streaming environments. The changes in behavior processes that were revealed during the study emphasize how deliberate use is shifted to routine. The significance of hedonic motivation emphasizes the fact that fun and emotional gratification are significant in applied entertainment technologies and support the need to include the experience aspect in UTAUT2 (Venkatesh et al., 2012). These experiences over time will form patterns of behavior that become consistent as demonstrated by the positive effect of habit on user intention.

This aligns with past research that has shown that with repetitive use, cognitive load reduces, and there is long time engagement (Limayem et al., 2007). The correlation between fun and habit shows that the use of OTT services is not only a one-time decision but is a process that gradually becomes a part of the lives of users.

The results emphasize the great impact of social influence, which makes digitally mediated social settings more and more relevant. Conventional theories often define social influence as a phenomenon which is defined by inter-personal pressure. But in the environment of over-the-top (OTT) elements, this power is extended to include social media interactions, online reviews and community-led discussions. The results of this research indicate that there is a significant influence, which means that the choice in terms of adoption becomes more dependent on the shared experiences of digital nature, and the theoretical perspective of social influence in the framework of the modern technology adoption is further expanded.

One theoretical finding is the non-substantial influence of the human innovativeness. As opposed to the past ideas that the innovationists are relevant in the spread of technologies, the statistics show that OTTs have reached a stage where adoption is no longer reliant on the willingness of users to adopt new technologies. The practicality, perceived worthiness, and fulfilment experienced are the major factors that contribute to adoption. It marks a broader shift in the technology adoption research, in which the focus moved towards mainstream users rather than early adopters, hence the normalisation of digital platforms in everyday life.

This notion of normalization is further supported by the absence of the moderating effects on gender and generational difference. The findings depict that the behavioral patterns of OTT adoption have a high level of consistency across different groups of people, which implies that digital technologies have received some universal access and involvement into daily activities. This is in line with the modern debates that indicate that the disparities between demographics in terms of technology adoption are reduced as the technologies become widespread and available (Venkatesh et al., 2012; Dwivedi et al., 2020).

When considered collectively, these findings suggest that the adoption of OTT services represents a complex phenomenon that extends beyond the explanatory power of conventional technology acceptance frameworks. Rather, it necessitates a more comprehensive framework that encompasses the intersection of technological utility, perceived value, content experience, and social interaction. The integration of these dimensions enhances theoretical comprehension and offers a comprehensive viewpoint on user behavior within contemporary digital ecosystems.

5.5 - Practical and Managerial Implications

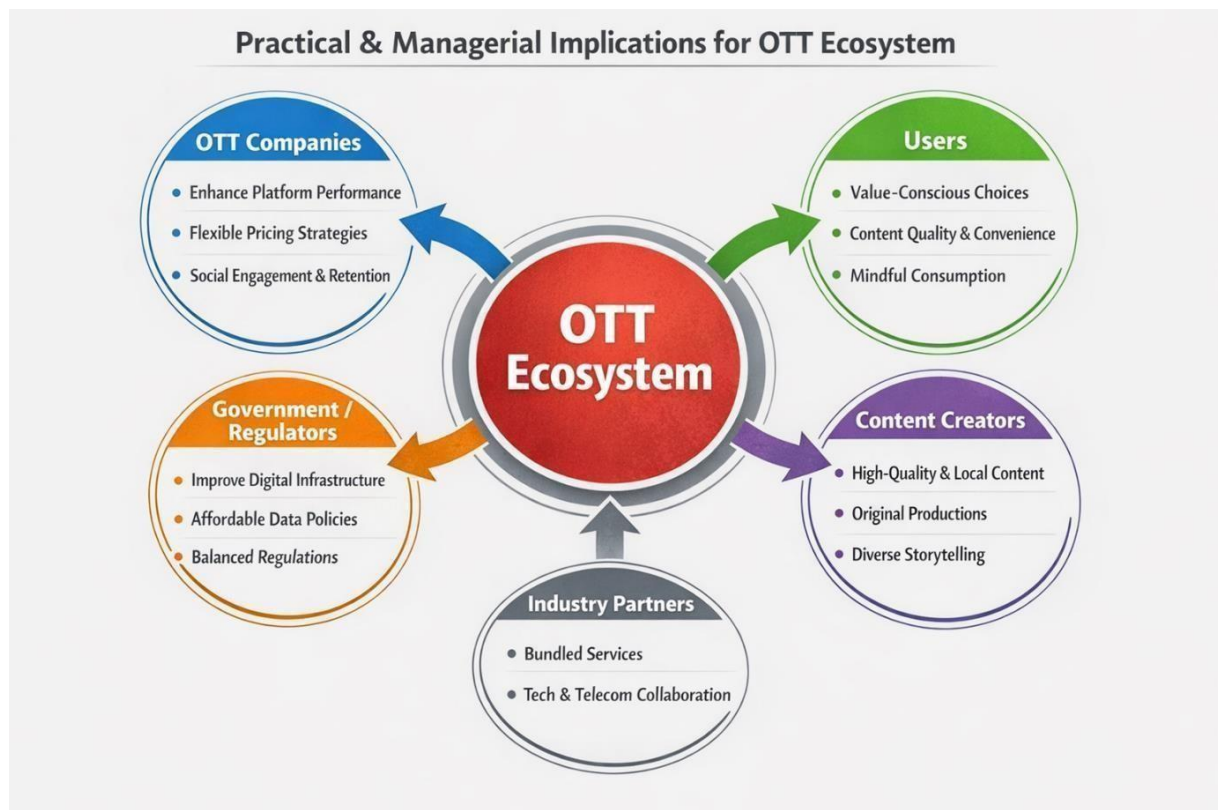


Figure 5.1 – OTT Ecosystem

The insights that were obtained from this study go beyond the methods that are implemented at the platform level and give significant implications for a variety of stakeholders participating in the over-the-top (OTT) ecosystem. These stakeholders include service providers, users, and legislators. Because of the linked nature of digital media consumption, it is necessary to take a coordinated strategy in which all participating stakeholders contribute to the improvement of the ecosystem as a whole.

5.5.1 - OTT service providers and companies

In the perspective of OTT service providers and companies, the findings clearly show that the expectancy of performance and perceived value are the two critical factors determining the adoption by the users. It means that platforms must go beyond content provision and focus on its ease, efficiency, and user-friendly experience. The platform optimization investments such as improvements in streaming speeds, minimization of buffering issues, and cross-device compatibility matters and is essential to match the expectations of users. At the same time the relatively lower performance of perceived value indicates that there is a difference between pricing and user expectations especially in price sensitive markets. Companies need to adopt flexible pricing mechanisms that include tiered subscription, bundled telecommunications alliances and advertising-based options to enhance affordability and the sense of equality.

The high role of social factors suggests that OTT platforms should incorporate applications of digital communities, influencer marketing, and social sharing facilities strategically to increase user adoption. Moreover, the high impact of habit also highlights the need of strategies targeted at retention such as personalized recommendation, AI-driven content selection, and a continuous interaction system that transforms the infrequent user into an active subscriber.

5.5.2 - Content creators and media producers

The results indicate the importance of offering high-quality, diversified, and culturally-relevant material to the responsible persons in the development of content and generation of media output. Though the quality of the material remains a factor of note, the fact that it still remains one of the benchmark expectations means that the sheer presence of material is no longer enough to make a difference. Rather, it is based on originality, richness of the story, and setting particularity. Localized content and stories that appeal to their respective cultures can have significant effect on increasing user

Engagement and expanding the edges of the market in diverse markets like India. This also provides a possible opportunity to the smaller producers and production firms situated in the regional areas to contribute greatly to the ecosystem of over-the-top (OTT) services.

