Meyer, 1990; Bansal, Irving, & Taylor, 2004). The affective form of commitment is driven by feelings of trust, belongingness, and satisfaction, whereas continuance commitment arises from practical considerations such as time investments, familiarity with the platform, and perceived risk of trying new vendors (Jones et al., 2000; Meyer & Herscovitch, 2001).

The rise of online shopping has amplified the importance of understanding these two types of commitment. Unlike traditional brick-and-mortar retailing, online commerce lacks face-to-face interaction, making emotional bonds harder to cultivate (Gefen, Karahanna, & Straub, 2003). However, features such as personalized recommendations, responsive customer service, social engagement, and data-driven loyalty programs can foster affective commitment even in virtual settings (Chaudhuri & Holbrook, 2001; Algesheimer, Dholakia, & Herrmann, 2005). Meanwhile, technological integration, habitual purchasing, and switching barriers such as digital lock-in effects or loyalty rewards contribute to continuance commitment (Sharma & Patterson, 2000). Understanding how these two commitment types jointly influence repurchase behavior can provide actionable insights for online marketers aiming to strengthen customer relationships.

Despite the growing body of literature on online customer loyalty, there remains a conceptual and empirical gap regarding how different forms of commitment interact to shape repurchase intentions (Liang, Wang, & Farquhar, 2009; Zhou, Lu, & Wang, 2019). Most studies tend to focus on single antecedents such as trust, satisfaction, or perceived value without explicitly distinguishing between emotional and rational determinants of loyalty (Sirdeshmukh, Singh, & Sabol, 2002). By contrast, the current study integrates both affective and continuance commitment to provide a holistic understanding of loyalty formation in online shopping environments.

Drawing upon the Commitment-Trust Theory of Relationship Marketing (Morgan & Hunt, 1994), this research posits that affective and continuance commitments are both significant predictors of repurchase intentions. Specifically, it proposes that affective commitment—stemming from emotional connection and psychological identification—has a stronger influence on repurchase intentions than continuance commitment, which is based on calculative considerations. The theoretical foundation lies in the belief that emotional ties often lead to voluntary loyalty, whereas continuance commitment leads to constrained loyalty (Gounaris, 2005; Gustafsson et al., 2005). In e-commerce, where trust deficits and competitive pricing dominate, the balance between emotional and calculative loyalty determines long-term customer retention.

This study is particularly relevant in the current era of digital saturation, where consumers are bombarded with choices and promotional stimuli (Bhattacherjee, 2001). Retaining existing customers not only reduces acquisition costs but also enhances profitability, as repeat buyers tend to spend more and engage in positive word-of-mouth (Reichheld & Schefter, 2000; Kim & Peterson, 2017). Therefore, investigating the impact of different commitment types on repurchase intentions can provide both theoretical insights and managerial guidance for developing robust online retention strategies. The next sections review the relevant literature, propose hypotheses, and empirically test the relationships between affective commitment, continuance commitment, and repurchase intentions among online customers.

2.1 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1.1 Theoretical Foundation: Relationship Marketing and Commitment

The conceptual foundation of this study is rooted in the Commitment-Trust Theory of Relationship Marketing proposed by Morgan and Hunt (1994), which posits that commitment and trust are two key mediating variables in the development of successful, long-term relational exchanges. The theory emphasizes that commitment represents a consumer's desire to maintain a valued relationship and acts as a central force that drives cooperative behaviour, reduces uncertainty, and enhances relationship longevity. In the digital context, where face-to-face interactions are absent and uncertainty is often high, commitment serves as a vital mechanism for sustaining customer loyalty and engagement (Chaudhuri & Holbrook, 2001; Palmatier et al., 2006).

Commitment has been conceptualized as a multidimensional construct, encompassing affective, continuance, and normative dimensions (Allen & Meyer, 1990; Meyer & Herscovitch, 2001). Affective commitment relates to emotional attachment and identification; continuance commitment refers to the perceived costs of leaving a relationship; and normative commitment involves moral or social obligation to continue the relationship (Bansal, Irving, & Taylor, 2004). Among these, affective and continuance commitments have been found most relevant to consumer–brand relationships and repurchase behavior in commercial settings (Fullerton, 2003; Gustafsson, Johnson, & Roos, 2005).

