ISSN 3123-6464 (Online)
JOMBINOV
Journal of Management and Business Innovation

Journal of Management and Business Innovation (JOMBINOV)
https://v-learnov.com/index.php/jombinov
Volume 02
Number 03
September 2026
Page: 272-286
ISSN: 3123-6464 (Online)

The Impact of AI Chatbot Implementation on Customer Satisfaction: A Study of Food and Beverage (F&B) Businesses in Labuan Bajo, Indonesia

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Article History:

Received: 07 August 2026
Revised: 25 August 2026
Accepted: 02 September 2026

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Abstract:

Research Aims:
This research aims to analyze the impact of AI chatbot implementation on customer satisfaction in the food and beverage (F&B) business in Labuan Bajo by examining the role of customer digital trust as a mediating variable.
Methodology:
This research uses an explanatory quantitative approach with purposive sampling technique on 131 F&B customers who have experience interacting with AI chatbots. The data were analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) method with the help of the SmartPLS 4 application to test the relationships between variables in the research model.
Findings:
The implementation of AI chatbots has been proven to have a positive and significant impact on digital trust and customer satisfaction directly. Additionally, digital trust also has a positive and significant impact on customer satisfaction. The results of the mediation test indicate the presence of complementary partial mediation, meaning that more than half of the AI chatbot's influence on customer satisfaction occurs thru the enhancement of customer digital trust.
Theoretical Contribution/Originality:
This research enriches the TAM and ERP by providing a mechanistic explanation of the conditions under which the relationship between AI chatbots and customer satisfaction holds, while also being the first study to test this mechanism in F&B businesses at Indonesia's super-priority tourist destinations.
Practitioners/Policy Implications:
F&B business operators need to develop chatbots that not only focus on response speed but also build credibility and customer trust. Meanwhile, local governments can use these findings as a basis for designing more effective digitalization support programs for MSMEs that meet the needs of business operators.
Research Limitations/Implications:
The research sample was dominated by domestic tourists and collected thru a cross-sectional design at a single destination, so the generalization of the findings needs to be done with caution. Future research is recommended to use a longitudinal design and a comparative approach between destinations to obtain a broader understanding.

Keywords: Artificial Intelligence Chatbot, Digital Trust, Customer Satisfaction, Technology Acceptance Model; Food and Beverage Business; Premium Tourism Destination.

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JOMBINOV
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INTRODUCTION

Business and consumer interactions are changing with the widespread use of AI-based chatbots. This technology has become an important instrument in the competition within the service industry because it can reduce costs while meeting consumer demands for fast and consistent service (Kamuri, 2026 ; Adam et al., 2021). The global chatbot market is projected to reach USD 7.01 billion by 2024, with an annual growth rate of 24.32 percent until 2029 (Thu et al., 2026; Pham et al., 2025). The food and beverage sector includes users with the fastest growth, and chatbots have proven to have a positive impact on customer satisfaction and acceptance in restaurants (Hitti & Ramadan, 2026).

In Indonesia, this development aligns with the growth of tourism, including Labuan Bajo, which has been designated as a super priority tourism destination since 2019, with the number of visits reaching 355,836 tourists by 2025 (Imania & Syfa, 2026. This increase encourages food and beverage (F&B) business operators to maintain service consistency amidst the rising transaction volume. Therefore, the adoption and implementation of AI chatbots in F&B businesses at tourist destinations like Labuan Bajo are important to study, especially because failure to meet customer expectations can reduce tourist loyalty.

Consumer demand for fast and personalized services is driving the service industry to shift from conventional interactions that rely entirely on human labor. The limitations of operational hours and the differences in service quality among employes are increasingly inconsistent with the expectation of services being available at any time (Kamuri, 2026). Rizomyliotis et al. (2022) found that AI chatbots in small and medium-sized businesses can enhance customer affective commitment thru quick and consistent responses. Meanwhile, Al-Shafei (2025) demonstrated that user satisfaction and engagement are also influenced by the chatbot's ability to tailor communication to customer preferences. Thus, AI chatbots have evolved from mere automation tools into strategic solutions to meet the demands for fast and personalized service.

This strategic change is evident in the tourism and hospitality sector. Thu et al. (2026), thru a bibliometric review of 253 publications from Scopus and Web of Science for the period 2013–2025, found that the strategic role of chatbots in the tourism ecosystem has become one of the four main emerging themes. This is supported by the ability of AI chatbots to adapt to various languages and service cultures. The findings are relevant to Indonesia because the F&B sector is an important part of the tourism service chain that directly interacts with tourists. However, research on the implementation of chatbots in F&B businesses at domestic tourist destinations is still limited. This condition highlights the gap between global evidence regarding the effectiveness of AI chatbots in enhancing customer satisfaction and the lack of contextual research in super-priority tourist destinations in Indonesia.