5.5.3 - OTT Users

The paper shows that there is a shift to consumer behavior which is more value-conscious and experience-driven per the view of the users. Instead of being concerned with novelty, people are also more likely to evaluate over-the-top (OTT) platforms by their price, convenience, and content relevancy. The fact that these platforms are trying to keep pace with the constantly evolving demands of its customers means that users of the platforms will have greater amounts of variety, competitive prices, and improved levels of service quality. Nevertheless, the increasing impact of habit suggests that the users must be aware of their consumption patterns especially with regards to binge-watching and time management. This particularly should be remembered when it comes to binge-watching. The more significant revolution in the media consuming behavior would be in the increasing adoption of the use of over-the-top (OTT) platforms into daily lives. This shift is defined by consumers proactively defining their entertainment experiences that they look at.

5.5.4 - Government and Policy makers

These findings reveal that there is a need to improve digital infrastructure in order to facilitate the incessant growth of over-the-top (OTT) between the government and policymakers. Access to high-speed internet that is reliable remains a critical element in achieving adoption especially in semi-urban and rural areas. The capacity of over-the-top (OTT) services can be considerably extended through the introduction of the policies promoting cheap access to data and digital inclusion. Moreover, with the current trend of over-the-top (OTT) platforms, there is an increased need to have regulatory frameworks that are well balanced and will guarantee fair competition, diversity of content and consumer protection without choking innovation. In order to make the digital ecosystem remain trustworthy and sustainable, one will have to address issues related to the security of personal data, the moderation of content, and the safeguarding of intellectual property rights.

5.5.5 - Industry perspective

The results point toward the importance of cooperation in the perspective of an industrial ecosystem, comprising the members, like technology partners, and telecommunications services suppliers. The bundled services can be perceived as adding over-the-top (OTT) subscriptions to either mobile or internet plans and this can be enhanced, which consequently encourages adoption. Scalable cloud infrastructure, potent analytics, and AI-based tools of user Personalization are vital prerequisites of high-quality user experiences. Over-the-top (OTT) platforms can be supported by technology providers through the provision of these features.

Overall, the implications according to the stakeholder perspective are that the success of over-the-top (OTT) platforms will depend upon a concerted effort where companies focus on improving the user experience and value, content creators focus on differentiation and relevance, users focus on conscious use of digital media, and policymakers focus on creating an enabling and balanced environment in regard to regulation. This combined approach is also required as a means of sustaining development and competitiveness in the over-the-top (OTT) environment, which is constantly changing and expanding.

5.6 - SOCIAL IMPLICATIONS:

5.6.1- Implications for Policy and Digital Media Governance

The earlier sections focus on the management goals of OTT service providers, although the results of this research also hold significant consequences for policymakers and regulatory entities overseeing India's digital media landscape. As the integration of OTT services deepens in daily consuming habits, the legal framework governing these platforms need a more coherent alignment with the behavioral, technical, and structural elements highlighted in this study.

Content Regulation and Platform Accountability

India's OTT industry presently functions under a self-regulated system - the Digital Media Ethics Code (2021) - instead of a cohesive regulating authority similar to those overseeing conventional broadcast media. The results of this research indicate that content quality and perceived value are crucial determinants of adoption intention, implying that erratic content standards or unforeseen regulatory

actions may jeopardize the elements fostering platform confidence and user involvement. Policymakers can contemplate the establishment of more explicit and uniformly applied content categorization standards that reconcile artistic liberty with audience safeguarding, thereby diminishing the uncertainty that now defines platform-specific self-regulation.

Data Privacy and Algorithmic Transparency

The increasing dependence on AI-based customization and recommendation systems - fundamental to the technological aspects analyzed in this research - prompts concurrent governance inquiries around data protection and algorithmic transparency. As platforms amass more detailed behavioral data to enhance recommendation systems, legislators might need to fortify data protection regulations tailored to streaming and entertainment services, guaranteeing that users maintain significant authority over the collection, storage, and utilization of their viewing data for algorithmic customization.

Digital Infrastructure and Equitable Access:

The results on the influence of technological and infrastructural elements on adoption intention also have governance ramifications that extend beyond content and data policy. The ongoing urban-rural digital disparity highlighted in this study indicates a sustained need for policies like Digital India to enhance accessible broadband and mobile networks in neglected areas. In the absence of continuous infrastructure investment, the demographic and regional inequalities in OTT adoption shown in this research are expected to endure, hindering the sector's capacity to fairly serve India's populace.

Toward a Coherent Digital Media Governance Framework:

Collectively, these results indicate that India's OTT governance framework might improve with a more unified approach - one that systematically tackles content standards, data protection, and infrastructural parity, instead of relying on disjointed, platform-specific self-regulation. This framework would safeguard consumer interests while simultaneously promoting the long-term viability and credibility of the industry by cultivating the essential conditions of trust, accessibility, and perceived value identified in this study as crucial for user adoption.

5.6.2 - Societal and Behavioral Impact of OTT Services:

The rapid development of OTT platforms as stressed in the present study represents a broader change in the way users approach media and online information. According to the results, the convenience,

value, and social influence are an increasingly active driver of OTT services use, with significant implications to society behavior and cultural trends.

One of the most important social impacts that has taken place in the recent years is the shift towards collective to individualized media consumption. Conversely, the over-the-top (OTT) services allow a person to experience personalized viewing using personal gadgets like smartphones, unlike the usual family viewing often done on the television. Perhaps, this shift can narrow down the scope of mutual socialization that takes place within families, yet it will enhance the freedom of users and the choice of content. Simultaneously, the launch of a service such as watch parties, and sharing of content, proves that digital platforms are redefining, and not eliminating, a communal viewing experience.

The research emphasizes the increased importance of online communities and peer-based consumerism by pointing at the high role played by social influence in shaping the consumer purchasing behaviors. It is increasingly becoming usual that users are influenced by the recommendations of their friends, trends on the social media as well as discussions on the internet.

Popularity is shaped collectively and thus, to such phenomena as the binge-watching trends and viral shows at Netflix. Although this promotes community participation and the experience of other cultures, this can also result in herd behavior and the fear of missing out (FOMO), which affect the watching behavior of users, not just their own tastes.

Another important conclusion that can be made out of this discussion is the development of the routine consumption behaviors. The data shows that the consumption of the over-the-top (OTT) is becoming more and more embedded in the daily life of consumers. Although this renders entertainment and accessibility more accessible, it also gives cause to concern over overuse of the screen and behavior that contains binge viewing. Prolonged exposure to over-the-top (OTT) services can possibly impact productivity, sleeping and overall well-being, especially among younger users. This implies that more awareness regarding the consumption of media mindfully should be addressed.

Besides, the paper highlights the importance of cultural representation and content diversity. OTT platforms provide a chance to expand audiences to regional and specialty content, thus leading to the inclusion and representation of a culture. This can lead to the growth of cultural identification and provide an avenue in which voices that are generally underrepresented are heard. The international nature of over-the-top (OTT) content, in its turn, is associated with the risk of cultural homogeneity,

where the overwhelming international discourses could ruin local norms and values.

