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CUSTOMER CITIZENSHIP BEHAVIOR ON BUSINESS PERFORMANCE: ARTIFICIAL INTELLIGENCE AS MODERATION IN SMES

Andyan Pradipta Utama ✉[1], Aldina Shiratina[2], Eri Marlapa[3], Anees Janee Ali[4]
Universitas Mercu Buana[1,2,3,4]
✉[1] andyanpradipta@mercubuana.ac.id
Jl. Meruya Selatan, RT.4/RW.1, Joglo, Kec. Kembangan, Jakarta Barat, DKI Jakarta 11650, Indonesia

Abstract

The purpose of this study is to analyze the influence of Customer Experience (CE) and Brand Commitment (BC) on Business Performance (BP) and to examine the mediating role of Customer Citizenship Behavior (CCB). The study also aims to evaluate the moderating role of Artificial Intelligence (AI) in the relationship between CE and BC with BP. This research employs a quantitative approach with a survey design. The sample consists of 150 MSMEs in Tasikmalaya City, analyzed using SEM-SmartPLS4. The findings reveal that CE and BC have a positive and significant effect on CCB and BP. Additionally, CCB has a positive and significant impact on BP and mediates the influence of CE and BC on BP. However, AI does not moderate the relationships between CE and BP or BC and BP.

Keywords: customer experience; brand commitment; business performance; customer citizenship behavior; artificial intelligence

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INTRODUCTION

Community contributions to national development can be realized through Micro, Small, and Medium Enterprises (MSMEs). Most MSMEs in Indonesia are home-based businesses with a substantial capacity to absorb labor. According to data from the Ministry of Cooperatives and SMEs, in 2019, there were 65.4 million MSME units recorded in Indonesia (Direktorat Jenderal Perbendaharaan, 2023). This significant number of business units was able to absorb 123.3 thousand workers. This highlights the vital role and impact of MSMEs in reducing unemployment rates in Indonesia. Additionally, the MSME sector contributes approximately 61% to the Gross Domestic Product (GDP), with a value reaching IDR 9,580 trillion (Limanseto, 2023). Furthermore, MSMEs play a significant role in employment absorption, accounting for 97% of the total workforce. Based on data from the Ministry of Cooperatives and SMEs, the number of MSMEs in Indonesia reached 65.5 million units, representing around 99% of all business units in the country (Limanseto, 2023). Therefore, micro-enterprises need to be continuously studied from various perspectives, including marketing management and human resource management. MSME marketing management is closely related to consumer behavior, specifically focusing on customer experience, which "represents consumers' internal and subjective responses to direct or indirect engagement with the company" (Christian et al., 2023). In the context of MSMEs in Indonesia, research on marketing management and consumer behavior still reveals significant gaps. For instance, there is a lack of in-depth studies examining how customer experience directly impacts the success of MSMEs. Brakus et al., (2009) define customer experience as the internal and subjective responses of consumers to their direct or indirect interactions with a company. Christian et al., (2023) extend this concept by demonstrating that customer experience is a key element in building consumer loyalty and enhancing business performance, particularly in increasingly competitive environments. However, research connecting this concept to MSMEs in Indonesia remains limited. Most studies focus on large corporations or established service sectors, while MSMEs have unique characteristics, such as limited resources, smaller market reach, and a high reliance on personal relationships with consumers.

This research gap can be addressed by analyzing how customer experience influences Customer Citizenship Behavior (CCB) in MSMEs, particularly in local contexts such as Tasikmalaya, which hosts many community-based enterprises. The relevance of customer experience in marketing management is crucial, as it affects consumer perception and loyalty. In small business settings, customer experience can be enhanced through personal interactions, product quality, or services that exceed expectations. The internet era has ushered in a digital transformation across nearly all aspects of life, including micro to medium-scale enterprises (Sari et al., 2024). Research that integrates marketing management with consumer behavior in Indonesian MSMEs, especially those leveraging artificial intelligence (AI) to enhance customer experience, can provide significant contributions to developing more effective strategies for the sector. This approach not only addresses research gaps but also supports the sustainability of MSMEs in facing global competition.

