A Structural Equation Modeling Approach in Determining the Role of User Interface in Driving E-Impulsive Buying Behaviour

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Abstract

The buying habits and lifestyles of consumers have undergone significant transformations due to digital innovation. This study investigates the impact of user interface mechanisms in stimulating e-impulsive buying in developing countries like India. A quantitative approach using Partial Least Squares Structural Equation Modelling (PLS-SEM) approach was adopted to identify the constructs using the Theory of Planned Behaviour and predict the relationship between these latent constructs, i.e. Online reviews (OR), Social Influencers (SI) and Augmented Reality (AR), with the e-impulsive buying behaviour in the digital market. Primary data was collected from 322 respondents across Tier-1 Indian cities using a purposive and random sampling approach. The findings reveal a significant positive relationship between all the constructs, i.e. augmented reality ($\beta = 0.319$, $P = 0.000$), online reviews ($\beta = 0.208$, $P = 0.004$) and social influencers ($\beta = 0.272$, $P = 0.000$) with e-impulsive buying. By mapping all these factors, the study offers practical & valuable insights for interface designers, e-marketers & e-businesses to increase their e-market reach.

Keywords: Consumer Behaviour, Digitalisation, E-Commerce, Impulsive Buying, SMARTPLS, User Interface, Theory of Planned Behaviour (TPB)

Introduction

The rapid progression of digital technologies has fundamentally transformed consumer attitudes and purchasing patterns, marking a significant shift from traditional offline to online buying. Contemporary consumers increasingly favour online shopping platforms due to their enhanced convenience, adaptability, and streamlined purchasing processes. According to Statista 2024, online shopping is projected to become the prevailing mode of retail in India, with the e-commerce market anticipated to exceed USD 145 billion by 2025, reflecting the accelerating digitalisation of consumer commerce and its widespread acceptance.

The emergence of online shopping platforms has given birth to the phenomenon of impulsive purchasing in digital environments. Impulse buying is characterised by spontaneous, unplanned acquisitions where consumers act on immediate desires without prior evaluation or research (Chan et al., 2016; Xiang et al., 2016; Parboteeah 2005; Vohs & Faber 2003). Within e-commerce, this behaviour evolves into e-impulsive or e-spontaneous buying—marked by unplanned transactions prompted by enticing online stimuli such as product recommendations, promotional cues, and visually attractive interfaces (Verhagen & van Dolen, 2011). Previous literature emphasises that consumers with a higher inherent tendency toward impulsiveness show greater susceptibility to such triggers, especially in the presence of personalised recommendations, flash sales, and influencer endorsements (Hu et al., 2019; Akram et al., 2018).

The user interface is found to be one of the pivotal elements in e-impulsive buying (Kaur et al., 2024). The determinants of the user interface, such as social influencers, mannequin displays, and website rewards, increase the intention to engage in e-impulsive buying (Wells et al., 2011). Social influencers have the power to build personal connections and trust with online consumers, triggering unplanned purchases through emotional and persuasive interactions (Shamim & Azam, 2024; Liu et al., 2025). Mannequin displays (dynamic product imagery and engaging visual merchandising) serve to enhance product attractiveness, stimulate customer interest, and elicit impulse-driven decisions, especially in digital fashion contexts. Website rewards, such as discounts, cashback offers, and personalised incentives, increase the perceived value and urgency, further boosting e-impulsive buying tendencies (Ngo et al., 2024). E-vendors need to implement these strategies to trigger unplanned buying by shoppers in the e-markets.

Research Gap

While prior studies have extensively examined the augmented reality (AR) features, interactive user experiences, and digital brand engagement, having the potential to stimulate impulse buying behaviour in online retail, existing research remains limited in developing e-markets in India. Most recent work has focused either on isolated AR experiences in specific product categories or on the general effects of influencer marketing, leaving a gap in understanding their impact within contemporary e-commerce environments. Similarly, little research has been done in Indian e-markets about the impact of influencers and online rewards on e-impulsive buying. Addressing these gaps, the present study aims to analyse the impact of these mechanisms on e-impulsive buying, along with offering holistic perspectives to user interface designers & e-markets.

