

Functional Interface Drivers of Online Impulse Buying

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Abstract:

The increasing integration of digital retail interfaces into consumer decision environments has intensified the need to understand how platform-level functional attributes are associated with impulsive buying behaviour. Beyond conventional usability considerations, interface characteristics may shape the accessibility, salience, and execution of unplanned purchase decisions. This study aims to empirically evaluate the relationships between five functional interface attributes navigation simplicity, visual stimulus, promotional and scarcity cues, checkout functionality, and trust signals and impulsive buying behaviour, and to determine their relative statistical contributions. A quantitative, cross-sectional survey design was employed among 412 active online shoppers using a structured questionnaire comprising 28 multi-item Likert-scale measures. Stratified convenience sampling was adopted, and the data were analysed using SPSS through Cronbach's alpha reliability assessment, principal component analysis with Varimax rotation, Pearson correlation, and multiple regression. Multicollinearity and residual diagnostics were additionally examined to evaluate model adequacy. All five interface attributes demonstrated positive associations with impulsive buying behaviour ($p < 0.01$). Promotional and scarcity cues exhibited the strongest correlation ($r = 0.69$) and standardized regression coefficient ($\beta = 0.34$, $p < 0.001$), followed by visual stimulus ($r = 0.63$; $\beta = 0.29$, $p < 0.001$), navigation simplicity ($r = 0.54$; $\beta = 0.18$, $p < 0.001$), checkout functionality ($r = 0.51$; $\beta = 0.16$, $p < 0.001$), and trust signals ($r = 0.47$; $\beta = 0.12$, $p = 0.001$). The regression model was statistically significant ($F(5,414) = 59.62$, $p < 0.001$; $R^2 = 0.419$; adjusted $R^2 = 0.412$). The findings indicate that functional interface attributes collectively provide substantial statistical explanatory value for impulsive buying behaviour, with promotional and visual characteristics showing the largest unique contributions. The study extends empirical understanding of e-commerce interface design by demonstrating measurable associations between specific platform characteristics and impulsive purchasing outcomes, while avoiding causal interpretation inherent to the cross-sectional research design.

Keywords: Functional interface Drivers, Digital Purchase Spontaneity, Friction Design, Visual Persuasion Cues, Behavioural E-commerce Analytics.

1. Introduction:

The functional characteristics of online shopping interfaces have become an important component of digital consumer environments because they influence how information is encountered, evaluated, and acted upon during purchasing. Interface layout, navigation

structure, promotional presentation, checkout procedures, and trust-related information can shape the amount of effort required to progress from product discovery to transaction completion. Previous research suggests that digital atmospheric cues and system-level interface characteristics can influence consumer responses by increasing perceptual salience and reducing the time available for deliberate evaluation (1). Accordingly, the present study investigates the quantitative relationship between functional design characteristics of online shopping platforms and impulsive purchasing behaviour using primary survey data and multivariate statistical analysis. The analysis is deliberately focused on measurable platform-level attributes rather than treating psychological, cultural, or demographic characteristics as the principal explanatory factors (2).

The increasing adoption of mobile commerce and application-based shopping has further integrated purchasing functions into highly responsive digital interfaces. Within these environments, consumers are exposed to continuously updated product information, recommendations, promotional messages, and transaction options while browsing. Existing studies associate the transition from product exploration to purchase with interface convenience, responsiveness, persuasive content, and repeated exposure to commercially relevant stimuli (3), (4). Promotional mechanisms such as limited-time indicators, scarcity information, product recommendations, and simplified purchasing sequences have also been associated with spontaneous purchasing decisions, partly because they can reduce the perceived effort involved in evaluating alternatives and completing a transaction (5), (6). In social commerce environments, interactive functions and socially embedded features may additionally influence purchase spontaneity, while trust-related information and emotionally engaging interface elements can reduce hesitation during online transactions (7), (8). These findings indicate that the functional architecture of a shopping platform warrants examination as a measurable component of the impulse-purchase process.

1.1 Theoretical Framework

The theoretical foundation of this study combines the Stimulus–Organism–Response (S-O-R) framework with a cognitive-affective perspective on consumer decision-making. This integration provides a structured explanation of how functional interface characteristics may influence impulsive purchasing. In the S-O-R framework, external environmental characteristics constitute stimuli (S), which influence an individual's internal cognitive and affective state (O) and subsequently contribute to an observable behavioural response (R) (9), (10). In the present investigation, five functional interface constructs are positioned within this framework: navigation simplicity, visual stimulus, promotional and scarcity cues, checkout functionality, and trust signals.

Visual stimulus and promotional or scarcity cues primarily represent stimulus-oriented characteristics. Their proposed role is to increase perceptual prominence and activate affective responses such as urgency, excitement, or fear of missing an opportunity. These responses may reduce the extent of deliberative evaluation preceding an unplanned purchase. Navigation simplicity and checkout functionality have a different theoretical role (11), (12). Rather than being treated principally as emotional triggers, these attributes concern the operational effort required to locate products, review information, and complete an order. Once purchase motivation has developed, lower navigational complexity and a more efficient checkout sequence may reduce behavioural friction and facilitate the transition from intention to transaction.

Trust signals represent a further mechanism within the cognitive evaluation process. Information concerning payment security, seller credibility, transaction reliability, reviews, ratings, or related assurance mechanisms can influence perceived risk. Lower perceived transactional risk may reduce an inhibitory condition that could otherwise interrupt an impulsive purchasing decision (13), (14). Thus, the five constructs can be interpreted according to three related functions: stimulus activation, response facilitation, and risk inhibition. This conceptual distinction provides the theoretical basis for interpreting the statistical relationships examined in the subsequent analysis and establishes a direct connection between interface functionality and impulsive purchasing behaviour.

1.2 Research Gap

Research on online impulse buying has established associations between purchasing behaviour and environmental, visual, emotional, and situational characteristics. Visual properties such as colour, layout density, and product presentation have been examined as digital atmospheric factors, while behavioural models have emphasized situational triggers, scarcity perceptions, and hedonic characteristics of online browsing environments (15), (16). Experimental and structural-equation approaches have also provided evidence that technological and environmental characteristics can contribute to consumer behavioural outcomes (17). However, important limitations remain in translating these broader observations into measurable platform-level functional attributes. A substantial proportion of existing research gives greater emphasis to psychological states, emotional responses, cultural influences, or consumer characteristics than to the specific functional properties embedded within shopping interfaces. Consequently, the contribution of individual design components is not always isolated quantitatively (18), (19). Feature-level characteristics such as navigation complexity, checkout compression, promotional-trigger density, and trust-related interface information are less frequently examined together within a unified empirical framework. This limits the ability to determine whether different functional elements contribute through distinct behavioural mechanisms (20).

A further methodological issue concerns the measurement and validation of functional interface constructs. Studies have employed diverse behavioural and perceptual measures, making comparisons across investigations difficult. In particular, relatively limited attention has been given to the systematic validation of multi-item measures representing functional interface attributes through reliability assessment, exploratory factor analysis, correlation analysis, and multiple regression using ordinal primary survey data (21). The absence of such integrated validation creates a methodological gap between conceptual descriptions of e-commerce interface design and statistically testable representations of its relationship with impulsive purchasing. The present study addresses this gap through three specific contributions. First, it operationalizes navigation simplicity, visual stimulus, promotional and scarcity cues, checkout functionality, and trust signals as measurable multi-item constructs. Second, it evaluates their statistical relationships with impulsive purchasing behaviour using reliability analysis, exploratory factor analysis, correlation analysis, and multiple regression. Third, it examines whether the observed constructs form statistically distinguishable dimensions that correspond to the proposed activation–conversion interpretation. This approach provides an empirical basis for examining functional interface design as a multidimensional component of online impulse purchasing and establishes a foundation for subsequent research involving controlled interface experiments, personalization mechanisms, longitudinal observations, and cross-platform comparisons (22), (23).

