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Conversational AI in Digital Marketing: Human-Like Interaction, Perceived Empathy, and Customer Loyalty

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Abstract: This study examined associations among Human-Like Interaction, Perceived Empathy, and Customer Loyalty in the use of conversational artificial intelligence (AI) for Indonesian e-commerce. A cross-sectional survey collected questionnaire responses from 300 purposively selected consumers who had experience with e-commerce chatbots or virtual assistants. The analysis used partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4 to assess 18 indicators across three reflective constructs. The reported measurement properties met the specified reliability and validity thresholds. The reported PLS-SEM results indicated positive direct associations among Human-Like Interaction, Perceived Empathy, and Customer Loyalty, alongside a positive specific indirect association through Perceived Empathy. However, discrepancies between the structural model and the direct-effects table prevent a definitive interpretation of the estimated effect magnitudes and mediation type. However, coefficients in the structural diagram differed from those in the direct-effects table, so the magnitudes and type of mediation could not be confirmed from the reported outputs. The study distinguishes perceived conversational naturalness from perceived understanding and company-directed loyalty intentions. These findings concern self-reported perceptions and intentions rather than observed repurchase behavior. Its cross-sectional design and purposive sample preclude causal conclusions and population-wide generalization. The results provide a basis for evaluating interaction quality and perceived understanding in chatbot-supported customer service.

Keywords: Conversational AI, Human-Like Interaction, Perceived Empathy, Customer Loyalty, E-Commerce

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INTRODUCTION

Conversational artificial intelligence (AI) increasingly mediates encounters between online retailers and their customers. Beyond supplying product information, chatbots may support recommendations, transaction-related requests, and the resolution of service problems (Fu et al., 2023; Cheng et al., 2022). Although conversational AI can efficiently address customer inquiries and service requests, successful interactions do not necessarily translate into stronger loyalty toward the service provider. Customers may perceive an automated interaction as useful without developing a corresponding intention to repurchase, recommend the company, or maintain a long-term relationship. Research on verbal embodiment shows that conversational properties can shape brand-related judgments, but it also suggests that the way people experience a dialogue matters more than the mere presence of an automated agent (Bergner et al., 2023). This distinction motivates an examination of whether customers' perceptions of human-like exchanges

and perceived understanding are associated with company-oriented loyalty in Indonesian e-commerce.

Human-like communication is multidimensional, and the perception of a natural exchange does not imply that an AI system possesses human emotions. In online shopping, empathy and social presence have been related to trust, whereas anthropomorphism can also produce unfavorable reactions, depending on the attribute and context being examined (Fu et al., 2023). Additional research connects interactivity and perceived humanness with trust (Ding & Najaf, 2024) and describes how people attribute social qualities to technology (Xu et al., 2022). Studies of chatbot anthropomorphism indicate that customer reactions can be shaped by perceived social presence (Konya-Baumbach et al., 2023) and by the combination of conversational language, perceived competence, and authenticity (Nguyen et al., 2023). Experimental evidence further indicates that the usefulness of human-like design is conditional rather than uniform across customer relationships (Han, 2021; Igarashi et al., 2026). Accordingly, this study treats Human-Like Interaction as the customer's evaluation of communication naturalness, contextual appropriateness, fluency, continuity, and personalization, rather than as a manipulation of chatbot design.

An encounter may appear conversationally fluent while still failing to address what a customer actually needs. Perceived Empathy captures a different judgment: whether customers feel that the conversational service recognizes their circumstances and responds attentively to their concerns (Markovitch et al., 2024). Research on artificial empathy has distinguished the experience of being understood from a system's underlying emotional capabilities (Liu-Thompkins et al., 2022). Research on emotional tone and empathic language suggests that perceived warmth is another relevant aspect of service evaluation (Rohden & Espartel, 2026; Yun & Park, 2022). Empathetic messages in service recovery may also elicit different evaluations from messages that emphasize a solution, indicating that warmth and task performance need not be interchangeable (Haupt et al., 2023). For this reason, separating Perceived Empathy from Human-Like Interaction is conceptually necessary before examining how both relate to loyalty.