Research Objectives

1) To assess the impact of online reviews on consumers' e-impulsive buying behaviour in the Indian E-Commerce market.
2) To assess the impact of Social Influencers on consumers' e-impulsive buying behaviour in the Indian E-Commerce market.
3) To assess the impact of Augmented Reality on consumers' e-impulsive buying behaviour in the Indian E-Commerce market.

Literature Review & Hypothesis Development

Theory of Planned Behaviour (TPB) offers a relative framework to determine the cognitive constructs' impact on unplanned buying in digital e-marketplaces. By using the theory of planned behaviour, this study determined the relationship between constructs – online reviews, social influencers and augmented reality with the e-impulsive buying.

Online Reviews and E-impulsive Buying

Customers who use internet technology to express their subjective thoughts about goods or services purchased from an e-platform are known as online reviewers. Online reviews are often cited as one of the significant determinants driving spontaneous buying from digital markets (Zhang et al., 2018). It has been observed via past studies (Zafar et al., 2021), internet reviews favourably impact a website's reach. It has been noted that before making a purchase, consumers frequently examine product reviews. Online reviews are typically used by consumers to express their thoughts about different products, which helps them form an impression of the brand (Költringer &

Dickinger, 2015). For consumers who shop online, internet reviews are a great source of information (Lee et al., 2021). It is believed by Wu et al. (2020) that trustworthy internet reviews significantly impact customers' decisions to buy and can motivate them to alter their intentions and shopping habits. Therefore, signifying the influence of online reviews, we tend to measure their impact in the Indian e-commerce market. Hence, a hypothesis is proposed as

H_1: Online reviews have a positive and significant effect on consumers' e-impulsive buying behaviour in E-Commerce.

Social Influencers and E-impulsive Buying

Social influencers are a result of social media marketing and advertising. Due to their high level of popularity and ease of disseminating information on e-platforms, they possess the ability to reach a larger audience at one go (McQuarrie et al., 2013). Consumers adopt their opinions easily as they are deemed to have product knowledge, which makes them popular and trustworthy. Moreover, the persuasive purchasing power of social influencers is contributing to the growth of the e-market (Liu et al., 2025; Ernestivita et al., 2023; Zafar et al., 2021, Chen et al.,2021). Hence, this research aims to determine their impact on the Indian e-commerce markets. So, the hypothesis proposed is

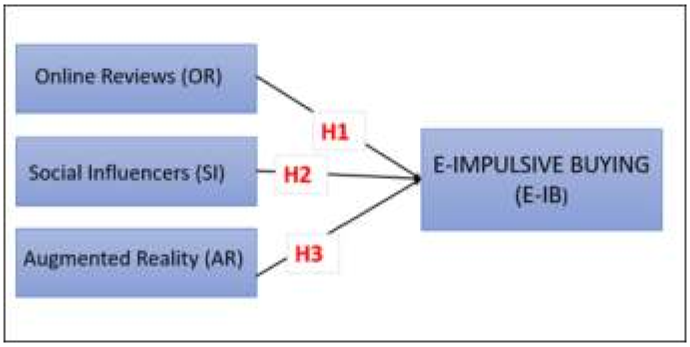
H_2: Social Influencers have a positive and significant effect on consumers' e-impulsive buying behaviour in E-Commerce

Augmented Reality and E-impulsive Buying

Augmented reality (AR) is a transformative technology that seamlessly integrates virtual objects with the physical world, cultivating an interactive and immersive user experience. By superimposing computer-generated elements directly onto real-world environments, AR acts as a bridge, generating a "mixed reality environment" that blurs the boundaries between physical and digital realms. The core concept of AR is to superimpose computer-generated digital information onto real-world objects and environments, displaying interactive data right where it is relevant (Azuma, 1997). By simulating real environments, AR effectively influences consumer behaviour by providing immersive product experiences that encourage online shopping. Slater (2003) noted that such technologies can occasionally alter internet shoppers' decision-making processes. Building on this, King et al. (2021) explored AR's potential to reshape online purchasing dynamics. Poushneh and Vasquez-Parraga (2017) highlighted that AR enhances interactivity by allowing consumers to access detailed product information, virtually try products, or visualise items within their own surroundings, thereby increasing engagement and purchase intention. Recent studies confirm AR's pivotal role in enriching customer experience and boosting online sales by bridging sensory gaps inherent in traditional e-commerce platforms (Guo et al., 2024; Yang et al., 2024). Therefore, this study aims to measure this concept in the Indian e-market, which is hypothesised as