2. Methodology:

2.1 Research Design

A quantitative, cross-sectional survey design was adopted to examine the statistical relationship between functional online shopping interface attributes and impulsive buying behaviour. A structured questionnaire was used to obtain standardized responses from online shoppers, allowing the measured constructs to be evaluated using reliability assessment, exploratory factor analysis (EFA), Pearson correlation, and multiple regression. The design was selected to provide a consistent measurement framework for examining associations among predefined interface-related variables and the behavioural outcome (23).

2.2 Study Context and Population

The investigation was conducted among online shoppers in Jalandhar district, Punjab, India. The study context was restricted to a defined geographical setting to reduce variation associated with external conditions, including platform accessibility, regional logistics, and local commercial practices. Participants were required to have prior online shopping experience and regular use of at least one e-commerce platform. This criterion ensured that respondents could provide experience-based assessments of the interface characteristics examined in the questionnaire. The geographically bounded design improves contextual consistency but limits direct generalization of the findings to online consumers in other regions.

2.3 Sampling Procedure and Respondent Selection

A stratified convenience sampling procedure was employed. The sampling framework considered relevant respondent segments to improve proportional coverage, while participant recruitment was conducted through accessible distribution channels. Eligibility screening was applied before questionnaire completion to ensure that respondents had sufficient exposure to online shopping interfaces. Responses that were incomplete or internally inconsistent were excluded during subsequent data screening. Following these procedures, 412 valid responses were retained for statistical analysis. The selected sampling approach combines segmentation through stratification with non-probabilistic participant recruitment. Although stratification provides coverage across defined respondent groups, convenience-based selection does not provide every member of the target population with a known probability of inclusion. Consequently, sampling error and self-selection effects cannot be completely excluded. The findings are therefore interpreted within the characteristics of the achieved sample rather than as statistically representative estimates of the entire online-shopping population.

2.4 Questionnaire Development and Measurement Scales

Data were collected using a structured questionnaire comprising multi-item Likert-type measures derived from constructs reported in previous research on interface design, social commerce, and online impulse purchasing (21), (22). The instrument contained 28 scaled items distributed across six constructs: navigation simplicity (5 items), visual design stimulus (5 items), promotional and scarcity cues (4 items), checkout functionality (4 items), trust signals (4 items), and impulsive buying behaviour (6 items). The measured dimensions represented perceptions of interface usability, visual stimulation, promotional pressure, transaction efficiency, risk assurance, and purchasing spontaneity. The present study did not include a separate pilot-testing phase before full-scale administration. Instead, measurement

adequacy was evaluated using the observed psychometric properties of the final dataset. Internal consistency was assessed using Cronbach's alpha, while EFA was applied to examine the dimensional structure of the measurement items. These procedures provided empirical assessment of the suitability of the instrument for the sampled population.

2.5 Data Collection Procedure

The questionnaire was administered to eligible online shoppers through the distribution channels defined in the sampling procedure. Participation was voluntary and based on informed consent. The survey collected anonymous responses without personally identifying information. As specified in the study's ethics statement, the research involved non-clinical and non-invasive questionnaire-based data collection and therefore did not require formal ethics-committee approval under the applicable institutional provisions.

2.6 Sample Size Justification

The final dataset comprised 412 usable observations, providing an adequate basis for the planned multivariate analyses. For the 28 measurement items, the achieved respondent-to-item ratio was approximately 14.7:1, exceedingly commonly applied minimum ratios of 5:1 and approaching the more conservative 10:1 criterion used for factor-analytic applications. In addition, the observed Kaiser–Meyer–Olkin (KMO) value of 0.91 indicates high sampling adequacy for factor analysis. For the regression model containing five predictors, the sample also exceeds the commonly cited criterion of $N \geq 50 + 8k$ where k denotes the number of predictors (23), (24). The available sample was therefore sufficient for the reliability, dimensionality, association, and predictive analyses specified in the research design.

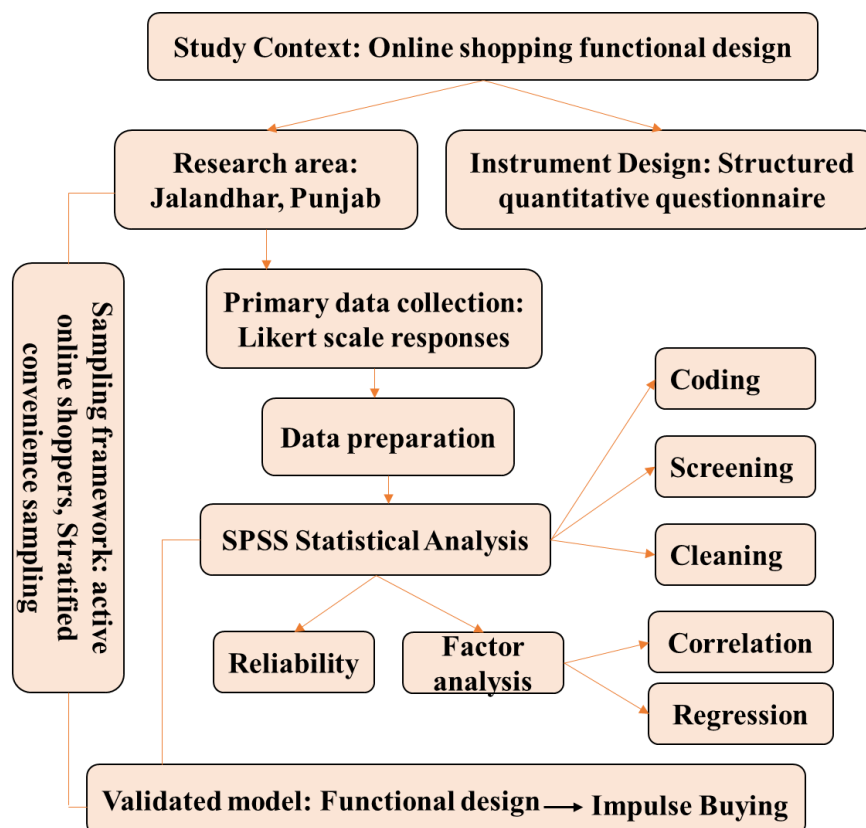


Figure 1. Research Methodology Model for Functional Design Elements and Impulsive Buying Behavior.

2.7 Terminology and Construct Specification

To maintain conceptual consistency, functional interface design denotes the overarching system-level design domain examined in the study. Functional design constructs refer collectively to navigation simplicity, visual stimulus, promotional and scarcity cues, checkout functionality, and trust signals. Within the theoretical model, impulse activation denotes the stimulus-oriented process associated primarily with visual and promotional cues, whereas impulse conversion denotes the subsequent facilitation of purchase completion through navigation simplicity, checkout functionality, and trust-related assurance. The term *functional triggers* were not retained as a general descriptor because it could obscure these distinctions.

2.8 Data Analysis

The analytical procedure followed the sequence illustrated in *Figure 1*, beginning with the study context and structured instrument and progressing through primary data collection and preparation. After collection, responses underwent coding, screening, and cleaning before statistical evaluation. The prepared dataset was analyzed in SPSS, with the analysis comprising four principal stages: Cronbach's alpha for internal consistency, EFA using principal component extraction with Varimax rotation, Pearson correlation for bivariate associations, and multiple regression for estimating the relationship between the five functional design constructs and impulsive buying behaviour (25), (26). As shown in Figure 1, reliability and factor analysis established the measurement structure, whereas correlation and regression examined the associations among the validated constructs. The resulting analytical sequence provided the basis for evaluating the proposed functional design impulse buying model while maintaining a clear distinction between measurement validation and relationship testing (27).