Research on AI chatbots and customer satisfaction is rapidly evolving, but the results have not been consistent. Chacon (2026) and Rizomyliotis et al. (2022) show that chatbots can enhance affective commitment and satisfaction thru quick and reliable responses. On the other hand, Ranieri et al. (2024) found that chatbots can trigger negative experiences, such as stress and decreased digital trust, when the system fails to understand user needs. Xu et al. (2023) refer to this condition as mixed effects, so the impact of chatbots on satisfaction cannot be explained solely thru direct relationships. The difference indicates the presence of a theoretical gap. Models like TAM focus more on functional aspects and have not yet explained why chatbots that are equally fast and efficient can enhance satisfaction in one context but cause frustration in another. Relational and emotional dimensions in service interactions need to be considered. Therefore, a mediator or moderator is needed to explain the relationship between chatbots and customer satisfaction. Sidlauskiene et al. (2023) emphasize that the influence of chatbots depends on the context and cannot be generalized without considering the underlying connecting mechanisms.

Although previous research provided empirical evidence, most of it was conducted on different populations and contexts. Chacom (2026) studied online retailers, Xu et al. (2023) chatbot-based sales services, while Rizomyliotis et al. (2022) and Hitti and Ramadan (2025) focused on the European and Middle Eastern contexts. This condition is different from Labuan Bajo as a super-priority tourism destination dominated by F&B SMEs with distinct characteristics in digital literacy, market structure, and tourists. This indicates the presence of a contextual/population gap. Methodologically, most studies use qualitative analysis or cross-sectional surveys without simultaneously testing the mediation mechanism. There are still not many quantitative models based on structural equation modeling that examine the mediating role of customer satisfaction in F&B SMEs in developing tourist destinations. This condition indicates the existence of a methodological gap that limits the application of previous findings in different contexts.

The literature has not yet examined the implementation of AI chatbots and customer satisfaction in F&B businesses at Indonesia's super priority tourism destinations, particularly Labuan Bajo, thru a quantitative model. These theoretical, empirical, contextual, and methodological gaps limit the development of service technology acceptance theory and increase the risk of inappropriate chatbot investments by F&B businesses. These conditions form the basis for the formulation of this research's objectives.

The limitations of the Technology Acceptance Model (TAM) in explaining the relationship between chatbots and customer satisfaction indicate a theoretical gap in the literature. Al-Adwan et al. (2024) state that TAM research related to AI chatbot adoption is still in its early stages. They also emphasize that studies placing trust as a mediator have not clearly explained when and how trust bridges the influence of chatbots on customer behavior. This research fills the gap by integrating the Technology Acceptance Model (TAM) and the Expectation-Confirmation Theory (ECT), with customer digital trust as the main mediator. This approach aligns with Dubey and Meena (2025) , who demonstrate that the mismatch between customer expectations and chatbot performance can decrease trust more significantly than the increase when expectations are met. By testing this mechanism on F&B businesses in super priority tourist destinations, this research not only adds variables to TAM and ECT but also explains why the impact of chatbots on customer satisfaction can vary across service contexts. This contribution clarifies the direction of further research, which has so far provided minimal explanation regarding the mechanism.

Based on theoretical, empirical, contextual, and methodological gaps, this study aims to examine the impact of AI chatbot implementation on customer satisfaction in the food and beverage (F&B) business in Labuan Bajo, with digital trust as a mediating variable to explain the inconsistencies in previous findings. This research addresses three main questions: (1) to what extent does the implementation of AI chatbots affect F&B customer satisfaction in super priority tourism destinations; (2) does digital trust mediate this relationship; and (3) how are the relationships between variables confirmed thru a quantitative approach based on structural equation modeling among F&B customers in Labuan Bajo. Thus, this research not only reexamines the relationship between chatbots and customer satisfaction but also explains the mechanisms in the context of SMEs in developing tourist destinations, which differ from online retail or restaurants in developed countries.

METHODS

This research uses a quantitative approach with an explanatory research type to test the cause-and-effect relationship between variables based on (Sugiyono, 2022). This approach was chosen to measure the direction and strength of the influence between variables thru standardized instruments, statistically test hypotheses, and support the generalization of the relationship between AI chatbots, digital trust, and customer satisfaction among F&B business customers in Labuan Bajo.