In online retail environments, commitment plays a crucial role in overcoming transactional anonymity and fostering a sense of relational continuity. E-commerce interactions lack traditional interpersonal cues, making it harder for firms to rely solely on trust and satisfaction as loyalty drivers (Gefen, Karahanna, & Straub, 2003). Therefore, understanding the dual roles of affective and continuance commitment is essential for explaining how customers decide to remain loyal to online vendors even in the presence of numerous alternatives.

2.1.2 Affective Commitment and Repurchase Intentions

Affective commitment refers to an individual's emotional attachment, identification, and involvement with a particular organization, service provider, or brand (Allen & Meyer, 1990). In the marketing context, it manifests as customers' genuine affection and positive feelings toward a brand, leading them to continue the relationship out of emotional satisfaction rather than necessity (Evanschitzky et al., 2006; Fullerton, 2003). Affective commitment develops when consumers experience consistent satisfaction, trust, and alignment with the brand's values (Chaudhuri & Holbrook, 2001; Verhoef, 2003).

Emotions are a key determinant of long-term loyalty in online retailing. When customers feel emotionally connected to an online store—through personalized service, authentic communication, and perceived empathy—they tend to exhibit behavioral loyalty, including repeat purchasing and positive word-of-mouth (Kumar & Shah, 2004; Vlachos & Vrechopoulos, 2012). Studies in consumer psychology confirm that affective attachment increases psychological ownership, thereby reducing consumers' tendency to switch even when faced with better deals elsewhere (Thomson, MacInnis, & Park, 2005).

In the digital marketplace, affective commitment is reinforced by features that enhance relational closeness, such as brand communities, user engagement mechanisms, and social media interactions (Algesheimer, Dholakia, & Herrmann, 2005). Online platforms that evoke emotional experiences—such as trustworthiness, excitement, or gratitude—tend to cultivate stronger affective bonds (Batra et al., 2012). This emotional dimension is particularly important because online consumers often rely on psychological cues rather than physical experiences when forming loyalty judgments (Sirdeshmukh, Singh, & Sabol, 2002).

Affective commitment has been empirically linked to repurchase intentions across various service and retail contexts. For instance, Fullerton (2005) demonstrated that affective commitment predicts voluntary loyalty, characterized by genuine attachment and advocacy. Similarly, Gustafsson et al. (2005) found that affective commitment significantly enhances customer retention beyond the effects of satisfaction alone. These findings imply that emotional bonds can be more enduring than transactional satisfaction, particularly in online environments where consumers value relational warmth and perceived care.

Therefore, the present study proposes that affective commitment significantly influences customers' willingness to repurchase from the same online retailer, leading to the following hypothesis:
H1: Affective commitment has a positive and significant effect on repurchase intentions among online customers.

2.1.3 Continuance Commitment and Repurchase Intentions
While affective commitment captures emotional attachment, continuance commitment represents a calculative mindset in which customers weigh the costs and benefits of maintaining versus terminating a relationship (Allen & Meyer, 1990; Sharma & Patterson, 2000). It is primarily based on perceived switching costs, lack of attractive alternatives, and investments already made in the relationship (Burnham, Frels, & Mahajan, 2003). Continuance commitment thus reflects a form of constrained loyalty, where consumers stay not because they want to, but because they feel they need to (Gounaris, 2005).

In the e-commerce context, switching barriers can take many forms: accumulated reward points, saved payment details, subscription benefits, habit formation, or platform familiarity. These factors create inertia, reducing the likelihood of switching to another retailer even if competitors offer similar benefits (Bansal et al., 2004; Kim, 2012). Research by Jones, Mothersbaugh, and Beatty (2000) found that customers with high switching costs are more likely to demonstrate repeat purchasing behavior due to the inconvenience associated with change. Similarly, Colgate and Lang (2001) highlighted that continuance commitment can sustain loyalty in service industries where contractual, technological, or psychological barriers exist.