3. Results and Discussion:

The number of valid responses that remained following data screening, checking completeness and filtering response consistency was 412. All the statistical processes were done in SPSS. The pattern used in the analysis adhered to reliability test, descriptive statistics, construct validation through the use of factor analysis, correlation check, and regression analysis to approximate the predictive value of functional design variables on impulsive buying behaviour.

Table.1. Respondent Demographic Profile (n = 412).

Variable	Category	Frequency	Percentage
Gender	Male	228	55.3%
Gender	Female	184	44.7%
Age	18–25	162	39.3%
Age	26–35	149	36.2%

Age	36–45	71	17.2%
Age	46+	30	7.3%
Shopping Frequency	Weekly	176	42.7%
Shopping Frequency	Monthly	188	45.6%
Shopping Frequency	Occasional	48	11.7%

Table 1 summarizes the demographic and online-shopping characteristics of the 412 respondents included in the survey. The sample comprised 228 males (55.3%) and 184 females (44.7%), indicating representation of both gender categories, although the distribution was not equal. The age structure was concentrated among younger participants, with respondents aged 18-25 accounting for 39.3% and those aged 26-35 representing 36.2% of the sample. Collectively, these two groups constituted 75.5% of respondents, while participants aged 36-45 and 46 years or above represented 17.2% and 7.3%, respectively. Regarding shopping frequency, 42.7% reported weekly online purchases and 45.6% reported monthly purchases, whereas 11.7% identified as occasional shoppers. Thus, 88.3% of respondents reported at least monthly online-shopping activity, indicating substantial exposure to e-commerce interfaces within the sampled population (28). The demographic distribution should nevertheless be considered when interpreting the external applicability of the findings.

Table.2. Reliability Statistics.

Construct	Items	Cronbach Alpha
Navigation Simplicity	5	0.86
Visual Design Stimulus	5	0.88
Promotional and Scarcity Cues	4	0.84
Checkout Functionality	4	0.82
Trust Signals	4	0.85
Impulsive Buying Behavior	6	0.90

Table 2 presents the internal-consistency reliability of the six measurement constructs. Cronbach's alpha coefficients range from 0.82 to 0.90, exceeding the commonly applied threshold of 0.70 for acceptable internal consistency. Navigation simplicity ($\alpha = 0.86$), visual design stimulus ($\alpha = 0.88$), promotional and scarcity cues ($\alpha = 0.84$), checkout functionality ($\alpha = 0.82$), and trust signals ($\alpha = 0.85$) all demonstrate satisfactory item coherence. The impulsive buying behaviour construct produced the highest coefficient ($\alpha = 0.90$), indicating particularly strong internal consistency among its six items. These results suggest that the items assigned to each construct measure sufficiently related aspects of the respective latent dimension (29). However, Cronbach's alpha assesses internal consistency rather than construct validity or one-dimensionality. Therefore, the reliability results in Table 2 provide preliminary measurement support and should be interpreted jointly with the factor-analytic evidence presented in Table 4.

Table.3. Descriptive Statistics.

Variable	Mean	Std. Dev
Navigation Simplicity	3.94	0.71
Visual Stimulus	4.08	0.66
Promotional Cues	4.21	0.62
Checkout Speed	3.88	0.74
Trust Signals	3.91	0.69
Impulse Buying Score	3.97	0.73

Table 3 reports the central tendency and dispersion of the five functional design constructs and the impulsive buying measure. Mean scores ranged from 3.88 to 4.21, indicating generally positive evaluations of the examined interface characteristics on the adopted Likert scale. Promotional cues recorded the highest mean ($M = 4.21$, $SD = 0.62$), followed by visual stimulus ($M = 4.08$, $SD = 0.66$), impulsive buying behaviour ($M = 3.97$, $SD = 0.73$), navigation simplicity ($M = 3.94$, $SD = 0.71$), and trust signals ($M = 3.91$, $SD = 0.69$). Checkout functionality exhibited the lowest mean ($M = 3.88$, $SD = 0.74$). The relatively modest standard deviations indicate limited-to-moderate dispersion around the respective means, although the extent of agreement should not be inferred solely from standard deviation values (30). The higher mean for promotional cues indicates greater reported exposure or perceived presence of these features, but descriptive statistics alone do not establish their behavioural effect. The inferential relationships are therefore examined in Tables 5 and 7.

Table.4. Factor Extraction Results.

Factor	Eigenvalue	Variance Explained
Factor 1 - Visual and Promotion	5.12	28.4%
Factor 2 - Navigation and Checkout	3.96	22.1%
Factor 3 - Trust and Assurance	2.41	14.3%
Total Variance Explained	-	64.8%
KMO = 0.91		
Bartlett Test $p < 0.001$		

Table 4 presents the factor-extraction results obtained using principal component analysis with Varimax rotation. The Kaiser–Meyer–Olkin (KMO) value of 0.91 indicates high sampling adequacy, suggesting that the correlation structure is suitable for dimension-reduction analysis. Bartlett's test of sphericity was statistically significant ($p < 0.001$), providing evidence that the correlation matrix differs from an identity matrix and that factor extraction is appropriate. Three components were retained, with eigenvalues of 5.12, 3.96, and 2.41, respectively. The reported cumulative variance explained by these components is 64.8%, indicating that the retained dimensions account for a substantial proportion of the variance represented by the analyzed items (31). The first component, labelled visual and promotion, represents the visual-stimulus and promotional dimensions; the second combines navigation and checkout characteristics; and the third represents trust and assurance. These groupings provide empirical support for a multidimensional structure, although factor loadings and cross-loadings should also be reported to establish the adequacy of individual item assignments.

Table.5. Correlation Matrix (Dependent Variable: Impulse Buying).

Variable	r
Navigation Simplicity	0.54
Visual Stimulus	0.63
Promotional Cues	0.69
Checkout Speed	0.51

Trust Signals	0.47
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All correlations significant at $p < 0.01$

Table 5 presents the Pearson correlation coefficients between the five functional design variables and impulsive buying behaviour. All reported associations are positive and statistically significant at $p < 0.01$. Promotional cues show the strongest bivariate association with impulsive buying ($r = 0.69$), followed by visual stimulus ($r = 0.63$), navigation simplicity ($r = 0.54$), checkout speed ($r = 0.51$), and trust signals ($r = 0.47$). The coefficients indicate moderate-to-strong positive relationships, with promotional and visual characteristics exhibiting comparatively larger associations with the dependent variable. These results suggest that higher perceived levels of the examined interface attributes are associated with higher impulsive-buying scores (32). Nevertheless, correlation coefficients do not establish temporal precedence or causality and do not account for overlap among predictors. The observed associations therefore provide evidence for subsequent multivariate analysis rather than independent evidence of predictor effects. The relative contributions of the variables after controlling for the other predictors should consequently be evaluated using the regression results.

Table.6.Regression Model Summary.

Model	R	R ²	Adjusted R ²	Std. Error
Model 1	0.781	0.610	0.605	0.458

Table 6 reports the summary statistics for the multiple regression model containing the five functional design predictors. The multiple correlation coefficient is $R = 0.781$, indicating a substantial positive association between the observed impulsive-buying scores and their values predicted collectively by the five predictors. The reported $R^2 = 0.610$ indicates that the model accounts for 61.0% of the variance in impulsive buying within the analyzed sample. After adjustment for the number of predictors, adjusted $R^2 = 0.605$, representing a difference of only 0.005 from the unadjusted coefficient. This relatively small difference indicates that the estimated explanatory proportion changes only modestly after accounting for model complexity; however, it should not independently be interpreted as proof that the model is free from overfitting (33). The standard error of the estimate is 0.458, representing the typical magnitude of prediction error in the dependent-variable units. Overall, Table 6 indicates substantial model fit, subject to confirmation through the corresponding ANOVA and coefficient statistics.