Customer Loyalty in the present study refers to stated preferences and intentions toward an e-commerce company or brand, including repurchase, recommendation, and relationship-maintenance intentions. It is not measured as the frequency of chatbot use or as observed retention. This operationalization is informed by research on e-satisfaction and e-loyalty (Anderson & Srinivasan, 2003). Earlier work distinguishes satisfaction with a chatbot from loyalty to the system (Hsu & Lin, 2023), while research on chatbot affordances and identification links the interaction to relationship-related outcomes (Lee & Li, 2023). Other studies connect AI service quality with e-brand loyalty through trust and customer experience (Shahzad et al., 2024) and examine service encounters in which chatbot-related judgments can have consequences for customer loyalty (Ozuem et al., 2024). These findings make a company-level outcome relevant, although they do not imply that any particular conversational characteristic alone determines loyalty.

Theoretically, the Computers Are Social Actors (CASA) perspective explains why people may respond socially to cues produced by a technological interface (Nass & Moon, 2000). The conditions under which CASA applies to contemporary technology have also been questioned (Heyselaar, 2023). Social Presence Theory offers an adjacent account of perceived interpersonal proximity, but social presence is not measured as a separate variable in this study (Poinsot et al., 2022; Jin & Youn, 2023). Relationship Marketing Theory directs attention to sustained evaluations of the company rather than satisfaction with a single exchange (Morgan & Hunt, 1994). Studies of

service assistants also show that anthropomorphism and trust can coexist with concerns about how customers engage with machines (Fakhimi et al., 2023; Song et al., 2024). These perspectives support interpreting the proposed paths as associations among three perceptions, not as a test of the full mechanisms proposed by the theories.

Recent scholarship already addresses chatbot-assisted retention, conversational trust, perceived empathy, and brand loyalty, so the general connection between conversational AI and loyalty is not unexplored (Chen et al., 2023; Chi & Hoang Vu, 2023; Shahzad et al., 2024). Nevertheless, the referents and intermediate judgments are often different: chatbot continuance, encounter satisfaction, rapport, and loyalty toward a company cannot be used as interchangeable outcomes. For example, research on rapport and electronic word of mouth focuses on a different response from company-oriented purchase intentions (Fatima et al., 2024), while studies of conversational style examine customer engagement under specific service conditions (Roy Bhattacharjee et al., 2025). Research on chatbot identity framing also situates trust and brand loyalty in a distinct consumer evaluation setting (Umair et al., 2026). Research in digital banking further underscores that the provider, setting, and service construct matter when interpreting a relationship with loyalty (Hang et al., 2026). Although previous studies have examined chatbot characteristics in relation to trust, customer engagement, and loyalty, important distinctions remain between favorable evaluations of conversational technology and loyalty intentions toward the company providing the service. This study addresses that distinction by examining Human-Like Interaction and Perceived Empathy as separate but potentially related customer judgments associated with loyalty toward the same e-commerce provider in Indonesia.

The study therefore examines whether Human-Like Interaction is positively associated with Customer Loyalty (H1) and Perceived Empathy (H2), and whether Perceived Empathy is positively associated with Customer Loyalty (H3). It additionally examines the specific indirect association from Human-Like Interaction to Customer Loyalty through Perceived Empathy (H4). All three constructs refer to the same e-commerce company or brand identified by each respondent, preserving the distinction between evaluations of an interaction and judgments about a provider. Partial least squares structural equation modeling (PLS-SEM) evaluates the measurement model and the reported direct and indirect relationships. The proposed contribution is a bounded comparison of conversational characteristics, perceived understanding, and provider-directed loyalty intentions within one survey model, without claiming causal mediation or observed behavioral change.

METHOD

Research Design

This study used a quantitative explanatory cross-sectional survey to examine relationships among Human-Like Interaction (X), Perceived Empathy (M), and Customer Loyalty (Y). The unit of analysis was an individual consumer who had used conversational AI provided by an e-commerce company or brand. The proposed model included a direct X-to-Y path, an X-to-M path, an M-to-Y path, and their specific indirect association. SmartPLS 4 was used for partial least squares structural equation modeling (PLS-SEM). As all constructs were measured in the same survey, the design describes contemporaneous associations and cannot establish the sequence or causal direction of these relationships.

Research Context and Participants

The study was situated in Indonesia's e-commerce and online retail sector. The sample comprised 300 respondents selected through purposive sampling. The reported eligibility criteria

were a minimum age of 18 years, prior use of an e-commerce company's conversational AI for information or problem resolution, purchase or service experience with the company being evaluated, AI-service use within the preceding six months, and identification of that company or brand. Respondents were asked to anchor all three construct assessments to the same provider, reducing ambiguity between evaluations of a chatbot and loyalty to the company it represented. The nonprobability sample was not designed to represent all Indonesian online shoppers.