The meta-analysis of the literature indicates that companies can enhance business performance (BP) through predicting customer experience and product quality (Alawiah & Utama, 2023; and Spiess et al., 2014). Business performance itself is defined as a measure of the overall achievements of a company's marketing activities (Zainul et al., 2016), which includes five key dimensions: balancing profits, growth, and control; balancing short-term results with long-term capabilities and growth opportunities; balancing performance expectations from various stakeholders; balancing opportunities and focus; and balancing human behavioral motives (Kellen, 2003). In relation to customer experience, previous studies have shown its significant impact on various aspects of performance, although most of these studies did not explicitly use the term "business performance." For example, Mbama (2018) found that customer experience contributes to strengthening customer relationships through digital services, which ultimately impacts profitability and company reputation. (Hariandja & Vincent, 2022) also highlighted the importance of customer experience in boosting brand success, especially through interactions that build loyalty and positive perceptions of the company. However, other research tends to focus more on customer experience in relation to customer satisfaction. For instance, Lee & Lee (2022) demonstrated that positive customer experiences increase satisfaction, which leads to repeat purchase intentions. Ningsih & Hurnis (2023) discovered that customer experience serves as a key predictor of strengthening long-term relationships between consumers and brands. Other studies, such as those by Suharto & Yuliansyah (2023), Fadli et al., (2023), (Klink et al., 2020), Nurul Sabrina et al., 2023), and Saputra et al., (2023), tend to focus on customer loyalty or perceived value without exploring the impact of customer experience on operational or financial business performance. Furthermore, Masoud & Basahel (2023) concluded that customer experience and innovation contribute significantly to business performance in the service sector, which is measured by operational efficiency, market growth, and stakeholder satisfaction. However, their study only used samples from managers and executives, making it less relevant for micro-business contexts.

Despite providing valuable insights, most of these studies still fail to directly connect customer experience with business performance, especially in operational aspects such as production efficiency, cost control, or internal resource management. This study offers a unique contribution by examining the direct relationship between customer experience and business performance using a sample of micro-business consumers. This approach allows for a more relevant examination within the context of community-based businesses and micro-enterprise activities. In the framework of this research, business performance is measured not only in financial terms but also in balancing long-term growth with short-term profits, as well as efficiency in service delivery. Therefore, this study is expected to fill gaps in the existing literature while broadening the understanding of how customer experience contributes to business performance across various dimensions.

Business performance can be influenced by various factors, one of which is brand commitment and Customer Citizenship Behavior (CCB). Previous studies have shown that brand commitment positively affects employees' trust in the brand, but it does not always directly relate to employees' brand citizenship behavior (Erkmen & Hancer, 2014). Existing research has mostly focused on the relationship between brand commitment and brand trust or Word-of-Mouth (WOM), but it has yet to thoroughly examine its direct connection to business performance (Dam, 2020; and Cuong, 2020). In Indonesia, while some studies have found an impact of brand image on SME performance, the terminology used often differs from brand commitment (Wong & Sijabat, 2022). This indicates a gap in research on internal commitment to the brand, which generally focuses more on organizational commitment, while brand commitment refers to an employee's psychological attachment to the brand, influencing their efforts to achieve brand goals (Erkmen & Hancer, 2014). On the other hand, Customer Citizenship Behavior (CCB) has been proven to significantly affect business performance (Gong & Yi, 2021). However, CCB is often not analyzed explicitly but is linked to factors such as customer loyalty, efficiency-based business model design, and emotional attachment to the brand (Hu et al., 2020; and Sharif & Sidi Lemine, 2021). Other studies suggest that the quality of customer experience positively influences CCB (Kim & Choi, 2016; and Gao & Fan, 2021).

Most previous studies conducted in the hospitality sector, such as those by Shaari et al., (2012); Piehler (2018); Putra et al., (2020); and Adileh & Cengel, 2021), focused on hotel employees and how brand commitment can strengthen the relationship between Customer Citizenship Behavior (CCB) and business performance. These studies indicate that brand commitment plays an essential role in building customer trust and loyalty, as well as encouraging positive customer behavior that directly impacts business performance. However, similar research has not been widely applied to SMEs, which have distinct characteristics and challenges, such as limited resources and more direct, personal relationships with customers. In the SME sector, customer experience both external (from direct interaction with products or services) and internal (from the psychological and emotional aspects of customers) has a significant impact on Customer Citizenship Behavior. Therefore, this research focuses on how brand commitment in the context of SMEs can mediate the relationship between customer experience and business performance. In more recent research, technologies such as Artificial Intelligence (AI) have also been shown to mediate the relationship between e-commerce adoption and business performance, highlighting the great potential of technology in improving business performance (Fonseka et al., 2022; and Arif et al., 2023).