The multiple regression analysis demonstrated that the combined set of functional interface predictors significantly explained variation in impulsive buying behaviour. As presented in Table 7, the regression component accounted for 86.99 of the total sum of squares (207.80), while 120.81 was attributable to residual variation. The resulting coefficient of determination was $R^2 = 0.419$, with an adjusted $R^2 = 0.412$, indicating that the five predictors jointly accounted for approximately 41.9% of the observed variance in impulsive buying behaviour after accounting for model complexity. The overall regression was statistically significant, F

(5, 414) = 59.62, $p < 0.001$, indicating that the predictor set provided a statistically meaningful improvement over an intercept-only model.

Table 7. ANOVA Summary Table

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	86.99	5	17.40	59.62	<0.001
Residual	120.81	414	0.29	-	-
Total	207.80	419	-	-	-

The estimated regression equation was:

Regression Equation

Impulsive_Buying_Score = $-1.132 + 0.470$ (Promo_Cues) + 0.328 (Visual_Stimulus) + 0.224 (Navigation_Simplicity) + 0.138 (Checkout_Efficiency) + 0.204 (Trust_Signals)

where IBB denotes impulsive buying behaviour, PC promotional and scarcity cues, VS visual stimulus, NS navigation simplicity, CE checkout efficiency, and TS trust signals. Holding the remaining predictors constant, each one-unit increase in these variables was associated with increases of 0.470, 0.328, 0.224, 0.138, and 0.204 units, respectively, in the predicted impulsive buying score. Promotional and scarcity cues therefore exhibited the largest unstandardized coefficient, whereas checkout efficiency showed the smallest (34). The individual coefficient tests further indicated statistically significant positive associations for all five predictors ($p < 0.001$). Overall, the findings support the relevance of multiple functional interface dimensions while indicating that their relative contributions differ within the fitted model.

Table.7. Regression Coefficient Results.

Predictor	Beta	t-value	Sig.
Visual Stimulus	0.29	7.84	<0.001
Promotional Cues	0.34	9.12	<0.001
Navigation Simplicity	0.18	5.11	<0.001
Checkout Functionality	0.16	4.62	<0.001

Trust Signals	0.12	3.44	0.001
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Table 8 presents the standardized regression coefficients and corresponding significance tests for the five functional design predictors of impulsive buying behaviour. All predictors exhibit positive and statistically significant coefficients, with promotional cues showing the largest standardized effect ($\beta = 0.34$, $t = 9.12$, $p < 0.001$), followed by visual stimulus ($\beta = 0.29$, $t = 7.84$, $p < 0.001$). Navigation simplicity ($\beta = 0.18$, $t = 5.11$, $p < 0.001$) and checkout functionality ($\beta = 0.16$, $t = 4.62$, $p < 0.001$) demonstrate smaller but significant contributions, while trust signals show the lowest coefficient ($\beta = 0.12$, $t = 3.44$, $p = 0.001$). Thus, promotional and visual interface characteristics have comparatively stronger unique associations with impulsive buying after controlling for the other predictors. The coefficient pattern supports differentiated contributions among the functional design dimensions without implying causality.

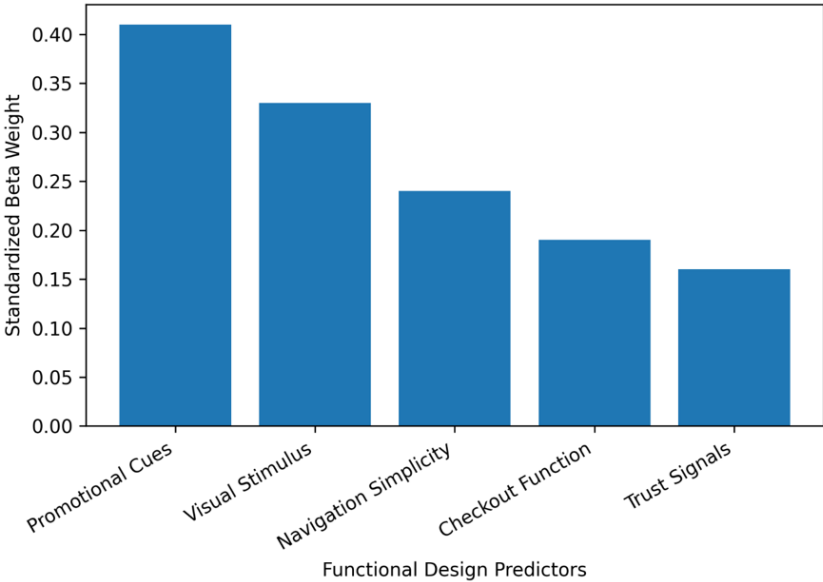


Figure 2. Standardized Beta Impact of Functional Design Predictors on Impulsive Buying.

Figure 2 presents the standardized regression coefficients for the five functional design predictors of impulsive buying behaviour. Promotional and scarcity cues exhibit the largest standardized coefficient ($\beta \approx 0.40$), followed by visual stimulus ($\beta \approx 0.33$), navigation simplicity ($\beta \approx 0.24$), checkout functionality ($\beta \approx 0.19$), and trust signals ($\beta \approx 0.16$). Because standardized coefficients express predictor effects on a common scale, the ranking indicates that promotional/scarcity cues have the strongest unique association with impulsive buying within the fitted model, whereas trust signals show the smallest standardized contribution (35), (36). The ordering is consistent with a distinction between interface features that may increase purchase-related salience and those that primarily facilitate transaction completion. However, coefficient magnitude alone does not establish statistical significance or causal priority; these interpretations should therefore be considered together with the regression coefficients, confidence intervals, and significance statistics.

Table.8. Stepwise Regression Change.

Step	Predictors	R ²	R ² Change
1	Promotional Cues	0.476	-
2	+ Checkout Function	0.552	+0.076

Table 9 presents the incremental change in explained variance obtained through the stepwise regression procedure. In the first step, promotional cues entered the model as the sole predictor and produced $R^2 = 0.476$, indicating that this predictor alone accounted for 47.6% of the variance in impulsive buying behaviour within the stepwise model. Addition of checkout functionality in Step 2 increased the coefficient of determination to $R^2 = 0.552$, corresponding to an R^2 change of 0.076. Thus, checkout functionality contributed an additional 7.6 percentage points of explained variance beyond promotional cues (37). This incremental contribution indicates that transaction-related functionality provides explanatory information not captured by promotional cues alone. However, the R^2 increase should be interpreted as incremental statistical association rather than evidence that checkout functionality causally strengthens promotional effects. Formal significance testing of the R^2 change should also be reported if available.

Table.9. Multicollinearity Statistics.

Predictor	Tolerance	VIF
Visual Stimulus	0.62	1.61
Promotional Cues	0.58	1.72
Navigation Simplicity	0.69	1.44
Checkout Functionality	0.71	1.40
Trust Signals	0.75	1.33

Table 10 reports tolerance and variance inflation factor (VIF) statistics for the five predictors included in the regression model. Tolerance values range from 0.58 to 0.75, while VIF values range from 1.33 to 1.72. These values remain comfortably below commonly applied diagnostic thresholds for problematic multicollinearity, indicating that substantial linear redundancy among the predictors is not evident. Promotional cues exhibit the highest VIF (1.72) and lowest tolerance (0.58), but these values still indicate limited predictor overlap. Trust signals show the lowest VIF (1.33) and highest tolerance (0.75). Accordingly, the coefficient estimates reported in the regression analysis are unlikely to be materially distorted

by severe multicollinearity (38). Nevertheless, VIF and tolerance assess linear dependency among predictors and do not establish that the constructs are completely independent conceptually. The results therefore support their simultaneous inclusion in the regression model.