H_3: Augmented reality has a positive and significant effect on consumers' e-impulsive buying behaviour in E-Commerce

Figure 1: Conceptual Framework of the Study



Research Methodology

This section outlines the research design, including the sampling strategy, sample size determination, geographical area of the study, and data collection instrument & process.

Research Design & Sampling Technique

A quantitative research approach was adopted to determine the explanatory and causal relationship between the impact of user interface drivers on e-impulsive buying behaviour in the Indian e-market. This technique is appropriate for testing hypotheses and identifying relationships between variables. A purposive and random sampling technique was adopted to select the sample for collecting relevant and comprehensive data. The reason behind adopting purposive sampling was to select a sample that has done online buying impulsively at least once in the last 6 months. And this was done to ensure the inclusion of respondents whose input is pertinent to the research objectives.

Scale Development

To validate the model, a structured questionnaire was developed based on measurement scales (Table 1) from previous studies to ensure its reliability and validity. The Questionnaire was divided into two sections – section 1 consisted of demographic questions like age, gender, monthly family income, frequency of online shopping and amount spend once in online shopping, while Section 2 consisted of 16 items for measurement on a 5-point Likert scale (1-Strongly Disagree to 5-Strongly Agree) of constructs; Online reviews (OR)- 4 items, Social Influencers (SI)- 4 items, Augmented reality (AR)- 4 items and E-Impulsive Buying (E-IB)- 4 items. These constructs and items were derived through a systematic search from SCOPUS & WOS databases and finalised via user interface expert discussions. The questionnaire was designed after the validation of the pilot survey. And they were measured and tested through the SMARTPLS using the Partial Least Squares Structural Equation Modelling technique.

DATA COLLECTION INSTRUMENT

For designing & validating this model, an empirical investigation was conducted with the help of a survey and a structured questionnaire as an instrument. The questionnaire was validated through a pilot survey, which was conducted between December 2024 to January 2025, with five user interface experts and five respondents who shopped for fashionable category items from e-commerce sites impulsively in the last 6 months. The inputs shared by them were incorporated. And the final questionnaire was shared through popular social networking sites like Instagram, WhatsApp, Facebook and LinkedIn for collecting the data. The data was collected from participants between January 2025 to April 2025, in Tier 1 Indian cities.

Sample Size Determination

According to Boomsma & Hoogland (2001), for using SEM through SMARTPLS, the minimum sample size requirement is 200. Hair et al. (2021) stated that the sample size should be 10 times the number of items in the study. Around 370 questionnaires were distributed through social networking sites in Tier 1 Indian cities like Delhi, Bangalore, Mumbai, Pune, Chandigarh, etc. Out of these, 350 responses were collected, and after data cleaning, 28 (8%) were rejected, and 322 (92%) were included in the analysis.

Data Analysis Technique

The descriptive statistics were anlayzed through SPSS and for analysing the model and understand the relationship between variables, path analysis was employed using Partial Least Squares Structural Equation Modeling via Smart PLS 4.0 software.

