

When Satisfaction is Not Enough: The Anchoring Role of Perceived Price on Influencer and Personalization-Driven Loyalty

Yocky Ananda

yocki_pram@trilogi.ac.id

State University of Jakarta

Agung Handaru

State University of Jakarta

Umi Widyastuti

State University of Jakarta

Research Article

Keywords: Digital Influencers, Personalization, Customer Satisfaction, Perceived Price Fairness, Customer Loyalty, Digital MSMEs, PLS-SEM

Posted Date: August 26th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10330315/v1>

License:  This work is licensed under a Creative Commons Attribution 4.0 International License.
[Read Full License](#)

Additional Declarations: No competing interests reported.

Abstract

Objective

This study examines how digital influencer endorsements and platform personalization drive customer loyalty within Indonesian digital retail SMEs, highlighting the mediating role of customer satisfaction and the moderating effect of perceived price fairness. Methodology: A quantitative approach was deployed, gathering data through online surveys from a purposive sample of digital MSME consumers. The structural framework was analyzed using PLS-SEM with 5,000 bootstrap resamples.

Results

Personalization emerges as the primary driver of satisfaction over influencers. Customer satisfaction partially mediates loyalty, but this relationship depends strictly on price perceptions. Latent interaction analysis confirms that price fairness significantly moderates the satisfaction–loyalty link $\beta = 0.156$, $p < 0.001$.

Conclusion

Experiential satisfaction alone cannot secure loyalty; it must be anchored by perceived price equity to prevent customer switching

Introduction

The global retail landscape has undergone a seismic shift toward digital ecosystems, placing Small and Medium Enterprises (SMEs) at a critical juncture between technological adaptation and market obsolescence. In the Indonesian context—where SMEs account for 99% of total business entities and 98% of national employment (BKPM, 2020)—the digital transformation of these enterprises is no longer a peripheral strategy but a fundamental necessity for survival (Ananda, 2022). However, the primary challenge has evolved beyond mere digital adoption; the current struggle lies in cultivating sustainable customer loyalty amidst chronic information overload and exponential price competition within e-commerce platforms (Islam et al., 2021). Despite their economic weight, the vulnerability of SMEs remains high, with statistics indicating a 35% failure rate within the first two years and over 50% collapsing within five (Snider & Davies, 2018); (Manikandan & Sengottuvel, 2021).

Current marketing literature has largely treated Personalization (PZ) and Perceived Price (PP) as independent predictors of satisfaction. However, this study identifies a critical theoretical "blind spot" regarding the boundary conditions of digital customization in the SME sector. While personalization is designed to increase value, it can inadvertently heighten a consumer's price awareness. When an SME

platform offers a highly tailored recommendation, the consumer's internal "utility-to-cost" calculus becomes more rigorous.

The contribution of this research is twofold. First, it challenges the universal efficacy of digital stimuli by positioning Perceived Price as a "gatekeeper" (moderator). We argue that the bridge from Customer Satisfaction (CS) to Loyalty (CL) is not automatic; it is contingent upon whether the consumer perceives the customized experience as "worth the premium." Second, by focusing on SMEs—which lack the massive brand equity of global corporations—this study provides a more nuanced understanding of how limited digital resources can be optimized. Unlike large-scale retailers where brand trust may overshadow price concerns, in the SME context, the "Satisfaction-Loyalty" link is highly volatile and susceptible to price fluctuations.

Customer loyalty serves as a strategic cornerstone for SME sustainability, providing revenue stability through repetitive purchase mechanisms and minimized acquisition costs (Lei et al., 2022); (Agha et al., 2021) Beyond mere retention, a loyal customer base facilitates competitive differentiation and organic growth through consumer advocacy in dynamic market environments (Manikandan & Sengottuvel, 2021). Consequently, fostering loyalty not only optimizes Customer Lifetime Value (CLV) but also secures a critical feedback loop essential for product adaptation and long-term resilience.

Drawing upon the Stimulus-Organism-Response (S-O-R) framework, this study conceptualizes Digital Influencers and Personalization as external environmental stimuli (S) that influence the consumer's internal emotional state or 'organism' (O), manifested here as Customer Satisfaction. This internal state subsequently triggers the behavioral response (R) of Customer Loyalty. By integrating Perceived Price as a boundary condition, we expand the S-O-R model to account for the economic constraints inherent in the SME ecosystem."

Literature review

Customer loyalty

Customer loyalty is increasingly conceptualized not merely as a repetitive purchasing pattern, but as a multi-dimensional construct encompassing behavioral commitment and psychological advocacy (Kayumov et al., 2024)(Khan et al., 2022). In the digital era, this loyalty manifests through sustained engagement and the proactive intention to provide organic recommendations, which are pivotal for long-term brand equity (Wallström et al., 2023), (Dhaigude et al., 2023).

For Small and Medium Enterprises (SMEs), customer loyalty functions as a critical survival mechanism. Unlike large corporations with extensive marketing budgets, SMEs rely heavily on the "amplification effect" of loyal customers who act as unpaid brand ambassadors, driving growth through electronic word-of-mouth (e-WOM) and community-based trust (Budiarto et al., 2023), (Ginting et al., 2023). Furthermore, loyalty provides a "financial buffer" by securing consistent revenue streams, which mitigates the high costs associated with constant customer acquisition (Endwia et al., 2021). From a

strategic perspective, a loyal customer base serves as a source of "co-creation," where ongoing feedback loops allow SMEs to pivot their product offerings and innovate in alignment with shifting market complexities. Consequently, fostering loyalty is not just a marketing goal but a fundamental requirement for achieving resilience and competitive differentiation in highly saturated digital marketplaces.

Customer satisfaction

Customer satisfaction is increasingly defined in the digital SME era as a cumulative, post-consumption evaluative judgment that integrates both cognitive performance and affective response (Ali et al., 2021) (Zouari & Abdelhedi, 2021), (Nguyen et al., 2021). Within the Stimulus-Organism-Response (S-O-R) paradigm, satisfaction serves as the internal "organism" state that processes external digital stimuli—such as influencer credibility and personalized algorithms—into internalized value (Casaló et al., 2020), (Huang et al., 2019). In the competitive SME landscape, satisfaction is no longer a static outcome but a dynamic experience shaped by the alignment between digital expectations and the actual value delivered through e-commerce touchpoints (Thi & Thu, 2022).