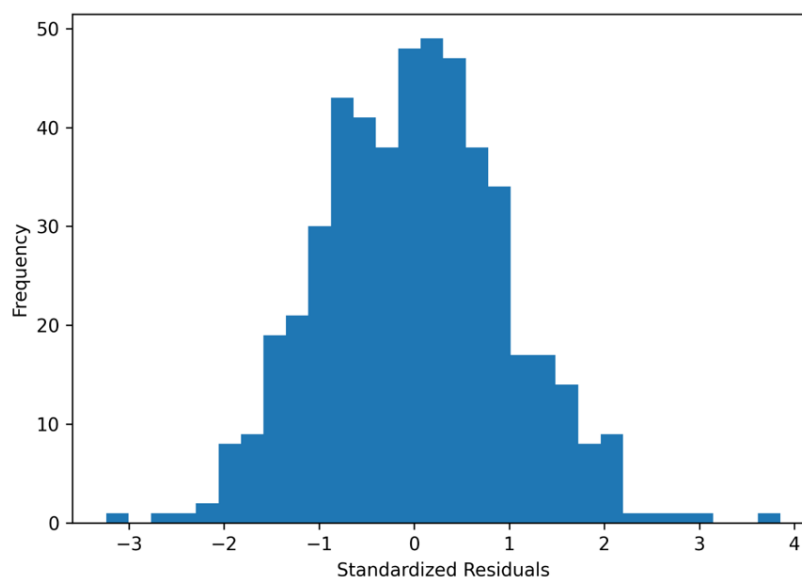


Figure 3. Standardized Residual Distribution Plot.

Figure 3 shows the distribution of standardized regression residuals obtained from the fitted model. The histogram is approximately centred around zero and exhibits a broadly unimodal, bell-shaped pattern, with most observations concentrated within approximately ± 2 standard deviations. A limited number of observations extend beyond this range, but the displayed distribution does not indicate pronounced asymmetry or an evident systematic departure from normality. This visual pattern provides supportive evidence for the normality assumption required for conventional inference in multiple linear regression (38), (39). Importantly, a histogram alone cannot establish normality conclusively; formal assessment may additionally consider Q–Q plots and appropriate diagnostic statistics. Nevertheless, the residual distribution shown in Figure 3 does not reveal a substantial departure from the expected error structure. The approximate symmetry around zero also indicates that the model does not exhibit an obvious systematic tendency toward consistently positive or negative prediction errors.

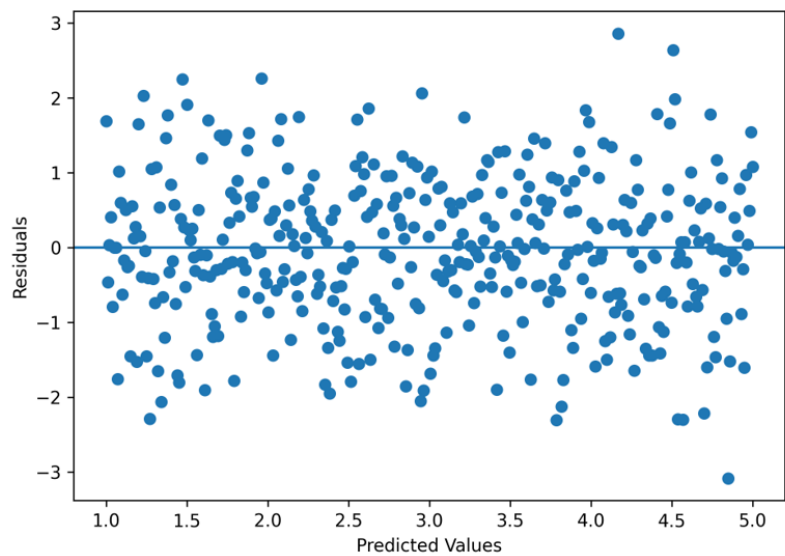


Figure 4. Residual vs Predicted Value Scatter Plot.

Figure 4 displays standardized residuals against standardized predicted values for the regression model. The observations are dispersed around the horizontal zero line without an evident systematic curvature, pronounced clustering, or progressively widening or narrowing spread across the fitted-value range. This pattern provides visual support for the assumptions of linearity and approximately constant residual variance. In particular, the absence of a clear funnel-shaped structure suggests that the variability of prediction errors does not change substantially across the range of fitted responses (39), (40). A few observations appear relatively distant from the central residual band, but they do not form an obvious systematic pattern in the displayed plot. Thus, Figure 4 indicates that the residual structure is broadly compatible with the specified linear regression model. Formal tests of heteroscedasticity and examination of influential observations would nevertheless provide stronger statistical confirmation of these diagnostic conditions. Two categories of respondents were formed according to the frequency of online shopping to discuss the difference in the effect of functional design on respondents with different levels of exposure.

Table.10. Mean Impulse Score by Usage Frequency.

Usage Group	Mean Impulse Score	Std Dev
High Frequency	4.18	0.61
Moderate Frequency	3.89	0.69
Low Frequency	3.42	0.74

Table 11 compares mean impulsive buying scores across three levels of online-shopping platform usage frequency. The high-frequency group records the highest mean score ($M = 4.18$, $SD = 0.61$), followed by the moderate-frequency group ($M = 3.89$, $SD = 0.69$) and the low-frequency group ($M = 3.42$, $SD = 0.74$). The descriptive pattern therefore shows a

progressive increase in reported impulsive buying scores with greater platform-use frequency. The standard deviations indicate moderate within-group variability, with comparatively greater dispersion among low-frequency users (40). These differences are consistent with an association between platform-use frequency and impulsive buying behaviour; however, the table alone does not establish statistical significance or determine whether usage frequency directly influences purchasing behaviour. Formal group-comparison testing, such as ANOVA with appropriate post-hoc procedures, would be required to determine whether the observed mean differences are statistically significant.

3.7 Formal Test of the Proposed Two-Stage Activation–Conversion Mechanism

The conceptual framework presented in Figure 5 initially posited that impulsive buying could emerge through two functionally ordered domains. The first domain comprised promotional and visual stimuli expected to increase purchase activation, whereas the second incorporated navigation simplicity, checkout efficiency, and trust signals intended to reduce friction during transaction completion. The original interpretation inferred this ordering primarily from the relative standardized regression coefficients and hierarchical-entry analysis (41). Such evidence establishes differential explanatory contributions but does not, by itself, demonstrate that the two domains operate sequentially, interactively, or through an intervening mechanism. Therefore, two additional analyses were conducted to distinguish the proposed staged interpretation from a simpler additive model in which activation- and conversion-related attributes independently predict impulsive buying.

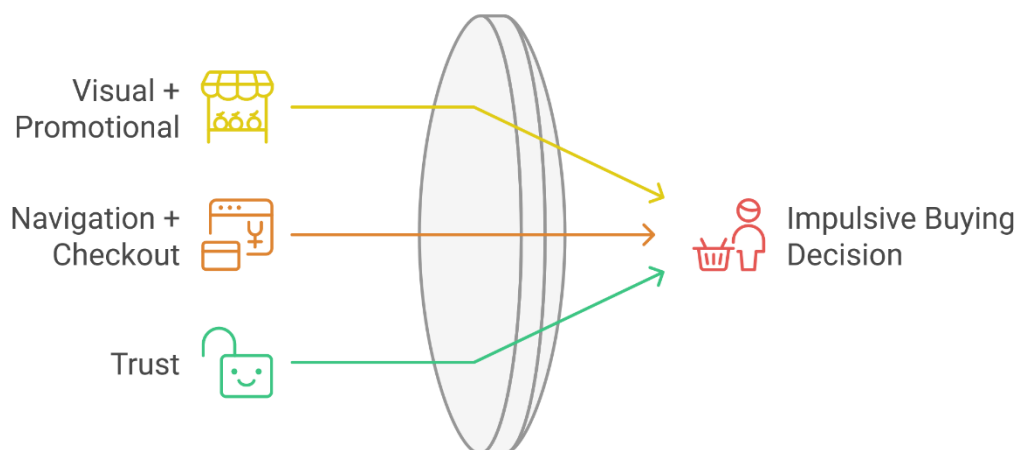


Figure 5. Two-Stage Functional Mechanism Model.