This study aims to fill the existing gap by analyzing the direct relationship between customer experience, brand commitment, CCB, and business performance, specifically in the context of Micro, Small, and Medium Enterprises (MSMEs) in the culinary sector. Previous research has not fully explored this relationship, particularly regarding brand commitment and customer experience in relation to customer satisfaction and brand performance (Hariandja & Vincent, 2022). In this context, it is crucial to further explore the relationship between CCB and business performance, considering aspects that may not have been observed in previous studies. One such aspect is how AI, as a moderating technology, could strengthen or even alter the interaction between CCB and business performance. This study also emphasizes the importance of using more accurate analytical methods to capture these dynamics comprehensively, as well as how the characteristics of the micro-sector, often facing resource limitations and operational challenges, can affect the research outcomes. Thus, this research is expected to provide new insights into understanding the role of CCB and technology in enhancing business performance, particularly in the SME sector.

METHOD

This type of research uses survey research methods with a quantitative research approach. The goal of survey research is to explain cause-and-effect relationships and test hypotheses. The method chosen for research data analysis was PLS-SEM. Hair et al., (2017) have clarified the nature and role of PLS-SEM in social science research, "according to him: researchers need to realize that PLS-SEM analytical tools are tools that will enable researchers to pursue "research opportunities in new fields." and different ways" (opportunities in new and different ways)". PLS-SEM was carried out to evaluate the outer and inner models (measurement model evaluation and structural model evaluation).

Evaluation of the measurement model (outer model) reflective model: Convergent Validity (AVE), Discriminant Validity (Fornell-Larcker Criteria and Heterotrait-Monotrait Ratio), and Composite Reliability. The structural evaluation model (inner model) consists of: Collinearity (VIF), R2value, Q2value, and PLSpredict (Hair et al., 2019). The research population was 150 SMEs in the food sector in Tasikmalaya City. The sample in this study refers to (Hair et al., 2017), who state that the sample size for PLS-SEM should be 10 times the largest number of structural paths directed at a particular construct in the structural model. The construct with the highest number of indicators or paths in this study is the business performance variable, which amounts to 10. Therefore, the sample size required for this study is 10 x 10 = 100, which meets the minimum sample requirement. Meanwhile, the sample for this study consists of 150 SMEs in the food and beverage sector in Tasikmalaya City, which exceeds the minimum requirement. Furthermore, the research model also has a statistical power of 80% to detect an R^2 value of 0.25 with a 5% error (Hair et al., 2014)(Hair et al., 2017). Since the actual sample size is 150 and the maximum number of independent variables in the SEM is 10, the minimum sample required to achieve 80% statistical power is 91 observations. Given that the population (food and beverage sector) is homogeneous, the sampling technique used is simple random sampling.

RESULTS

The first step to assess a reflective measurement model involves assessing indicator loading. The next steps respectively are convergent validity, discriminant validity (HTMT), and Composite Reliability. The results of the outer model test using SEM-SmartPls 4.1.0.2 are the first to show that there are indicators which have a loading factor smaller than 0.708, namely: M4, and Y2.9. Apart from this indicator, all of them have a loading factor > 0.70. Therefore, indicators of exogenous variables and endogenous variables that are not yet valid are removed and tested again. A summary of the reflective measurement model after the second estimation can be seen in Table 1.

