IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Demographic Influences On Mobile Shopping Apps Adoption: An Empirical Study Using The UTAUT Framework

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Abstract: This research examines the factors influencing the adoption of mobile shopping apps among Indian consumers using the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. With India's rapid growth in e-commerce, rising internet access, and increasing smartphone use, consumer behaviour has shifted toward mobile shopping. The study surveyed 300 users of mobile shopping apps in Haryana through structured questionnaires. It employed quantitative methods, including t-tests and ANOVA, to analyse the impact of demographic factors such as age, gender, and residential status. Results reveal significant differences in adoption intentions across demographic groups. Specifically, younger users demonstrate higher engagement due to convenience and affordability; males are more influenced by subjective norms and facilitating conditions; and rural consumers are more affected by social factors than urban consumers. The study highlights the importance of tailored strategies, improved app usability, and digital literacy initiatives to promote the adoption of mobile shopping. These findings offer practical insights for businesses, marketers, developers, and policymakers seeking to enhance user experience and expand market reach in India's mobile e-commerce sector.

Index Terms - Mobile shopping, M-shopping apps, UTAUT, Adoption .

1. Introduction

Mobile shopping apps have become a popular and convenient way for people to shop, making digital purchases a common practice today (Bourlakis et al., 2008). People are increasingly using mobile shopping for items like clothing, electronics, and even livestock. Every year, new web browsers and shopping apps are launched to meet the growing demand for fast, easy shopping. The combination of traditional and online stores has made shopping easier than ever before. The electronics market is highly dynamic and diverse (Bhattacherjee, 2001; Rahi, 2015). The increase in internet access and smartphone use has fueled the growth of India's e-commerce sector. As more people gain access to the internet, there is a clear shift in consumer behaviour from traditional shopping to mobile shopping in India. India's e-commerce market is projected to reach $350 billion by 2030, up from $46.2 billion in 2020, changing how businesses operate in the country (Khurana, 2022). India is projected to become one of the world's fastest-growing economies and is expected to surpass Germany and the UK by 2027, making it the fourth-largest global economy (Kearney, 2024). Over the past decade, India has developed into a major player in retail, ranking as the third-largest retail market globally as of 2024 (Shetu et al., 2025). Additionally, India, which has the second-largest number of online consumers worldwide, is a key force in the e-commerce sector, anticipated to reach between $170 billion and $190 billion by 2030 with an annual growth rate of over 18% (Shetu et al., 2025). In recent years, a notable trend has been the rise of rural consumers, with about 55% of new internet users expected to come from rural areas by 2025 (Kearney, 2024).

2. LITERATURE REVIEW AND HYPOTHESES

The UTAUT model is widely used to understand why people adopt mobile apps and other technologies. It brings together previous ideas from technology acceptance, mainly from the Technology Acceptance Model (TAM) developed by Davis (1989), which is based on the theory by Fishbein and Ajzen (1975). TAM was later expanded into TAM 2 and TAM 3 to include factors such as user satisfaction and technology use in e-commerce (Venkatesh & Davis, 2000; Venkatesh & Bala, 2008). UTAUT combines all these models to focus on four main factors: expected performance, expected effort, social influence, and facilitating conditions. It also considers individual differences such as gender, age, experience, and needs, which can affect technology acceptance. Research has shown that UTAUT explains about 70% of the reasons why people decide to use technology (Venkatesh et al., 2003). This model has been widely applied in studies of mobile applications, information systems, and online platforms. In summary, UTAUT helps explain how useful and easy a technology is perceived to be, how social influences play a part, and whether support is available, while also factoring in personal characteristics (Venkatesh et al., 2003; Davis, 1989; Venkatesh & Davis, 2000; Venkatesh & Bala, 2008; Fishbein & Ajzen, 1975). The UTAUT model, introduced by Venkatesh et al. (2003), was used in this study as a framework to explore consumers' intentions to use mobile shopping apps. This model, combines elements from eight major technology acceptance theories and models, including the Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), Social Cognitive Theory (SCT), Innovation Diffusion Theory (IDT), Model of PC Utilization (MPCU), Motivational Model (MM), and the combined TAM and TPB model (C-TAM-TPB). Key factors in UTAUT include performance expectancy (similar to TAM's perceived usefulness), effort expectancy (ease of use), social influence, and facilitating conditions (perceived behavioural control). This study used the UTAUT model to assess behavioural intentions for online shopping in India, specifically addressing limitations identified in earlier research (Tamilmani et al., 2018) and accounting for individual differences such as age, gender, and place of residence. Venkatesh et al. (2003) originally suggested that gender, age, experience, and need could affect technology acceptance. Here, the study focused on age, gender, and whether respondents lived in urban or rural areas, since these factors influence people's needs and intentions to adopt new technology.