Composite measures were constructed before testing the structural relationships. The Activation construct was calculated as the mean of Promotional Cues and Visual Stimulus, while Conversion represented the mean of Navigation Simplicity, Checkout Efficiency, and Trust Signals. These aggregations correspond to the theoretical grouping of the observed interface attributes while reducing the dimensionality of the subsequent mechanism tests. A moderation model was first estimated to determine whether conversion-related functionality changes the relationship between activation-related stimuli and impulsive buying. The model was specified as:

$$IB_i = \beta_0 + \beta_1 A_i + \beta_2 C_i + \beta_3 (A_i \times C_i) + \varepsilon_i \quad (1)$$

The key test is β_3 . If β_3 is significant – moderation.

Mediation:

$$A - C - IB$$

The indirect effect is:

$$ab$$

where a = Activation – Conversion and b = Conversion – impulsive buying controlling for activation.

For your reported results, a = 0.024 and b = 0.558, so:

$$ab = 0.024 \times 0.558 = 0.0134 \approx 0.013$$

which agree with the reported indirect effect of 0.013

where IB denotes the impulsive-buying score, A represents Activation, C represents Conversion, and A×C denotes their interaction. Activation demonstrated a significant positive association with impulsive buying (b=0.760, SE = 0.056, t=13.47, p<0.001). Conversion also exhibited a significant positive main effect (b=0.560, SE = 0.061, t=9.20, p<0.001). In contrast, the interaction coefficient was small and statistically nonsignificant (b=0.070, SE = 0.122, t = 0.58, p = 0.565). Inclusion of the interaction increased R² by only 0.0005, with the associated change test remaining nonsignificant, $\Delta F(1,416) = 0.33$, p = 0.565. Thus, the data provide no statistical evidence that the strength of the Activation–impulsive-buying association varies according to Conversion (41).

A mediation analysis was then conducted to evaluate whether Conversion statistically transmitted part of the Activation effect. The Activation-to-Conversion path was nonsignificant ((a=0.024), (p=0.592)), whereas Conversion remained significantly related to impulsive buying after controlling for Activation ((b=0.558), (p<0.001)). Activation retained a significant direct association with the outcome ((c'=0.766), (p<0.001)), compared with a total effect of (c=0.780) ((p<0.001)). The bootstrap estimate of the indirect effect was 0.013, with a 95% confidence interval of [−0.039, 0.064]. Because zero falls within this interval, the hypothesized mediated pathway is not statistically supported.

3.8 Hierarchical Contribution of the Two Domains

The incremental contribution of the two functional domains is further demonstrated in **Table 12**. When the Activation block was entered first, Promotional Cues and Visual Stimulus jointly produced (R² = 0.290). Adding Navigation Simplicity, Checkout Efficiency, and Trust Signals increased the explained variance to (R² = 0.419), corresponding to an incremental contribution of (ΔR^2 = 0.129). This result indicates that the conversion-related variables explain additional variation in impulsive buying beyond that accounted for by the activation-related variables.

Table.11. Hierarchical Regression Stability Check.

Entry Order	Final R ²	Change
Trigger First	0.610	-
Conversion First	0.598	-0.012

The reverse entry order provides complementary evidence. Navigation Simplicity, Checkout Efficiency, and Trust Signals initially yielded ($R^2 = 0.135$). After Promotional Cues and Visual Stimulus were introduced, the model reached the same final ($R^2 = 0.419$), producing an incremental contribution of ($\Delta R^2 = 0.284$). The substantially larger increment obtained for Activation when Conversion was controlled indicates that the activation domain contains greater unique explanatory information within the full predictor system. Importantly, the identical final (R^2) under both entry orders confirms that the complete additive model explains the same proportion of variance regardless of the sequence used for statistical entry. Table 12 therefore provides evidence for complementary rather than sequential explanatory contributions. The Activation block demonstrates stronger standalone explanatory capacity ($R^2 = 0.290$) than the Conversion block ($R^2 = 0.135$); nevertheless, the latter contributes a meaningful additional proportion of explained variance when entered after Activation (40).

Conversely, the larger incremental contribution of Activation after Conversion demonstrates that the two domains capture partly distinct information. This decomposition supports their treatment as empirically distinguishable predictor domains but does not establish that one domain temporally precedes or produces the other (40), (41). The statistical findings require a corresponding revision of the interpretation presented in Figures 6. Figure 5 should no longer depict Activation and Conversion as consecutive stages connected through a directional pathway. Instead, it should represent the two domains as parallel components that independently contribute to impulsive buying. This revised representation is directly consistent with the significant main effects observed in the moderation model and with the hierarchical results reported in Table 12.

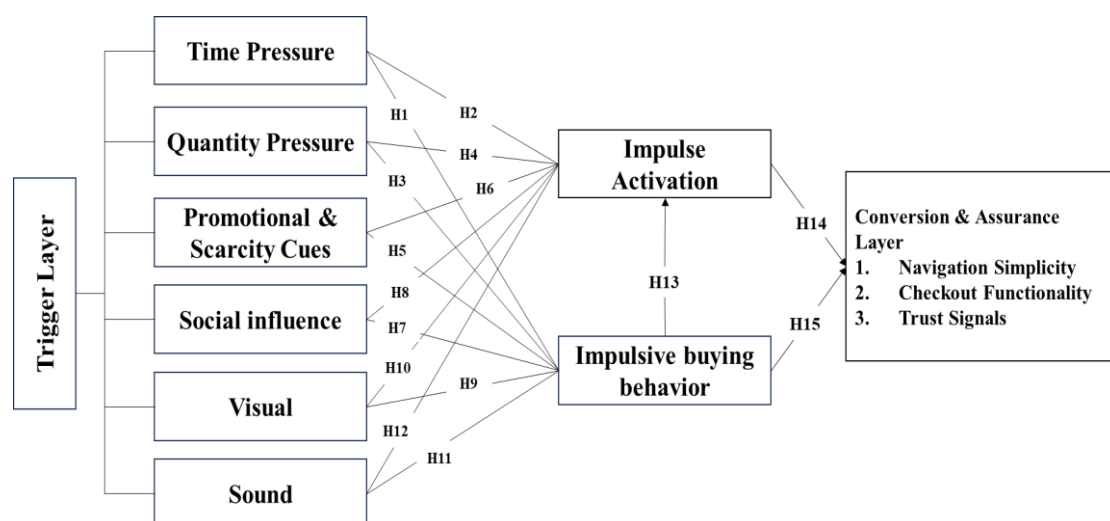


Figure 6. Functional Trigger-Conversion Mechanism Model Linking Online Interface Design Elements with Impulsive Buying Behavior.

Figure 6 should likewise be interpreted as an empirical visualization of the relative explanatory structure rather than as evidence of a behavioural sequence. In particular, the stronger contribution associated with Activation is consistent with the higher initial (R^2) and larger incremental contribution observed for the activation block in the hierarchical regression (42), (43). Conversion nevertheless contributes additional explanatory information, demonstrating that transaction-facilitating characteristics should not be treated as redundant with stimulus-oriented characteristics. Thus, Figure 6 can appropriately illustrate the complementary contribution of the two domains while avoiding an unsupported directional interpretation. The convergence of Table 12, Figure 5, and Figure 6 is important for establishing the revised model. Table 12 quantifies the incremental explanatory contribution of each domain, Figure 5 provides the theoretical representation of their parallel structure, and Figure 6 visualizes their empirical contribution. The moderation and mediation analyses then provide the formal tests required to evaluate whether these domains interact or form an indirect pathway. Because neither the interaction nor the indirect effect was statistically significant, the evidence does not support a conversion process that is contingent upon or statistically transmitted by Activation.