For SMEs, the role of customer satisfaction is fundamentally dualistic: it acts as a primary defensive strategy to prevent customer churn and a proactive catalyst for brand advocacy. High satisfaction levels reduce the "perceptual friction" caused by price competition, allowing SMEs to maintain a premium positioning despite limited resource configurations (Taştan & Soylu, 2023). Furthermore, recent scholarly evidence suggests that in digital environments, satisfaction is the critical bridge that converts short-term promotional engagement (influencer marketing) into long-term psychological attachment (Shih et al., 2024). Consequently, SMEs that prioritize satisfaction as a central mediator in their digital marketing strategy are better positioned to optimize the transition from transient platform traffic to sustainable customer loyalty (Balci et al., 2019).

Perceived price

Perceived price is no longer viewed as a static monetary figure but as a complex psychological trade-off between the perceived sacrifice and the total utility derived from a digital transaction (So et al., 2024), (Bernarto et al., 2022). In the hyper-competitive SME digital landscape, price perception acts as a subjective lens through which consumers evaluate the fairness and equity of their consumption experience (Hoe & Mansori, 2018). Unlike large-scale retailers, SMEs often lack the economies of scale to engage in predatory pricing; therefore, the "price-value" alignment becomes a critical determinant of whether a customer transitions from being merely satisfied to becoming loyal (Bernarto et al., 2022a)

Within the SME context, perceived price functions as a boundary condition that dictates the strength of the relationship between psychological states (satisfaction) and behavioral outcomes (loyalty). Recent scholarship suggests that high price sensitivity in digital platforms can lead to "deal-seeking" behavior, where even satisfied customers may switch brands if the perceived price of the current provider is

deemed disproportionate to the market average (Ratasuk & Buranasompob, 2022). Consequently, perceived price is conceptualized in this study as a "gatekeeper" variable; it moderates the loyalty bridge by either reinforcing the commitment of satisfied users when prices are perceived as fair, or acting as a deterrent that triggers churn when the perceived sacrifice outweighs the personalized benefits (Setiawan, 2021).

Personalization

Personalization is the procedure of collecting customers' information which helps the firm to create products and services that perfectly provide the customer's desires and needs (Halimi et al., 2011)

In modern digital marketing environments, personalization has evolved beyond basic cosmetic adjustments, such as using a buyer's name; instead, it operates as a sophisticated, data-driven architecture that minimizes cognitive overload while amplifying situational relevance. Personalization can be synthesized as a strategic, customer-centric process that involves gathering individual customer data and preferences, customizing products, services, or special benefits to meet those specific needs, and establishing effective two-way communication to clearly define personalization parameters. (Satpal, 2026), (Carvajal et al., 2011), (Ball & Coelho, 2006)

For small and medium enterprises (SMEs) navigating hyper-congested digital channels, deploying customized communication and tailored product suggestions is essential to pierce through market noise and capture immediate user engagement (Al-Refai et al., 2025; Nguyen et al., 2022). Within the architectural boundaries of the Stimulus-Organism-Response (S-O-R) paradigm, this study operationalizes personalization strictly as a Functional/Algorithmic Stimulus. It functions as a systemic mechanism that converts standardized e-commerce touchpoints into highly individualized, value-centric consumer encounters (Liu & Tan, 2024).

The core strategic value of digital personalization for resource-constrained SMEs rests on its capacity to replicate the 'high-touch, intimate service' of physical retail environments within a scalable web-based interface. By utilizing algorithmic tracking to forecast individual consumer requirements, small firms can instill a deep sense of being 'heuristically understood,' effectively neutralizing the cold, detached nature of standard electronic commerce (Zhao et al., 2023). Crucially, contemporary marketing literature indicates that precise algorithmic personalization triggers a strategic 'lock-in effect' (Hassan et al., 2026). When customized digital storefronts systematically maximize user utility, they inherently increase the psychological and operational switching costs for the customer (Hassan et al., 2026). Hence, personalization is modeled in this investigation as a fundamental technological anchor that drives customer satisfaction by aligning an SME's finite resource capacities with the complex, heterogeneous demands of contemporary digital buyers."

Digital influencers

Digital influencers are increasingly conceptualized as pivotal social intermediaries that bridge the psychological distance between SMEs and their target audiences through perceived authenticity and relatability (Shamim & Islam, 2022), (Sookkaew & Saephoo, 2021). In the contemporary digital marketing discourse, influencers do not merely act as promotional channels; they facilitate Parasocial Interaction (PSI), where consumers develop a sense of pseudo-intimacy and trust that mimics real-life social bonds (Wang et al., 2025). For SMEs, leveraging influencer credibility is a strategic imperative to overcome the lack of established brand equity, as influencers provide a "humanized" validation that reduces consumer skepticism in anonymous e-commerce environments (Boerman, 2020).

Under the expanded Stimulus-Organism-Response (S-O-R) framework proposed in this study, digital influencers strictly operate as a distinct Social/Affective Stimulus. Unlike automated digital architecture, this human-centric stimulus targets the emotional and relational dimensions of the consumer experience. The efficacy of digital influencers in the SME sector lies in their role as high-impact social stimuli within the S-O-R framework. By providing semi-organic content that integrates product utility with lifestyle narratives, influencers trigger a positive affective state—internalized as Customer Satisfaction—before a physical transaction even occurs (Harrigan et al., 2021). Recent scholarly evidence suggests that the "micro-influencer" niche is particularly effective for SMEs, as their higher engagement rates and niche-specific expertise provide a more authentic endorsement than traditional mass-market celebrities (Pinto & Paramita, 2021). Consequently, digital influencers are positioned in this study as a critical external driver of satisfaction, functioning as a social catalyst that represents the affective counterpart to algorithmic customization, converting passive platform traffic into emotionally invested and loyal SME customers."

Hypotheses Development

2.1. Digital Stimuli and the Consumer "Organism" (Satisfaction)

"Within the digital SME ecosystem, **Digital Influencers (DI)** and **Personalization (PZ)** function as key digital stimuli that drive consumer satisfaction. Specifically, DI serves as a social stimulus that reduces perceived risk through 'human-centric' validation (Casaló et al., 2020), (Casaló et al., 2020;(Han & Park, 2022), while PZ acts as a functional stimulus that mitigates choice overload and streamlines the user experience (Ball & Coelho, 2006) (Satpal, 2026); together, these stimuli positively shape the consumer 'organism' by directly elevating satisfaction.

- **H1:** Digital Influencer engagement has a positive and significant effect on Customer Satisfaction
- **H2:** Personalization has a positive and significant effect on Customer Satisfaction.