This research uses Partial Least Squares Structural Equation Modeling (PLS-SEM) to test causal and mediating relationships because it aligns with the characteristics of predictive and exploratory research. PLS-SEM is suitable for testing models with mediators that have not been extensively studied in new contexts, does not require strict multivariate normality, and is appropriate for medium-sized samples (Hair et al., 2023). This method is relevant for survey data of F&B SMEs customers in Labuan Bajo, which may not be normally distributed.

The population of this study consists of food and beverage (F&B) business customers in Labuan Bajo who have directly interacted with the AI chatbot when making orders, reservations, or using customer service. This limitation is set so that respondents have relevant experience, allowing for a more accurate assessment of digital trust and customer satisfaction. The research uses purposive sampling techniques with three main criteria, namely: (1) aged at least 17 years and having transacted with F&B businesses in Labuan Bajo during the research period; (2) having interacted with an AI chatbot thru instant messaging applications, websites, or booking applications; and (3) being willing to provide informed consent. The selection of these criteria is important because the accuracy of estimation in PLS-SEM is not only determined by the sample size but also by the uniformity of the characteristics of the respondents being studied (Kock & Hadaya, 2018).

The sample size is determined using two approaches. First, the 10-times rule sets a minimum of 10 times the highest number of indicators for a single construct (Hair et al., 2019). With six indicators, the minimum sample size is 60 respondents. Second, the research uses the *inverse square root method* by Kock and Hadaya (2018), which considers the significance level and *effect size* for greater precision. Based on these two approaches, the research sets a target of 150–200 respondents to meet the analysis needs while anticipating invalid or incomplete data.

There are two types of potential biases controlled in this study. First, self-selection bias is reduced by distributing the questionnaire to various types of F&B businesses, such as casual cafes, restaurants, and establishments serving tourists. This strategy was implemented to obtain a more diverse range of respondent characteristics. Second, common method bias is controlled thru the application of ex-ante procedures developed by Podsakoff et al. (2012), namely by maintaining respondent anonymity, using varied scale formats, and systematically arranging the order of questions. Next, the potential bias was statistically tested using the full collinearity test.

Data collection was conducted using a mixed-mode approach thru a combination of online and offline surveys to reach F&B customers with diverse digital literacy characteristics and visit patterns. The online survey was conducted via Google Forms distributed thru the social media of partner F&B businesses, tourist communities, and local residents. Meanwhile, the offline survey was conducted using the intercept survey method with customers encountered directly. The use of these two data collection methods aims to reduce the potential for representation bias that may occur if the research only involves respondents with high digital literacy levels and active use of online platforms.

Data were analyzed using a two-step approach in PLS-SEM with the help of SmartPLS. The first stage involved evaluating the measurement model (outer model) to ensure the validity and reliability of the indicators. Subsequently, the structural model (inner model) evaluation was conducted to test the relationships between variables in the research model (Hair et al., 2021).

The evaluation of the outer model is conducted thru three main aspects. First, convergent validity is tested by looking at the outer loading value, which must reach ≥ 0.70 and an AVE value ≥ 0.50 (Hair et al., 2022). Second, discriminant validity is evaluated using the Fornell-Larcker criterion, which states that the square root of the AVE value of each construct must be higher than the correlation with other constructs. Additionally, the HTMT value < 0.85 is also used as a more sensitive testing criterion. Third, internal consistency reliability is tested thru the Cronbach's Alpha and Composite Reliability values, with an acceptance threshold of ≥ 0.70

After the outer model meets the criteria of validity and reliability, the evaluation continues on the inner model*thru R^2, Q^2, f^2, and path coefficient. R^2 assesses the ability of exogenous variables to explain the endogenous construct, Q^2 evaluates predictive relevance, while f^2 measures the contribution of each construct to R^2. The significance of the relationship is tested thru bootstrapping with a minimum of 5,000 resampling, using t-statistics and p-value as the basis for hypothesis testing (Hair et al., 2022).

The testing of the mediating role of digital trust was conducted following the procedure by Zhao et al. (2010) by examining the significance of the indirect effect using the bootstrapping method. Next, the type of mediation is determined based on the significance and direction of the direct and indirect influence relationships, which can be full mediation, complementary/competitive partial mediation, or no mediation. Mediation testing thru the indirect effect does not require a significant direct influence first, thus being more capable of capturing the mediation mechanisms occurring in the research model.

RESULTS

Respondent Profle

This section presents the research results based on data from 131 respondents who meet the research criteria. The analysis was conducted using a two-stage approach in PLS-SEM. The presentation of results begins with a description of the respondents' profiles, followed by the evaluation of the measurement model (outer model), the evaluation of the structural model (inner model), and hypothesis testing, concluding with the testing of the mediating effect of customer digital trust as the main finding of this research. This presentation structure is used to ensure that the analysis flows systematically, from the characteristics of the respondents to the testing of relationships between variables in the research model.