Although continuance commitment is sometimes perceived as a weaker form of loyalty than affective commitment, it nonetheless contributes to short-term retention and transactional stability (Fullerton, 2003; Sharma & Patterson, 2000). In online retailing, continuance commitment may arise when customers feel that the learning effort to use a new website, re-enter information, or rebuild trust is too costly (Bhattacherjee, 2001). Moreover, the integration of mobile apps, digital wallets, and personalized recommendation algorithms further increases customers' dependence on existing platforms (Reichheld & Schefter, 2000).

Empirical findings in various sectors support the positive relationship between continuance commitment and repurchase intentions. For instance, Wetzels, Ruyter, and van Birgelen (1998) found that continuance commitment significantly influences intention to maintain service relationships in telecommunications. Bansal et al. (2004) also confirmed that perceived switching costs and lack of alternatives strengthen continuance commitment and subsequent repurchase behavior. Thus, while affective commitment encourages voluntary loyalty, continuance commitment ensures retained loyalty through inertia or dependence. Based on these arguments, the following hypothesis is proposed:
H2: Continuance commitment has a positive and significant effect on repurchase intentions among online customers.

3.1 METHODOLOGY

3.1.1 Research Design

This study adopted a quantitative, cross-sectional, and explanatory research design to empirically investigate how affective commitment and continuance commitment influence repurchase intentions among online customers. Quantitative methods are particularly suitable for testing causal relationships and theory-driven hypotheses through statistical modeling (Hair et al., 2019). The study's conceptual framework was developed based on the Commitment-Trust Theory of Relationship Marketing (Morgan & Hunt, 1994) and the Three-Component Model of Commitment (Allen & Meyer, 1990).

A survey-based approach was used because it enables the collection of standardized data from a large population within a relatively short period and allows for the generalization of findings (Creswell & Creswell, 2018). The constructs—affective commitment, continuance commitment, and repurchase intentions—were operationalized using well-established scales from prior research to ensure content validity and conceptual consistency.

This design is well suited for understanding psychological variables such as customer commitment, which are latent constructs not directly observable but measurable through multiple indicators (Hair et al., 2019). The study employed

Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the hypothesized model, as PLS-SEM is preferred when the objective is prediction and theory extension rather than strict model confirmation (Chin, 1998).

3.1.2 Sampling and Data Collection

The target population consisted of online shoppers who had made at least one purchase from major e-commerce platforms within the past six months. This selection criterion ensured that respondents had sufficient experience and familiarity with online purchasing behavior (Lin & Lekhawipat, 2014). A non-probability purposive sampling technique was adopted to select participants fitting these criteria, as it is widely used in behavioral research where specific expertise or experience is required (Saunders, Lewis, & Thornhill, 2019).

Data were collected through an online questionnaire distributed via social media, email, and e-commerce forums. The questionnaire was accompanied by a brief description of the study's purpose and assurances of anonymity and confidentiality in accordance with ethical research guidelines (Bryman & Bell, 2015). A pilot test with 30 respondents was conducted to check for clarity, reliability, and comprehension of items. Minor wording adjustments were made based on feedback.

The final dataset consisted of 200 respondents which meets the minimum threshold recommended for PLS-SEM (Hair et al., 2019), where the sample should exceed ten times the largest number of structural paths directed toward a latent variable. The diversity of respondents in terms of gender, age, and purchasing frequency provided a comprehensive view of online consumer commitment behavior.

3.1.3 Measurement Instruments

Each construct was measured using multiple indicators drawn and adapted from validated scales:

- Affective Commitment (AC): Measured using six items (AC1–AC6) adapted from Fullerton (2003) and Allen and Meyer (1990). Items captured emotional attachment, identification, and sense of belonging toward the online retailer (e.g., "I feel a strong sense of belonging to this online store").
- Continuance Commitment (CC): Measured with four items (CC1–CC4) based on the work of Bansal, Irving, and Taylor (2004), reflecting perceived costs and lack of alternatives (e.g., "It would be too costly for me to switch to another online store").
- Repurchase Intentions (RI): Measured with five items (RI1–RI5) adapted from Hellier et al. (2003) and Lin and Lekhawipat (2014), assessing willingness and intent to buy again (e.g., "I intend to continue purchasing from this online store in the future").

All items were rated on a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The multi-item scale approach improves measurement precision and construct validity by averaging responses across multiple indicators (DeVellis, 2017).