2.2. The Mediating Role of Customer Satisfaction

According to the S-O-R framework, the "Organism" (Satisfaction) is the internal processor that converts external stimuli into behavioral outcomes. For SMEs, an influencer might grab attention (S), but without the internal state of satisfaction (O), that attention rarely translates into long-term commitment (R). Similarly, personalization creates a sense of being "understood," which deepens the emotional bond necessary to move from a single transaction to sustained loyalty (Pappas et al., 2014). Extensive literature indicates that customer satisfaction robustly mediates the relationship between digital influencer marketing and brand loyalty (Nugraha & Nasir, 2026) as well as the path from personalization to customer retention (Tong et al., 2012) (BALLI, 2024)

- **H3:** Customer Satisfaction has a positive and significant effect on Customer Loyalty.
- **H4:** Customer Satisfaction mediates the relationship between Digital Influencers and Customer Loyalty.
- **H5:** Customer Satisfaction mediates the relationship between Personalization and Customer Loyalty.

2.3. The Boundary Condition: Perceived Price as a Moderator

The most critical contribution of this model is the moderating role of Perceived Price (PP). While high satisfaction typically leads to loyalty, this path is non-linear in the SME context due to high price sensitivity. We argue that even satisfied customers may exhibit "switching behavior" if the perceived price is seen as unfair or excessively high compared to competitors (Xu, 2025). Price acts as a gatekeeper; if the price-value equation is unfavorable, the "Satisfaction-to-Loyalty" bridge collapses.

- **H6:** Perceived Price significantly moderates the relationship between Customer Satisfaction and Customer Loyalty, such that the relationship is stronger when price perception is favorable.

Research Methodology

3.1. Population and Sampling Strategy

3.1. Target Population and Structural Sampling Strategy

The empirical target population of this investigation comprises digital consumers who actively engage with Small and Medium Enterprises (SMEs) within the Greater Jakarta metropolitan area (Jabodetabek). Given the operational parameters of electronic commerce, the absolute universe of this consumer base is unquantifiable and dynamic. Consequently, this study deploys a non-probability, purposive sampling mechanism to systematically gather data from highly informative subjects who correspond strictly with the theoretical boundary conditions of the conceptual model (Creswell & Hirose, 2019).

To ensure the statistical robustness of the model configuration, the sample size was determined through structural criteria rather than traditional descriptive population formulas. While conventional frameworks often rely on the (Cochran & Wiley, n.d.) approach, modern implementations of Partial Least Squares Structural Equation Modeling (PLS-SEM) necessitate a power-analytic calculation. Applying the Inverse Square-Root Method (Kock & Hadaya, 2016), a minimum sample threshold of 160 respondents is required to achieve a statistical power of 80% $\beta = 0.80$ at a significance level of 5% for a model containing three structural predictors. To maximize predictive accuracy and insulate the estimations from potential statistical anomalies, a final validated sample of 224 respondents was achieved, comfortably exceeding both the power-analytic baseline and the traditional heuristic thresholds outlined by (Hair et al., 2021).

3.2. Respondent Screening: Inclusion and Exclusion Parameters

To safe-keep structural data validity and actively insulate the empirical observations from systemic response bias, all participating subjects were filtered through rigorous, multi-stage inclusion criteria prior to full survey administration:

1. Cognitive and Financial Autonomy: Respondents were required to be at least 20 years of age, ensuring the necessary psychological maturity and independent financial capability to execute autonomous purchasing allocations.
2. Digital Touchpoint Familiarity: Participants must have actively initiated and completed commercial transactions through the digital infrastructure (e-commerce platforms, social commerce, or specialized applications) of Indonesian SMEs.
3. Transactional Recency: To precisely map the non-linear conversion of satisfaction into sustainable retention without introducing selection artifacts, subjects must have executed at least one verified transaction with the same SME within the preceding six months. By shifting from a hyper-restrictive baseline of pre-existing behavioral loyalty to transactional recency, the sample preserves the essential variance necessary to test the "gatekeeping" intercept of perceived price fairness.

3.3. Survey Instrumentation and Common Method Variance Safeguards

Primary data collection was executed through an anonymous, self-administered web-based questionnaire. Recognizing that gathering data from a single informant source using self-reported measures can inadvertently introduce Common Method Variance (CMV), this study instituted rigid procedural and statistical countermeasures recommended by (Podsakoff et al., 2003).

Procedurally, complete psychological separation was established by restructuring the survey flow; the indicators measuring the external stimuli (Digital Influencers and Personalization) were separated from the mediator (Customer Satisfaction) and the ultimate outcome variable (Customer Loyalty). The survey

interface explicitly guaranteed absolute respondent anonymity and emphasized that there were no correct or incorrect configurations of answers, thereby neutralizing social desirability artifacts. Statistically, the data structure was subjected to a Full Collinearity Assessment VIF (Kock, 2015) post-collection. This comprehensive approach ensures that any latent inflation originating from the measurement mechanism is transparently detected and controlled prior to structural hypothesis testing.

1.1 Measurement Model Evaluation (Outer Model)

Before conducting structural path analysis to test the hypothesized relationships, the measurement model must be rigorously evaluated for construct validity and reliability. In line with the framework established by Hair et al. (2021), this study systematically assesses convergent validity, internal consistency reliability, and discriminant validity using Partial Least Squares Structural Equation Modeling (PLS-SEM).

Convergent Validity and Internal Consistency Reliability

Convergent validity evaluates the extent to which an indicator correlates positively with alternative indicators of the same construct. This is systematically assessed via indicator loadings and the Average Variance Extracted (AVE). Internal consistency reliability is evaluated using both Cronbach's alpha (α) and Composite Reliability (P_c).

During the initial estimation of the measurement model, a critical anomaly was observed within the Customer Satisfaction (CS) construct. Specifically, indicators CS3 (loading = 0.214) and CS6 (loading = -0.105) failed to meet the mandatory threshold of 0.50 (Hair et al., 2017). Statistically, these substandard and negative loadings suggest either an issue with reverse-coded item comprehension among respondents or substantial measurement error. Retaining these indicators significantly distorts the construct's systematic variance. Consequently, to optimize model fit and ensure parameters were unbiased, CS3 and CS6 were purged from the final measurement specification.

Following the exclusion of the problematic indicators, the refined outer model demonstrated exceptional psychometric properties. As summarized in Table 1, all remaining standardized factor loadings range from 0.798 to 0.912, comfortably exceeding the conservative threshold of 0.70. This confirms that a substantial proportion of each indicator's variance is shared with its respective latent construct.

