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Original Article

Exploring the Link between Behavioural Intention and Actual Use Behaviour in Mobile Shopping Applications: A PLS-SEM Approach

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Abstract: *This study investigates the relationship between behavioural intention and actual use behaviour of mobile shopping applications among consumers in Haryana, India. Using a quantitative research design, data were collected from 560 active mobile shopping app users through a structured questionnaire. The study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the proposed hypothesis. The results indicate that there is a highly positive and statistically significant correlation between behaviour intention and actual use behaviour. Suited to the measurement model, assessments of reliability and validity confirmed its robustness. This shows supports of the UTAUT framework which assumes that behavioral intention may lead to action and impact on consumer actual adoption as well as continued use of mobile shopping applications.*

Keywords: *Behavioural Intention, Mobile Shopping Apps, Consumer Adoption, Use Behaviour.*

I. INTRODUCTION

Over the last ten years, software for mobile applications (apps) on smartphones and wearables, also called "Applications," has developed at an unprecedented rate because of increasing popularity with these gadgets. These applications are used to gather data and to increase overall productivity, and they can include social networking through e-books as well as cover many domains like news, weather, stock markets, email etc. The phenomenon of e-commerce and rise in internet penetration as well as the online infrastructure in India has led to a transform of consumer purchasing behavior (Minhas, 2025). Also, changing consumer buying habits after the pandemic and growing share of the organized sector in retail markets have laid a huge foundation for e-commerce in the market (Minhas, 2025). Online buying (Sawhney, 2025) is the process of purchasing goods through mobile applications or e-commerce. In total 16% of rural households and 39.4% of urban households purchase online (Sawhney, 2025). According to the "State of Mobile-2024" report, Indian users spent 12.84 billion hours on shopping apps last year, and accounted for 13% of all mobile consumers' time in shopping apps worldwide in the year 2023 (Gupta, G. X., Srivastava & Gupta). Mobile applications, or "apps", are software programs loaded onto mobile devices that often display a unique brand identity (Bellman et al., 2011; Kumar et al., 2018). Mobile apps, or M-apps are software programs designed to perform specific functions on mobile devices (Hew et al., 2015). Mobile payment solutions and shopping apps in India has increase due times of the COVID-19 pandemic (Basuroy, 2025). Companies such as Amazon and Flipkart, which have made substantial marketing investments in mobile commerce, have generated considerable interest; more recent players have focused on niches of food delivery and travel services (Basuroy, 2025).

Over the years, many researchers have studied consumers' online shopping behaviour on websites. However, few studies have been conducted on shopping apps. Further, most studies are conducted in developed nations, leaving room for research on shopping apps in India, a diverse country. This research study focuses on the adoption and usage of shopping apps in Haryana, India. This study explore the effect of intention to adopt shopping apps on use behaviour, providing insights into the Indian shopping app market.

II. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

The UTAUT, UTAUT2, Technology Adoption Model (TAM), Theory of Reasoned Action (TRA) and Theory of Planned behavior (TPB) were among the first IS/IT Theories that developed behavioral intention. Behavioural intention (Ajzen & Fishbein, 1980; Ajzen, 1991) is characterised as the function of a person that he/she intends to undertake for different activities. Behavioral intention (Davis, 1989) predicts customers' actual adoption and use of technology. As clearly defined by Ajzen and Fishbein (1980), the behavioral intention is an evaluation of people who are going to do a certain activity. Behavioral intention can actually predict behavior or actual mileage of a particular technology, according to Venkateshk et al (2003). All previous studies (Tak & Panwar, 2017; Chopdar & Sivakumar, 2019; Rehman et al., 2019; Celik, 2016; Singh & Srivastava, 2018; Singh

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et al., 2019; Lim et al., 2016; Kaplan, Patel-Kaplan & Kumaradithya Jain, K. B. You first need to see if customers behavioural intention to use retailers' websites or apps. The preceding debate results in the following hypotheses:

H: Behavioural intention (adopt intention) affects user behavior (actual adoption)