The sociological aspect of over-the-top (OTT) platforms contributes to the democratization of entertainment by providing people with high quality content and is accessible to people with different social economic backgrounds. Due to the relatively low responsiveness of income to adoption, it seems to be the case that the over-the-top (OTT) services are becoming increasingly accessible. This is supported by the data that is cheap and prices schemes flexible. Such an enhanced access can potentially shatter the entertainment industry barrier and enhance digital inclusiveness.

At the same time, the growth of dependence on digital platforms also brings concern about the privacy of data and the reliance on the digital technology. The issue of data security and ethical use is becoming more critical due to the over-the-top (OTT) services that obtain user data to enhance Personalization. In the name of ensuring the trustworthiness of the users, there is need to ensure transparency and proper data practices.

Generally, the conclusions indicate that over-the-top (OTT) platforms are not just Technological Innovations, but also social systems whose existence can influence the manner in which individuals interact with each other, acquire knowledge, and form cultural connections. Despite the reality that they place new challenges in regard to behavioral patterns, social connection, and online well-being, they also have significant advantages in regard to accessibility, Personalization, and interactivity. To combat these ramification, a holistic approach that encompasses the users, platforms and politicians, must be put in place.

5.7 - CONCLUSION

Having a special focus on the integration of the technological, experiential, and perceptual factors into a holistic theoretical framework, the present study was conducted with the aim to explore the factors, which affect the willingness to accept Over-The-Top (OTT) platforms in users. The foundation of this study was provided by the rising importance of over-the-top (OTT) platforms in the digital entertainment environment as it was suggested in the introduction chapter, which highlighted the shift towards the post-traditional media consumption experience and towards flexible, on-demand, and user-centric viewing experiences. The study was done within the framework of the clearly defined aims, and the objective was to learn not only about the determinants of adoption, but also about the relative importance of these determinants, and the moderating effects, and implications that the study will have in practice on the stakeholders.

The literature review was capable of developing a strong theoretical base through the synthesis of insights of the available models, including the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2) and the views of the media consumption and behavioral theories. Although conventional frameworks can explain functional aspects of technology adoption quite well, this synthesis enabled the realization that the conventional models need to be extended to a contextual level to explain the experience and content-based nature of over-the-top online technology platforms. This made the research offer a comprehensive framework that encompassed the concepts of content quality, perceived value, hedonic motivation, habit, and social impact. This was to fill the divide between the literature on the adoption of technologies and the literature on consumption of digital media.

A systematic and empirical approach of assessing the proposed model was provided in the paragraph on research methods. A quantitative study method was determined and a structured questionnaire, which was developed on the basis of the measurement scales, was utilized to gather primary data on 998 respondents. In conducting the data analysis, the study made use of the Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS. This approach made the data reliable both with regard to measurement and evaluation of structural model. Reliability and validity assessments indicated that reliability measurement of the dimensions was reliable. In addition, advanced techniques like Multi-Group Analysis (MGA) and Importance-Performance Map Analysis (IPMA) were applied in an attempt to provide deeper information on the moderating factors, and management priorities.

The experimental data that explained the recommended model was provided in the part that entailed the data analysis. The study indicates that the highest determinants that dictate the intention of a user to utilize the over-the-top (OTT) platforms include user performance expectations, perceived value expectations, and social influence expectations. Some other variables such as content quality, hedonic motivation, habit and price value were found to possess significant beneficial effects, although the impact of these variables was quite low. Personal innovativeness, in turn, did not demonstrate a significant impact, which is why the introduction of over-the-top (OTT) services is no longer a phenomenon motivated by innovation but a behavioral pattern that is more widespread in the mainstream society. The extent of variance in user intention which could be attributed to the specified predictors was very high which proved the fact that the model is characterized by a high degree of explanatory power. Moreover, the lack of significant moderating influence of gender and age difference showed that the behavior of an individual with regard to adoption of over-the-top (OTT)

services remains the same in all the demographic groups.

Considering all these data, the study concludes that the use of over-the-top (OTT) services is a phenomenon that is complex and constantly evolving. It is shaped through a combination of functional effectiveness, value perception, social bondage and experience. No longer are the tech-specifics the primary motivating force behind users, but instead, it is the effectiveness, with which platforms bring convenience, low prices, and meaningful content experiences that tend to get people excited. The shift of primary acceptance to habitual use is additional confirmation that over the top (OTT) tools are integrated into the daily life of the consumer as a matter of fact, which is indicative of a broader revolution in the behavior of digital consumption.

The paper highlights the reality that over-the-top (OTT) services are positioned at the intersections of technology, media, and society since it is a more holistic way of addressing the issues. Their success depends on their ability to integrate performance, value, content, and social interaction in an ecosystem that is coherent. Although technology infrastructure is under consideration very crucial, the results underline the reality that user experience, perceived benefits, and unceasing engagement are the drivers of long-term sustainability.

To sum up, this study provides a deep and empirically validated understanding of the adoption of over-the-top (OTT) services through the integration of the theoretical concepts and real-life information. By proving that the future of over-the-top (OTT) platforms lies in delivering not only content but also a holistic, value-driven, and social-connected consumer experience, it contributes to both the scholarly literature and the practice in the industry at one and the same time. With the further development of the consumption of digital content, the platforms that can effectively adjust to the complex needs of their users will have a greater chance of reaching sustainable development and be able to compete efficiently.

5.8 - FUTURE SCOPE AND LIMITATIONS

5.8.1 – Limitations

In spite of the fact that the current study provides great insights into the behavior of over-the-top (OTT) implementation, there are several limitations, which can be prone to, when interpreting the findings. The area of the research is also limited, as the information was collected in one specific place, which

is one of the main limitations. This can create a challenge in generalizing the results to other settings in different cultures or economies. Another benefit of cross-sectional study approach is that it enables the researcher to see what the users are doing at this single point in time, and the trends of usage of over-the-top (OTT) services are dynamic and constantly evolving. There is also the threat of the response bias, as the information that is self-reported is not necessarily the appropriate reflection of the actual behavior of the participants.

Also, the study focuses on specific constructs, i.e., performance anticipation, perceived value, quality of content, and social impact. The study did not cover other factors, which may be theoretically significant, like psychological factors, content preferences and platform-specific features. Regardless of the fact that advanced quantitative tools like PLS-SEM were applied, the absence of qualitative understandings prevents the formation of a deeper understanding of the reasons and outcomes of user experiences. Such limitations are the cause to be concerned about the significance of being cautious. When interpreting the data and precondition the further research, which can be constructed on the basis of the analysis and expands its area.

5.8.2 - Future Research Avenues -

Future Research Avenues

While this study offers meaningful insights into the technological, experiential, and perceptual determinants of OTT adoption in India, several avenues remain open for future research to extend and deepen this understanding.

Longitudinal Studies

This research employs a cross-sectional framework, assessing user perceptions and adoption intentions at a certain moment. Considering that OTT consumption patterns change as platforms develop, content collections grow, and pricing strategies alter, further studies might gain from a longitudinal methodology – monitoring the same users' adoption intentions and actual use behaviors over various time intervals. This would enable researchers to differentiate between the initial motivators for adoption and the elements that promote enduring engagement and loyalty, a dimension that the cross-sectional methodology of this study cannot adequately explore.

AI-Powered Recommendation Systems

As platforms progressively depend on AI and machine learning for tailoring content suggestions, forecasting watching inclinations, and enhancing user interaction, forthcoming research could investigate the unique function of algorithmic customization as a separate element in adoption frameworks. This would surpass the overarching technology elements encompassed in UTAUT3, providing a more detailed insight into how AI-driven customization uniquely influences user trust, happiness, and ongoing platform engagement.