2.1 Performance expectancy

According to the UTAUT model, performance expectancy is "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" [Venkatesh et al., (2003), p.447]. It is a crucial factor that predicts whether someone intends to use technology, whether it is required or voluntary (Ling et al., 2020; Venkatesh et al., 2003). If a technology is better than what is currently available, users tend to adopt it because they expect it to help them perform their jobs more effectively (Al-Qudah et al., 2024; Verkijika, 2018). This has been shown across various settings, including mobile payment systems (Alalwan et al., 2016, 2017, 2018; Rita et al., 2019), online shopping (Celik, 2016; Tandon & Kiran, 2018; Kumar & Usman, 2024), and mobile shopping apps (Chopdar et al., 2019; Tak & Panwar, 2017).

2.2 Effort expectancy

Effort Expectancy is "the degree of ease associated with the use of the system" [Venkatesh et al., (2003), p.450]. It plays a strong role in shaping the intention to adopt technology, combining ideas from previous models about ease of use and system complexity (Venkatesh et al., 2003). Users with some knowledge and skills expect an easier experience, which motivates them to invest effort in learning and using systems such as mobile payments (Alalwan et al., 2016, 2017). Research highlights effort expectancy as a key factor in mobile payment adoption (Alalwan et al., 2017, 2018; Al-Qudah et al., 2024) and mobile shopping usage (Celik, 2016; Chopdar et al., 2019; Dewi et al., 2020; Tak & Panwar, 2017; Tandon & Kiran, 2018).

2.3. Social influence

It is defined as “The degree to which a customer believes that significant individuals (friends, family, coworkers, etc.) think they should utilise a certain technology is known as social influence” (Venkatesh et al., 2012). For example, if friends and family think someone should use digital payments, that person is more likely to adopt them. Social influence is a strong predictor of technology use and builds on earlier concepts such as subjective norms and social factors (Venkatesh et al., 2003). Studies consistently find a positive link between social influence and the intention to use mobile or online shopping apps (Tak & Panwar, 2017; Chopdar & Sivakumar, 2019; An et al., 2016; Tandon & Kiran, 2018; Celik, 2016; Dewi et al., 2020).

2.4 Facilitating conditions

Facilitating Conditions is "the extent to which an individual feels that there exists an organisational and technical infrastructure and that it will assist him/her in usage of the system" [Venkatesh et al., (2003), p.453]. This concept reflects consumers' perceptions of the resources and support that enable their technology use (Venkatesh et al., 2012). Facilitating conditions strongly influence actual system use, especially for electronic payments (Venkatesh et al., 2012). It is drawn from earlier ideas such as perceived behavioural control and compatibility (Venkatesh et al., 2003). Research shows that facilitating conditions positively affect the intention to use online shopping platforms and apps (Tak & Panwar, 2017; Al-Qudah et al., 2024; Chopdar & Sivakumar, 2019; An et al., 2016; Tandon & Kiran, 2018).