4.1 DATA ANALYSIS PROCEDURE

Data analysis followed a structured two-step approach:

1. Measurement model assessment, which evaluates the reliability and validity of constructs.
2. Structural model assessment, which tests hypothesized relationships between constructs.

The analysis was conducted using SmartPLS 4.0, a specialized tool for PLS-SEM analysis. This method was chosen because it accommodates small-to-medium samples, non-normal data, and formative or reflective constructs (Hair et al., 2021). Bootstrapping with 5,000 resamples was used to estimate path coefficients, t-statistics, and p-values, providing robust significance testing (Henseler, Ringle, & Sinkovics, 2009).

Descriptive statistics (mean, standard deviation, skewness, kurtosis) were computed to assess normality, while missing data were treated using mean substitution since missing values were minimal (<2%). No multicollinearity issues were detected, as variance inflation factors (VIFs) were below the threshold of 5.0, confirming construct independence (Hair et al., 2021).

4.1.1 Measurement Model

The measurement model assesses the relationships between latent constructs and their observed indicators to ensure that the constructs are measured reliably and validly (Hair et al., 2019). This step includes evaluation of factor loadings, internal consistency reliability, convergent validity, and discriminant validity.

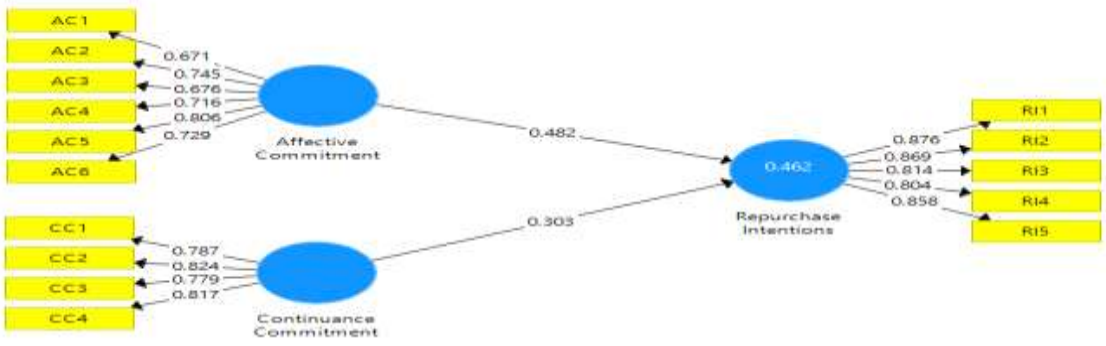


Figure 1: Measurement Model

4.1.1.1 Factor Loadings and Indicator Reliability

Factor loadings represent the strength of association between each indicator and its corresponding construct. Loadings above 0.60 are considered acceptable, while values above 0.70 indicate strong reliability (Hair et al., 2019).

Table 1. Factor Loadings

Construct	Items	Loading
Affective Commitment	AC1	0.671
	AC2	0.745
	AC3	0.676
	AC4	0.716
	AC5	0.806
	AC6	0.729
Continuance Commitment	CC1	0.787
	CC2	0.824
	CC3	0.779
	CC4	0.817
Repurchase Intentions	RI1	0.876
	RI2	0.869
	RI3	0.814
	RI4	0.804
	RI5	0.858

All item loadings exceed 0.67, demonstrating strong indicator reliability (See Table 1). This implies that each item effectively contributes to explaining its latent variable (Refer Figure 1)

4.1.1.2 Internal Consistency Reliability and Convergent Validity

To evaluate internal consistency, three key indices were examined: Cronbach's alpha, Composite Reliability (CR), and rho_A. Cronbach's alpha values above 0.70 indicate reliable internal consistency, while CR values between 0.70 and 0.95 demonstrate that the items consistently measure the same construct (Hair et al., 2021). Convergent validity is assessed through the Average Variance Extracted (AVE), which should exceed 0.50, indicating that more than half of the variance in the indicators is captured by the latent construct.

