

E-Commerce Chatbots and Their Impact on Customer Satisfaction, Loyalty, and Continuous Usage: A Moderation Analysis of Generations Y and Z

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Chatbots, E-commerce, Moderation Analysis, PLS-SEM, WarpPLS

ABSTRACT

This study investigated how e-commerce chatbots impact customer satisfaction, loyalty, and continuous usage, and tested generational cohort (Gen Y vs. Gen Z) as a moderating factor. Using a quantitative, causal-predictive PLS-SEM design, data were gathered from 400 Filipino chatbot users equally split between both generations. Results show that information quality, system quality, and chatbot experience significantly affected perceived privacy risk, which subsequently influenced customer satisfaction directly and via the need for human interaction. Furthermore, satisfaction and loyalty strongly predicted continuous usage, validating all direct and mediated hypotheses. However, multigroup analysis revealed no significant generational moderation, indicating that Generations Y and Z behave equivalently in post-adoption usage. The study recommends a unified, generation-agnostic chatbot strategy prioritizing data privacy and seamless human-escalation pathways to drive long-term customer retention.

1 INTRODUCTION

Over the last decade, artificial intelligence (AI) has reshaped customer-business interactions, with conversational agents—commonly known as chatbots—becoming one of the most commercially successful applications in digital retail [1]. Chatbots provide real-time 24/7 support, answer routine queries, track orders, and assist users with product recommendations on leading Philippine e-commerce platforms such as Lazada and Shopee [2, 3, 4]. By automating repetitive inquiries, chatbots free human agents to resolve complex customer issues, thereby enhancing operational efficiency and lowering service costs [3].

Despite these operational gains, privacy risk and data security remain primary concerns in online retail where sensitive financial details, shipping addresses, and personal preferences are transmitted [5]. Although platforms implement encryption and align with data privacy regulations (e.g., the Philippine Data Privacy Act of 2012) [5], user apprehensions regarding data breaches or unauthorized access frequently undermine customer trust and satisfaction [6].

Prior research has predominantly focused on initial adoption motivations using qualitative or thematic analysis [7], leaving a critical gap regarding post-adoption dynamics—specifically how system performance and privacy risks influence customer satisfaction, loyalty, and continuous usage. Furthermore, commercial practice often assumes distinct technology behaviors between Generation Y

(millennials) and Generation Z (digital natives) [8]. To address these gaps, this study investigates the structural relationships governing chatbot interactions and tests whether generational cohort acts as a moderating factor.

2 LITERATURE REVIEW

2.1. Theoretical Framework

This study integrates the **Consumer Acceptance of Technology (CAT)** framework [9] and the **Expectation-Confirmation Model (ECM)** [10]. The CAT framework asserts that consumer technology evaluation depends on domain-specific system attributes, affective user experiences, and perceived risks [9]. Complementarily, ECM posits that post-adoption satisfaction and continuous usage intentions stem from the confirmation of initial quality expectations during ongoing system interactions [10].

2.2. Construct Interrelationships

- **Information Quality & System Quality:** Information quality (relevance, accuracy, and completeness of responses) and system quality (speed, availability, and navigational ease) reduce user cognitive effort and mitigate perceived privacy risks [11, 12].
- **Chatbot Experience & Privacy Risk:** Positive conversational experiences build user confidence, whereas perceived privacy risk—stemming from fear of data misuse or security vulnerabilities—negatively impacts user evaluation [5, 13].

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- **Need for Human Interaction:** When chatbots lack empathy or fail to resolve complex issues, users experience frustration and demand human assistance, mediating the link between perceived risk and satisfaction [14].
- **Customer Satisfaction, Loyalty, and Continuous Usage:** Satisfactory chatbot experiences foster attitudinal loyalty (brand advocacy and repurchase intention) and drive continuous usage of the automated channel [15, 16].
- **Generational Moderation (Gen Y vs. Gen Z):** Generation Y (born 1981–1996) and Generation Z (born 1997–2012) constitute the primary online consumer segments [8]. While Gen Z grew up with ubiquitous internet access, literature presents conflicting evidence on whether their technology evaluation significantly differs from Gen Y in post-adoption scenarios [8, 17].