Table 1. Respondent Profile

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	58	44.3
	Female	73	55.7
Age	< 20 years	9	6.9
	20–29 years	61	46.6
	30–39 years	41	31.3
	40–49 years	15	11.5
	≥ 50 years	5	3.8
Respondent Status Frequency of Chatbot Interaction	Local resident	42	32.1
	Domestic tourist	71	54.2
	International tourist	18	13.7
	1 time	47	35.9
	2–3 times	58	44.3
	> 3 times	26	19.8
Type of F&B Business	Café	54	41.2
	Restaurant	62	47.3
	Bar/Lounge	15	11.5

Source: Processed Primary Data, 2026

Of the 131 respondents who participated, slightly more were female (55.7%) compared to male (44.3%). The largest age group was 20–29 years old (46.6%), followed by the 30–39 age group (31.3%). Based on the respondents' status, the majority were domestic tourists (54.2%), followed by local residents (32.1%) and international tourists (13.7%). This composition indicates that the research results more accurately reflect the perceptions of domestic customers. Looking at the intensity of chatbot usage, 44.3% of respondents interacted with the chatbot 2–3 times, while 19.8% interacted more than three times. These findings indicate that the assessment of digital trust and customer satisfaction is generally based on repeated usage experiences, not just a single interaction.

Measurement Model Evaluation (Outer Model)

The evaluation of the measurement model is conducted in stages thru testing for convergent validity, discriminant validity, and internal consistency reliability before the structural model is further analyzed. The results of the outer loading test show that all indicators in the three research constructs, namely AI Chatbot Implementation, Customer Digital Trust, and Customer Satisfaction, have values above the minimum threshold of 0.70 according to the criteria of Hair et al. (2022). Thus, all indicators are deemed worthy of being retained in the model, and no indicators were eliminated.

In addition, the Average Variance Extracted (AVE) values for the three constructs are also above 0.70. This result indicates that each construct is able to explain more than 50% of the variance of its constituent indicators, thus the convergent validity of the model can be considered fulfilled. The results of the internal consistency reliability test in Table 2 show that the Cronbach's Alpha and Composite Reliability values for all constructs are above the minimum threshold of 0.70, with most approaching or exceeding 0.85. These results indicate that each construct has a strong level of internal consistency.

Tabel 2. Results of Convergent Validity and Reliability

Construct	Indicator	Outer Loading	AVE	Cronbach's Alpha	Composite Reliability (CR)
Chatbot AI Implementation (CAI)	CAI1	0.812	0.641	0.878	0.914
	CAI2	0.798			
	CAI3	0.834			
	CAI4	0.771			
	CAI5	0.805			
	CAI6	0.759			
Digital Trust (DT)	DT1	0.841	0.667	0.851	0.899
	DT2	0.822			
	DT3	0.796			
	DT4	0.803			
Customer Satisfaction (CS)	CS1	0.857	0.689	0.869	0.907
	CS2	0.833			
	CS3	0.812			
	CS4	0.804			

Source: Output SEM-PLS 4, 2026

The next step is the discriminant validity test, which is conducted using two criteria to strengthen the results. Based on the Fornell-Larcker criterion, the square root of the AVE value for each construct (the diagonal values in Table 3) is higher than its correlation with other constructs. This result shows that the discriminant validity has met the conventional criteria. To ensure these results, testing was also conducted using the Heterotrait-Monotrait Ratio (HTMT), as this method is more sensitive when the correlation between constructs is relatively high.

All HTMT values are below the conservative threshold of 0.85 as recommended by Henseler et al. (2016). Thus, the discriminant validity between the constructs of AI Chatbot Implementation, Digital Trust, and Customer Satisfaction can be confidently stated as fulfilled.

Table 3. Discriminant Validity (Fornell-Larcker Criterion and HTMT)

Construct	CAI	DT	CS
Chatbot AI Implementation (CAI)	**0.801**		
Digital Trust (DT)	0.612 (HTMT: 0.719)	**0.817**	
Customer Satisfaction (CS)	0.588 (HTMT: 0.697)	0.671 (HTMT: 0.781)	**0.830**

Note: Diagonal values (bold) represent the square root of AVE; off-diagonal values below represent inter-construct correlations, with HTMT ratios in parentheses.

Source: Output SEM-PLS 4, 2026

Because all criteria for convergent validity, discriminant validity, and reliability have been met, the measurement model is declared qualified and eligible to proceed to the structural model evaluation stage.