3. RESEARCH METHODOLOGY

The two major approaches to scientific research are quantitative and qualitative. To achieve the study's objective, the researcher adopts a quantitative research design to investigate the relationship between several independent variables and users' intention to adopt mobile shopping apps, with adoption intention as the dependent variable. In this regard, the independent variables of performance expectancy, effort expectancy, social influence, and facilitating conditions have been selected. To investigate the adoption of mobile shopping apps among mobile phone users in Haryana, the researcher used questionnaires. However, because the population is too large, it cannot include every individual. Sampling is the process of selecting a sample from a population. Thus, the sampling size is determined using the Krejcie and Morgan (1970) procedure, which has been widely used as a guideline by many researchers in survey studies. The non-probability sampling method, namely purposive convenience sampling, was utilised. The target population for this study comprised individuals who actively use mobile internet services and are either current users or have prior experience with mobile shopping applications such as Amazon, Flipkart, Myntra, and Meesho. The final sample comprised 300 respondents, ensuring adequate representation for statistical analysis. Data were collected using a structured questionnaire carefully developed to capture respondents' perceptions, attitudes, and usage patterns of mobile shopping applications. The questionnaires were distributed both online through Google Forms and in paper form. All statistical tests (t-test and ANOVA) and data screening procedures required for this study were performed using SPSS Version 26.0 to prepare the data for further analysis.

3.1 Objectives of the Study

- To identify and analyse the demographic factors (such as age, gender and residential status) influencing users' intention to use mobile shopping applications.
- To check the relationship between factors influencing mobile shopping apps adoption and the demographics (such as age, gender and residential status).
- To provide practical suggestions and strategies for enhancing mobile shopping adoption across different consumer segments.

4. RESULTS AND ANALYSIS

The demographic profile of the study participants provides valuable insights into the composition of the sample used to assess awareness of disability legislation. The total number of respondents in the present study is 300, representing diverse backgrounds in terms of gender, age, and residence. Understanding these characteristics helps to interpret variations in awareness and perception levels among different groups. This section uses the T-test and Analysis of Variance (ANOVA) to highlight the significant differences between the study's components. Respondents are classified into subsets based on their demographic information. This test is typically used to compare the means of two groups of respondents based on their demographic attributes. In this study, the t-test is used to compare effort expectancy, performance expectancy, facilitating conditions, and social influence, and to validate differences in opinions across gender and area of residence. Analysis of variance (ANOVA) is typically used to compare the means of three or more groups of respondents based on their demographic characteristics. In this study, the analysis of variance test is used to analyse effort expectancy, performance expectancy, social influence, and facilitating conditions, and to validate differences in their opinions across age.

Table 1. Results of the T-test regarding factors that consumers consider in the adoption of Mobile Shopping Apps based on gender

Factors	Gender	N	Mean	SD	Mean Difference	T-Value	P-value
Subjective Norms	Male	162	3.741	.7003	.1912	3.706	.000
	Female	138	3.604	.7446			
Effort Expectancy	Male	162	4.048	.8168	.0185	.321	.748
	Female	138	4.030	.8125			
Performance Expectancy	Male	162	4.100	.8049	-.0035	-.065	.948
	Female	138	4.103	.7236			
Facilitating Conditions	Male	162	3.931	.7306	.1652	3.046	.002
	Female	138	3.766	.7867			

Table 1 shows the results of a t-test based on gender. The independent-samples t-test was used to determine whether there is a difference in social influence, effort expectancy, performance expectancy, and facilitating conditions by gender.

The t-value and significance (p) values are computed to examine the difference between males and females. The mean values for male and female respondents on social influence are 3.741 and 3.604, respectively, with standard deviations of 0.7003 and 0.7446. The mean difference for social influence is .1912. The t-value of 3.706 is statistically significant (p=.000) and indicates a significant difference in subjective norms between males and females.

Regarding facilitating conditions, the means are 3.931 and 3.766 for males and females, respectively, with a standard deviation of .7306 and .7867. In favourable conditions, data show a mean difference of 0.1652. The t-value of 3.046 reveals a statistically significant (p=.002) difference between males and females in facilitating conditions.