III. RESEARCH METHODOLOGY

A) Research Design, Sample, and Procedure

This study used a quantitative approach using survey methods and a descriptive research design. The quantitative approach allowed for testing hypotheses using structural equation modeling and statistical evaluation of correlations between constructs. The target group was owners of smartphones in Haryana, India, who had previously validated a successful transaction. The study site (Haryana) was selected due to its resemblance to Indian consumers living in the cities and semi-urban areas who are increasingly resorting to mobile commerce. A non-probability sampling strategy was used, purposive sampling techniques, because the size of the target population was huge and uncertain. Using purposive sampling, the researcher selected participants who met specific criteria (internet connection, smartphone ownership, and active use of mobile shopping applications). The total number of respondents who filled out the structured questionnaire was 560, exceeding Krejcie and Morgan's (1970) determination technique minimal sample size of 384 (95% confidence interval, 5% significance level). The sample size allowed for a reliable estimation of sufficient statistical power for structural equation modeling analysis. Eligible respondents received a structured questionnaire via electronic distribution (email links, mobile messaging).

B) Measurement

All measurement constructs were assessed using 5-point Likert scale items ranging from "strongly disagree" (1) to "strongly agree" (5). The selection of Likert scaling facilitated respondent comprehension, enabled sophisticated statistical analyses, and permitted comparison with prior research utilizing identical scales (Hair et al., 2012). Table 1 shows that Behavioural intention was assessed using three items, and use behaviour assessed using four items adopted from Venkatesh et al. (2012).

Table 1: Variable, Authors, and Items Description

Behaviour Intention (BI1 to BI3)	I intend to shop by the Mobile Shopping Applications in the future.	Venkatesh et al. (2012)
	I will always try to use Mobile Shopping Applications in the daily life.	
	I plan to continue using Mobile Shopping Applications for shopping than traditional channel (shopping malls or shopping centers).	
Use Behaviour (UB1 to UB4)	Using Mobile Shopping Applications is a pleasant experience.	Venkatesh et al. (2012)
	I am currently using Mobile Shopping Applications.	
	In the past year, I have used Mobile Shopping Applications to purchase online products.	
	In the past year, I have used different kinds of Mobile Shopping Applications.	

IV. RESULTS

A) Sample Characteristics

560 active users of mobile shopping apps from Haryana, India, made up the final sample. Respondents' demographics include: the sample included a wide range of age groups, which reflects the diversity of mobile app users. Ages 25 to 35 made up the biggest percentage (42%), followed by 36 to 45 (28%), 18 to 24 (18%), and 46 and over (12%). The average age was almost thirty-two years old (SD = 9.2). With 56% of respondents being men and 44% being women, the sample was fairly balanced in terms of gender, roughly mirroring the gender distribution of smartphone users in India. With 45% of respondents having a bachelor's degree, 28% having a master's degree, and 15% having a postgraduate diploma, educational attainment was usually high. Only 12% of respondents had finished high school, suggesting that the sample was made up of people who were quite tech-savvy. With a mean tenure of 4.2 years (SD = 2.1), respondents claimed significant familiarity with mobile shopping applications. The average weekly frequency of app usage was 5.3 times (SD = 2.8), suggesting consistent use of mobile commerce. The average daily internet usage reported by respondents was 5.4 hours (SD = 2.2), showing a high level of digital engagement. For 78% of respondents, mobile devices were their main means of accessing the internet.

B) Measurement Model Results of Behavioural Intention to Use Mobile Shopping Apps and their Actual Usage Behaviour

This study aims to achieve the **objective "to examine the relationship between users' intention to use mobile shopping apps and their actual usage behaviour,**" providing insights into how intention leads to adoption and continued engagement. A related figure is below:

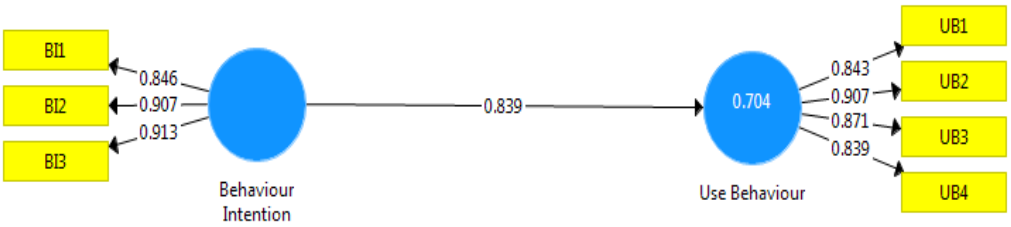

Figure 1. Relationship of Behavioural Intention to Use Mobile Shopping Apps and Actual Use Behaviour

In the case of mobile shopping applications, the aforementioned model, depicted in Figure 1, demonstrates the clear correlation between Intention to Use and Actual Use Behavior. Use Behavior (UB) is the actual execution of that intention through the use of the program, whereas Behavioral Intention (BI) reflects a person's willingness or likelihood to utilize the application.

a. External Loadings of Actual Use Behavior and Intention to Use

Outer loadings, which show how well each observed item reflects its corresponding latent construct, are used to evaluate the measurement model. "Outer loadings above 0.60" suggest that an indicator significantly contributes to the measurement of its construct and offers adequate reliability, according to Garson's (2016) recommended threshold.