Table 1.1
Measurement Model Re-specification, Validity, and Reliability

Latent Construct	Indicator	Standardized Loading	Cronbach's Alpha (α)	Composite Reliability (P_c)	Average Variance Extracted (AVE)
Digital Influencer (DI)	DI1	0.884	0.932	0.948	0.785
	DI2	0.912			
	DI3	0.895			
	DI4	0.876			
	DI5	0.891			
Personalization (PZ)	PZ1	0.843	0.901	0.926	0.709
	PZ2	0.865			
	PZ3	0.812			
	PZ4	0.850			
	PZ5	0.838			
Percieved Price (PP)	PP1	0.821	0.886	0.916	0.676
	PP2	0.798			
	PP3	0.845			
	PP4	0.811			
	PP5	0.834			
Customer Satisfaction (CS)	CS1	0.856	0.880	0.918	0.735
	CS2	0.872			
	CS4	0.839			
	CS5	0.861			
Customer Loyalty (CL)	CL1	0.882	0.947	0.957	0.758
	CL2	0.864			
	CL3	0.891			
	CL4	0.875			
	CL5	0.859			
	CL6	0.870			
	CL7	0.843			

The AVE values for all five latent constructs range between 0.676 and 0.785. Because every value strictly exceeds the benchmark of 0.50, it is empirically verified that the latent constructs explain more than half of the variance of their indicator metrics, establishing robust convergent validity. Regarding construct reliability, Cronbach’s alpha values range from 0.880 to 0.947, while the Composite Reliability (Pc) scores range from 0.916 to 0.957. These values sit well above the 0.70 threshold, signaling excellent internal consistency across all measurement scales without indicating excessive indicator redundancy.

Discriminant Validity Assessment

To confirm that each construct captures a unique phenomenon not accounted for by other latent variables in the structural model, discriminant validity was evaluated using a dual approach: the traditional Fornell-Larcker criterion and the advanced Heterotrait-Monotrait (HTMT) ratio of correlations. According to Fornell and Larcker (1981), discriminant validity is established when the square root of the AVE ($\sqrt{\text{AVE}}$) for each construct exceeds its highest correlation with any other latent variable.

Table 1.2
Discriminant Validity Assessment (Fornell-Larcker Criterion)

Latent Construct	Customer Loyalty (CL)	Customer Satisfaction (CS)	Digital Influencer (DI)	Personalization (PZ)	Perceived Price (PP)
Customer Loyalty (CL)	0.871				
Customer Satisfaction (CS)	0.642	0.857			
Digital Influencer (DI)	0.589	0.495	0.886		
Personalization (PZ)	0.612	0.512	0.534	0.842	
Percieved Price (PP)	0.556	0.478	0.441	0.498	0.822

While the Fornell-Larcker criterion offers a foundational assessment, contemporary PLS-SEM methodology emphasizes that it may lack sensitivity in detecting subtle cross-construct overlap (Henseler et al., 2015). Therefore, the Heterotrait-Monotrait (HTMT) ratio of correlations was computed. In a well-specified model, HTMT values between distinct latent constructs should strictly remain below the conservative threshold of 0.85, or the more liberal benchmark of 0.90 for closely related constructs (Kline, 2016).

Table 1.3
Heterotrait-Monotrait (HTMT) Ratio Matrix

Latent Construct	Customer Loyalty (CL)	Customer Satisfaction (CS)	Digital Influencer (DI)	Personalization (PZ)	Perceived price (PP)
Customer Loyalty (CL)	—				
Customer Satisfaction (CS)	0.631	—			
Digital Influencer (DI)	0.711	0.721	—		
Personalization (PZ)	0.753	0.721	0.725	—	
Perceived Price (PP)	0.595	0.512	0.485	0.546	—

As illustrated in Table 3, the highest recorded HTMT ratio occurs between Personalization (PZ) and Customer Loyalty (CL) at 0.753, which safely rests below the conservative 0.85 threshold. All other inter-construct ratios, including those for Perceived Price (PP), range from 0.485 to 0.725. Because no single value approaches or exceeds the 0.85 boundary, it is empirically established that each latent construct represents a mathematically distinct phenomenon. This dual-layered verification confirms complete discriminant validity across the entire measurement model.

1.2 Structural Model Evaluation (Inner Model) and Explanatory Power

In line with the recommendations of Hair et al. (2021), global goodness-of-fit (GoF) metrics are structurally unsuited for PLS-SEM because the algorithm does not optimize a global covariance matrix. Instead, the quality and substantive significance of the structural paths are assessed using path coefficients, R^2 scores, and Cohen's f^2 effect sizes. The model demonstrates high explanatory capacity, with an R^2 value of 0.648 for Customer Loyalty. This indicates that Digital Influencers, Personalization, Perceived Price, and Customer Satisfaction collectively account for 64.8% of the total variance in Customer Loyalty, representing a robust and highly substantive framework.

To isolate the specific incremental predictive capacity of each independent construct, Cohen's f^2 effect sizes were calculated. According to Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. These values reveal the precise mechanical impact of omitting a specific variable from the model.

1.2 Structural Model Assessment (Inner Model)

Following the confirmation of the measurement model's reliability and validity, the structural inner model was evaluated to rigorously test the hypothesized direct, indirect, and interaction boundaries. This structural framework was quantified using Variance-Based Structural Equation Modeling (PLS-SEM). To ascertain statistical significance, a non-parametric bootstrapping routine was executed with 5,000 resamples at a 95% confidence interval using the bias-corrected and accelerated (BCa) approach. Prior to demonstrating the outcome of each individual hypothesis, the model's overall explanatory capabilities were verified by scrutinizing both the R-Square (R^2) and R-Square Adjusted indices to map out the variance accounted for within the endogenous variables.

1.2.1 Explanatory Power and Coefficients of Determination (R-Square)

The R-Square (R^2) metric provides an explicit measurement of a structural network's predictive accuracy, illustrating the precise fraction of variance in an endogenous phenomenon that can be attributed to the designated antecedent blocks. The empirical output for both the standard R^2 and its adjusted variant is documented within Table 1.

Table 2.1
Quantified Coefficients of Determination (R^2 & R^2 Adjusted)

No.	Endogenous Target Construct	R^2 Value	Adjusted R^2	Predictive Power Threshold (Chin, 1998)
1	Customer Satisfaction (CS)	0.524	0.519	Moderate Strength
2	Customer Loyalty (CL)	0.648	0.641	Strong / Approaching Substantial

The empirical evidence presented in Table 1 yields an R^2 value of 0.524 for Customer Satisfaction (CS). This outcome uncovers that approximately 52.4% of the variance inherent to customer contentment is driven by the synchronous influence of Digital Influencers (DI) and Personalization mechanisms (PZ) within the Indonesian SME retailing context. The remaining 47.6% of the variance points to latent environmental disturbances or peripheral strategic constructs omitted from the current path network. In alignment with Chin's (1998) traditional milestones, an explanatory capability of this size establishes a moderate yet highly meaningful foundation, confirming that both digital-driven stimuli serve as substantial antecedents in shaping consumer evaluative experiences

1.2.2 Verification of Direct Structural Paths (Direct Effects)

Direct pathway estimation focuses on isolating the unmediated linear dependencies running between the exogenous components and the endogenous targets. Statistical validity requires an empirical t-statistic equal to or exceeding 1.96 alongside a two-tailed p-value bounded at or below the 0.05 alpha threshold. Table 2 details the outcomes of these direct estimations.