Table 1: Measurement Scale

Variables	No. of Items	Sources of Adoption & Adaption
Online Reviews (OR)	4	Ampadu et al., 2021
Social Influencers (SI)	4	Chen et al., 2021
Augmented Reality (AR)	4	Yang & Lin, 2024
E-Impulsive Buying (E-IB)	4	Xiang et al., 2016

Results & Discussion

Descriptive Statistics - Respondent Demographics

The questions covered in the first section of the Questionnaire, i.e Demographic profile, are elaborated in Table 2. The demographic profile indicates an equal gender ratio, i.e 152 (47%) males and 170 (53%) females. Among the age group distribution, the majority belong to the age group of 15-24, i.e 145 (45%), followed by 80 (25%) respondents between 25-34 age and 97 (30%) respondents belong to the 35-44 age group. Talking about family income, 40 (12.5%) respondents' monthly family income is below 1 lac, 65(20%) respondents monthly family income is between 1.1 – 2 lac, 58 (18%) respondents monthly family income is between 2.1 – 3 lac, 64 (20%) respondents monthly family income is between 3.1- 4 lac, 52 (16%) and 43 (13.5%) respondents monthly family income is between 4.1 – 5 lac and above 5.1 lac respectively. Concerning online shopping, the majority of respondents, i.e. 106(33%), do online shopping monthly, around 36(11%) shop online quarterly, 42(13%) respondents shop six-monthly and 138(43%) respondents shop occasionally.

Table 2: Demographic Profile Of Respondents

Demographics	Frequency	Percentage
Gender		
Male	152	47%
Female	170	53%
Age		
15-24	145	45%
25-34	80	25%
35-44	97	30%
Monthly Family Income		
Below 1 Lac	40	12.5%
1.1 Lac – 2 Lac	65	20%
2.1 Lac – 3 Lac	58	18%
3.1 Lac – 4 Lac	64	20%
4.1 Lac – 5 Lac	52	16%
5.1 Lac & Above	43	13.5%
Frequency of Online Shopping		
Monthly	138	43%
Quarterly	42	13%
Six-Monthly	36	11%
Occasionally	106	33%
Spend Once in Online Shopping		
Rs.500 – Rs.2000	161	50%
Rs.2001 – Rs.5000	106	33%
Rs.5001 – Rs. 10000	36	11%
Above Rs.10000	19	6%

The second section of the questionnaire consists of 5-point Likert scale questions of the latent constructs – OR, AR, SI & E-IB, which are measured through a structural equation modelling approach.

Structural Equation Modelling Results

Validity and Reliability Test

After the pilot data survey, a total of 16 items under 4 latent constructs – Online reviews, Social Influencers, Augmented reality and E-Impulsive Buying were taken into consideration for the study. Table 3 represents the measurement model - Loading, Cronbach's alpha, Composite Reliability and AVE. For checking the indicator reliability, the overloading values are examined, and they should be greater than 0.7, which is considered a good value as recommended by Hair et al. (2014). We can observe that all the items loading values are good, i.e above 0.7, except the loading value of OR4. But the value is above 0.5 (Fornell and Larcker, 1981; Hair et al., 2013), which is acceptable for the study. This indicates that all the items considered under constructs are suitable to measure in this study. Table 3 also represents Cronbach's alpha value, for E-Impulsive buying is 0.877, Social Influencers – 0.787, Online Reviews – 0.776 & Augmented Reality– 0.888; all the values are above 0.7, which validates and verifies the convergent validity.

The composite reliability of all the constructs (indicated in Table 3) was above 0.792, i.e AR = 0.890, OR = 0.885, SI = 0.792 and E-IB = 0.887, all surpassed the minimum threshold of 0.7, indicating a high degree of reliability. Furthermore, the Average Variance Extracted (AVE) of each latent construct exceeded the threshold value of 0.7. Hence, these values verify and validate the convergent validity and employed that all constructs and items used in this study were reliable and valid.

Reflective Measurement Model

A total of 16 items and 4 constructs were considered under the reflective measurement approach. SEM-SMARTPLS was used to measure and analyse the loading values, validity, and reliability of the indicator. To understand this model, the recommendations set by Chin (1998a; 1998b) and Hair et al. (2013) were considered, and Cronbach's alpha, composite reliability, VIF & AVE were extracted. According to Hair et al. (2020), the VIF (Variance Inflation Factor) value assesses multicollinearity issues, and it should be less than 5.0. As all (VIF) values fall within the permitted range of 1.203 to 3.307, i.e less than 5, as indicated in Table 3, Column 4: VIF. Hence, the model stated no issues with multicollinearity.