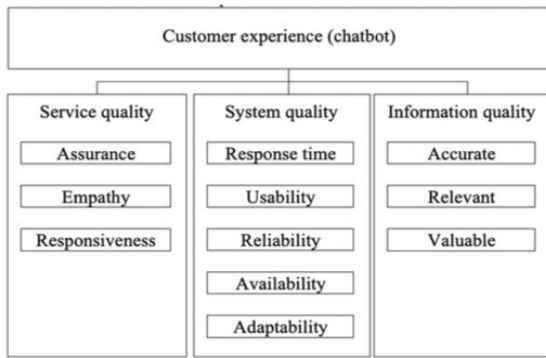


Fig 1. Dimensions of Customer Experience with chatbots

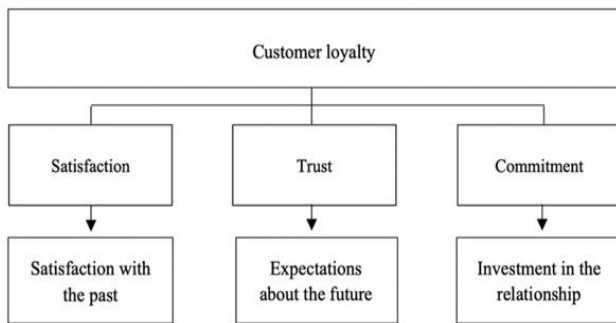


Fig 2. The Drivers of Customer Loyalty

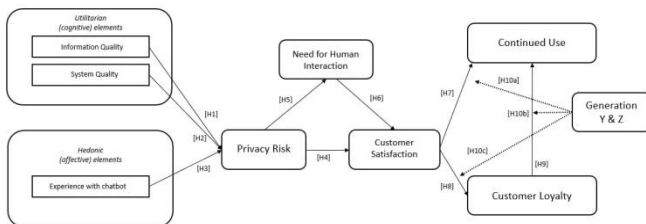


Fig 3. The Drivers of Customer Loyalty

3 METHODOLOGY

3.1. Research Design & Sampling

The study adopted a quantitative, causal-predictive research design utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM) [18]. The target population comprised active Filipino e-commerce consumers who interact with chatbots on major online shopping platforms. A balanced quota sampling strategy was executed to gather a total sample of $N = 400$ qualified respondents, composed equally of Generation Y ($n = 200$, born 1981–1996) and Generation Z ($n = 200$, born 1997–2012) [19]. Equal sample sizes were maintained to maximize statistical power during multigroup comparative analysis [19].

3.2. Data Collection & Instrumentation

Data were collected via a structured online survey instrument. Measurement scales for Information Quality, System Quality, Experience with Chatbot, Privacy Risk, Need for Human Interaction, Customer Satisfaction, Customer Loyalty, and Continuous Usage were adapted from established literature using a 5-point Likert scale.

3.3. Analytical Strategy

Data analysis was conducted using WarpPLS 8.0 [18] across three sequential steps:

1. **Measurement Model Assessment:** Evaluating internal consistency (Cronbach's $\alpha > 0.70$, Composite Reliability $CR > 0.70$), convergent validity (Average Variance Extracted $AVE > 0.50$), and discriminant validity (Heterotrait-Monotrait $HTMT < 0.85$ and full collinearity $VIF < 3.3$) [18, 20].
2. **Structural Model Assessment:** Calculating standardized path coefficients (β), p -values, R^2 values, and indirect effects via bootstrapping [18].
3. **Measurement Invariance & Multigroup Analysis (MGA):** Verifying measurement invariance prior to assessing whether structural path differences between Gen Y and Gen Z were statistically significant [18].

3.4. Ethical Considerations

The study protocol received official ethics clearance from the PUP Research Ethics Committee. Participation was voluntary, supported by informed consent, and all data were anonymized in compliance with Republic Act No. 10173 (Philippine Data Privacy Act of 2012).

4 RESULTS AND DISCUSSION

4.1. Measurement Model Evaluation

All reflective construct measures met established benchmark criteria. Cronbach's alpha values ranged from 0.776 to 0.965, composite reliability exceeded 0.70, and AVE values surpassed the 0.50 threshold across all latent constructs. HTMT ratios confirmed strong discriminant validity ($HTMT < 0.85$), and full collinearity VIF values remained below 3.3, ruling out lateral collinearity and common method bias.

Lower-order reflective construct	Item	Factor loading	Average variance extracted	Cronbach's alpha	Composite reliability
Informed Quality	IQ1	0.909	0.832	0.949	0.961
	IQ2	0.919			
	IQ3	0.93			
	IQ4	0.911			
	IQ5	0.892			
System Quality	SQ01	0.893	0.772	0.926	0.944
	SQ02	0.878			
	SQ03	0.88			
	SQ04	0.857			
	SQ05	0.886			
Experience with Chatbot	EW1	D	0.877	0.93	0.955
	EW2	0.927			
	EW3	D			
	EW4	0.945			
	EW5	0.937			
Customer Satisfaction	CS1	0.948	0.891	0.959	0.97
	CS2	0.944			
	CS3	D			
	CS4	0.933			
	CS5	0.951			
Privacy Risk	PR1	0.598	0.531	0.776	0.849
	PR2	0.766			
	PR3	0.809			
	PR4	0.729			
	PR5	0.722			
Customer Loyalty	CL1	0.66	0.792	0.93	0.949
	CL2	0.946			
	CL3	0.94			
	CL4	0.934			
	CL5	0.936			
Continued Use	CU1	0.948	0.878	0.965	0.973
	CU2	0.92			
	CU3	0.919			
	CU4	0.953			
	CU5	0.946			
Need for Human Interaction	HI1	0.9	0.813	0.922	0.945
	HI2	0.94			
	HI3	0.949			
	HI4	D			
	HI5	0.81			