After the measurement model is declared valid and reliable, the analysis continues with the structural model to assess the model's ability to explain endogenous variables, predictive relevance, and the contribution of each exogenous construct. Before interpreting the path coefficients, a collinearity test using the Variance Inflation Factor (VIF) is conducted to ensure that there is no multicollinearity among the exogenous constructs that could affect the estimation results. The test results show that all VIF values are well below the conservative threshold of 3.0 as recommended by Hair et al. (2022). Thus, the structural model is declared free from significant collinearity issues and is suitable for further testing of inter-variable relationships.

Table 4. Collinearity Statistics (VIF)

Path	VIF
Chatbot AI Implementation → Digital Trust	1.000
Chatbot AI Implementation → Customer Satisfaction	1.598
Digital Trust → Customer Satisfaction	1.598

Source: Output SEM-PLS 4, 2026

Structural Model Evaluation (Inner Model)

After the measurement model has been deemed valid and reliable, the study moves on to the evaluation of the inner or structural model. This step is intended to evaluate the interactions between variables in the study model, such as the direction and strength of materialism's influence on status consumption and the status consumption trap, as well as the role of status consumption as a mediating variable. The structural model is evaluated in four stages: assessing the coefficient of determination (R^2), effect magnitude (f^2), predictive relevance (Q^2), and hypothesis testing.

The results of the coefficient of determination (R^2) show that the implementation of the AI Chatbot can explain 37.5% of the variation in Customer Digital Trust ($R^2 = 0.375$). Meanwhile, the implementation of the AI Chatbot and Digital Trust together can explain 51.2% of the variation in Customer Satisfaction ($R^2 = 0.512$). Based on the category of Hair et al. (2022), the value falls within the moderate to nearly strong range for social science research.

In addition, the predictive relevance (Q^2) results obtained thru the blindfolding procedure also indicate the model's good predictive ability. The Q^2 value for Digital Trust is 0.241 and for Customer Satisfaction is 0.334. Because both values are greater than zero, the model can be stated to have predictive relevance and is capable of predicting data outside the sample used in the estimation process.

Table 5. R^2 and Q^2 Values

Endogenous Construct	R^2 (Coefficient Determination)	Q^2 (Predictive Relevance)
Digital Trust (DT)	0.375	0.241
Customer Satisfaction (CS)	0.512	0.334

Source: Output SEM-PLS 4, 2026

The most prominent finding from the effect size (f^2) analysis is the difference in the strength of influence between variables. The implementation of the AI Chatbot has a significant impact on Digital Trust ($f^2 = 0.601$). Conversely, the direct impact of the AI Chatbot implementation on Customer Satisfaction is relatively small ($f^2 = 0.087$), while the impact of Digital Trust on Customer Satisfaction falls into the moderate category ($f^2 = 0.267$).

The pattern indicates that the influence of AI chatbots on customer satisfaction is likely not direct, but rather thru the enhancement of customers' digital trust. These findings serve as an initial indication of a mediation mechanism and will be further tested thru hypothesis testing and mediation effect analysis in the next section.

Table 6. Effect Size (f^2)

Path	f^2	Category
Chatbot AI Implementation → Digital Trust	0.601	Large
Chatbot AI Implementation → Customer Satisfaction	0.087	Small
Digital Trust → Customer Satisfaction	0.267	Medium

Source: Output SEM-PLS 4, 2026

ISSN 3123-6464 (Online)
JOMBINOV
Journal of Management and Business Innovation

The analysis's findings indicate that materialism has a considerable influence on status consumption, with an effect size (f^2) of 0.825. This suggests that materialism has a significant role in the development of status-consuming behavior. With a f2 value of 0.458, the impact of status consumption on the status consumption trap likewise belongs to the substantial group. The direct impact of materialism on the status consumption trap, on the other hand, has a moderate f2 value of 0.182. These results suggest that materialism has a greater impact on the status consumption trap when status consumption acts as a mediator.

Hypothesis Testing (Path Coefficient & Significance)

Hypothesis testing was conducted using the bootstrapping procedure with 5,000 subsamples to obtain path coefficient values, t-statistics, and p-values at a significance level of 0.05 (t-statistic > 1.96), in accordance with the procedure described in the methods section.

The test results show that all direct relationship hypotheses in this study are statistically supported. However, the magnitude of the influence of each relationship differs significantly. The difference in the strength of these influences becomes an important substantive finding because it shows that each relationship between variables does not have the same contribution in the research model, thus requiring further interpretation in the discussion section.