Trust Mechanisms

This research did not specifically conceptualize trust as an independent variable, even tho it is probably pertinent to the uptake of OTT services - especially in light of increasing apprehensions over data privacy, algorithmic clarity, and platform dependability. Subsequent investigations might integrate trust-comprising aspects like platform trust, data privacy trust, and content authenticity trust-as a direct predictor or a mediating variable in the adoption framework, thereby providing enhanced understanding of the interplay between trust and the technological, experiential, and perceptual elements analyzed herein.

Comparative Interstate or Cross-Cultural Studies

Considering India's considerable linguistic, cultural, and socio-economic variety, the results of this study may not be universally applicable to all areas and demographic groups. Future investigations may employ a comparative framework - analyzing adoption trends across various states, linguistic areas, or urban-rural settings within India - to discern regional discrepancies in the determinants of OTT uptake. Furthermore, cross-cultural research contrasting Indian OTT adoption trends with those in other emerging or developed countries may aid in determining the applicability of the UTAUT3-based paradigm beyond India.

The findings of the current research leave several potential paths of further research in the framework of the rapidly evolving ecosystem of over-the-top firms. Longitudinal research designs are a critical field that needs to be sought to explore the changing behavior of the users with time. This is particularly important as regards to undergoing transition of first adoption to long term engagement and devotion. It would be better to increase the breadth of the study by using cross-cultural or cross-country studies to ascertain the generalizability of the findings. This would also provide more in-depth information

regarding the influence of the cultural, economic, and regulatory variables on the trends of over-the-top (OTT) adoption.

It is possible to study the impact of advanced technologies on the behavior of the user in the future. Artificial intelligence, recommendation systems, and Personalization algorithms are some of the examples of such technologies. To make a contribution to the theoretical and practical knowledge, it would be useful to explore the impact of these technologies on the discovery of information, user happiness, and habit development. Moreover, it is possible to explore psychological and behavioral factors, including the predisposition to binge-watching, the digital well-being condition, and the broader social consequences of the over-the-top (OTT) consuming behavior, to a considerable extent.

Even more so, to build an even more comprehensive model of over-the-top (OTT) adoption, future research may incorporate additional characteristics like brand loyalty, switching behavior, subscription fatigue, and use of multiple platforms. The employment of mixed-method techniques, i.e. the combination of quantitative and qualitative techniques, would lead to the development of more detailed results regarding the experiences and motivations of users. The use of complex analytical tools like machine learning and big data analytics could be used to further enhance predictive capabilities and expose complex behavioral patterns in the use of digital media.

REFERENCES

- Abbasi, G.A., Tiew, L.Y., Tang, J., Goh, Y.-N., & Thurasamy, R. (2021). The adoption of cryptocurrency as a disruptive force: Deep learning-based dual stage structural equation modelling and artificial neural network analysis. *PLOS ONE*, 16(3), Article e0247582. <https://doi.org/10.1371/journal.pone.0247582>
- Abdul Latiff, D. I., Muhamed Ayub, M. S., Kamal, S., Megat Zambri, W. A. A., & Salleh Abdul Latif, A. S. S. (2022). The role of personal innovativeness and social influence towards over-the-top (OTT) video streaming during the Covid-19 pandemic. *International Journal of Academic Research in Business and Social Sciences*, 12(6). <https://doi.org/10.6007/ijarbss/v12-i6/13998>
- Abdulwahab, L., & Dahalin, Z. M. (2010). A conceptual model of unified theory of acceptance and use of technology (UTAUT) modification with management effectiveness and program effectiveness in context of telecentre. *African Scientist*, 11(4).
- Aguiar, L., & Waldfogel, J. (2017). Netflix: Global hegemon or facilitator of frictionless digital trade? *Journal of Cultural Economics*, 42(3), 419–445. <https://doi.org/10.1007/s10824-017-9315-z>
- Alalwan, A. A., Dwivedi, Y. K., Rana, N. P., & Algharabat, R. (2018). Examining factors influencing Jordanian customers' intentions and adoption of internet banking: Extending UTAUT2 with risk. *Journal of Retailing and Consumer Services*, 40, 125–138. <https://doi.org/10.1016/j.jretconser.2017.08.026>
- Alalwan, A. A., Dwivedi, Y. K., Rana, N. P., Lal, B., & Williams, M. D. (2015). Consumer adoption of internet banking in Jordan: Examining the role of hedonic motivation, habit, self-efficacy and trust. *Journal of Financial Services Marketing*, 20(2), 145–157. <https://doi.org/10.1057/fsm.2015.5>
- Almarashdeh, I., Eldaw, K. E., Alsmadi, M., Alghamdi, F., Jaradat, G., Althunibat, A., Alzaqebah, M., & Mohammad, R. M. A. (2021). The adoption of bitcoins technology: The difference between perceived future expectation and intention to use bitcoins: Does social influence matter? *International Journal of Electrical and Computer Engineering*, 11(6), 5351–5366. <https://doi.org/10.11591/ijece.v11i6.pp5351-5366>

Arias-Oliva, M., Pelegrín-Borondo, J., & Matías-Clavero, G. (2019). Variables influencing cryptocurrency use: A technology acceptance model in Spain. *Frontiers in Psychology, 10*. <https://doi.org/10.3389/fpsyg.2019.00475>

Arjona Martín, J. B. (2021). Convergencia de medios. Plataformas audiovisuales por Internet (Over-The-Top) y su impacto en el mercado audiovisual en España. *Revista Latina de Comunicación Social, 79*, 35–52. <https://doi.org/10.4185/rlcs-2021-1496>

Arruda Filho, E. J. M., Simões, J. D. S., & De Muylder, C. F. (2019). The low effect of perceived risk in the relation between hedonic values and purchase intention. *Journal of Marketing Management, 36*(1–2), 128–148. <https://doi.org/10.1080/0267257x.2019.1697725>

Arun, T. M., Singh, S., Khan, S. J., Akram, M. U., & Chauhan, C. (2021). Just one more episode: Exploring consumer motivations for adoption of streaming services. *Asia Pacific Journal of Information Systems, 31*(1), 17–42.

Ayedh, A., Echchabi, A., Battour, M., & Omar, M. (2020). Malaysian Muslim investors' behavior towards the blockchain-based Bitcoin cryptocurrency market. *Journal of Islamic Marketing, 12*(4), 690–704. <https://doi.org/10.1108/jima-04-2019-0081>

Baki, M., & Amoozegar, A. (2021). The decision to adopt blockchain digital currency for the central bank in UAE. *Review of International Geographical Education, 11*(12), 567–583. <https://doi.org/10.48047/rigeo.11.12.54>

Baldry, S., Steingröver, M., & Hessler, M. A. (2014). *The rise of OTT players: What is the appropriate regulatory response?* Paper presented at the 25th European Regional Conference of the International Telecommunications Society (ITS).