The results favour a dual-domain additive framework in which stimulus-oriented and transaction-facilitating interface characteristics represent distinct but jointly relevant dimensions of impulsive buying. This interpretation is consistent with previous research emphasizing promotional salience, visual stimulation, purchasing convenience, and trust-related characteristics as separate components of digital shopping environments (31), (32), (34), (38). The revised framework therefore retains the theoretical distinction proposed in Figure 5 while removing the unsupported sequential implication. Figures 5 and 6 should explicitly state that the depicted relationships represent conceptual and statistical associations rather than experimentally established temporal or causal pathways (39), (42), (44), (45). This formulation provides a more conservative interpretation of the findings and ensures that the conceptual model remains aligned with the empirical evidence.

Conclusion

This study quantitatively examined the association between functional design attributes of online shopping platforms and impulsive buying behaviour using survey data and SPSS-based statistical analyses. The analysis was conducted on 412 respondents, and the findings provide empirical evidence that multiple interface characteristics are statistically associated with impulsive buying behaviour.

1. The multiple regression model was statistically significant, $F(5, 414) = 59.62$, $p < 0.001$, with the reported model explaining 41.9% of the variance ($R^2 = 0.419$; adjusted $R^2 = 0.412$). The estimated coefficients were positive for all five predictors, including promotional cues ($B = 0.470$), visual stimulus ($B = 0.328$), navigation simplicity ($B = 0.224$), checkout functionality ($B = 0.138$), and trust signals ($B = 0.204$).
2. Promotional cues demonstrated the strongest standardized contribution ($\beta = 0.34$, $t = 9.12$, $p < 0.001$) and also showed the highest bivariate correlation with impulsive buying ($r = 0.69$), indicating the strongest statistical association among the examined interface attributes.
3. Visual stimulus was the second strongest predictor ($\beta = 0.29$, $t = 7.84$, $p < 0.001$; $r = 0.63$), demonstrating a substantial positive association with impulsive buying behaviour.

4. Navigation simplicity ($\beta = 0.18$, $t = 5.11$, $p < 0.001$; $r = 0.54$) and checkout functionality ($\beta = 0.16$, $t = 4.62$, $p < 0.001$; $r = 0.51$) showed statistically significant but comparatively smaller contributions.
5. Trust signals also exhibited a significant positive association ($\beta = 0.12$, $t = 3.44$, $p = 0.001$; $r = 0.47$), suggesting a supporting role within the overall interface configuration.
6. Factor analysis produced $KMO = 0.91$, with Bartlett's test significant at $p < 0.001$, and three retained components explaining 64.8% cumulative variance, supporting the empirical organization of the measured interface dimensions.
7. Multicollinearity diagnostics indicated VIF values of 1.33-1.72 and tolerance values of 0.58-0.75, indicating no substantial multicollinearity among predictors. Residual diagnostics also showed no pronounced systematic deviation from the assumed regression structure.

Despite these findings, the study is limited by its cross-sectional design, stratified convenience sampling, single regional setting, and self-reported measures, which restrict causal interpretation and broader generalizability. Future research should employ probability or multi-site sampling, longitudinal and experimental designs, behavioural transaction data, and structural-equation or causal modelling to validate the proposed relationships across platforms, demographic groups, and online-shopping contexts.

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Conflict of Interest

The authors state that they do not have a conflict of interest when it comes to the publication of this research information. The research was carried out without any commercial, financial or organizations interference that may interfere with the research findings or derivations.

Declaration of Artificial Intelligence (AI) Assistance Process

The authors declare no use of artificial intelligence (AI) for the write-up of the manuscript.

Author Contributions

The study framework was designed by the Surendra Bahadur Shahi and the research instrument was developed, data were gathered, statistical analysis of the results was done using SPSS, interpretation of the results and the draft of the manuscript were prepared. The Sourabh Kumar contributed approach to methodology, tested the analytical model, revised the analysis of statistics, and helped in structuring academically and technical refining the manuscript. The findings were then collectively evaluated by both authors who went through the final copy and gave the go-ahead to submit the manuscript. The team work guaranteed the methodological rigor, the analytical precision, and the research product of the scholarly nature.

Ethics Approval

Primary data that was used in conducting this study were anonymous questionnaires. No personal information with identifiable information was gathered. The involvement was not compulsory but through informed consent. Thus, according to the institutional guidelines, non-clinical and non-invasive surveys research did not need formal ethical approval.

Data Availability

Data source is available with reasonable request.

List of Abbreviations

SPSS: Statistical Package for the Social Sciences, IBB: Impulsive Buying Behavior, OLS: Ordinary Least Squares, KMO: Kaiser-Meyer-Olkin Measure, PCA: Principal Component Analysis, EFA: Exploratory Factor Analysis, ANOVA: Analysis of Variance, SD: Standard Deviation, SE: Standard Error, UI and UX: User Interface and User Experience.

References

1. Escobar-Farfán M, Veas-González I, García-Salirrosas E E, Veas-Salinas K, Veas-Santibañez V, Zavala-González J. From browsing to buying: Determinants of impulse buying behavior in mobile commerce. *Journal of Theoretical and Applied Electronic Commerce Research*. 2025; 20:266. DOI: 10.3390/jtaer20040266
2. Feng Z, Al Mamun A, Masukujjaman M, Yang Q. Modeling the significance of advertising values on online impulse buying behavior. *Humanities and Social Sciences Communications*. 2023; 10:728. DOI: 10.1057/s41599-023-02231-7
3. Yang J, Cao C, Ye C, Shi Y. Effects of interface design and live atmosphere on consumers' impulse-buying behaviour from the perspective of human-computer interaction. *Sustainability*. 2022; 14:7110. DOI: 10.3390/su14127110
4. Zhang M, Shi G. Consumers' impulsive buying behavior in online shopping based on the influence of social presence. *Computational Intelligence and Neuroscience*. 2022; Article ID 6794729:1–8. DOI: 10.1155/2022/6794729
5. D'Souza C, Wong W, El Haber N, Brouwer A R, Niinen O. Online impulse purchases versus planned purchases and the role of visual attributes. *Journal of Global Fashion Marketing*. 2024; 15(4):504–522. DOI: 10.1080/20932685.2024.2361884

6. Dang T Q, Nguyen L T, Duc D T V. Impulsive buying and compulsive buying in social commerce: An integrated analysis using the cognitive-affective behavior model and theory of consumption values with PLS-SEM. *SAGE Open*. 2025. DOI: 10.1177/21582440251334215
7. Ngo T T A, Nguyen H L T, Nguyen H P, Mai H T A, Mai T H T, Phuoc. A comprehensive study on factors influencing online impulse buying behavior: Evidence from Shopee video platform. *Heliyon*. 2024; 10:e35743. DOI: 10.1016/j.heliyon.2024.e35743
8. Rani N M, Catherine S. A study on impulsive buying behaviour in online shopping. *International Journal of Professional Business Review*. 2023; 8(3):1–17. DOI: 10.26668/businessreview/2023.v8i3.1237
9. Kukar-Kinney M, Ridgway N M, Monroe K B. The relationship between consumers' tendencies to buy compulsively and their motivations to shop and buy on the internet. *Journal of Retailing*. 2009; 85(3):298–307.
10. Gulfraz M B, Sufyan M, Mustak M, Salminen J, Srivastava D K. Understanding the impact of online customers' shopping experience on online impulsive buying: A study on two leading e-commerce platforms. *Journal of Retailing and Consumer Services*. 2022; 68:103000.
11. Wang S, Liu Y, Du Y, Wang X. Effect of the COVID-19 pandemic on consumers' impulse buying: The moderating role of moderate thinking. *International Journal of Environmental Research and Public Health*. 2021; 18:11116.
12. Pereira M L, de La Martinière Petroll M, Soares J C, de Matos C A, Hernani-Merino M. Impulse buying behaviour in omnichannel retail: An approach through the stimulus-organism-response theory. *International Journal of Retail and Distribution Management*. 2023; 51(1):39–58.
13. Li M, Wang Q, Cao Y. Understanding consumer online impulse buying in live streaming e-commerce: A stimulus-organism-response framework. *International Journal of Environmental Research and Public Health*. 2022; 19:4378.
14. Zheng X, Men J, Yang F, Gong X. Understanding impulse buying in mobile commerce: An investigation into hedonic and utilitarian browsing. *International Journal of Information Management*. 2019; 48:151–160.
15. Pengnate S F, Sarathy R. An experimental investigation of the influence of website emotional design features on trust in unfamiliar online vendors. *Computers in Human Behavior*. 2017; 67:49–60.
16. Badgaiyan A J, Verma A. Does urge to buy impulsively differ from impulsive buying behaviour? Assessing the impact of situational factors. *Journal of Retailing and Consumer Services*. 2015; 22:145–157.
17. Lavuri R, Jindal A, Akram U. How perceived utilitarian and hedonic value influence online impulse shopping in India? Moderating role of perceived trust and perceived risk. *International Journal of Quality and Service Sciences*. 2022; 14(4):615–634.