To assess the reliability of the measurement model, loading values were assessed. All items were deemed satisfactory or higher than the threshold value of 0.7, as exhibited in Table 3. Overall, the model demonstrates strong psychometric properties and the convergent validity is also validated and verified because latentconstructs' Cronbach's alpha, composite reliability, and AVE values are higher than the suggested values, which are 0.7, 0.7, and 0.5, respectively.

Hence, the reflective measurement model indicates that it is appropriate for further structural model evaluation.

Table 3: Measurement Model - Loading, VIF, Cronbach's alpha, Composite Reliability, AVE

Constructs	Items	Weights	VIF	Cronbach's alpha	Composite reliability	Composite reliability	Average variance extracted (AVE)
E- Impulsive Buying	**IB1**	0.795	1.894	**0.877**	**0.887**	**0.916**	**0.731**
	IB2	0.848	2.065				
	IB3	0.900	2.803				
	IB4	0.873	2.465				
Augmented Reality	**AR1**	0.890	2.854	**0.888**	**0.89**	**0.923**	**0.75**
	AR2	0.850	2.755				
	AR3	0.899	3.037				
	AR4	0.822	2.162				

Constructs	Items	Weights	VIF	Cronbach's alpha	Composite reliability	Composite reliability	Average variance extracted (AVE)
Online Reviews	OR1	0.848	2.215	0.776	0.885	0.854	0.608
	OR2	0.871	2.358				
	OR3	0.877	1.93				
	OR4	0.530	1.203				
Social Influencers	SI1	0.772	1.552	0.787	0.792	0.862	0.61
	SI2	0.742	1.784				
	SI3	0.739	1.335				
	SI4	0.863	1.662				

Structural Model

In the Partial Least Squares Structural Equation Modelling approach, after measuring the measurement model, the structural model is assessed. The structural model is validated to check the robustness of the study. And the hypothesised relationship between the latent constructs is tested. The discriminant validity, a crucial component of the structural model, is validated by HTMT ratio (Table 4). It should be below the threshold value 0.9, and all the constructs satisfy the condition as their values fall below the 0.9 threshold. Hence, indicating their uniqueness & appropriateness for the study.

Table 4: Discriminant Analysis

	AR	E-IB	OR	SI
Augmented Reality (AR)	0.868			
E-Impulsive Buying (E-IB)	0.926	0.854		
Online Reviews (OR)	0.889	1.061	0.777	
Social Influencers (SI)	0.993	0.889	0.898	0.781

The consistent bootstrapping was performed using 5000 resamples at 95% confidence interval employing the two-tailed percentile bootstrap confidence interval method. Furthermore, the structural (SEM) model & path coefficient (Table 5 & Fig 2) were validated through beta value, t-value & p-value for assessing the significance, testing the hypothesis and determining the relationship among the constructs.

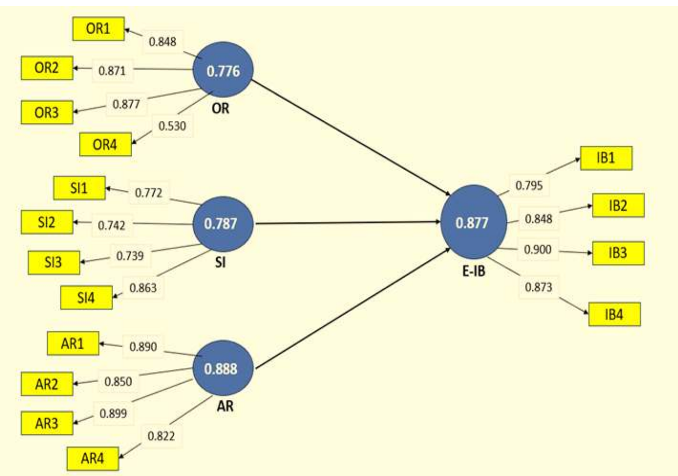
Table 5: Path Coefficient

Path	Hypothesis	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Hypothesis Result
OR->E-IB	H1	0.208	0.222	0.073	2.853	0.004	Accepted
SI -> E- IB	H2	0.272	0.271	0.062	4.371	0	Accepted
AR->E-IB	H3	0.319	0.31	0.078	4.077	0	Accepted

Hypothesis Testing Results

After the validation of the Structural Model & Measurement Model, the Structural Equation Model (SEM), as illustrated through Figure 2 and Path Coefficient (Table 5), was developed through SMART PLS Software to examine the hypothesised relationship between constructs and represent the strength and direction of the hypothesised relationships.