Table 2.2
Estimated Coefficients for Direct Structural Paths

Hyp.	Postulated Direct Structural Path	Path Coeff. (β)	t-Statistic	p-Value	95% BCa CI Range	Empirical Status
H1	Digital Influencer (DI) -> Customer Satisfaction (CS)	0.342	7.125	< 0.001	[0.245, 0.432]	Supported
H2	Personalization (PZ) -> Customer Satisfaction (CS)	0.415	9.222	< 0.001	[0.322, 0.499]	Supported
H3	Customer Satisfaction (CS) -> Customer Loyalty (CL)	0.388	7.462	< 0.001	[0.282, 0.485]	Supported

The micro-level breakdowns of the individual direct hypotheses summarized in Table 2 are detailed below:

1. The Nexus Between Digital Influencers and Customer Satisfaction (H1): The bootstrapping operation exposed a positive path coefficient (β) of 0.342, coupled with an prominent t-statistic of 7.125 and a p-value below 0.001. Because the t-value easily surpasses the critical 1.96 marker and the 95% BCa confidence interval [0.245, 0.432] completely excludes zero, Hypothesis 1 is fully supported. This signifies that influencer expertise and content relevance act as direct catalysts in elevating initial consumer satisfaction.
2. The Nexus Between Personalization and Customer Satisfaction (H2): Tailored digital experiences yielded the most substantial path coefficient within the satisfaction block, with a β value of 0.415, a t-statistic of 9.222, and a highly significant p-value (< 0.001). Consequently, Hypothesis 2 is robustly accepted. Modifying user interfaces and custom product journeys represents the single most dominant strategic element in generating consumer satisfaction.
3. The Nexus Between Customer Satisfaction and Customer Loyalty (H3): Evaluating the link between satisfaction and user retention yielded a path coefficient (β) of 0.388 ($t = 7.462$, $p < 0.001$), validating Hypothesis 3. Fulfilling transactional expectations directly converts transient satisfaction into sustainable, long-term brand adherence.

1.2.3 Investigation of Intervening Path Mechanics (Indirect/Mediation Effects)

Mediation testing was deployed to capture the exact manner in which Customer Satisfaction (CS) serves as an intervening vehicle that carries and translates the primary momentum of exogenous triggers into actual loyalty. Table 3 concentrates on the specific bootstrapped indirect effects.

Table 2.3
Bootstrapped Specific Indirect Effects (Mediation Analysis)

Hyp.	Postulated Indirect Path (Mediation)	Indirect Coeff.	t-Statistic	p-Value	95% BCa CI Range	Mediation Typology
H4	Digital Influencer (DI) -> CS -> CL	0.133	5.115	< 0.001	[0.085, 0.188]	Partial Mediation
H5	Personalization (PZ) -> CS -> CL	0.161	5.552	< 0.001	[0.108, 0.221]	Partial Mediation

The structural breakdowns of the intervening mechanisms detailed in Table 3 are interpreted as follows:

1. The Intervening Role of Satisfaction on Influencer Dynamics (H4): The indirect sequence of DI -> CS -> CL produced a statistically significant indirect effect coefficient of 0.133 ($t = 5.115$, $p < 0.001$). The BCa confidence interval range of [0.085, 0.188] remains entirely positive, confirming the validity of Hypothesis 4. Given that the direct path from influencer exposure to loyalty was previously verified as significant, Customer Satisfaction operates as a partial mediator. This implies that while influencers spark retention on their own, their true strategic potential is unlocked when their content directly targets and satisfies consumer experiential expectations.
2. The Intervening Role of Satisfaction on Personalization Implementations (H5): The indirect path mapped as PZ -> CS -> CL generated a mediation coefficient of 0.161 ($t = 5.552$, $p < 0.001$), validating Hypothesis 5. Algorithmic personalization relies heavily on the psychological conduit of user satisfaction to successfully cultivate loyalty. This partial mediation architecture underscores that custom platform features must be backed by genuine transactional satisfaction to turn user engagement into persistent brand loyalty.

1.2.4 Boundary Condition Testing via Interaction Terms (Moderation Effects)

To determine the boundary constraints of the retention framework, Perceived Price (PP) was introduced as a latent moderator. This step was designed to observe whether physical product standards alter, amplify, or restrict the linear bridge connecting Customer Satisfaction to Customer Loyalty. The interaction term was developed using the Two-Stage Product Indicator approach within PLS-SEM, with results isolated in Table 4.

Table 2.4
Structural Estimation of the Interaction/Moderation Term

Hyp.	Latent Interaction Pathway	Interaction Coeff. (β)	t-Statistic	p-Value	95% BCa CI Range	Empirical Outcome
H6	CS $\times$ PP -> Customer Loyalty (CL)	0.156	4.105	< 0.001	[0.082, 0.231]	Supported (Positive Buffering)

The statistical parameters provided in Table 7 reveal that the multiplicative interaction construct representing Customer Satisfaction and Perceived Price (CS × PP) exerts a positive and statistically significant impact on Customer Loyalty, quantified by an interaction coefficient (β) of 0.156 ($t = 4.105$, $p < 0.001$). Because the significance marker safely clears the 5% alpha criteria and the 95% BCa confidence interval [0.082, 0.231] remains bounded above zero, Hypothesis 6 is unreservedly supported.

The positive direction of the β coefficient (0.156) establishes a quasi-moderation architecture that acts as a strengthening mechanism within the path network. From a theoretical standpoint, this indicates that the relationship between consumer satisfaction and ultimate loyalty is not uniform; instead, it is highly dependent on Perceived Price (PP).

When an organization delivers fair, transparent, and attractive pricing standards (at + 1 SD above the mean), any increase in customer satisfaction is amplified, translating into an exceptional surge in brand loyalty, repeat purchases, and organic consumer advocacy. Conversely, when price perceptions drop into an unfavorable or unfair territory (-1 SD), even the highest levels of experiential or platform satisfaction fail to convert into long-term customer loyalty. Price fairness serves as the critical gatekeeper and baseline reality check in the model, ensuring that virtual engagement is securely anchored by perceived real-world transactional equity.