Measures and Research Instrument

The structured online questionnaire employed a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree) and contained 18 reflective indicators. Six Human-Like Interaction indicators addressed natural language, resemblance to human conversation, contextual appropriateness, fluency, continuity, and personalization. Six Perceived Empathy indicators addressed understanding of needs, situationally appropriate responses, attention to problems, recognition of customer needs, sensitivity to feelings, and consideration of customer circumstances. Six Customer Loyalty indicators concerned continued use of the company's offerings, company preference, recommendation, repurchase, maintenance of the relationship, and reluctance to switch. The source scales, verbatim items, and any adaptation or pilot-testing records are not presented in the available manuscript; conclusions about content validity should consequently remain limited to the documented construct definitions and model diagnostics.

Data Collection and Preparation

The available description identifies an online questionnaire administered with voluntary participation, consent, and confidentiality assurances. The reported data-handling procedure considered response completeness, participant eligibility, potential duplicates, unusual answer patterns, and missing information. The descriptive characteristics and subsequent model assessment were reported for 300 respondents. Specific fieldwork dates, recruitment sources, exclusion counts, and any pilot-stage outcomes were not included in the source account, so no additional procedure is inferred here. Because all three constructs were assessed by self-report from the same respondent, shared-method variation remains a relevant interpretive limitation.

Measurement and Structural Model Evaluation

The reflective measurement model was evaluated using indicator outer loadings, Cronbach's alpha, Dijkstra–Henseler's ρA, composite reliability (ρc), average variance extracted (AVE), and the heterotrait-monotrait ratio (HTMT). The manuscript used a loading criterion around 0.70, internal-consistency values above 0.70, AVE above 0.50, and an HTMT reference threshold of 0.85. Structural assessment included inner variance inflation factors (VIF), standardized path estimates, explained variance (R^2), effect size (f^2), and the reported PLSpredict results. Direct hypotheses H1 to H3 and the specific indirect association H4 were evaluated with bootstrap-based t-statistics and p-values at the stated 5% level. The source document does not specify bootstrap resample counts, confidence-interval bounds, or PLSpredict fold and repetition settings, which limits independent reproduction of those inferential and predictive assessments.

Interpretive Scope

Positive statistical paths were interpreted as associations among the perceptions reported by these respondents, not as intervention effects. Customer Loyalty operationalized stated company-oriented intentions rather than transaction logs or customer retention records. The direct-path estimates in Table 10 and those in Figure 1 are different; both original sets are retained in the results to avoid an unsupported numerical replacement. Accordingly, the existence of the reported indirect association can be described, whereas the magnitude of a unified final structural model and the mediation category cannot be settled from the displayed outputs alone.

RESULTS AND DISCUSSION

Results

Table 1. Respondent Characteristics

Characteristics	Category	Frequency (n)	Percentage (%)
Age	18–24 years	78	26.0
	25–34 years	111	37.0
	35–44 years	66	22.0
	45–54 years	30	10.0
	55 years and older	15	5.0
	Total	300	100.0
Gender	Women	154	51.3
	Men	137	45.7
	Choose not to answer	9	3.0
	Total	300	100.0
Highest educational attainment	High school/vocational school	77	25.7
	Diploma	34	11.3
	S1	162	54.0
	S2 or above	27	9.0
	Total	300	100.0
Frequency of use of Conversational AI	Less than once a month	29	9.7
	1–3 times a month	116	38.7
	1–3 times a week	100	33.3
	4 or more times a week	55	18.3
	Total	300	100.0
The purpose of interaction with Conversational AI	Product information	76	25.3
	Product recommendations	59	19.7
	Transaction assistance	52	17.3
	Complaints/problem solving	38	12.7
	Combination of several needs	75	25.0
	Total	300	100.0
Time since last use of Conversational AI	In the last 1 month	137	45.7
	Last 1–3 months	100	33.3
	Last 4–6 months	63	21.0
	Total	300	100.0

Table 1 summarizes respondent characteristics. The study included 300 respondents with varied demographic characteristics and Conversational AI experience. The largest age group was 25–34 years old, with 111 respondents (37.0%), followed by the 18–24 age group with 78 respondents (26.0%) and the 35–44 age group with 66 respondents (22.0%). The sample included 154 female respondents (51.3%) and 137 male respondents (45.7%). For educational attainment, 162 respondents (54.0%) held a bachelor's degree, making this the largest educational group in the sample.