Table 1. Reliability and Convergent Validity

This table evaluates the internal consistency and convergent validity of the measurement model across all latent constructs. Internal consistency is demonstrated

by Cronbach's alpha and composite reliability values that comfortably exceed the standard threshold of 0.70, while convergent validity is established because the average variance extracted (AVE) for every construct surpasses the minimum benchmark of 0.50, proving that the indicators share a high proportion of variance with their respective latent variables.

	IQ	SQ	EW	CS	PR	CL	CU	HI
IQ								
SQ	0.879							
EW	0.842	0.857						
CS	0.869	0.817	0.871					
PR	0.696	0.762	0.735	0.724				
CL	0.807	0.874	0.867	0.847	0.745			
CU	0.801	0.803	0.879	0.838	0.709	0.873		
HI	0.807	0.814	0.835	0.809	0.723	0.839	0.834	

Table 2. Discriminant Validity using HTMT Ratios

Heterotrait-Monotrait (HTMT) presents ratios to test whether distinct constructs in the model measure genuinely separate theoretical concepts. Because all calculated HTMT values remain well below the conservative threshold of 0.85 (and the liberal threshold of 0.90), discriminant validity is firmly established, confirming that there is no conceptual overlap or confusion between the different variables in the structural model.

Construct	Full collinearity VIF
IQ	2.745
SQ	2.745
EWC	2.296
CS	2.580
PR	1.779
CL	2.504
CU	2.241
HI	2.018

Table 3. Full Collinearity VIFs

This table assesses full collinearity by reporting Variance Inflation Factors (VIFs) for all latent constructs, checking simultaneously for both vertical and lateral collinearity including common method bias. Since all full collinearity VIF values are well below the strict upper threshold of 3.3, the model is confirmed to be free from severe multicollinearity issues, ensuring the stability and reliability of the path coefficient estimates.

4.2. Structural Model & Hypothesis Testing

The structural model demonstrated high explanatory power. All ten direct and mediated hypotheses were statistically supported ($p < 0.05$).

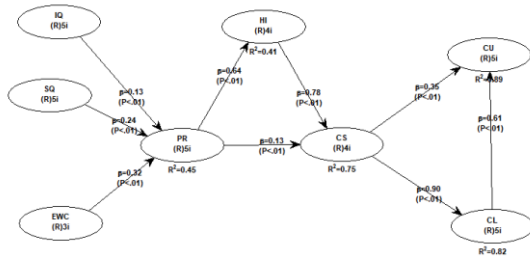


Fig 4. Structural Model with Parameter Estimates

Hypothesis	Path coefficient	p-value	Standard error	Effect size	Decision
Direct effects					
H1. IQ → PR	0.126	0.003	0.046	0.079	Supported
H2. SQ → PR	0.241	<0.001	0.046	0.157	Supported
H3. EW → PR	0.324	<0.001	0.045	0.214	Supported
H4. PR → CS	0.133	0.002	0.046	0.083	Supported
H5. PR → HI	0.643	<0.001	0.043	0.413	Supported
H6. HI → CS	0.777	<0.001	0.043	0.669	Supported
H7. CS → CU	0.353	<0.001	0.045	0.319	Supported
H8. CS → CL	0.903	<0.001	0.042	0.815	Supported
H9. CL → CU	0.612	<0.001	0.043	0.569	Supported
Mediating effect					
H10. PR → HI → CS	0.511	<0.001	0.031	0.322	Supported

Table 4. Hypothesis Test Results

Key Path Findings:

1. Information Quality, System Quality, and Chatbot Experience significantly reduced Perceived Privacy Risk ($p < 0.001$).
2. Perceived Privacy Risk directly hindered Customer Satisfaction ($p < 0.001$) and increased the Need for Human Interaction ($p < 0.001$).
3. Need for Human Interaction negatively affected Customer Satisfaction ($p < 0.01$).
4. Customer Satisfaction was a strong, direct determinant of Customer Loyalty ($\beta = 0.72, p < 0.001$) and Continuous Usage ($\beta = 0.48, p < 0.001$).