CONCLUSION

This study provides empirical clarity on the structural driving forces of consumer validation and behavioral retention within the digital marketing ecosystems of Indonesian MSMEs (UMKM). Based on the comprehensive PLS-SEM analysis, several fundamental conclusions can be established:

First, both social and functional digital stimuli act as critical direct drivers of customer satisfaction. However, algorithmic personalization ($\beta = 0.415$) exerts a more robust and statistically dominant influence on consumer contentment than the external pull of digital influencer endorsements ($\beta = 0.342$). While influencer campaigns are highly effective for capturing broad public attention, data-driven platform personalization is what successfully converts that temporary attention into meaningful, structured user satisfaction.

Second, Customer Satisfaction functions as a significant partial mediator within the theoretical model. While digital influencers and personalization mechanisms retain the capacity to stimulate direct, habitual repurchase behaviors due to platform convenience and social reinforcement, their true strategic potential to generate enduring customer loyalty is unlocked when routed through emotional and transactional validation.

Third, the conversion of platform satisfaction into long-term customer loyalty is strictly bounded by price fairness. Perceived Price acts as a powerful quasi-moderator and the ultimate gatekeeper in this model ($\beta = 0.156$). When pricing structures are perceived as fair, transparent, and competitive, the positive bridge between satisfaction and loyalty is heavily amplified. Conversely, if price perceptions drop into an

unfavorable territory, the structural connection collapses; even highly satisfied customers will display deal-seeking migration behaviors.

In summary, while interactive digital interfaces and social proof spark the initial transaction, a deeply satisfying user experience anchored by perceived price equity is what securely transforms virtual engagement into persistent, long-term brand loyalty.

IMPLICATIONS, LIMITATIONS, AND FUTURE DIRECTIONS

6.1. Theoretical Implications

This study advances the Stimulus-Organism-Response (S-O-R) framework by integrating a nuanced boundary condition into the digital SME context. The primary theoretical contribution lies in the empirical validation of Perceived Price (PP) as a critical "gatekeeper" variable that governs ultimate behavioral outcomes. While conventional marketing literature often assumes a linear, uninterrupted progression from customer satisfaction to brand loyalty, our structural findings reveal a more complex moderated-mediation mechanism.

Under this framework, the digital stimuli of influencer endorsements and algorithmic personalization do not automatically guarantee long-term retention; rather, they are rigorously filtered through the consumer's internal "utility-to-cost" calculus. When evaluating the direct structural drivers, the data demonstrates that algorithmic personalization exerts a more profound and structurally stable influence on customer satisfaction ($\beta = 0.415$) than the external pull of digital influencers ($\beta = 0.342$). From a behavioral standpoint, this variance suggests that while modern consumers are initially attracted to a digital SME through third-party social proofs (influencers), their sustained psychological comfort within the digital ecosystem is ultimately determined by how seamlessly the platform adapts to their individual preferences.

Furthermore, by positioning Perceived Price as a boundary condition, this study shifts the academic discourse. Personalization is no longer viewed merely as a hedonic or novelty driver, but as a functional utility tool that must be balanced against perceived price fairness. The underlying mediation mechanics clarify that while convenience and social validation might spark initial transactions, a deeply satisfying user experience—safeguarded by a fair pricing structure—is what prevents consumers from migrating to competitors.

6.2. Managerial Implications for SMEs

For SME owners, digital marketing practitioners, and enterprise decision-makers operating within resource-constrained environments, the empirical findings offer three definitive strategic pillars:

- The Human-Algorithm Synergy: Digital SMEs must move away from an "either-or" approach when allocating marketing budgets. The results prove that organizations should not choose between influencers and personalization; instead, they must integrate both into a cohesive ecosystem. Digital

influencers provide the vital "affective trust" needed to capture initial market attention, whereas data-driven personalization provides the "functional efficiency" that streamlines the user journey. Together, they create a robust, dual-track satisfaction base that effectively anchors the consumer.

- **The Price-Sensitivity Safeguard:** Managers must recognize that achieving high customer satisfaction does not grant complete immunity from aggressive price competition. Because Perceived Price acts as a powerful gatekeeper, SMEs should utilize deep personalization to explicitly maximize the consumer's perceived value rather than just to push transactional sales. If a customer feels a digital service or product recommendation is "uniquely theirs," their psychological sensitivity to market price fluctuations may decrease, though it never completely disappears.
- **Strategic Resource Allocation:** Given that SMEs typically operate with limited capital, these structural results offer a clear roadmap for optimization. Personalization demonstrates a more enduring, long-term effect on customer loyalty through what is known as the "lock-in effect." While digital influencers are highly excellent for driving initial awareness and generating immediate satisfaction spikes, the algorithmic "understanding" of the customer—built through continuous personalization—is what secures long-term behavioral retention and true customer asset value.

6.3. Limitations and Future Research

While this study utilized a robust sample of 224 respondents drawn from the Jabodetabek region, the empirical findings may exhibit variances when applied across different cultural, regulatory, or geographical landscapes. To build upon the boundaries established in this paper, future research should consider executing a Multi-Group Analysis (MGA) to systematically compare consumer behavior across distinct product categories, such as Food & Beverage (F&B) versus Fashion ecosystems. Additionally, future frameworks could incorporate "Privacy Concerns" as a negative moderator to personalization. Introducing this counter-variable would provide an even more balanced and comprehensive view of the digital SME ecosystem, capturing the delicate tension between data-driven customization and consumer data protection.

Declarations

Author Contribution

Y.P.A. and A.W.H. conceptualized the study and designed the research methodology. Y.P.A. handled the data collection and performed the PLS-SEM statistical analysis. U.W. provided supervision, verified the structural model evaluations, and critically revised the theoretical framework. Y.P.A. wrote the original draft and the main manuscript text. A.W.H. and U.W. contributed to the review, editing, and refinement of the final manuscript. All authors reviewed and approved the final version to be published.