Table 7. Path Coefficients and Hypothesis Testing Results

Hypothesis	Path	Path Coefficient (β)	t-statistic	p-value	Decision
H_1	Chatbot AI Implementation → Digital Trust	0.612	9.847	0.000	Supported
H_2	Chatbot AI Implementation → Customer Satisfaction	0.219	2.684	0.007	Supported
H_3	Digital Trust → Customer Satisfaction	0.428	5.912	0.000	Supported

Source: Output SEM-PLS 4, 2026

The first hypothesis (H_1) shows that the implementation of the AI Chatbot has a positive and significant effect on Customer Digital Trust ($\beta = 0.612$; $t = 9.847$; $p < 0.001$). This influence is the strongest among all paths in the model and is consistent with the large effect size (f^2) value in the previous analysis.

The second hypothesis (H_2) shows that the implementation of AI Chatbots also has a direct positive effect on Customer Satisfaction ($\beta = 0.219$; $t = 2.684$; $p = 0.007$). However, the magnitude of this influence is much smaller compared to its influence on Digital Trust.

Next, the third hypothesis (H_3) shows that Digital Trust has a positive and significant effect on Customer Satisfaction ($\beta = 0.428$; $t = 5.912$; $p < 0.001$). The strength of this influence is more than twice that of the direct effect of AI Chatbot Implementation on Customer Satisfaction.

Overall, the path thru Digital Trust (H_1 and H_3) shows coefficients that are much larger compared to the direct path (H_2). These findings indicate that Digital Trust is not merely a supporting variable, but rather the main mechanism that channels the influence of AI Chatbot Implementation on Customer Satisfaction. The hypothesis was then further tested thru mediation effect analysis in the following section.

Mediation Analysis

According to the procedure described in the methods section, the testing of the mediation effect of Customer Digital Trust is conducted by examining the significance of the indirect effect

ISSN 3123-6464 (Online)
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thru the bootstrapping method. This approach is used without requiring the prior existence of a significant direct effect, unlike the classical mediation procedure of Baron and Kenny. The test results show that the indirect influence of AI Chatbot Implementation on Customer Satisfaction thru Digital Trust is proven to be significant (β = 0.262; t = 4.912; p < 0.001; 95% CI [0.156; 0.372]). The confidence interval values do not include the number zero, thus meeting the criteria of Zhao et al. (2010) to state that the mediation effect in this research model is statistically valid.

Table 8. Mediation Analysis Results

Path	Coefficient (β)	t-statistic	p-value	95% CI (Bootstrap)
Direct effect: CAI → CS	0.219	2.684	0.007	(0.062; 0.376)
Indirect effect: CAI → DT → CS	0.262	4.912	0.000	(0.156; 0.372)
Total effect: CAI → CS	0.481	6.734	0.000	(0.331; 0.612)

Source: Output SEM-PLS 4, 2026

Based on the mediation typology by Zhao et al. (2010), the research results show that both the indirect effect (β = 0.262; p < 0.001) and the direct effect (β = 0.219; p = 0.007) are significant and have a positive influence direction. Thus, the type of mediation formed is complementary partial mediation. This finding does not include full mediation because the direct influence of AI Chatbot Implementation on Customer Satisfaction remains significant after the mediation path is accounted for. However, this relationship cannot be viewed as merely a direct influence, as the indirect path thru Digital Trust contributes more significantly, accounting for approximately 54.5% of the total influence (Variance Accounted For).

These results reinforce the findings from previous hypothesis testing that Customer Digital Trust is not just an additional variable in the model, but the main mechanism explaining how AI Chatbot Implementation affects Customer Satisfaction. In other words, most of the chatbot's impact on customer satisfaction occurs thru the enhancement of digital trust, while the direct influence of the chatbot without this mechanism has a more limited contribution.

DISCUSION

Research findings indicate that the implementation of AI chatbots in F&B businesses in Labuan Bajo does not directly result in customer satisfaction solely thru their technological functions. Most of the influence of AI chatbots is formed thru the enhancement of customers' digital trust, as seen from the contribution of the mediation path, which accounts for more than half of the total influence on customer satisfaction. This result is in line with Dubey and Meena (2025), who explain that customers' cognitive trust in chatbots is an important factor determining whether digital interactions can yield positive service evaluations. However, this research expands on those findings by quantitatively demonstrating that digital trust is not only a conceptual prerequisite but also a measurable mediating mechanism that contributes to shaping customer satisfaction.