Baptista, G., & Oliveira, T. (2015). Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators. *Computers in Human Behavior, 50*, 418–430. <https://doi.org/10.1016/j.chb.2015.04.024>

- Baur, A. W., Bühler, J., Bick, M., & Bonorden, C. S. (2015). Cryptocurrencies as a disruption? Empirical findings on user adoption and future potential of Bitcoin and Co. In *Lecture Notes in Computer Science* (pp. 63–80). Springer International Publishing. https://doi.org/10.1007/978-3-319-25013-7_6
- Bischof, S. F., Boettger, T. M., & Rudolph, T. (2020). Curated subscription commerce: A theoretical conceptualization. *Journal of Retailing and Consumer Services*, 54, Article 101822. <https://doi.org/10.1016/j.jretconser.2019.04.019>
- Bradley, G. T., & LaFleur, E. K. (2016). Toward the development of hedonic-utilitarian measures of retail service. *Journal of Retailing and Consumer Services*, 32, 60–66. <https://doi.org/10.1016/j.jretconser.2016.06.001>
- Bridges, E., & Florsheim, R. (2008). Hedonic and utilitarian shopping goals: The online experience. *Journal of Business Research*, 61(4), 309–314. <https://doi.org/10.1016/j.jbusres.2007.06.017>
- Brodie, R. J., Hollebeek, L. D., Jurić, B., & Ilić, A. (2011). Customer engagement. *Journal of Service Research*, 14(3), 252–271. <https://doi.org/10.1177/1094670511411703>
- Brown, S. A., Dennis, A. R., & Venkatesh, V. (2010). Predicting collaboration technology use: Integrating technology adoption and collaboration research. *Journal of Management Information Systems*, 27(2), 9–54. <https://doi.org/10.2753/mis0742-1222270201>
- Cesareo, L., & Pastore, A. (2014). Consumers' attitude and behavior towards online music piracy and subscription based services. *Journal of Consumer Marketing*, 31(6/7), 515–525. <https://doi.org/10.1108/JCM-07-2014-1070>
- Chakraborty, S., & Ghosh, A. (2021). Over-the-top (OTT) media platforms in India: Growth, opportunities and challenges. *International Journal of Creative Research Thoughts*, 9(3), 5832–5838.
- Chang, H. H., & Chen, S. W. (2008). The impact of online store environment cues on purchase intention: Trust and perceived risk as a mediator. *Online Information Review*, 32(6), 818–841. <https://doi.org/10.1108/14684520810923953>

Chauhan, S., & Jaiswal, M. (2016). Determinants of acceptance of ERP software training in business schools: Empirical investigation using UTAUT model. *The International Journal of Management Education*, 14(3), 248–262. <https://doi.org/10.1016/j.ijme.2016.05.005>

Chen, Y.-N. K. (2019). Competitions between OTT TV platforms and traditional television in Taiwan: A niche analysis. *Telecommunications Policy*, 43(9), Article 101793. <https://doi.org/10.1016/j.telpol.2018.10.006>

Cheung, R., & Vogel, D. (2013). Predicting user acceptance of collaborative technologies: An extension of the technology acceptance model for e-learning. *Computers & Education*, 63, 160–175. <https://doi.org/10.1016/j.compedu.2012.12.003>

Chopdar, J., & Tarafdar, T. (2021). A study on consumers' perception towards Over The Top (OTT) platforms with special reference to Guwahati city. *International Journal of Advanced Research in Commerce, Management & Social Science*, 4(2-II), 245–254.

Dasgupta, S., & Grover, P. (2019). Understanding adoption factors of over-the-top video services among millennial consumers. *International Journal of Computer Engineering & Technology*, 10(1), 61–71.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340.

De Matos, M., Ferreira, P., & Smith, M. D. (2018). The effect of subscription video-on-demand on piracy: Evidence from a household-level randomized experiment. *Management Science*, 64(12), 5610–5630. <https://doi.org/10.1287/mnsc.2017.2875>

Dhir, A., Kaur, P., & Rajala, R. (2018). Why do young people tag photos on social networking sites? Explaining user intentions. *International Journal of Information Management*, 38(1), 117–127. <https://doi.org/10.1016/j.ijinfomgt.2017.07.004>

Elagin, V. S., Belozertsev, I. A., Goldshtein, B. S., Onufrienko, A. V., & Vladyko, A. G. (2019). Models of QoE ensuring for OTT services. *2019 Systems of Signal Synchronization, Generating and Processing in Telecommunications*, 1–4.

Escobar-Rodríguez, T., & Carvajal-Trujillo, E. (2013). Online drivers of consumer purchase of website airline tickets. *Journal of Air Transport Management*, 32, 58–64. <https://doi.org/10.1016/j.jairtraman.2013.06.018>

Escobar-Rodríguez, T., & Carvajal-Trujillo, E. (2014). Online purchasing tickets for low cost carriers: An application of the unified theory of acceptance and use of technology (UTAUT) model. *Tourism Management*, 43, 70–88. <https://doi.org/10.1016/j.tourman.2014.01.017>

Etemad-Sajadi, R., & Ghachem, L. (2015). The impact of hedonic and utilitarian value of online avatars on e-service quality. *Computers in Human Behavior*, 52, 81–86. <https://doi.org/10.1016/j.chb.2015.05.048>

Evens, T. (2014). *Clash of TV platforms: How broadcasters and distributors build platform leadership*. Paper presented at the 25th European Regional Conference of the International Telecommunications Society (ITS).

Farooq, A., Dubinina, A., Virtanen, S., & Isoaho, J. (2021). Understanding dynamics of initial trust and its antecedents in password managers adoption intention among young adults. *Procedia Computer Science*, 184, 266–274. <https://doi.org/10.1016/j.procs.2021.03.036>

Farooq, M., & Raju, V. (2019). Impact of over-the-top (OTT) services on the telecom companies in the era of transformative marketing. *Global Journal of Flexible Systems Management*, 20(2), 177–188. <https://doi.org/10.1007/s40171-019-00209-6>

Farzin, M., Sadeghi, M., Yahyayi Kharkeshi, F., Ruholahpur, H., & Fattahi, M. (2021). Extending UTAUT2 in M-banking adoption and actual use behavior: Does WOM communication matter? *Asian Journal of Economics and Banking*, 5(2), 136–157. <https://doi.org/10.1108/ajeb-10-2020-0085>

Gimpel, G. (2015). The future of video platforms: Key questions shaping the TV and video industry. *International Journal on Media Management*, 17(1), 25–46. <https://doi.org/10.1080/14241277.2015.1014039>

Gupta, G., & Singharia, K. (2021). Consumption of OTT media streaming in COVID-19 lockdown: Insights from PLS analysis. *Vision: The Journal of Business Perspective*, 25(1), 36–46.

<https://doi.org/10.1177/0972262921989118>

Gupta, S. (2023). The impact of e-WOM on users' attitudes toward over-the-top (OTT) streaming video content and its subscription intention. *International Journal of Professional Business Review*, 8(2), Article e01046. <https://doi.org/10.26668/businessreview/2023.v8i2.1046>

Gupta, S., Gupta, S., Mathew, M., & Sama, H. R. (2020). Prioritizing intentions behind investment in cryptocurrency: A fuzzy analytical framework. *Journal of Economic Studies*, 48(8), 1442–1459. <https://doi.org/10.1108/jes-06-2020-0285>

Habib, S., Hamadneh, N. N., & Hassan, A. (2022). The relationship between digital marketing, customer engagement, and purchase intention via OTT platforms. *Journal of Mathematics*, 2022(1). <https://doi.org/10.1155/2022/5327626>

Hair, J. F., Astrachan, C. B., Moisesescu, O. I., Radomir, L., Sarstedt, M., Vaithilingam, S., & Ringle, C. M. (2021). Executing and interpreting applications of PLS-SEM: Updates for family business researchers. *Journal of Family Business Strategy*, 12(3), Article 100392. <https://doi.org/10.1016/j.jfbs.2020.100392>

Haritha, T., & Joseph, V. (2021). A study on the forthcoming revolution of entertainment service: Over the top (OTT). *International Research Journal of Modernization in Engineering Technology and Science*, 3(9), 1643–1646.