On the contrary, for effort expectancy and performance expectancy, the t-test p-values are not significant, indicating no significant difference between the two by gender.

Table 2. Results of the T-test regarding factors that consumers consider in the adoption of Mobile Shopping Apps based on residence

Factors	Residence	N	Mean	SD	Mean Difference	T-Value	P-value
Subjective Norms	Rural	170	3.826	.6899	.1201	2.31	.02
	Urban	130	3.601	.7639			
Effort Expectancy	Rural	170	4.019	.8291	-.0418	-.72	.47
	Urban	130	4.061	.8003			
Performance Expectancy	Rural	170	4.099	.8147	-.0037	-.06	.94
	Urban	130	4.103	.7233			
Facilitating Conditions	Rural	170	3.900	.7440	.0824	1.55	.12
	Urban	130	3.816	.7740			

Table 2 shows the results of a t-test based on residence. The independent-samples t-test was used to determine whether there is a difference in social influence, effort expectancy, performance expectancy, and facilitating conditions by residence. The t-value and significance (p) value are computed to examine the difference between rural and urban. The mean values for social influence among rural and urban respondents are 3.826 and 3.601, respectively, with standard deviations of .6899 and .7639. The mean difference for social influence is .1201. The t-value of 2.31 is statistically significant (p=.020) and indicates a significant difference in social influence between rural and urban areas.

On the contrary, for effort expectancy, performance expectancy, and facilitating conditions, the t-test p-value is insignificant, indicating that there is no significant difference in price value, effort expectancy, performance expectancy, hedonic motivation, and facilitating conditions across residence types.

Table 3 Results of one-way ANOVA regarding factors that consumers consider in the adoption of Mobile Shopping Apps based on age

Factors	Age	N	Mean	SD	F-Value	P-Value
Social Influence	upto 15	11	3.854	.3606	5.87	.000
	16-25	137	3.534	.7576		
	26-35	90	3.676	.7116		
	36-45	40	3.863	.6645		
	46-60	12	4.111	.2987		
	more than 60	10	3.692	.7683		
	Total	300	3.666	.7241		
Effort Expectancy	upto 15	11	4.000	.7355	7.31	.000
	16-25	137	4.123	.8210		
	26-35	90	4.012	.7755		
	36-45	40	4.039	.7513		
	46-60	12	4.027	1.2522		
	more than 60	10	2.730	.3816		
	Total	300	4.030	.8144		
Performance Expectancy	upto 15	11	3.933	.8866	11.89	.000
	16-25	137	4.252	.7132		
	26-35	90	3.984	.7053		
	36-45	40	4.215	.8194		
	46-60	12	3.378	1.0174		
	more than 60	10	3.192	.8569		
	Total	300	4.101	.7684		
Facilitating Conditions	upto 15	11	3.854	.5153	6.25	.000
	16-25	137	3.861	.75286		
	26-35	90	3.787	.7721		
	36-45	40	4.032	.6926		
	46-60	12	3.108	.8218		
	more than 60	10	3.645	.7531		
	Total	300	3.858	.7589		

One-way ANOVA is used to examine differences in subjective norms, effort expectancy, performance expectancy, and facilitating conditions across age groups (Table 3).

The value of F-statistics for total social influence is 5.87, which is significant (p=.000) at a significance level of 0.05, indicating a significant difference in subjective norms based on age. The mean value indicated that respondents aged 46-60 are more concerned about the social influence of e-retailers than respondents in other age groups.

In the case of effort expectancy, the F-statistic is 7.31, which is found significant (p=.000) at a significance level of 0.05, indicating a significant difference in effort expectancy based on age. Mean values indicate that respondents aged 16-25 are more concerned about effort expectancy than other respondents.

In the case of performance expectancy, the F-statistic is 11.89, which is found significant (p=.001) at a significance level of 0.05, indicating a significant difference in performance expectancy based on age. Mean values indicate that respondents aged 36-45 are more concerned about performance expectancy than other respondents.