In terms of Conversational AI use, 116 respondents (38.7%) used it 1–3 times a month, while 100 respondents (33.3%) used it 1–3 times a week. Product information was the most frequently reported interaction purpose, cited by 76 respondents (25.3%), followed by use for multiple purposes, reported by 75 respondents (25.0%). In addition, 59 respondents (19.7%) used Conversational AI to obtain product recommendations, while 52 respondents (17.3%) used it for transaction assistance and 38 respondents (12.7%) used it to submit complaints or resolve issues. Regarding recency of use, 137 respondents (45.7%) used Conversational AI in the past month. These distributions describe the sampled consumers and their interaction patterns; they

provide context for the model estimates rather than evidence of relationships among the constructs.

Table 2. Descriptive Statistics

Variables	N	Mean	Standard deviation	Minimum	Maximum
Human-Like Interaction (X)	300	2.984	0.942	1.000	5.000
Perceived Empathy (M)	300	3.092	0.956	1.000	5.000
Customer Loyalty (Y)	300	2.993	0.986	1.000	5.000

The three constructs had mean scores close to the midpoint of the five-point response scale. Perceived Empathy had the highest mean (M = 3.092, SD = 0.956), followed by Customer Loyalty (M = 2.993, SD = 0.986) and Human-Like Interaction (M = 2.984, SD = 0.942). The mean scores clustered around the midpoint of the five-point scale, indicating that respondents, on average, expressed relatively neutral evaluations of Human-Like Interaction, Perceived Empathy, and Customer Loyalty. This pattern is particularly relevant because the positive structural associations should not be interpreted as evidence that respondents experienced uniformly high levels of perceived empathy or company loyalty. The descriptives characterize this respondent group and do not establish the direction or strength of relationships among the constructs.

Measurement Model Assessment

Table 3. Outer Loadings

Construct	Indicator	Outer loading	Criterion	Assessment
Perceived Empathy (M)	M.1	0.765	> 0.70	Valid
	M.2	0.760	> 0.70	Valid
	M.3	0.787	> 0.70	Valid
	M.4	0.746	> 0.70	Valid
	M.5	0.812	> 0.70	Valid
	M.6	0.796	> 0.70	Valid
Human-Like Interaction (X)	X.1	0.715	> 0.70	Valid
	X.2	0.773	> 0.70	Valid
	X.3	0.793	> 0.70	Valid
	X.4	0.772	> 0.70	Valid
	X.5	0.779	> 0.70	Valid
	X.6	0.799	> 0.70	Valid
Customer Loyalty (Y)	Y.1	0.771	> 0.70	Valid
	Y.2	0.790	> 0.70	Valid
	Y.3	0.789	> 0.70	Valid
	Y.4	0.798	> 0.70	Valid
	Y.5	0.790	> 0.70	Valid
	Y.6	0.815	> 0.70	Valid

Table 3 reports the 18 standardized outer loadings for the reflective measurement model. The values range from 0.715 to 0.815, exceeding the manuscript's threshold of 0.70. The respective ranges are 0.715–0.799 for Human-Like Interaction, 0.746–0.812 for Perceived Empathy, and 0.771–0.815 for Customer Loyalty. These values support the reported indicator-level reliability, while internal consistency, convergent validity, and the conceptual adequacy of item wording require separate consideration.

Table 4. Construct Reliability and Validity

Construct	Cronbach's alpha	Dijkstra–Henseler's ρA	Composite reliability (ρc)	AVE	Assessment
Perceived Empathy (M)	0.870	0.872	0.902	0.605	Reliable and valid
Human-Like Interaction (X)	0.864	0.866	0.899	0.596	Reliable and valid
Customer Loyalty (Y)	0.881	0.882	0.910	0.628	Reliable and valid

Table 4 indicates adequate internal consistency for each construct under the stated thresholds. Cronbach's alpha ranged from 0.864 to 0.881, Dijkstra–Henseler's ρA from 0.866 to 0.882, and composite reliability (rho_C) from 0.899 to 0.910. The AVE values were 0.596 for Human-Like Interaction, 0.605 for Perceived Empathy, and 0.628 for Customer Loyalty, all above 0.50. These figures support the reported reliability and convergent validity of the measurement model but do not establish content validity without the complete questionnaire.

Table 5. Discriminant Validity (HTMT)

Interconstruct relationships	HTMT	Criterion	Assessment
Perceived Empathy – Human-Like Interaction	0.600	< 0.85	Met
Perceived Empathy – Customer Loyalty	0.705	< 0.85	Met
Human-Like Interaction – Customer Loyalty	0.586	< 0.85	Met

The HTMT values reported in Table 5 were 0.600 for Perceived Empathy with Human-Like Interaction, 0.705 for Perceived Empathy with Customer Loyalty, and 0.586 for Human-Like Interaction with Customer Loyalty. All three were below the stated 0.85 threshold. The results are consistent with discriminant validity within this model, although the distinction between interaction appropriateness and empathy-related responsiveness also warrants examination at the item-content level.