Results of the outer loadings are as follows:

Table 2: Outer Loadings of Behavioural Intention and Use Behaviour

Items	Behaviour Intention	Use Behaviour
BI1	0.846	
BI2	0.907	
BI3	0.913	
UB1		0.843
UB2		0.907
UB3		0.871
UB4		0.839

Source: *Primary Data*

The findings demonstrate that every item has significant standardized loadings, with Behavioral Intention ranging from 0.846 to 0.913 and Use Behavior from 0.839 to 0.907. These values show strong indicator reliability and internal consistency, above the suggested criterion of 0.70 (Hair et al., 2019). BI3 (0.913) had the highest loading among the behavioral intention indicators, indicating that it is the most representative item for this construct and that respondents have a strong and persistent intention to use mobile shopping applications. Similarly, UB2 (0.907) showed the highest loading for Use Behavior, indicating that this metric significantly reflects genuine engagement and ongoing app usage.

Both constructions are robust, well-defined, and have low measurement error, as confirmed by the overall high loadings. These findings support the theoretical presumptions of the "Technology Acceptance Model" (Davis, 1989) and the UTAUT framework (Venkatesh et al., 2003) that behavioral intention is a reliable predictor of actual technology use by confirming that respondents' stated intentions (Behavioral Intention) closely match their actual actions (Use Behavior).

b. Reliability and Validity Behavioural Intention and Use Behaviour

The reliability and convergent validity statistics for the constructs Behavioral Intention and Use Behavior, which were obtained using "Partial Least Squares Structural Equation Modeling (PLS-SEM)," are shown in Table 3 Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) are crucial metrics for evaluating the measurement model's validity and internal consistency (Hair et al., 2019). AVE assesses the degree to which indicators share a common variation that represents the underlying latent variable, whereas Cronbach's Alpha and CR gauge the stability or dependability of items within each construct. A table is as follows:

Table 3: Reliability and Validity of 'Behavioural Intention' and 'Use Behaviour'

Constructs	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Behaviour Intention	0.867	0.919	0.790
Use Behaviour	0.888	0.923	0.749

Source: *Primary Data*

Cronbach's Alpha (0.867) and Composite Reliability (0.919) for Behavioral Intention both surpass the suggested cutoff point of 0.70, indicating good internal reliability. The construct itself accounts for more than 79% of the variance in its indicators, as indicated by the AVE value of 0.790, which exceeds the conventional minimum of 0.50. Similar to this, Use Behavior exhibits strong reliability with a Composite Reliability of 0.923 and a Cronbach's Alpha of 0.888, both of which point to strong item intercorrelation. Convergent validity is supported by the AVE value of 0.749, which shows that the indicators together account for a significant amount of the construct's variance. These findings confirm the conceptual soundness and dependability of both constructs, giving the structural model a solid measurement basis.

C) Structural Model of Behavioural Intention and Use Behaviour

The relationship between "Behavioral Intention" and "Use Behavior" in the context of mobile shopping app adoption is depicted in the structural model above. This model evaluates the degree to which users' behavioral goals are reflected in their actual usage behavior. Multiple indicators (BI1–BI3 for behavioral intention and UB1–UB4 for use behavior) are used to represent each construct, and the related outer loadings and t-values indicate the measurement reliability of each indicator. The direction and strength of the relationship between the two constructs are shown by the structural path coefficient.