Table 1. Summary of Reflective Outer Models

Laten Variable	Indicators	Loading Factor	AVE	CR*	Cronbach's alpha
Customer Experience (X1)	X1.1 <- X1_(Customer _Experience)	0.904	0.551	0.830	0.727
	X1.2 <- X1_(Customer _Experience)	0.882			
Brand Commitment (X2)	X2.1 <- X2_(Brand _Commitment)	0.844	0.764	0.928	0.898
	X2.2 <- X2_(Brand _Commitment)	0.838			
	X2.3 <- X2_(Brand _Commitment)	0.900			
	X2.4 <- X2_(Brand _Commitment)	0.909			
Customer Citizenship Behaviour CCB-Y1)	Y1.1 <- Y1_(Customer Citizenship _Behavior)	0.896	0.782	0.956	0.944
	Y1.2 <- Y1_(Customer Citizenship _Behavior)	0.907			
	Y1.3 <- Y1_(Customer Citizenship _Behavior)	0.882			
	Y1.5 <- Y1_(Customer Citizenship _Behavior)	0.871			
	Y1.6 <- Y1_(Customer Citizenship _Behavior)	0.866			
Business Performance (Y2)	Y2.1 <- Y2_(Business _Performance)	0.752	0.552	0.925	0.909
	Y2.3 <- Y2_(Business _Performance)	0.852			
	Y2.4 <- Y2_(Business _Performance)	0.834			
	Y2.5 <- Y2_(Business _Performance)	0.779			
	Y2.6 <- Y2_(Business _Performance)	0.769			
	Y2.7 <- Y2_(Business _Performance)	0.830			
Artificial Intelence (M)	M1 <- M_(Artificial _Intelligence)	0.984	0.689	0.891	0.811
	M2 <- M_(Artificial _Intelligence)	0.956			
	M3 <- M_(Artificial _Intelligence)	0.963			

*= Composite Reliability; **=discriminant validity; ***=convergent validity
Source: Processed by the Authors, 2024.

Based on Table 1, the data indicates that the loading factor refers to the strength of the relationship between an indicator and the latent construct it measures. An ideal value is ≥ 0.7, which signifies that the indicator makes a significant contribution to explaining the construct. Average Variance Extracted (AVE) evaluates the extent to which a construct can explain the variance of its indicators. An AVE value greater than 0.50 indicates that more than 50% of the variance in the indicators is explained by the construct, serving as a good measure of convergent validity. Composite Reliability (CR) assesses the internal consistency of the indicators within a construct, where a value above 0.7 is considered adequate, and a value exceeding 0.8 reflects excellent reliability. Meanwhile, Cronbach's Alpha is a commonly used reliability measure to test internal consistency.

Although a value above 0.7 is sufficient, CR is more recommended in SEM analysis because it provides greater accuracy, especially when loading factors vary. In addition, the Customer Experience (X1) variable has an AVE of 0.551, indicating adequate convergent validity, with a CR of 0.830 and Cronbach's Alpha of 0.727, reflecting good reliability. The Brand Commitment (X2) variable shows an AVE of 0.764, with a CR of 0.928 and Cronbach's Alpha of 0.898, confirming strong validity and reliability. For Customer Citizenship Behaviour (Y1), an AVE of 0.782 demonstrates that the indicators effectively represent the research variable, supported by a CR of 0.956 and Cronbach's Alpha of 0.944, indicating exceptionally high internal consistency. Regarding Business Performance (Y2), while the AVE is at the minimally adequate level of 0.552, the CR of 0.925 and Cronbach's Alpha of 0.909 still signify strong reliability. Lastly, the Artificial Intelligence (M) variable has an AVE of 0.689, indicating very good convergent validity, with a CR of 0.891 and Cronbach's Alpha of 0.811.

Overall, the values in the table demonstrate that all constructs meet the criteria for convergent validity, as indicated by AVE > 0.50. Additionally, high CR and Cronbach’s Alpha values confirm strong reliability, ensuring that the measurement instruments consistently reflect the constructs being studied. These findings provide a solid foundation for concluding that the reflective measurement model used has fulfilled the necessary standards of validity and reliability to support subsequent structural analysis.

Table 2. Fornell-Larcker Criterion

Matrix	M_ (Artificial Intelligence)	X1 (Customer Experience)	X2 (Brand Commitment)	Y1 (Customer Citizenship Behavior)	Y2 (Business Performance)
M_(Artificial _Intelligence)	0.968				
X1_(Customer _Experience)	0.213	0.893			
X2_(Brand _Commitment)	0.590	0.467	0.873		
Y1_(Customer Citizenship _Behavior)	0.406	0.593	0.826	0.885	
Y2_(Business _Performance)	0.365	0.617	0.744	0.805	0.804