Structural Model Assessment

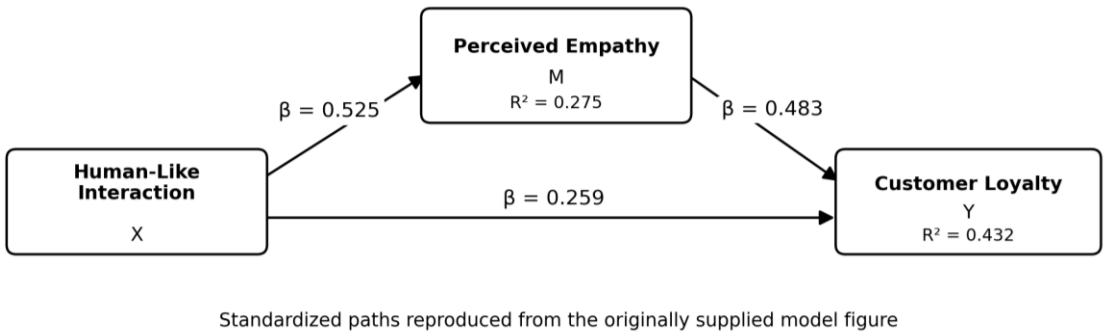


Figure 1. Reported Structural Paths (Redrawn from the Source Model)

Figure 1 presents one set of standardized coefficients: 0.525 for Human-Like Interaction to Perceived Empathy, 0.259 for Human-Like Interaction to Customer Loyalty, and 0.483 for Perceived Empathy to Customer Loyalty. The figure also reports $R^2 = 0.275$ for Perceived Empathy and $R^2 = 0.432$ for Customer Loyalty. These values indicate positive paths and show that the fitted predictors account for 27.5% and 43.2% of the respective endogenous construct variance. Figure 2 reports standardized coefficients of 0.525 for Human-Like Interaction → Perceived Empathy, 0.259 for Human-Like Interaction → Customer Loyalty, and 0.483 for Perceived Empathy → Customer Loyalty. However, Table 10 presents corresponding coefficients of 0.537, 0.340, and

0.411. Because these estimates are inconsistent, the final structural relationships cannot be interpreted conclusively until the reported values are reconciled using the original SmartPLS output. As the two sets are not identical, they should not be combined to characterize a single confirmed structural model; the reported values are retained without numerical alteration.

Table 6. Collinearity Statistics (Inner VIF)

Interconstruct relationships	VIF	Criterion	Assessment
Perceived Empathy → Customer Loyalty (M → Y)	1.380	< 5.00	There is no indication of multicollinearity
Human-Like Interaction → Perceived Empathy (X → M)	1.000	< 5.00	There is no indication of multicollinearity
Human-Like Interaction → Customer Loyalty (X → Y)	1.380	< 5.00	There is no indication of multicollinearity

The inner VIF estimates in Table 6 were 1.000 for the predictor of Perceived Empathy and 1.380 for each predictor of Customer Loyalty. They fall below the reference value of 5.00 and do not suggest problematic predictor collinearity in the reported structural equations. These statistics do not address shared-method variation across survey responses and should not be presented as evidence that common-method bias is absent.

Table 7. Coefficients of Determination (R^2)

Endogenous Construct	R^2	Adjusted R^2	Interpretation
Perceived Empathy (M)	0.275	0.273	27.5% of the variance is explained by the predictors
Customer Loyalty (Y)	0.432	0.428	43.2% of the variance is explained by the predictors

The reported R^2 values were 0.275 (adjusted R^2 = 0.273) for Perceived Empathy and 0.432 (adjusted R^2 = 0.428) for Customer Loyalty. Thus, the fitted model accounted for 27.5% of the variation in the former and 43.2% in the latter within the analyzed sample. The remaining variation is not explained by these predictors; its sources cannot be identified from the available model. These estimates concern within-sample explanatory performance rather than causal attribution.