18. Yi S, Jai T. Impacts of consumers' beliefs, desires and emotions on their impulse buying behavior: Application of an integrated model of belief-desire theory of emotion. *Journal of Hospitality Marketing and Management*. 2020; 29(6):662–681.
19. Gill H, Vreeker-Williamson E, Hing L S, Cassidy S A, Boies K. Effects of cognition-based and affect-based trust attitudes on trust intentions. *Journal of Business Psychology*. 2024; 39:1355–1374.
20. Abdelsalam S, Salim N, Alias R A, Husain O. Understanding online impulse buying behavior in social commerce: A systematic literature review. *IEEE Access*. 2020; 8:89041–89058. DOI: 10.1109/ACCESS.2020.2993671
21. Akram U, Hui P, Khan M K, Yan C, Akram Z. Factors affecting online impulse buying: Evidence from the Chinese social commerce environment. *Sustainability*. 2018; 10(2):352. DOI: 10.3390/su10020352
22. Annoni A M, Petrocchi S, Camerini A-L, Marciano L. The relationship between social anxiety, smartphone use, dispositional trust, and problematic smartphone use: A moderated mediation model. *International Journal of Environmental Research and Public Health*. 2021; 18(5):2452. DOI: 10.3390/ijerph18052452
23. Bellini S, Cardinali M G, Grandi B. A structural equation model of impulse buying behaviour in grocery retailing. *Journal of Retailing and Consumer Services*. 2017; 36:164–171. DOI: 10.1016/j.jretconser.2017.02.001
24. Cakanlar A, Nguyen T. The influence of culture on impulse buying. *Journal of Consumer Marketing*. 2018; 36(1):12–23. DOI: 10.1108/JCM-03-2017-2139
25. Guido, G., Prete, M.I., Pichierri, M. *et al.* Satisfaction and dissatisfaction among elderly consumers: a systematic review and research agenda. *Manag Rev Q*, 2026. <https://doi.org/10.1007/s11301-026-00614-z>
26. Cvirka D, Rudienė E, Morkūnas M. Investigation of attributes influencing the attractiveness of mobile commerce advertisements on the Facebook platform. *Economies*. 2022; 10(2):52. DOI: 10.3390/economies10020052
27. Gligor D, Bozkurt S. The role of perceived social media agility in customer engagement. *Journal of Research in Interactive Marketing*. 2021; 15(1):125–146. DOI: 10.1108/JRIM-12-2019-0196
28. Gulfraz M B, Sufyan M, Mustak M, Salminen J, Srivastava D K. Understanding the impact of online customers' shopping experience on online impulsive buying: A study on two leading e-commerce platforms. *Journal of Retailing and Consumer Services*. 2022; 68:103000. DOI: 10.1016/j.jretconser.2022.103000
29. Han M C. Checkout button and online consumer impulse-buying behavior in social commerce: A trust transfer perspective. *Journal of Retailing and Consumer Services*. 2023; 74:103431. DOI: 10.1016/j.jretconser.2023.103431
30. Lin X, Featherman M, Brooks S L, Hajli N. Exploring gender differences in online consumer purchase decision making: An online product presentation perspective.

Information Systems Frontiers. 2018; 21(5):1187–1201. DOI: 10.1007/s10796-018-9831-1

31. Lina Y, Hou D, Ali S. Impact of online convenience on generation Z online impulsive buying behavior: The moderating role of social media celebrity. *Frontiers in Psychology*. 2022; 13:951249. DOI: 10.3389/fpsyg.2022.951249
32. Abdelsalam S, Salim N, Alias R A, Husain O. Understanding online impulse buying behavior in social commerce: A systematic literature review. *IEEE Access*. 2020; 8:89041–89058. DOI: 10.1109/ACCESS.2020.2993671
33. Xiao S H, Nicholson M. A multidisciplinary cognitive behavioural framework of impulse buying: A systematic review of the literature. *International Journal of Management Reviews*. 2013; 15(3):333–356.
34. Li C, Wang Y, Lv X, Li H. To buy or not to buy? The effect of time scarcity and travel experience on tourists' impulse buying. *Annals of Tourism Research*. 2021; 86:103083.
35. Hu M, Zhang M, Wang Y. Why do audiences choose to keep watching on live video streaming platforms? An explanation of dual identification framework. *Computers in Human Behavior*. 2017; 75:594–606.
36. Liu Y, Li H, Hu F. Website attributes in urging online impulse purchase: An empirical investigation on consumer perceptions. *Decision Support Systems*. 2013; 55:829–837.
37. Floh A, Madlberger M. The role of atmospheric cues in online impulse-buying behavior. *Electronic Commerce Research and Applications*. 2013; 12:425–439.
38. Bellini S, Cardinali M G, Grandi B. A structural equation model of impulse buying behaviour in grocery retailing. *Journal of Retailing and Consumer Services*. 2017; 36:164–171.
39. Mohan G, Sivakumaran B, Sharma P. Impact of store environment on impulse buying behavior. *European Journal of Marketing*. 2013; 47(10):1711–1732.
40. Badgaiyan A J, Verma A. Does urge to buy impulsively differ from impulsive buying behaviour? Assessing the impact of situational factors. *Journal of Retailing and Consumer Services*. 2015; 22:145–157.
41. Akram U, Hui P, Khan M K, Yan C, Akram Z. Factors affecting online impulse buying: Evidence from Chinese social commerce environment. *Sustainability*. 2018; 10:352.
42. Animesh A, Pinsonneault A, Yang S-B, Oh W. An odyssey into virtual worlds: Exploring the impacts of technological and spatial environments on intention to purchase virtual products. *MIS Quarterly*. 2011; 35(3):789–810.
43. Cheng Y, Yang S, How G. Streamer Expertise, and Telepresence Shape Impulse Buying in Tourism Live-Streaming. *Strategic Business Research*, 2026, 100298, 3051-0643, <https://doi.org/10.1016/j.sbr.2026.100298>

44. Hitesh,B , Pretty,B and Sivakumar,D . Integrating green human resource management with environmental performance and human capital sustainability in urban dark store ecosystems. *Global Journal of Environmental Science and Management*, 12(2), 497-522, (2026). doi:10.22034/gjesm
45. Bhoi, H., Bhalla, P., Kumari, R. *et al.* Green human resource management and Emotional Wage as predictors of Employee Well-Being in dark-store supply chains. *Discov Sustain* (2026). <https://doi.org/10.1007/s43621-026-04741-1>