Source: Processed by the Authors, 2024

The Fornell-Larcker criterion is used to evaluate discriminant validity, which refers to the extent to which a construct can be empirically distinguished from other constructs in the structural model. In this case, discriminant validity is tested by comparing the square root of the average variance extracted (AVE) for each construct with the correlation values between that construct and the other constructs. Based on Table 2 provided, all the square root values of the AVE for the constructs are greater than the correlation values between constructs, indicating that each construct has good discriminant validity. For example, for the construct of Artificial Intelligence (AVE = 0.968), the correlations with other constructs such as Customer Experience (0.213), Brand Commitment (0.590), Customer Citizenship Behavior (0.406), and Business Performance (0.365) are all lower than its AVE square root, suggesting that Artificial Intelligence can be clearly distinguished from the other constructs. Similarly, for the construct of Customer Experience, with an AVE square root of 0.893, it is greater than the correlations with other constructs, including Brand Commitment (0.467), Customer Citizenship Behavior (0.593), and Business Performance (0.617), which indicates its discriminant validity. Likewise, for Brand Commitment (AVE = 0.873), Customer Citizenship Behavior (AVE = 0.885), and Business Performance (AVE = 0.804), all of which show good discriminant validity because the square root of their AVE is greater than the correlation values between constructs. Therefore, all constructs in this study can be considered valid and can be used for further analysis. This means that the square root of the AVE for each construct is greater than the correlation values between constructs, indicating that each construct clearly measures a different concept. Hence, these constructs can be used in further analysis without any concerns about overlap or multicollinearity affecting the research results.

Table 3. Heterotrait-monotrait Ratio (HTMT)

Construct	M	X1	X2	Y1	Y2	M x X2
M_(Artificial _Intelligence)						
X1_(Customer _Experience)	0.249					
X2_(Brand _Commitment)	0.662	0.560				
Y1_(Customer Citizenship _Behavior)	0.429	0.709	0.887			
Y2_(Business _Performance)	0.385	0.742	0.812	0.874		
M x X2	0.297	0.457	0.584	0.557	0.521	
Mx X1)	0.183	0.254	0.491	0.518	0.504	0.763

Source: Processed by the Authors, 2024

Heterotrait-Monotrait Ratio (HTMT) is the correlation ratio between different constructs compared to the correlation among items within the same construct. Henseler et al. (2015), as cited by Hair et al. (2019), explain that the Fornell-Larcker criterion does not work well, especially when the indicator loadings on constructs differ only slightly, such as when all indicator loadings fall between 0.65 and 0.85. Therefore, they propose using HTMT as a more effective method for assessing discriminant validity. Based on Table 3, the HTMT values recorded for all construct combinations in this study are 0.887, 0.874, 0.521, and 0.763. Since all these HTMT values are below 0.90, it can be concluded that all constructs in this study meet the criteria for good discriminant validity. Generally, HTMT values lower than 0.85 or even below 0.90 indicate that the constructs in question have good discriminant validity. These calculations also show that HTMT values lower than 0.90 indicate that the constructs do not overlap significantly, meaning each construct measures a different dimension of the phenomenon being analyzed. Thus, researchers can be more confident that each construct in this research model accurately reflects the intended aspect without ambiguity or overlap in measurement, which in turn strengthens the discriminant validity of the model used.

The final step is to assess composite reliability. Assessing internal consistency reliability, most often uses Jöreskog's (1971) composite reliability. For example, reliability values between 0.60 and 0.70 are considered “acceptable in exploratory research,” values between 0.70 and 0.90 range from “satisfactory to good” (Hair et al., 2019). Based on the SmartPLS output results in table 4.1, it shows that all constructs have composite reliability values above 0.60 to 0.70. In addition, Cronbach's alpha is above 0.60. So it can be stated that the construct has good reliability as according to Hair et al., (2019) that, Cronbach's alpha is another measure of internal consistency reliability which assumes the same threshold, but produces a lower value than composite reliability. Hair et al., also emphasized that in particular, Cronbach's alpha is an inappropriate measure of reliability, because the items are not weighted. In contrast, with composite reliability, items are weighted based on the individual loadings of the construct indicators and, therefore, this reliability is higher than Cronbach's alpha. Thus, this research data has internal consistency reliability in the good category.