Fig 2: SEM Model



Hypothesis Results

The conceptual model framework and hypothesis relationship were tested using PLS-SEM, and the results are discussed below-

H1: Online Reviews (OR) E-Impulsive Buying (E-IB): The obtained t-statistic value is 2.853, which exceeds the t-statistic value = 1.96. Further, the obtained p-value = 0.004, which satisfies the threshold value = <0.5. The coefficient value of beta should be >= 0.2, and the obtained value of this construct = 0.208. Hence, all the obtained values of Hypothesis 1 are positive and significant, signifying that the hypothesis is accepted. Therefore, it indicates the positive impact of online reviews on e-impulsive buying. Shoppers get influenced through online reviews, which results in immediate buying from e-markets.

H2: Social Influencers (SI) E-Impulsive Buying (E-IB): The obtained t-statistic value = 4.371and p value =0.000, exceeding the threshold value >1.96 of t-statistics and p threshold value <0.5, respectively. The Beta of this construct = 0.272, which is >0.2. Hence, all the obtained values met the threshold values signifying a positive and significant relationship, emphasising a connection between social influencers and e-impulsive buying. Hence, it can be likely said that social influencers are capturing e-shoppers or influencing them to do spontaneous buying or unplanned buying from e-markets.

H3: Augmented Reality (AR) E-Impulsive Buying (E-IB): The obtained beta value = 0.319, which surpasses the threshold value of >0.20. The t-statistic value = 4.077 & p-value = 0.000, affirming the threshold of >1.96 & <0.05 respectively. Therefore, it signifies a positive relationship between augmented reality and e-impulsive buying constructs. The enhanced AR experiences directly foster spontaneous and unplanned online purchases. This study has demonstrated through structural equation modelling that AR features—such as interactivity, vividness, and enjoyment—significantly boost brand engagement and consumer involvement, which in turn lead to higher impulse buying behaviour on digital platforms. The immersive and engaging nature of AR technology reduces purchase risk, increases perceived hedonic value, and stimulates emotional triggers that make consumers more likely to buy spontaneously while shopping from e-markets.

Conclusion

This study enhances understanding of how key digitalisation drivers within user interfaces—namely, online reviews (OR), social influencers (SI), and augmented reality (AR), impact e-impulsive buying (E-IB) behaviour in the contemporary e-commerce environment. The findings decisively confirm that digital platforms have revolutionised consumer purchasing habits by fostering spontaneous and unplanned buying decisions. Online reviews emerge as a powerful factor, building consumer trust through their credibility, unbiased nature, and provision of relevant product information that significantly motivates impulsive purchases. Additionally, social influencers serve as authentic and reliable intermediaries, whose recommendations strongly affect consumers' impulse buying tendencies. While augmented reality is a relatively newer and evolving element, its capacity to engage consumers through immersive and interactive product visualisation shows promising potential in further driving impulsive purchases.

Practical Implications of the Study

The insights of this study offer some valuable practical implications which can be followed by user interface designers, e-businesses, and e-markets to boost their digital presence and customer engagement. The findings highlight that online reviews, social influencers, and augmented reality significantly influence impulsive buying, urging marketers to strategically invest in these digital tools to boost spontaneous purchases, enhance customer engagement, and drive sales conversion. The designs of E-commerce platforms must prioritise seamless integration of interactive elements such as AR technology and social media features alongside credible review systems to stimulate impulse buying effectively and offer a compelling, engaging shopping environment.

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