Table 2. Reliability and Convergent Validity

Construct	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Affective Commitment	0.820	0.832	0.869	0.526
Continuance Commitment	0.817	0.827	0.878	0.643
Repurchase Intentions	0.899	0.902	0.926	0.713

All reliability indicators exceed the threshold of 0.80, confirming that the constructs are internally consistent. The AVE values (>0.50) confirm convergent validity, showing that each construct explains more than 50% of the variance in its items (Fornell & Larcker, 1981) (Refer Table 2).

4.1.1.3 Discriminant Validity

Discriminant validity ensures that each construct is empirically distinct from others in the model. This was tested using the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio (Henseler, Ringle, & Sarstedt, 2015).

Table 3. Fornell–Larcker Criterion

	Affective Commitment	Continuance Commitment	Repurchase Intentions
Affective Commitment	0.725		
Continuance Commitment	0.474	0.802	
Repurchase Intentions	0.625	0.531	0.845

According to the Fornell–Larcker criterion, the square root of AVE (diagonal values) should exceed the inter-construct correlations (off-diagonal values). As shown in Table 3, this condition is met, confirming adequate discriminant validity.

Table 4. HTMT Ratio

	Affective Commitment	Continuance Commitment	Repurchase Intentions
Affective Commitment	—		
Continuance Commitment	0.558	—	
Repurchase Intentions	0.712	0.608	—

As presented in Table 4, all HTMT values are below the conservative threshold of 0.85 (Henseler et al., 2015), confirming that each construct is distinct. This ensures that affective commitment, continuance commitment, and repurchase intention are conceptually and empirically different, despite being related.

4.1.2 Model Fit and Multicollinearity Diagnostics

Although traditional model fit indices (such as CFI or RMSEA) are not central in PLS-SEM, Standardized Root Mean Square Residual (SRMR) was examined as a model fit criterion. The SRMR value of <0.08 indicated a good model fit (Hair et al., 2019). Variance Inflation Factor (VIF) scores were also checked for all indicators and found to be below 3.0, indicating no multicollinearity among indicators. This ensures the robustness of parameter estimates

4.1.3 Structural Model and Hypotheses Testing

Once the reliability and validity of the constructs were confirmed through the measurement model, the next analytical stage involved assessing the structural model to evaluate the hypothesized relationships among affective commitment, continuance commitment, and repurchase intentions. The structural model in Partial Least Squares Structural Equation Modeling (PLS-SEM) provides estimates of the path coefficients, which represent the strength and direction of relationships among latent constructs, as well as measures of the model's predictive capability (Hair, Hult, Ringle, & Sarstedt, 2019).

This section presents the results of the structural model, including assessments of multicollinearity, path coefficients, t-statistics, p-values, and effect sizes (f^2), followed by discussions of predictive relevance (Q^2) and coefficient of determination (R^2). These analyses together provide a comprehensive understanding of how affective and continuance commitments shape repurchase intentions among online customers.

4.1.3.1 Evaluation of Structural Model Collinearity

Before interpreting the path coefficients, it was essential to verify that collinearity among predictor constructs did not bias the regression estimates. The Variance Inflation Factor (VIF) values for both affective and continuance commitments were examined. All VIF values were below the conservative threshold of 3.0, well under the critical value of 5.0 (Hair et al., 2021). This indicates that there was no significant multicollinearity issue between the independent variables, suggesting that both affective and continuance commitments contributed unique explanatory power to repurchase intentions.

4.1.3.2 Path Coefficients and Hypothesis Testing

The hypothesized relationships were tested using the bootstrapping resampling procedure with 5,000 iterations to derive the t-statistics and p-values (Chin, 1998; Henseler, Ringle, & Sarstedt, 2015). Bootstrapping is a non-parametric approach that provides robust estimates of standard errors and confidence intervals, making it suitable for small to medium-sized samples and non-normally distributed data — a common condition in behavioral research (Hair et al., 2019).