Table 8. Effect Size (f^2)

Interconstruct relationships	f^2	Interpretation
Human-Like Interaction → Perceived Empathy (X → M)	0.380	Large effect
Perceived Empathy → Customer Loyalty (M → Y)	0.297	Medium effect
Human-Like Interaction → Customer Loyalty (X → Y)	0.086	Small effect

The f^2 statistics in Table 8 were 0.380 for Human-Like Interaction to Perceived Empathy, 0.297 for Perceived Empathy to Customer Loyalty, and 0.086 for Human-Like Interaction to Customer Loyalty. Under the conventional categories used by the manuscript, these correspond to a large, medium, and small incremental contribution, respectively. The pattern suggests that perceptions of human-like communication are more closely tied to the variation in perceived understanding than to the incremental variation in company-oriented loyalty once Perceived Empathy is also included. Nevertheless, these indices are conditional on consistent estimation of the structural model and cannot substitute for inferential testing.

Predictive Assessment

Table 9. PLSpredict

Indicator	Q^2predict	PLS-SEM RMSE	PLS-SEM MAE	LM RMSE	LM MAE
M.1	0.129	1.145	0.937	1.151	0.949
M.2	0.176	1.159	0.979	1.176	0.992
M.3	0.176	1.120	0.914	1.138	0.927
M.4	0.093	1.155	0.965	1.168	0.976
M.5	0.214	1.065	0.859	1.076	0.869
M.6	0.174	1.124	0.936	1.131	0.942
Y.1	0.121	1.130	0.935	1.148	0.952
Y.2	0.153	1.197	1.010	1.215	1.025
Y.3	0.197	1.094	0.907	1.110	0.912
Y.4	0.157	1.146	0.961	1.153	0.963
Y.5	0.148	1.141	0.968	1.156	0.977
Y.6	0.176	1.152	0.977	1.157	0.977

The PLSpredict results in Table 9 show positive Q^2predict values for all twelve indicators of the endogenous constructs, ranging from 0.093 to 0.214. The reported PLS-SEM RMSE values were lower than the linear-model benchmark for every displayed indicator, while MAE values were lower for eleven and identical for Y.6 (0.977) in the remaining comparison. These comparisons are consistent with favorable indicator-level prediction errors in the reported analysis. They do not establish performance on another dataset or retailer because the validation folds, repetitions, and other settings are not documented.

Hypothesis Testing

Table 10. Direct Effects

Hypothesis	Interconstruct relationships	Original sample (O)	Sample mean (M)	Standard deviation	t-statistics	p-values	Decision
H1	X → Y	0.340	0.342	0.051	6.736	0.001	Accepted
H2	X → M	0.537	0.538	0.042	12.894	0.001	Accepted
H3	M → Y	0.411	0.409	0.049	8.396	0.001	Accepted

Table 10 reports positive direct coefficients for H1 (X → Y: β = 0.340, t = 6.736, p = 0.001), H2 (X → M: β = 0.537, t = 12.894, p = 0.001), and H3 (M → Y: β = 0.411, t = 8.396, p = 0.001). The corresponding narrative and Figure 2 instead present β = 0.259, 0.525, and 0.483, with different t-statistics. Table 10 reports positive and statistically significant relationships for H1, H2, and H3, with reported p-values of 0.001. Figure 2 also presents positive path coefficients, although their magnitudes differ from those reported in the hypothesis-testing table and the figure does not provide corresponding significance statistics. Consequently, the hypothesis decisions should be finalized using a single, consistent set of SmartPLS estimates to ensure accurate interpretation of the structural relationships. Comparisons of effect magnitudes and claims about the final structural parameters must therefore remain conditional on this inconsistency.

Mediation Analysis

Table 11. Specific Indirect Effects

Hypothesis	Interconstruct relationships	Original sample (O)	Sample mean (M)	Standard deviation	t-statistics	p-values	Decision
H4	X → M → Y	0.253	0.255	0.034	7.408	< 0.001	Accepted

The specific indirect association in Table 11 is reported as β = 0.253, t = 7.408, and p < 0.001. The product of the two figure-based component paths (0.525 × 0.483) is approximately 0.254, whereas the corresponding product using Table 10 (0.537 × 0.411) is approximately 0.221. Consequently, the model coefficients need to originate from one consistent SmartPLS estimation before numerical statements about mediation can be finalized. Table 11 reports a positive specific indirect association between Human-Like Interaction and Customer Loyalty through Perceived Empathy (β = 0.253, t = 7.408, p < 0.001). Nevertheless, inconsistencies between the component path coefficients reported in Figure 2 and Table 10, together with the absence of an indirect-effect confidence interval, limit the interpretation of this result. Therefore, the findings support a reported positive indirect association, while the precise mediation classification remains unresolved. The cross-sectional design further prevents the indirect relationship from being interpreted as evidence of a causal process.