Data Availability

References

1. Agha, A. A., Rashid, A., Rasheed, R., Khan, S., & ... (2021). Antecedents of customer loyalty at telecomm sector. In *Turkish Online Journal ...*. researchgate.net.
https://www.researchgate.net/profile/Aamir-Rashid-2/publication/354496899_Antecedents_of_Customer_Loyalty_at_Telecomm_Sector/links/613b4745f07b08309084c665/Antecedents-of-Customer-Loyalty-at-Telecomm-Sector.pdf
2. Ali, B. J., Gardi, B., Othman, B. J., Ahmed, S. A., Ismael, B., Hamza, P. A., Aziz, H. M., & Sabir, B. Y. (2021). *SSRN-id3851330.pdf*. 3, 14–28.
3. Ananda, Y. P. (2022). Marketing Mix Strategy in Building Msme Competitiveness in Indonesia. *Indonesian Journal of Multidisciplinary Science*, 1(11), 1534–1540.
<https://doi.org/10.55324/ijoms.v1i11.232>
4. Balci, G., Caliskan, A., & Yuen, K. F. (2019). Relational bonding strategies, customer satisfaction, and loyalty in the container shipping market. In *International Journal of Physical ...*. emerald.com.
<https://doi.org/10.1108/IJPDLM-02-2019-0051>
5. Ball, A. D., & Coelho, P. S. (2006). *DigitalCommons @ University of Nebraska - Lincoln Service Personalization and Loyalty*.
6. BALLI, A. (2024). *The Effect of Product Personalization on Consumer Purchasing Intention, Customer Satisfaction, Brand Loyalty and Artificial Intelligence Applications with Machine Learning*. 8(3), 1240–1263. <https://doi.org/10.25295/fsecon.1449755>
7. Bernarto, I., Purwanto, A., & Masman, R. R. (2022a). *The Effect of Perceived Risk, Brand Image and Perceived Price Fairness on Customer Satisfaction*. XXVI(01), 35–50.
8. Bernarto, I., Purwanto, A., & Masman, R. R. (2022b). The Effect of Perceived Risk The Effect of Perceived Risk, Brand Image and Perceived Price Fairness on Customer Satisfaction. *Jurnal Manajemen*, Volume XXV(01), 35–50.
9. Boerman, S. C. (2020). The effects of the standardized instagram disclosure for micro- and meso-influencers. *Computers in Human Behavior*, 103, 199–207.
<https://doi.org/10.1016/j.chb.2019.09.015>
10. Budiarto, B. W., Putri Ekaresty Haes, Winanto Nawarcono, Ainil Mardiah, & Tri Apriyono. (2023). The Influence Of E-Customer Satisfaction, E-Service Quality And Sales Promotion On E-Customer Loyalty Of Tokopedia Customers. *JEMSI (Jurnal Ekonomi, Manajemen, Dan Akuntansi)*, 9(6), 2472–2479.
<https://doi.org/10.35870/jemsi.v9i6.1656>
11. Carvajal, S. A., Ruzzi, A. L., Nogales, Á. F., & Moreno, V. M. (2011). The impact of personalization and complaint handling on customer loyalty. *African Journal of Business Management*, 5(34), 13187–13196. <https://doi.org/10.5897/ajbm11.1162>

12. Casaló, L. V, Flavián, C., & Ibáñez-sánchez, S. (2020). *In fl uencers on Instagram : Antecedents and consequences of opinion leadership*. 117(July 2018), 510–519.
<https://doi.org/10.1016/j.jbusres.2018.07.005>
13. Cochran, W. G., & Wiley, J. 1977). *Sampling techniques* (3rd ed.). John Wiley & Sons.
14. Creswell, J. W., & Hirose, M. (2019). *Mixed methods and survey research in family medicine and community health*. 1–6. <https://doi.org/10.1136/fmch-2018-000086>
15. Dhaigude, A. S., Vinod Tapar, A., Shameem Jawed, M., & Kamath, G. B. (2023). Is perceived value enough to create loyalty for m-wallets? Exploring the role of trust and satisfaction. *Cogent Business and Management*, 10(3). <https://doi.org/10.1080/23311975.2023.2281050>
16. Endwia, S. M., Kusumawati, N., & Irawan, A. (2021). Factors Influencing Customer Satisfaction and Loyalty of Online Educational Platform in Indonesia: Analysis of E-Service Quality Factors. In *no. August*. researchgate.net. https://www.researchgate.net/profile/Nurrani-Kusumawati-2/publication/358090257_Factors_Influencing_Customer_Satisfaction_and_Loyalty_of_Online_Educational_Platform_in_Indonesia_Analysis_of_E-Service_Quality_Factors/links/61efccbcdafcdb25fd4e9175/Factors-
17. Ginting, Y. M., Chandra, T., Miran, I., & Yusriadi, Y. (2023). Repurchase intention of e-commerce customers in Indonesia: An overview of the effect of e-service quality, e-word of mouth, customer trust, and customer satisfaction mediation. *International Journal of Data and Network Science*, 7(1), 329–340. <https://doi.org/10.5267/j.ijdns.2022.10.001>
18. Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R*. Springer.
19. Halimi, A. B., Chavosh, A., Namdar, J., Espahbodi, S., & Esferjani, P. S. (2011). The Contribution of Personalization to Customers' Loyalty Across the Bank Industry in Sweden. *International Conference on Social Science and Humanity*, 5, 382–386.
20. Han, M., & Park, J. (2022). A Study on the Effect of Fashion Influencer Characteristics on Customer Loyalty. *The Academic Society of Global Business Administration*, 19(1), 100–118.
<https://doi.org/10.38115/asgba.2022.19.1.100>
21. Harrigan, P., Daly, T. M., Coussement, K., Lee, J. A., Soutar, G. N., & Evers, U. (2021). Identifying influencers on social media. *International Journal of Information Management*, 56(June 2020).
<https://doi.org/10.1016/j.ijinfomgt.2020.102246>
22. Hoe, L. C., & Mansori, S. (2018). The Effects of Product Quality on Customer Satisfaction and Loyalty: Evidence from Malaysian Engineering Industry. *International Journal of Industrial Marketing*, 3(1), 20. <https://doi.org/10.5296/ijim.v3i1.13959>
23. Huang, P. L., Lee, B. C. Y., & Chen, C. C. (2019). The influence of service quality on customer satisfaction and loyalty in B2B technology service industry. *Total Quality Management & ...*
<https://doi.org/10.1080/14783363.2017.1372184>
24. Islam, T., Islam, R., Pitafi, A. H., Xiaobei, L., & ... (2021). The impact of corporate social responsibility on customer loyalty: The mediating role of corporate reputation, customer satisfaction, and trust.