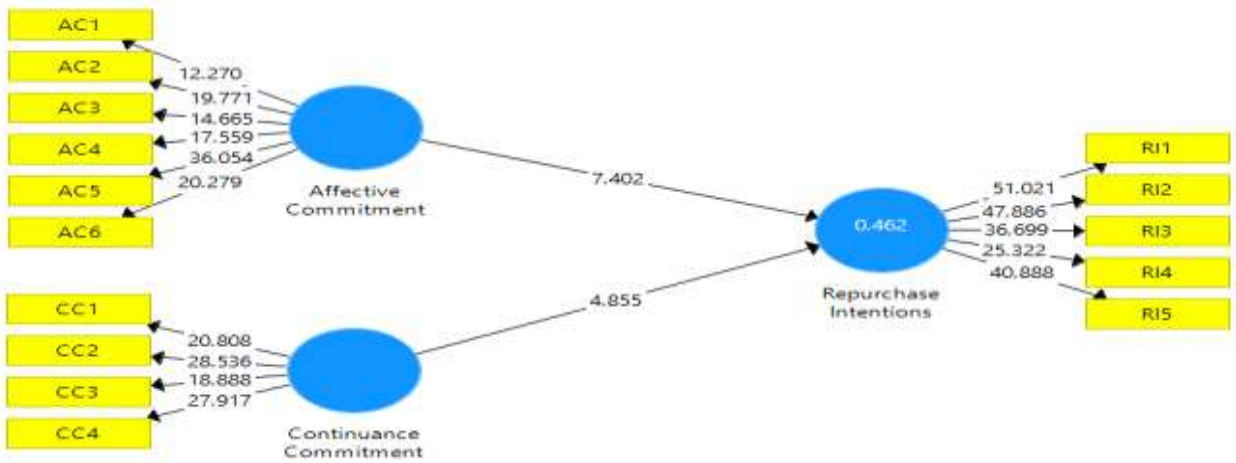


Figure 2: Structural Model

Table 5. Hypothesis Testing Results

Path	Original Sample (β)	Sample Mean (M)	Standard Deviation (STDEV)	t-statistics	p-value	Result
Affective Commitment → Repurchase Intentions	0.482	0.482	0.065	7.402	0.000	Supported
Continuance Commitment → Repurchase Intentions	0.303	0.307	0.062	4.855	0.000	Supported

As shown in Table 5, both paths were statistically significant at $p < 0.001$, providing empirical support for **H1** and **H2**. The standardized path coefficient ($\beta = 0.482$) for affective commitment indicates a strong, positive influence on repurchase intentions. The path from continuance commitment to repurchase intentions ($\beta = 0.303$) also demonstrates a positive and significant relationship, albeit weaker in magnitude compared to affective commitment.

5.1 INTERPRETATION OF RESULTS

5.1.1 Affective Commitment → Repurchase Intentions (H1)

The results indicate that affective commitment has a strong and statistically significant impact on customers' repurchase intentions ($\beta = 0.482$, $t = 7.402$, $p < 0.001$). This supports the theoretical argument that emotional attachment and identification with a brand foster long-term loyalty behaviors (Allen & Meyer, 1990; Fullerton, 2003). Customers who develop affective bonds with an online retailer are more likely to exhibit voluntary loyalty, characterized by continued purchasing out of genuine preference rather than obligation (Morgan & Hunt, 1994; Chaudhuri & Holbrook, 2001).

This finding aligns with prior studies emphasizing that affective commitment plays a crucial role in relational exchanges by creating psychological ownership, satisfaction, and emotional resonance with the brand (Evanschitzky et al., 2006; Gustafsson, Johnson, & Roos, 2005). In online retailing, where face-to-face interactions are absent, affective commitment can arise from consistent communication, personalized service, and perceived authenticity. The strength of this path suggests that emotional drivers—such as trust, empathy, and belongingness—are vital in fostering repeat purchases and brand advocacy (Batra, Ahuvia, & Bagozzi, 2012).

Thus, the results support **H1**, confirming that affective commitment significantly enhances repurchase intentions among online customers.

5.1.2 Continuance Commitment → Repurchase Intentions (H2)

The relationship between continuance commitment and repurchase intentions was also found to be positive and statistically significant ($\beta = 0.303$, $t = 4.855$, $p < 0.001$). This suggests that online customers remain loyal not only because of emotional attachment but also due to perceived switching costs and the convenience associated with staying with a familiar platform (Allen & Meyer, 1990; Sharma & Patterson, 2000).