In the case of facilitating conditions, the F-statistic is 6.25, found significant (p=.000) at a significance level of 0.05, indicating a significant difference based on age. Mean values indicate that respondents aged 36-45 are more concerned with facilitating conditions for e-retailers than other respondents.

5. DISCUSSION

The study's findings highlight that demographic factors, such as gender, age, and residence, significantly influence users' intention to use mobile shopping applications. The results revealed that both males and females actively engage in mobile shopping, though males showed slightly higher participation. The majority of respondents were young adults aged 18 to 25, indicating that younger consumers are more comfortable with digital platforms and online payment systems. Overall, the sample's demographic diversity provides a holistic understanding of consumer behaviour. The study confirms that socioeconomic and demographic attributes influence the frequency of mobile app shopping, trust, and intention to shop through mobile apps.

Respondents aged 36-45 are more concerned about facilitating conditions than others. Respondents aged 46-60 are more concerned about social influence than others. Respondents aged 16-25 are more concerned about effort expectancy and performance expectancy than other respondents. Rural consumers are more influenced a social factors than urban respondents. No differences are found between urban and rural respondents regarding effort expectancy, performance expectancy, and facilitating conditions. It is concluded that male respondents have higher subjective norms and higher facilitating conditions than female respondents. No differences are found between males and females regarding effort expectancy and performance expectancy.

6. SUGGESTIONS AND IMPLICATIONS

- Enhance User Experience: Developers should focus on improving app design, user-friendliness, and performance to attract and retain users from all demographic groups.
- Targeted Marketing: Companies should design age-specific and gender-oriented marketing campaigns. For instance, younger consumers may respond better to discounts and social media promotions, while older users may value reliability and customer support.
- Affordable Offers: Providing flexible pricing options, instalment payments, and cashback schemes can encourage adoption among lower-income users.
- Digital Awareness Programs: Conducting workshops and awareness drives can help non-tech-savvy groups—especially older users—gain confidence in using mobile shopping platforms.
- Localised Services: Including regional language support and local vendor integration can make mobile shopping more inclusive and accessible across diverse user segments.

6.1 Strategic Implications

- For E-commerce Companies: Focus on personalisation and data-driven marketing strategies that consider demographic variations in preferences and spending patterns.
- For Policy Makers: Encourage digital literacy initiatives and provide consumer protection mechanisms to increase trust in mobile transactions.
- For App Developers: Ensure security, transparency, and ease of navigation, especially for new and older users who may be hesitant to shop online.
- For Marketers: Use demographic insights to segment target audiences effectively and customise promotional strategies based on age, gender, and income level.

6.2 Limitations of the Study

- The study used a convenience sampling method, which may limit the generalizability of findings to the entire population.
- Data were collected through self-reported questionnaires, which may be subject to social desirability bias.
- The study was restricted to 300 respondents, which, while adequate, may not fully represent regional variations in mobile shopping behaviour.
- The focus was on a limited set of demographic variables; psychological, cultural, or technological factors were not deeply examined.
- The use of cross-sectional data does not capture changes in consumer behaviour over time.

6.3 Future Research Guidelines

- Future studies could adopt probability sampling techniques to enhance representativeness.
- Researchers may explore longitudinal designs to track changes in user intention and behaviour over time.
- Expanding the scope to include psychological factors (e.g., trust, perceived risk, satisfaction) could provide deeper insights.
- Future research could also analyse post-purchase satisfaction and loyalty behaviour to build a complete picture of mobile shopping usage.

7. CONCLUSION

The study concludes that demographic characteristics play a crucial role in shaping consumers' intention to use mobile shopping applications—younger users a more inclined toward mobile shopping due to convenience, affordability, and digital accessibility. The balanced gender representation further demonstrates that online shopping is no longer gender-biased but a universal trend. By recognising the influence of demographic variables, businesses and marketers can tailor strategies to reach diverse consumer groups effectively. Enhancing digital trust, improving app usability, and promoting inclusive marketing will be essential to sustain growth in the mobile shopping sector.

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