- Sustainable Production* <https://www.sciencedirect.com/science/article/pii/S2352550919304944>
25. Kayumov, A., Ahn, Y. joo, Kiatkawsin, K., Sutherland, I., & Zielinski, S. (2024). Service quality and customer loyalty in halal ethnic restaurants amid the COVID-19 pandemic: a study of halal Uzbekistan restaurants in South Korea. *Cogent Social Sciences*, 10(1). <https://doi.org/10.1080/23311886.2024.2301814>
 26. Khan, R. U., Salamzadeh, Y., Iqbal, Q., & ... (2022). The impact of customer relationship management and company reputation on customer loyalty: The mediating role of customer satisfaction. *Journal of Relationship* <https://doi.org/10.1080/15332667.2020.1840904>
 27. Kock, N. (2015). *Common method bias in PLS-SEM : A full collinearity assessment approach*. 1–10.
 28. Kock, N., & Hadaya, P. (2016). *Minimum sample size estimation in PLS-SEM : The inverse square root and gamma-exponential methods*. <https://doi.org/10.1111/isj.12131>
 29. Lei, Z., Duan, H., Zhang, L., Ergu, D., & Liu, F. (2022). The main influencing factors of customer satisfaction and loyalty in city express delivery. *Frontiers in Psychology*, 13(October), 1–9. <https://doi.org/10.3389/fpsyg.2022.1044032>
 30. Manikandan, M. E., & Sengottuvel, C. (2021). Performance indicators and trends of small and medium enterprises of economic development in India. *Zien Journal of Social Sciences* ..., 1(1), 104–110. <http://zienjournals.com/index.php/zjssh/article/view/44>
 31. Nguyen, M. D., Chi, D. T. P., Tien, N. H., & Hong, T. T. K. (2021). Factors affecting customer satisfaction at Vietinbank in Vietnam. *International Journal of Research in Human Resource Management*, 3(2), 62–70. <https://doi.org/10.33545/26633213.2021.v3.i2a.72>
 32. Nugraha, A. P., & Nasir, M. (2026). *Analisis Pengaruh Penggunaan Influencer Marketing Dan Electronic Word of Mouth Terhadap Brand Loyalty yang Dimediasi oleh C onsumer Satisfaction Pada Tiga Produk Shampo Terpopuler di Soloraya*. 782–797.
 33. Pinto, P. A., & Paramita, E. L. (2021). Social media influencer and brand loyalty on generation Z: the mediating effect of purchase intention. *Diponegoro International Journal of Business*, 4(2), 105–115. <https://doi.org/10.14710/dijb.4.2.2021.105-115>
 34. Podsakoff, P. M., Mackenzie, S. B., Lee, J., & Podsakoff, N. P. (2003). *Common Method Biases in Behavioral Research : A Critical Review of the Literature and Recommended Remedies*. 88(5), 879–903. <https://doi.org/10.1037/0021-9010.88.5.879>
 35. Ratasuk, A., & Buranasompob, A. (2022). Contributions of Marketing Factors on Customer Repurchase intentions in Convenience Store Coffee Shops in Bangkok and Mediating Role of Brand Image. *SSRN Electronic Journal*, 3(1), 11–28. <https://doi.org/10.2139/ssrn.3998409>
 36. Satpal, M. (2026). *AI-Driven Marketing Personalization and Customer Loyalty*. 2(1), 75–83.
 37. Setiawan, E. B. (2021). How to build customer loyalty: Through customer experience, perceived price, and customer satisfaction. *Turkish Journal of Computer and Mathematics* <http://nn-pub.com/index.php/turkbilmat/article/view/1410>
 38. Shamim, K., & Islam, T. (2022). Digital influencer marketing: How message credibility and media credibility affect trust and impulsive buying. *Journal of Global Scholars of Marketing Science: Bridging*

- Asia and the World*, 32(4), 601–626. <https://doi.org/10.1080/21639159.2022.2052342>
39. Shih, I. T., Silalahi, A. D. K., & Eunike, I. J. (2024). Engaging audiences in real-time: The nexus of socio-technical systems and trust transfer in live streaming e-commerce. *Computers in Human Behavior Reports*, 13(168), 100363. <https://doi.org/10.1016/j.chbr.2023.100363>
40. Snider, J. H., & Davies, K. J. (2018). Success Strategies for Small Financial Planning Firms. *International Journal of Applied Management and Technology*, 17(1), 22–34. <https://doi.org/10.5590/ijamt.2018.17.1.02>
41. So, K. K. F., Yang, Y., & Li, X. (2024). Fifteen Years of Research on Customer Loyalty Formation: A Meta-Analytic Structural Equation Model. *Cornell Hospitality Quarterly*, 66(2), 253–272. <https://doi.org/10.1177/19389655241276506>
42. Sookkaew, J., & Saephoo, P. (2021). “Digital Influencer”: Development and Coexistence with Digital Social Groups. *International Journal of Advanced Computer Science and Applications*, 12(12), 326–332. <https://doi.org/10.14569/IJACSA.2021.0121243>
43. Taştan, H., & Soylu, A. G. (2023). *The impact of perceived cleanliness on customer satisfaction, revisiting intention and complaining behaviors : The case of restaurants by S-O-R Model*. 8(1), 27–38.
44. Thi, B. N., & Thu, H. N. T. (2022). Effects of supply chain collaboration on customer loyalty for household electronic appliances in Vietnam. *Journal of Asian Business and Economic Studies*, 29(4), 280–298. <https://doi.org/10.1108/JABES-11-2021-0189>
45. Tong, C., Wong, S. K.-S., & Lui, K. P.-H. (2012). The Influences of Service Personalization, Customer Satisfaction and Switching Costs on E-Loyalty. *International Journal of Economics and Finance*, 4(3), 105–114. <https://doi.org/10.5539/ijef.v4n3p105>
46. Wallström, S., Hjelm Lidholm, S., & Sundström, M. (2023). Retailers view on customer loyalty—a social resource theory perspective. *International Review of Retail, Distribution and Consumer Research*. <https://doi.org/10.1080/09593969.2023.2287998>
47. Wang, P., Huang, Q., & Davison, R. M. (2025). How do digital influencers affect social commerce intention ? The roles of social power and satisfaction © Emerald Publishing Limited. This AAM is provided for your own personal use only. It may not be used for resale, reprinting, systematic distribut. *Information Technology & People*, 34(3).
48. Xu, Z. (2025). *Perceived Price Fairness as a Mediator in Customer Green Consumption : Insights from the New Energy Vehicle Industry and Sustainable Practices*.
49. Zouari, G., & Abdelhedi, M. (2021). Customer satisfaction in the digital era: evidence from Islamic banking. *Journal of Innovation and Entrepreneurship*, 10(1). <https://doi.org/10.1186/s13731-021-00151-x>

Tables

Tables 1,2,3,4, and 7 are not available with this version

Figures



Figure 1

Unnumbered image in the Literature review Section