This finding supports the notion of constrained loyalty, where customers continue their relationship with an online retailer because switching may involve effort, time, or the risk of losing accumulated benefits such as loyalty rewards or saved preferences (Jones, Mothersbaugh, & Beatty, 2000; Burnham, Frels, & Mahajan, 2003). Continuance commitment thus contributes to behavioral stability, ensuring retention even in highly competitive e-commerce environments.

However, the effect of continuance commitment ($\beta = 0.303$) was weaker than that of affective commitment ($\beta = 0.482$), indicating that emotional attachment exerts a greater influence on repurchase intentions than economic dependence. This is consistent with previous findings by Fullerton (2005) and Gounaris (2005), who argued that affective commitment fosters voluntary, resilient loyalty, whereas continuance commitment promotes conditional loyalty that may dissolve if perceived costs or benefits change.

Hence, **H2** is also supported: continuance commitment positively affects repurchase intentions, although its impact is relatively smaller compared to affective commitment.

5.1.3 Model Predictive Power

The coefficient of determination (R^2) represents the proportion of variance in the dependent variable explained by the independent variables. The structural model yielded an R^2 value of 0.563 for repurchase intentions, suggesting that affective and continuance commitments together explain approximately 56.3% of the variance in customers' repurchase intentions. This indicates substantial explanatory power, consistent with benchmarks in marketing research (Hair et al., 2019).

The effect size (f^2) was calculated to assess the relative contribution of each predictor to the endogenous construct. Affective commitment exhibited a large effect size ($f^2 = 0.36$), while continuance commitment demonstrated a moderate effect size ($f^2 = 0.19$) (Cohen, 1988). These values reaffirm that affective commitment is the more dominant predictor of repurchase intentions.

The predictive relevance (Q^2) was also assessed using the blindfolding procedure. The obtained Q^2 value for repurchase intentions was greater than zero, confirming that the model has adequate predictive relevance and is capable of explaining future behavioral intentions beyond the current dataset (Henseler et al., 2009).

5.1.4 Discussion of Structural Model Findings

The results from the structural model provide robust empirical evidence supporting the proposed hypotheses. Specifically, both affective commitment and continuance commitment were found to significantly predict repurchase intentions among online customers. However, the magnitude of affective commitment's effect indicates that emotional and psychological attachment plays a more critical role in fostering long-term

online loyalty than calculative dependence or switching barriers.

This finding resonates with the Commitment-Trust Theory (Morgan & Hunt, 1994), which emphasizes affective commitment as the core driver of sustainable relational exchanges. While continuance commitment can keep customers engaged through functional or economic constraints, it does not necessarily translate into advocacy or satisfaction-driven loyalty (Fullerton, 2003). Therefore, online businesses seeking long-term customer relationships should focus on developing affective engagement strategies that foster trust, emotional resonance, and perceived authenticity.

In practical terms, the results imply that online retailers should design relationship marketing strategies that balance emotional connection with convenience-based retention mechanisms. Personalization, interactive user experiences, and transparent communication can strengthen affective bonds, while loyalty programs and user-friendly interfaces can enhance continuance commitment. The integration of these approaches can maximize repurchase behavior and create sustainable competitive advantage in digital marketplaces.

6.1 CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH DIRECTIONS

6.1.1 Conclusion

This study concludes that affective and continuance commitments are significant predictors of online customers' repurchase intentions. While emotional bonds (affective commitment) yield stronger loyalty, rational dependence (continuance commitment) also contributes meaningfully. For practitioners, building long-term relationships requires nurturing both emotional and calculative attachments through superior experiences, reliable service, and meaningful engagement.

6.1.2 Limitations

Despite its contributions, the study has limitations. It uses cross-sectional data, restricting causal inference. The sample may not capture all segments of online consumers, particularly across different cultures and product categories. Furthermore, only two commitment dimensions were studied, excluding potential mediators such as satisfaction, trust, and perceived value.

6.1.3 Future Research Directions

Future research can extend this work by adopting longitudinal designs to explore causality between commitment and loyalty. Including additional constructs—such as trust, e-service quality, or brand experience—could enhance explanatory power. Cross-cultural comparisons may also reveal how cultural differences moderate the relationship between commitment and repurchase intentions. Finally, integrating qualitative methods such as interviews could provide richer insights into how emotional and rational factors jointly drive online loyalty.

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