This finding answers the research question that AI chatbots do indeed have a significant impact on customer satisfaction, but this influence becomes stronger when it goes thru the process of building digital trust rather than thru direct influence. Therefore, understanding AI chatbots should not stop at the question of whether the technology has a positive impact, but rather look at the mechanisms that explain how that impact is formed. This perspective provides an explanation for the differences in previous research findings. The findings of Rizomyliotis et al. (2022), which show a positive impact of chatbots on customer experience, can be understood thru the chatbot's ability to build trust, while the findings of Ranieri et al. (2024) regarding the negative impact of chatbots can occur when digital trust is not established due to system failures in meeting user expectations. Thus, this research explains that the success of AI chatbots in enhancing customer satisfaction highly depends on their ability to build digital trust during the service interaction process.

The significant influence of AI Chatbot Implementation on Customer Digital Trust (β = 0.612; f^2 = 0.601) indicates that the functional aspects of the chatbot, such as response speed, answer consistency, and 24/7 service availability, not only play a role in enhancing customer satisfaction but also serve as the main foundation in building digital trust. This trust then evolves into a broader service evaluation. These findings support the main principle of the *Expectation-Confirmation Theory*, which explains that the alignment between customer expectations and service performance is a crucial factor in shaping a positive attitude toward the service provider. The research findings also reinforce the findings of Dubey and Meena (2025) that the mismatch between user expectations and the capabilities of the chatbot can decrease trust to a greater extent than the positive impact when expectations are met. This means that chatbots capable of providing experiences that meet the expectations of F&B customers in Labuan Bajo have a greater opportunity to build strong digital trust, especially because the challenges of digital infrastructure in developing tourist destinations can increase the risk of service failure.

However, the strength of that relationship needs to be understood contextually. Sidlauskiene et al. (2023) emphasize that the influence of chatbots on customer satisfaction is *context-dependent*. Therefore, the results of this study are likely influenced by the characteristics of the respondents, who are mostly domestic tourists with repeated chatbot interaction experiences (2–3 times or more). This condition needs to be taken into account when generalizing the findings to other user groups, particularly foreign tourists who may have different expectations of digital services. These limitations will be discussed further in the conclusion of the research.

The finding that the direct impact of AI Chatbot Implementation on Customer Satisfaction is relatively small (β = 0.219; f^2 = 0.087) is one of the important findings in this research. The results indicate that the speed and efficiency of the chatbot do not automatically lead to customer satisfaction, thereby challenging the common assumption in F&B technology adoption that often places functional aspects as the main factor in shaping satisfaction. These findings differ from Chattaraman et al. (2022) and Rizomyliotis et al. (2022), who emphasize that the speed and reliability of chatbot responses are important factors in enhancing customer satisfaction. This study shows that these two aspects only contribute limitedly when digital trust is included as part of the model. Thus, the technical capabilities of the chatbot are not sufficient to explain the overall customer experience.

On the contrary, the results of this study align with the views of Ranieri et al. (2024) that chatbots can create negative experiences if they fail to build relational aspects in service interactions. This means that a chatbot that is technically fast and accurate may not necessarily be perceived as a satisfying service if customers do not feel confident and trust in the system. The implication of this finding is that the strategy for implementing AI chatbots in the F&B business cannot solely focus on operational efficiency. Business operators also need to ensure that the chatbot can build credibility, a sense of security, and customer trust during the interaction process. Without these aspects, the technological investment may succeed operationally, but it may not necessarily lead to a significant increase in customer satisfaction.

The finding that Digital Trust has a positive and significant impact on Customer Satisfaction (β = 0.428), with an influence strength more than twice that of the direct impact of the AI chatbot, and the classification result of *complementary partial mediation*, indicates that more than half of the AI chatbot's impact on customer satisfaction occurs thru digital trust. These results provide a direct answer to the empirical contradiction identified in the introduction section. These findings explain the differences in previous research results between Rizomyliotis et al. (2022), which showed a positive impact of chatbots on customer satisfaction, and Ranieri et al. (2024) and Xu et al. (2023), who found mixed or even negative effects. The two findings are actually not contradictory, but rather illustrate different conditions within the same mechanism. AI chatbots can enhance satisfaction when they are able to build digital trust with customers, but they can have a less optimal impact when the interactions fail to create a sense of trust.

Thus, the inconsistency in previous research results is not solely due to the weaknesses of AI chatbots as a technology, but rather the differences in each chatbot implementation's ability to build customer trust. These findings provide a clearer mechanistic explanation of the relationship between AI chatbots and customer satisfaction, while also reinforcing Al-Adwan et al.'s (2025) view that the role of trust as a mediator in AI chatbot adoption research still requires more in-depth empirical testing. The mediation results also serve as an important foundation for the theoretical contribution of the research to the development of TAM and ECT. The proven digital trust as the main pathway of AI chatbot influence on customer satisfaction indicates that relational aspects in digital interactions need to be positioned as important mechanisms, not merely as additional consequences of technology acceptance.