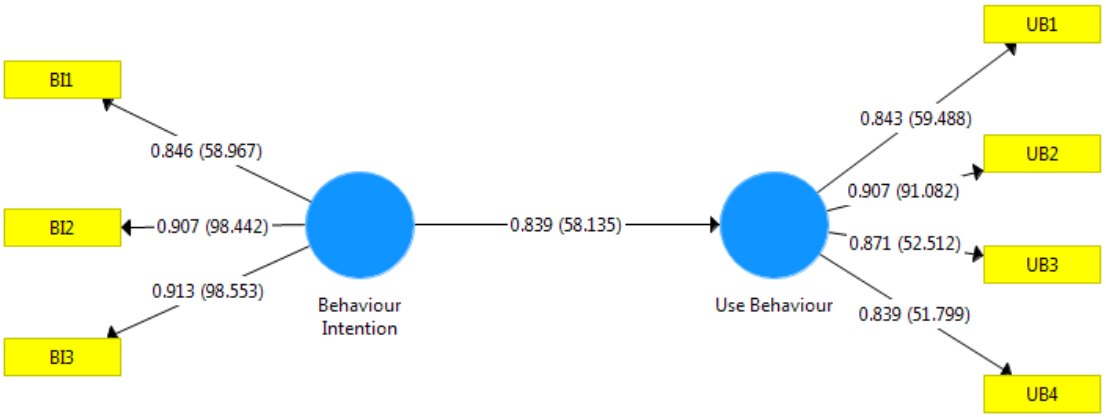

Figure 2: Structural Model of Behavioural Intention and Use Behaviour

The model results indicate a strong positive link between Behavioural Intention and Use Behaviour, reflected in a path coefficient of 0.839 and a t-value of 58.135, demonstrating high statistical significance ($p < 0.001$). This means that users who report higher behavioural intention are substantially more likely to actually use the app. A brief table is as follows:

Table 4: Hypotheses Path of Behavioural Intention and Use Behaviour

Path	Original Sample (O)	Standard Deviation (STDEV)	R^2	VIF	NFI	T Statistics (|O/STDEV|)	P Values	Hypotheses
Behaviour Intention -> Use Behaviour	0.839	0.014	0.704	1.000	0.912	58.135	0.000	Accepted (H)

Source: *Primary Data*

The structural link between Use Behavior (UB) and Behavioral Intention (BI) is shown in Table 4. Higher behavioral intention considerably improves people's use behavior, according to the path coefficient (O = 0.839), which shows a strong positive association. This link is statistically significant at the 0.05 level, as confirmed by the T-statistic value of 58.135 and p-value of 0.000. As a result, the hypothesis (H2) that claims that behavioral intention significantly improves use behavior is accepted. The model's stability is confirmed by the VIF (1.000), which shows the lack of multicollinearity, and the Standard Deviation (0.014), which shows consistency in the calculated path (Hair et al., 2017). Additionally, the NFI value (0.912), which indicates a solid model fit and adequate explanatory power, surpasses the suggested threshold of 0.90 (Byrne, 2010). These results align with the **"**Unified Theory of Acceptance and Use of Technology (UTAUT)" model proposed by Venkatesh et al. (2003)**,** which posits that behavioural intention is the most direct predictor of use behaviour**.** Thus, the findings empirically validate that users' intention to engage with a system or technology strongly determines their actual usage behaviour, and the study proves that: *There is a significant positive association between intention to use and use behaviour of mobile shopping apps*.

V. CONCLUSION

The study demonstrates that users' behavioral intentions have a significant impact on how they actually utilize mobile shopping apps. Both notions are sound and well-defined, as evidenced by strong measurement indicators and excellent reliability

and validity values. The UTAUT framework's concept that behavioral intention is the most direct predictor of technology usage is supported by the substantial structural path. Practically speaking, users' strong intentions to utilize mobile shopping apps result in persistent and real usage behavior. The findings support the hypothesis that boosting users' intention is a crucial tactic for increasing technology uptake and ongoing use.

VI. LIMITATIONS OF THE STUDY

This study has a number of shortcomings despite its merits. Geographically, the sample was limited to Haryana, which would limit its applicability to other Indian regions with different cultural, educational, and digital profiles (Alalwan et al., 2018). Self-selection bias might have been created by non-probability sampling since it attracted participants who were more active online. Reliance on self-reported data, which could be impacted by social desirability and recall bias, and a cross-sectional design that makes it impossible to demonstrate causation are two measurement limitations. Because the study only looked at mobile shopping apps, its contextual generalizability is restricted; effects in other digital contexts have not yet been investigated. Conceptually, use behaviour may also be influenced by unmeasured elements like risk aversion, product familiarity, and trust.

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