Discussion

The reported positive relationship between Human-Like Interaction and Perceived Empathy suggests that respondents who experienced more natural, continuous, and contextually appropriate chatbot communication also tended to feel better understood. CASA helps interpret why socially familiar cues might attract relational judgments from customers, without requiring the system to possess human intentions (Nass & Moon, 2000). Whereas Fu et al. (2023) examined the relationships between human-like chatbot characteristics and customer trust, the present study focuses on perceived understanding as a distinct relational judgment associated with conversational naturalness. This distinction is consistent with Liu-Thompkins et al. (2022), who differentiate the customer experience of artificial empathy from genuine human emotional experience. The reported positive association suggests that customers who perceive chatbot communication as natural and contextually appropriate also tend to feel better understood. Nevertheless, the findings concern perceived interaction quality rather than the actual emotional capabilities of conversational AI. Our result concerns this perceived relational quality, not a tested change in the chatbot's emotional intelligence. It is therefore compatible with prior work while remaining limited to the aggregate self-reported Human-Like Interaction construct.

The association involving Perceived Empathy becomes particularly meaningful when separated from an interface's general conversational fluency. Markovitch et al. (2024) examined perceived empathy in evaluations of chatbot versus human service, while Haupt et al. (2023) studied the differential effects of empathy-oriented and solution-oriented messages in service recovery. Work on empathy in service recovery and frontline human–AI encounters offers related, but not equivalent, perspectives (Carrilho et al., 2025; Yang et al., 2025). Those studies involve interaction features or service conditions that this survey does not experimentally vary. A chatbot could respond smoothly yet fail to recognize a complaint, and an informative response could be useful without being experienced as caring. The present indicators address consumers' judgments of being understood rather than objective recognition accuracy or emotional competence. This distinction makes the positive X-to-M relationship theoretically interpretable without overstating what was measured.

A positive direct association between Human-Like Interaction and Customer Loyalty was also reported, but the outcome differs from chatbot reuse. Bergner et al. (2023) show that verbal features of conversations can shape consumer–brand relationships, whereas Hsu and Lin (2023) examine satisfaction and loyalty associated with customer-service chatbots. Research on service-chatbot anthropomorphism and persuasion offers additional contexts for interpreting brand-directed evaluations (Hu et al., 2026; Yang et al., 2026). The present study refers all loyalty indicators to an e-commerce company or brand rather than to continued engagement with the conversational tool itself. Research on loyalty to chatbot usage itself reinforces this distinction (Rita et al., 2026). That difference is consequential: a customer may enjoy the chatbot without preferring the retailer, and may remain loyal to a retailer because of factors outside the chatbot. The smaller figure-based direct path relative to the empathy-to-loyalty path is suggestive, although the discordance with Table 10 prevents a settled numerical comparison.

The reported Perceived Empathy–Customer Loyalty relationship indicates that respondents who felt recognized in the service interaction also tended to express stronger company-oriented loyalty intentions. Related research has linked AI service quality to e-brand loyalty via customer trust and experience (Shahzad et al., 2024), and Ozuem et al. (2024) connect chatbot-based service recovery with loyalty in a different service context. Research on responsive and anthropomorphic exchanges similarly examines customer experience, which differs from company-level retention (Truong & Chen, 2025). Neither comparison establishes that perceived understanding independently causes repeat purchasing. Within this survey, loyalty was assessed through intentions and preferences rather than transaction records. Recent research on chatbots, satisfaction, and repeat purchase also emphasizes the importance of separating encounter evaluations from downstream behavior (Zhao et al., 2026). The result instead identifies perceived understanding as a relational evaluation worth distinguishing from technical competence, especially when companies use automated channels to manage customer contact.

The reported specific indirect path brings the three constructs together, but its interpretation must account for the contradictory coefficient sets. An indirect association of 0.253 is printed in Table 11, closely matching the product of the X-to-M and M-to-Y paths in Figure 2. Table 10 provides different direct-path estimates, and no confidence limits for the reported indirect effect are supplied. For that reason, the result supports only a qualified account of a positive reported indirect relationship; it does not establish partial mediation or the temporal process by which empathy might arise before loyalty. This restraint is consistent with the cross-sectional survey design and avoids transforming a statistical decomposition into a behavioral mechanism.