Hasan, S. Z., Ayub, H., Ellahi, A., & Saleem, M. (2022). A moderated mediation model of factors influencing intention to adopt cryptocurrency among university students. *Human Behavior and Emerging Technologies*, 2022, 1–14. <https://doi.org/10.1155/2022/9718920>

Hew, J.-J., Lee, V.-H., Ooi, K.-B., & Wei, J. (2015). What catalyses mobile apps usage intention: An empirical analysis. *Industrial Management & Data Systems*, 115(7). <https://doi.org/10.1108/IMDS-01-2015-0028>

Hoang, A. P. (2018). *From digital traces to marketing insights: Recovering consumer preferences for digital entertainment services and online shopping* [Doctoral dissertation, Singapore Management University]. https://ink.library.smu.edu.sg/etd_coll/178

Isa, A. M., Mahmud, W. A. W., Sulaiman, W. I. W., & Pitchan, M. A. (2021). The adoption and trend of over-the-top streaming media among the Malaysian audiences. *Annals of the Romanian Society for Cell Biology*, 25(5), 1109–1127.

Jariyapan, P., Mattayaphutorn, S., Gillani, S. N., & Shafique, O. (2022). Factors influencing the behavioral intention to use cryptocurrency in emerging economies during the COVID-19 pandemic: Based on technology acceptance model 3, perceived risk, and financial literacy. *Frontiers in Psychology*, 12. <https://doi.org/10.3389/fpsyg.2021.814087>

Jirakasem, M., & Mitomo, H. (2019). *Relationship of over-the-top (OTT) communications and traditional telecommunications services: The case of Thailand*. Paper presented at the 30th European Conference of the International Telecommunications Society (ITS).

Jolley, B., Mizerski, R., & Olaru, D. (2006). How habit and satisfaction affects player retention for online gambling. *Journal of Business Research*, 59(6), 770–777. <https://doi.org/10.1016/j.jbusres.2006.01.017>

Jose, R. J. (2020). Factors influencing the shift from traditional TV to OTT platforms in India. *International Journal of Advanced Science and Technology*, 29(7s), 4044–4051.

Joshi, S., Sarkar, S., Dewan, T., Dharmani, C., & Purohit, S. (2015). Impact of over the top (OTT) services on telecom service providers. *Indian Journal of Science and Technology*, 8(S4), 1–6.

Kamei, M. (2019). Trends and technology in the era of post TV: The rise of OTT platforms. *Think India Journal*, 22(33), 184–192.

Khechine, H., Raymond, B., & Augier, M. (2020). The adoption of a social learning system: Intrinsic value in the UTAUT model. *British Journal of Educational Technology*, 51(6), 2306–2325. <https://doi.org/10.1111/bjet.12905>

Kim, J., Kim, S., & Nam, C. (2016). Competitive dynamics in the Korean video platform market: Traditional pay TV platforms vs. OTT platforms. *Telematics and Informatics*, 33(2), 711–721. <https://doi.org/10.1016/j.tele.2015.06.014>

- Kim, M. S., Kim, E., Hwang, S., Kim, J., & Kim, S. (2017). Willingness to pay for over-the-top services in China and Korea. *Telecommunications Policy*, 41(3), 197–207. <https://doi.org/10.1016/j.telpol.2016.12.011>
- Kim, S., Lee, C., Lee, J., & Kim, J. (2021). Over-the-top bundled services in the Korean broadcasting and telecommunications market: Consumer preference analysis using a mixed logit model. *Telematics and Informatics*, 61, Article 101599. <https://doi.org/10.1016/j.tele.2021.101599>
- Kim, Y. H., Kim, D. J., & Wachter, K. (2013). A study of mobile user engagement (MoEN): Engagement motivations, perceived value, satisfaction, and continued engagement intention. *Decision Support Systems*, 56, 361–370. <https://doi.org/10.1016/j.dss.2013.07.002>
- Kumari, T. (2020). A study on growth of over the top (OTT) video services in India. *International Journal of Latest Research in Humanities and Social Science*, 3(9), 68–73.
- Kwak, D., & Kim, M. (2020). Trade negotiations in the digital era: The case of OTT video streaming services. *Global Policy*, 11(S2), 14–22. <https://doi.org/10.1111/1758-5899.12819>
- Lee, C. C., Nagpal, P., Ruane, S. G., & Lim, H. S. (2018). Factors affecting online streaming subscriptions. *Communications of the IIMA*, 16(1). <https://doi.org/10.58729/1941-6687.1394>
- Lee, H. Y., Qu, H., & Kim, Y. S. (2007). A study of the impact of personal innovativeness on online travel shopping behavior-A case study of Korean travelers. *Tourism Management*, 28(3), 886–897. <https://doi.org/10.1016/j.tourman.2006.04.013>
- Madhani, R., & Nakhate, V. (2020). Comparative study of viewers' behavior over traditional television channels and over OTT video platforms in Maharashtra. *International Journal of Advanced Science and Technology*, 29(12s), 1046–1057.
- Madnani, D., Fernandes, S., & Madnani, N. (2020). Analysing the impact of COVID-19 on over-the-top media platforms in India. *International Journal of Pervasive Computing and Communications*, 16(5), 457–475. <https://doi.org/10.1108/ijpcc-07-2020-0083>

- Magsamen-Conrad, K., Upadhyaya, S., Joa, C. Y., & Dowd, J. (2015). Bridging the divide: Using UTAUT to predict multigenerational tablet adoption practices. *Computers in Human Behavior*, 50, 186–196. <https://doi.org/10.1016/j.chb.2015.03.032>
- Marinković, V., Đorđević, A., & Kalinić, Z. (2019). The moderating effects of gender on customer satisfaction and continuance intention in mobile commerce: A UTAUT-based perspective. *Technology Analysis & Strategic Management*, 32(3), 306–318. <https://doi.org/10.1080/09537325.2019.1655537>
- Martins, C., Oliveira, T., & Popovič, A. (2014). Understanding the internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. *International Journal of Information Management*, 34(1), 1–13. <https://doi.org/10.1016/j.ijinfomgt.2013.06.002>
- Maslowska, E., Malthouse, E. C., & Viswanathan, V. (2017). Do customer reviews drive purchase decisions? The moderating roles of review exposure and price. *Decision Support Systems*, 98, 1–9. <https://doi.org/10.1016/j.dss.2017.03.010>
- Mazambani, L., & Mutambara, E. (2020). Predicting FinTech innovation adoption in South Africa: The case of cryptocurrency. *African Journal of Economic and Management Studies*, 11(1), 30–50. <https://doi.org/10.1108/AJEMS-04-2019-0152>
- McCarthy, D. M., Fader, P. S., & Hardie, B. G. S. (2017). Valuing subscription-based businesses using publicly disclosed customer data. *Journal of Marketing*, 81(1), 17–35. <https://doi.org/10.1509/jm.15.0519>
- Migliore, G., Wagner, R., Cechella, F. S., & Liébana-Cabanillas, F. (2022). Antecedents to the adoption of mobile payment in China and Italy: An integration of UTAUT2 and innovation resistance theory. *Information Systems Frontiers*, 24(6), 2099–2122. <https://doi.org/10.1007/s10796-021-10237>
- Moin, S. M. A., Devlin, J., & McKechnie, S. (2015). Trust in financial services: Impact of institutional trust and dispositional trust on trusting belief. *Journal of Financial Services Marketing*, 20(2), 145–157.
- Muchlis Gazali, H., Hafiz Bin Che Ismail, C. M., & Amboala, T. (2018). Exploring the intention to invest in cryptocurrency: The case of Bitcoin. *2018 International Conference on Information and*