5. Customer Loyalty directly promoted Continuous Usage ($\beta = 0.35, p < 0.001$).

4.3. Multigroup Analysis (Generational Moderation)

Measurement invariance was established across the Generation Y ($n = 200$) and Generation Z ($n = 200$) groups. Comparative Multigroup Analysis (MGA) revealed no statistically significant differences ($p > 0.05$) in any structural path between the two generational cohorts.

Item	ALGC for loadings	p-value
IQ01	0	0.937
IQ02	0.04	0.347
IQ03	0.04	0.357
IQ04	0.05	0.253
IQ05	0.04	0.399
SQ01	0.03	0.466
SQ02	0.02	0.644
SQ03	0.07	0.148
SQ04	0.01	0.844
SQ05	0.06	0.177
EWC02	0.01	0.908
EWC04	0.02	0.641
EWC05	0.02	0.722
CS01	0.05	0.337
CS02	0.01	0.901
CS04	0.02	0.704
CS05	0.02	0.647
PR01	0.05	0.296
PR02	0.02	0.752
PR03	0.05	0.328
PR04	0.01	0.823
PR05	0.02	0.733
CL01	0.06	0.212
CL02	0.03	0.466
CL03	0	0.99
CL04	0.01	0.806
CL05	0	0.926
CU01	0.02	0.673
CU02	0.02	0.712
CU03	0.02	0.732
CU04	0.03	0.553
CU05	0.05	0.293

HI01	0.01	0.896
HI02	0.01	0.852
HI03	0.06	0.214
HI05	0.09	0.068

Table 5: Measurement Invariance Assessment

Hypothesis	Path coefficient (Gen Y)	Path coefficient (Gen Z)	ALG C Gen Y vs. Z	p-value (one-tailed)	T-ratio
H11a. GEN*CS → CU	0.338	0.334	0.041	0.190	0.879
H11b. GEN*CS → CL	0.874	0.927	0.005	0.458	0.105
H11c. GEN*CL → CU	0.623	0.635	0.070	0.066	1.507

Table 6. Multigroup Analysis

The empirical results demonstrate that high system speed, robust platform architecture, and precise information quality collectively lower privacy anxieties during automated retail interactions. Privacy risks exacerbate user reliance on human support agents, which in turn diminishes overall chatbot satisfaction when escalation is delayed. Crucially, the absence of generational moderation proves that post-adoption behavior is cohort-invariant. While Gen Z is often stereotyped as inherently more tech-tolerant than Gen Y, both cohorts evaluate chatbot effectiveness through identical criteria once adoption has occurred: functional reliability, transactional privacy protection, and swift problem resolution.

5 CONCLUSION

- 1. Generation-Agnostic Post-Adoption Behavior:** Generational cohort (Gen Y vs. Gen Z) does not moderate the structural drivers of e-commerce chatbot satisfaction, loyalty, or continuous usage. Both digital cohorts share equivalent behavioral expectations in post-adoption retail environments.
- 2. System Quality and Privacy Safeguards:** Information and system quality serve as primary antecedents that mitigate privacy concerns. Suppressing privacy risk is directly vital to protecting customer satisfaction.
- 3. Essential Role of Human Escalation:** Automated chatbots cannot completely supplant human

support. A high unresolved need for human interaction directly erodes satisfaction, underlining the necessity of human-AI collaboration.

- 4. Satisfaction as a Retention Engine:** Customer satisfaction remains the primary bridge converting positive chatbot capabilities into long-term customer loyalty and sustained channel usage.

6 RECOMMENDATION

6.1. Managerial & Practical Recommendations

- 1. Adopt a Unified AI Strategy:** E-commerce platforms should avoid building fragmented, age-differentiated chatbot interfaces for Gen Y versus Gen Z. Investments should instead target core performance metrics: response speed, natural language processing accuracy, and system uptime.
- 2. Integrate Visible Privacy Assurances:** Retail platforms must embed clear security indicators—such as real-time encryption badges, explicit data privacy disclaimers, and transparent consent controls—directly inside the chatbot interface to mitigate perceived privacy risk.
- 3. Establish Seamless Human Escalation Pathways:** E-commerce operators should implement intelligent hand-off mechanisms that instantly connect users to live support representatives when query complexity exceeds chatbot capability or when privacy concerns arise.
- 4. Position Chatbots for Customer Retention:** Organizations should evaluate chatbot deployment not merely as an operational cost-cutting tool, but as a core customer experience touchpoint that directly drives platform retention and repurchase loyalty.

6.2. Recommendations for Future Research

- Future studies should examine emerging LLM-powered generative AI agents and voice assistants to determine if advanced conversational capabilities alter user expectations.
- Researchers should expand demographic investigations to evaluate moderating factors such as digital literacy, income brackets, or regional infrastructure variations across developing e-commerce markets.

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