Rather than proposing an entirely new relationship between conversational AI and customer loyalty, this study contributes to the literature by distinguishing three conceptually related but empirically separate evaluations: the perceived human-likeness of chatbot communication, the perceived understanding conveyed during the interaction, and loyalty intentions directed toward the service provider. This distinction provides a more specific perspective on customer relationships with AI-enabled services by separating favorable evaluations of conversational technology from intentions to maintain relationships with the company itself. Within the Indonesian e-commerce sample, the reported results offer a basis for examining these relationships without equating chatbot satisfaction with company loyalty. Chen et al. (2023), Lee and Li (2023), and Shahzad et al. (2024) already examine relational consequences of AI-enabled customer service. At the same time, other scholarship distinguishes social presence, rapport, trust, and engagement as separate responses to conversational

technology (Konya-Baumbach et al., 2023; Fatima et al., 2024; Fakhimi et al., 2023). The present study contributes by assessing perceived communication characteristics, perceived understanding, and intentions directed toward the same company in the Indonesian e-commerce sample. HTMT values below 0.85 are compatible with their empirical distinction, while access to exact items remains necessary for a stronger assessment of conceptual overlap.

Several boundary conditions matter when placing the results alongside international studies. A customer-journey perspective also suggests that the conversational encounter is only one part of a broader relationship with a retailer (Lemon & Verhoef, 2016). The respondents evaluated AI services used for product information, recommendations, transactions, and complaints, rather than a single controlled interaction type. Experiments on chatbot human-likeness indicate that results can depend on the interface, purchasing relationship, or treatment condition (Nguyen et al., 2023; Igarashi et al., 2026). Work on conversational styles in hospitality also addresses engagement under conditions that differ from this survey's provider-directed loyalty measure (Roy Bhattacharjee et al., 2025). The sample's heterogeneity in recent chatbot use may therefore coexist with unmeasured differences in service expectations and encounter severity. None of these contextual possibilities was separately tested, so they are treated as explanations for future investigation rather than results of the current model.

For managers, the findings justify examining the quality of chatbot exchanges as part of a wider customer relationship assessment, particularly whether conversations remain relevant, continuous, and responsive to stated needs. The analysis cannot rank these design features, show that adding anthropomorphic cues improves outcomes, or confirm reductions in customer churn. A practical evaluation would therefore distinguish chatbot satisfaction from brand preference and complement survey-based intentions with behavioral measures where available. The limitations are substantial: purposive recruitment restricts generalization, a single survey cannot determine temporal order, and same-source self-reports create potential common-method concerns. Unspecified fieldwork and measurement-development details, together with the inconsistent structural coefficients, further constrain reproducibility. Longitudinal, experimental, and cross-platform research could test when perceived understanding precedes loyalty and whether the reported associations correspond to actual behavior.

CONCLUSIONS

The study reports positive relationships among Human-Like Interaction, Perceived Empathy, and Customer Loyalty in a sample of 300 Indonesian e-commerce users. The findings indicate that Human-Like Interaction, Perceived Empathy, and Customer Loyalty represent empirically distinguishable constructs within the examined Indonesian e-commerce sample, as supported by the reported discriminant validity results. The positive direct and indirect associations suggest that perceived conversational naturalness and perceived understanding are relevant to customers' company-directed loyalty intentions. However, inconsistencies in the reported structural coefficients prevent definitive conclusions about effect magnitudes and mediation classification. Accordingly, these findings should be interpreted as associations among customer perceptions and intentions rather than evidence of causal changes in purchasing or retention behavior. Because the direct effects differ between Figure 2 and Table 10, the final magnitudes and classification of mediation cannot be inferred with confidence from the displayed figures. These findings concern self-reported company-related loyalty intentions, not observed customer retention or the causal effects of chatbot design.

This analysis positions Perceived Empathy as a distinct customer judgment within a parsimonious model of conversational AI and company-directed loyalty. The study draws on CASA, social presence, and relationship marketing as complementary perspectives without asserting that their full mechanisms were tested. The reported measurement properties are encouraging, but they do not eliminate limitations arising from missing item wording and common-method concerns. In managerial terms, conversational relevance and perceived understanding are reasonable aspects of service experience to evaluate, not proven methods for increasing purchases.

Future studies could combine documented questionnaire development and probability-based or diversified recruitment with longitudinal observations, experiments, and transaction-level outcomes. Such evidence would help determine whether customer interpretations of conversational AI precede changes in company loyalty and whether associations differ across retailers, service problems, or customer groups. The current cross-sectional results should be read as a bounded empirical account of perceptions within the sampled context.

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