Communication Technology for the Muslim World (ICT4M), 64–68.
<https://doi.org/10.1109/ict4m.2018.00021>

Nagaraj, S., Singh, S., & Yasa, V. R. (2021). Factors affecting consumers' willingness to subscribe to over-the-top (OTT) video streaming services in India. *Technology in Society*, 65, Article 101534.
<https://doi.org/10.1016/j.techsoc.2021.101534>

Narayan Subudhi, R., & Palai, D. (2020). Impact of internet use during COVID lockdown. *Journal of Humanities and Social Sciences Research*, 2(S), 59–66.
<https://doi.org/10.37534/bp.jhssr.2020.v2.ns.id1072.p59>

Nhedzi, A. (2018). The relationship between traditional and digital media as an influence on generational consumer preference. *COMMUNITAS*, 23(1), 18–38.
<https://doi.org/10.18820/24150525/comm.v23.2>

Nisal, K. S. (2020). The convergence model and content regulation of OTT platforms in India: An analytical study. *Sanshodhan: National Level Annual Peer Reviewed Research Journal*, 10, 36–41.

Oliveira, T., Faria, M., Thomas, M. A., & Popović, A. (2014). Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM. *International Journal of Information Management*, 34(5), 689–703. <https://doi.org/10.1016/j.ijinfomgt.2014.06.004>

Oyedele, A., & Simpson, P. M. (2018). Streaming apps: What consumers value. *Journal of Retailing and Consumer Services*, 41, 296–304. <https://doi.org/10.1016/j.jretconser.2017.04.006>

Pan, S., & Jordan-Marsh, M. (2010). Internet use intention and adoption among Chinese older adults: From the expanded technology acceptance model perspective. *Computers in Human Behavior*, 26(5), 1111–1119. <https://doi.org/10.1016/j.chb.2010.03.015>

Park, J., & Ha, S. (2016). Co-creation of service recovery: Utilitarian and hedonic value and post-recovery responses. *Journal of Retailing and Consumer Services*, 28, 310–316.
<https://doi.org/10.1016/j.jretconser.2015.01.003>

Park, S., & Kwon, Y. (2019). *Research on the relationship between the growth of OTT service market*

and the change in the structure of the pay-TV market. Paper presented at the 30th European Conference of the International Telecommunications Society (ITS).

Paul, D. V. (2020). A study on over the top platforms on DTH and its impact on consumer behavior. *International Journal of Research in Engineering, Science and Management*, 3(3), 457–460.

Poulose, S. (2020). A study on customer satisfaction towards cable TV network and online video streaming services in Chennai. *PalArch's Journal of Archaeology of Egypt/Egyptology*, 17(6), 1–15.

Ramkumar, B., & Woo, H. (2018). Modeling consumers' intention to use fashion and beauty subscription-based online services (SOS). *Fashion and Textiles*, 5(1), Article 22. <https://doi.org/10.1186/s40691-018-0137-1>

Reiter, U., Brunnström, K., De Moor, K., Larabi, M.-C., Pereira, M., Pinheiro, A., You, J., & Zgank, A. (2014). Factors influencing quality of experience. In *Quality of Experience: Advanced Concepts, Applications, and Methods* (pp. 55–72). Springer. https://doi.org/10.1007/978-3-319-02681-7_4

Roussou, I., Stiakakis, E., & Sifaleras, A. (2019). An empirical study on the commercial adoption of digital currencies. *Information Systems and E-Business Management*, 17, 223–259. <https://doi.org/10.1007/s10257-019-00426-7>

Ryu, H.-S. (2018). What makes users willing or hesitant to use Fintech?: The moderating effect of user type. *Industrial Management & Data Systems*, 118(3), 541–569. <https://doi.org/10.1108/imds-07-2017-0325>

Sagnier, C., Loup-Escande, E., Lourdeaux, D., Thouvenin, I., & Valléry, G. (2020). User acceptance of virtual reality: An extended technology acceptance model. *International Journal of Human–Computer Interaction*, 36(11), 993–1007. <https://doi.org/10.1080/10447318.2019.1708612>

Shankar, V., Smith, A. K., & Rangaswamy, A. (2003). Customer satisfaction and loyalty in online and offline environments. *International Journal of Research in Marketing*, 20(2), 153–175. [https://doi.org/10.1016/S0167-8116\(03\)00016-8](https://doi.org/10.1016/S0167-8116(03)00016-8)

Sharma, K. (2022). Analysis of cryptocurrency: An ethical conjecture with reference to Indian scenario. *Sachetas*, 1(1), 1–7.

Shen, C., Ho, J., Kuo, T.-C., & Luong, T. H. (2017). Behavioral intention of using virtual reality in learning. In *Proceedings of the 26th International Conference on World Wide Web Companion* (pp. 129–137). <https://doi.org/10.1145/3041021.3054152>

Shin, D.-H. (2009). Towards an understanding of the consumer acceptance of mobile wallet. *Computers in Human Behavior*, 25(6), 1343–1354. <https://doi.org/10.1016/j.chb.2009.06.001>

Shin, J., Park, Y., & Lee, D. (2016). Strategic management of over-the-top services: Focusing on Korean consumer adoption behavior. *Technological Forecasting and Social Change*, 112, 329–337. <https://doi.org/10.1016/j.techfore.2016.08.004>

Shin, S., & Park, J. (2021). Factors affecting users' satisfaction and dissatisfaction of OTT services in South Korea. *Telecommunications Policy*, 45(9), Article 102203 <https://doi.org/10.1016/j.telpol.2021.102203>

Singh, S., Singh, N., Kalinić, Z., & Liébana-Cabanillas, F. J. (2021). Assessing determinants influencing continued use of live streaming services: An extended perceived value theory of streaming addiction. *Expert Systems with Applications*, 168, Article 114241. <https://doi.org/10.1016/j.eswa.2020.114241>

Sujata, J., Sohag, S., Tanu, D., Chintan, D., Shubham, P., & Sumit, G. (2015). Impact of over the top (OTT) services on telecom service providers. *Indian Journal of Science and Technology*, 8(S4), 145. <https://doi.org/10.17485/ijst/2015/v8is4/62238>

Sundaravel, E., & Elangovan, N. (2020). Emergence and future of over-the-top (OTT) video services in India: An analytical research. *International Journal of Business, Management and Social Research*, 8(2), 489–499. <https://doi.org/10.18801/ijbmsr.080220.50>

Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly*, 24(1), 115–139. <https://doi.org/10.2307/3250981>

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1),

157–178. <https://doi.org/10.2307/41410412>

Verhoef, P. C., Reinartz, W. J., & Krafft, M. (2010). Customer engagement as a new perspective in customer management. *Journal of Service Research*, 13(3), 247–252. <https://doi.org/10.1177/1094670510375461>

Voss, K. E., Spangenberg, E. R., & Grohmann, B. (2003). Measuring the hedonic and utilitarian dimensions of consumer attitude. *Journal of Marketing Research*, 40(3), 310–320. <https://doi.org/10.1509/jmkr.40.3.310.19238>

Wan, X., Cenamor, J., & Chen, J. (2017). Exploring performance determinants of China's cable operators and OTT service providers in the era of digital convergence-From the perspective of an industry platform. *Sustainability*, 9(12), Article 2247. <https://doi.org/10.3390/su9122247>

Widodo, M., Irawan, M. I., & Sukmono, R. A. (2019). Extending UTAUT2 to explore digital wallet adoption in Indonesia. *2019 International Conference on Information and Communications Technology (ICOIACT)*, 599–604.

Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): A literature review. *Journal of Enterprise Information Management*, 28(3), 443–488. <https://doi.org/10.1108/jeim-09-2014-0088>

Woo, H., & Ramkumar, B. (2018). Who seeks a surprise box? Predictors of consumers' use of fashion and beauty subscription-based online services (SOS). *Journal of Retailing and Consumer Services*, 41, 121–130. <https://doi.org/10.1016/j.jretconser.2017.11.011>

Yadav, M., Singh, P., & Baral, S. K. (2023). A study on user acceptance of OTT platform: An extended UTAUT2 model. *Scope*, 13(2).

Yang, K., & Jolly, L. D. (2009). The effects of consumer perceived value and subjective norm on mobile data service adoption between American and Korean consumers. *Journal of Retailing and Consumer Services*, 16(6), 502–508. <https://doi.org/10.1016/j.jretconser.2009.08.003>

Yosser, I. M., Syed Idrus, S. Z. B., & Ali, A. A. E. (2020). Technology readiness index 2.0 as predictors

of e-health readiness among potential users: A case of conflict regions in Libya. *Journal of Physics: Conference Series*, 1529(3), Article 032009. <https://doi.org/10.1088/1742-6596/1529/3/032009>

APPENDIX – A

SURVEY QUESTIONNAIRE

I am VAGHELA NILRAJSINH JAYENDRASINH, a Ph.D. student enrolled at Gujarat Technological University, Ahmedabad. The data is being collected solely for research on “A Study of the Factors Affecting the Intention to Subscribe to OTT Services in Gujarat.” The information provided will be kept strictly confidential and will not be shared with any individual or organization.

ENTRY LEVEL QUESTION:

Are you using any OTT Platforms?

☐ Yes ☐ No

BASIC INFORMATION (Confidential)

Name: _____

Email: _____

Phone: _____

Gender:

☐ Male ☐ Female

Age Group:

☐ 18–21

☐ 22–25

☐ 26–35

☐ Above 36

Annual Income:

☐ Below 1,00,000

☐ 1,00,000 – 3,00,000

☐ 3,00,000 – 5,00,000

☐ 5,00,000 – 7,00,000

☐ Above 7,00,000

Education Level:

☐ Undergraduate

☐ Graduate

☐ Postgraduate

☐ Professional

☐ Other

Occupation:

☐ Self-Employed

[] Private Employee

- ☐ Government Employee
- ☐ Student
- ☐ Homemaker
- ☐ Retired
- ☐ Others

OTT Platforms Subscribed:

- ☐ Netflix
- ☐ Amazon Prime
- ☐ Disney+ Hotstar
- ☐ SonyLIV
- ☐ ZEE5
- ☐ JioCinema
- ☐ Others

1. Which device do you prefer most to use OTT apps?

- ☐ Smartphone
- ☐ Smart TV
- ☐ Laptop
- ☐ Tablet
- ☐ Desktop Computer
- ☐ Streaming Device
- ☐ Other

2. What features do you like the most in OTT apps?

- ☐ Wide Content Variety
- ☐ High-Quality Streaming
- ☐ Offline Viewing
- ☐ Personalized Recommendations
- ☐ Multiple User Profiles
- ☐ Ad-Free Option
- ☐ Cross-Platform Sync
- ☐ Customizable Subtitles

3. How much time do you spend weekly on OTT platforms?

- ☐ Less than 5 hours
 - ☐ 5–8 hours
 - ☐ 9–12 hours
 - ☐ 13–16 hours
 - ☐ 17–20 hours
 - ☐ More than 20 hours
-

4. What are the main reasons for using OTT platforms?

- ☐ Entertainment (Movies, TV Shows)
 - ☐ Original Content
 - ☐ Convenience (Anytime, Anywhere)
 - ☐ Cost
 - ☐ Variety of Content
 - ☐ Recommendations
 - ☐ Other
-

5. You have been using OTT platforms since:

- ☐ Less than 6 months
 - ☐ 6 months – 1 year
 - ☐ 1–3 years
 - ☐ 3–5 years
 - ☐ More than 5 years
-

LIKERT SCALE:

(1 = Strongly Disagree, 7 = Strongly Agree)

1. Personal Innovativeness

[1][2][3][4][5][6][7]

- I'd like to be one of the first to experience new things.
 - I'd like to experience a new internet function or service.
 - I think I'm a creative person.
 - I usually try new internet services before others.
-

2. Facilitating Conditions

[1][2][3][4][5][6][7]

- I have the resources necessary to use OTT platforms.
 - I have the knowledge necessary to use the platform.
 - The platform is compatible with other systems I use.
 - Assistance is available when I face difficulties.
-

3. Price Value

[1][2][3][4][5][6][7]

- OTT apps are reasonably priced.

- OTT apps offer good value for money.
 - At the current price, OTT apps provide good value.
-

4. Habit

[1][2][3][4][5][6][7]

- Using OTT services is natural for me.
 - Using OTT services has become automatic.
 - Choosing OTT is my habit for watching content.
 - I find OTT the easiest way to watch content.
 - I prefer OTT over other alternatives.
-

5. Social Influence

[1][2][3][4][5][6][7]

- I would consider paying if others around me do.
 - Paying for OTT improves my social image.
 - Paying helps me connect with others.
-

6. Hedonic Motivation

[1][2][3][4][5][6][7]

- Using OTT platforms is fun.
 - Using OTT platforms is enjoyable.
 - Using OTT platforms is entertaining.
-

7. Performance Expectancy

[1][2][3][4][5][6][7]

- OTT platforms are useful for accessing information.
 - They help me access information quickly.
 - They improve my productivity.
 - They help me get timely information.
-

8. Perceived Value

[1][2][3][4][5][6][7]

- Paid OTT improves viewing experience.
- Paid OTT provides better access to content.

- Paid OTT increases enjoyment.
 - Paid OTT makes life convenient.
-

9. Content Quality

[1][2][3][4][5][6][7]

- OTT provides unique and entertaining content.
 - OTT offers global content variety.
 - OTT provides regional/local content.
-

10. Purchase Intention

[1][2][3][4][5][6][7]

- I intend to pay for OTT services.
 - I will continue purchasing OTT services.
 - I would recommend OTT services to others.
-

List of Publications

1. "THE NEXT CLICK: FACTORS DRIVING OTT PLATFORMS ADOPTION" published by Nilrajsinh Vaghela and Dr. Kerav Pandya in ShodhKosh: Journal of Visual and Performing Arts under ISSN Number - 2582-7472 in January 2024.
2. "HABIT FORMATION AND CONTINUOUS USAGE OF OTT PLATFORMS: AN EXTENDED UTAUT PERSPECTIVE" published by Nilrajsinh Vaghela and Dr. Kerav Pandya in International Journal of Management, Economics and Commerce under ISSN Number - 2584-2609 in September 2025.