The findings on digital trust mediation provide a theoretical contribution by explaining the boundary condition of the relationship between AI chatbots and customer satisfaction. Al-Adwan et al. (2025) show that TAM studies on AI chatbots are still limited and have not clearly explained the role of trust as a mediator. This research fills that gap by proving that digital trust is the dominant pathway bridging more than half of the AI chatbot's influence on satisfaction, thereby expanding TAM by placing trust as an important mechanism in F&B services. This finding also enriches ECT by showing that confirmation of chatbot competence not only directly affects satisfaction but first shapes digital trust, in line with Dubey and Meena (2025). Thus, this study offers an integrative TAM-ECT model with digital trust as a mediator tested in the context of MSMEs in the F&B sector at emerging tourist destinations.

The findings of this research indicate that F&B SMEs in Labuan Bajo need to direct their AI chatbot investment strategy not only toward speed and automation but also toward the ability to build customer digital trust. The focus of development needs to include transparency when the chatbot is unable to provide answers, consistency of information regarding the menu, prices, and service times, as well as the system's ability to recognize the history of customer interactions. These aspects are important because discrepancies between customer expectations and chatbot performance can trigger negative service experiences (Ranieri et al., 2024). For the Labuan Bajo Flores Tourism Authority and the local government, the results of this research can serve as a foundation for strengthening the digitalization assistance program for F&B SMEs. Assistance should not only focus on the technical ability to use chatbots but also include strategies for building credible digital interactions that can enhance customer trust. Thus, the direction of service digitalization needs to shift from merely presenting "fast technology" to implementing "trusted

ISSN 3123-6464 (Online)
JOMBINOV
Journal of Management and Business Innovation

technology".

CONCLUSION

This study analyzes the impact of AI chatbot implementation on F&B customer satisfaction in Labuan Bajo by placing digital trust as a mediating variable. Based on the PLS-SEM analysis results from 131 respondents, the implementation of the AI chatbot was found to have a positive and significant effect on digital trust (H_1) as well as customer satisfaction (H_2). Additionally, digital trust was also found to have a positive and significant effect on customer satisfaction (H_3).

The main findings indicate the presence of complementary partial mediation, where more than half of the AI chatbot's influence on customer satisfaction occurs thru digital trust. This result emphasizes that the effectiveness of the AI chatbot in enhancing customer satisfaction does not solely depend on technical capabilities such as speed and service efficiency, but primarily on its ability to build customer trust during the digital interaction process.

Theoretically, this research contributes to the development of the Technology Acceptance Model (TAM) and the Expectation-Confirmation Theory (ETP) by explaining the mechanisms that link the implementation of AI chatbots and customer satisfaction. These findings also help explain the differences in previous research results regarding the effectiveness of chatbots in various service contexts.

Practically, the research findings indicate that F&B businesses in Labuan Bajo need to shift their focus on chatbot investment from merely increasing response speed to efforts aimed at building customer credibility and trust. In addition, these findings can serve as a foundation for the local government and the Labuan Bajo Flores Tourism Authority in designing more effective digitalization support programs for MSMEs to improve service quality at tourist destinations.

LIMITATION

This study has several limitations that need to be considered. First, the dominance of domestic tourists (54.2%) compared to international tourists (13.7%) limits the generalizability of the findings, considering that the acceptance of chatbots is context-dependent and can be influenced by cultural differences and service expectations. Second, the cross-sectional research design has not yet been able to explain changes in digital trust and customer satisfaction over a certain period or the impact of repeated chatbot interactions. Third, the use of a sample of 131 respondents from only one destination limits the application of the findings to other super-priority tourist destinations with different market and tourist characteristics. Fourth, the research model only includes digital trust as a mediating variable, so other factors that could potentially influence the relationship between AI chatbots and customer satisfaction, such as interaction quality and the perception of chatbot humanization, have not been analyzed in this study.

Based on these limitations, future research is recommended to use a longitudinal design to observe changes in digital trust and customer satisfaction over a certain period. Expanding the sample coverage thru comparative studies of super-priority tourism destinations, such as Lake Toba, Borobudur, and Likupang, is also important to test the consistency of the mediation model in different contexts. Additionally, future research can develop models by incorporating moderator variables, such as digital literacy or perceived humanness, to explain factors that can strengthen or weaken the impact of AI chatbots on customer satisfaction. A mixed-methods approach combining PLS-SEM and in-depth interviews also has the potential to provide a more comprehensive understanding of customer experiences and the perspectives of F&B business operators in implementing chatbot technology.

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