Variance Inflation Factor (VIF) is often used to evaluate collinearity of formative indicators. A VIF value of 5 or more indicates critical collinearity problems among the formatively measured construct indicators. However, collinearity problems can also occur at VIF values lower than 3 (Mason and Perreault, 1991; Becker et al., 2015 in Hair 2019). Furthermore, it is also explained that, in structural modeling evaluations, it is necessary to estimate the VIF value as calculated in the formative measurement model evaluation which uses the following criteria: the presence of critical collinearity problems if VIF ≥ 5, the possibility of collinearity problems if VIF ≥ 3-5, and ideally if VIF < 3 meaning the model does not have a collinearity problem. High collinearity among formative indicators can lead to unstable coefficient estimates, reduce the interpretability of the model, and increase uncertainty in the analysis results. A summary of the collinearity calculation results (VIF) is presented in Table 4 below:

Table 4. Summary of Reflective Inner Models

Structural Model	VIF	R^2	Effect Size- f^2	Q^2 predict
M_(Artificial _Intelligence) → Y2_(Business _Performance)	1.613	**Y1 = 0.737 Y2 = 0.711**	0.001	**Y1 = 0.728 Y2 = 0.612**
X1_(Customer_Experience) → Y1_(Customer Citizenship Behavior)	1.279		0.210	
X1_(Customer Experience) → Y2_(Business Performance)	1.689		0.134	
X2_(Brand_Commitment) → Y1_(Customer Citizenship_Behavior)	1.279		1.467	
X2_(Brand _Commitment) → Y2_(Business _Performance)	4.356		0.063	
Y1_(Customer Citizenship_Behavior) → Y2_(Business_Performance)	4.132		0.132	
M_(Artificial_Intelligence) x X2_(Brand_Commitment) -> Y2_(Business Performance)	2.918		0.010	
M_(Artificial_Intelligence) x X1_(Customer_Experience) -> Y2_(Business Performance)	2.690		0.035	

Source: Processed by the Authors, 2024

In PLS-SEM analysis, several key metrics are used to evaluate the quality of the structural model. The Variance Inflation Factor (VIF) is used to measure the presence of multicollinearity issues between independent variables. Based on Table 4, it can be explained that VIF values smaller than 5, such as 1.613 for M_(Artificial Intelligence) -> Y2_(Business Performance), indicate that there is no significant multicollinearity problem, which is important to ensure that the model's coefficient estimates remain valid. R^2 (Coefficient of Determination) measures the proportion of variance in the dependent variable that is explained by the independent variables in the model. High R^2 values, such as 0.737 for Y1 (Customer Citizenship Behavior) and 0.711 for Y2 (Business Performance), indicate that the model is able to explain most of the variation in the data well. This suggests strong predictive power, but lower R^2 values may indicate that other factors need to be considered. Effect size (f^2) measures the contribution of each independent variable to the dependent variable, with values greater than 0.02 indicating significant influence. For example, an f^2 value of 1.467 for X2 (Brand Commitment) -> Y1 (Customer Citizenship Behavior) shows a very large effect, while smaller f^2 values, such as 0.035 for M_(Artificial Intelligence) x X1 (Customer Experience) -> Y2 (Business Performance), indicate a small effect. Finally, Q^2 (Predictive Relevance) is used to assess the predictive capability of the model. Q^2 values greater than 0 indicate good predictive relevance, and in this table, Q^2 values of 0.728 for Y1 and 0.612 for Y2 suggest that the model has strong predictive power. Overall, these metrics provide a comprehensive view of the model's quality, with high R^2 values indicating that the model explains the variation in the data well, while the other values offer insights into the contributions of the variables and the model's predictive relevance.

Another evaluation is the PLSpredict inner model evaluation of the predictive power of a model. The method is to compare the root mean squared error (RMSE) value with the linear regression model (LM). The PLSpredict output is presented in Table 5.

Table 5. Ratio the Root Mean Squared Error (RMSE) With Linear Regression Model (LM)

Indikator	Q^2 predict	PLS SEM*		LM*	
		PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
Y1.1	0.540	0.444	0.342	0.450	0.325
Y1.2	0.602	0.406	0.301	0.403	0.255
Y1.3	0.582	0.408	0.311	0.414	0.289
Y1.5	0.521	0.489	0.351	0.503	0.324
Y1.6	0.538	0.461	0.334	0.460	0.297
Y2.1	0.495	0.516	0.359	0.531	0.339
Y2.3	0.412	0.568	0.385	0.570	0.371
Y2.4	0.446	0.534	0.363	0.524	0.353
Y2.5	0.278	0.654	0.448	0.687	0.464
Y2.6	0.236	0.679	0.477	0.679	0.488
Y2.7	0.395	0.609	0.461	0.640	0.494

Source: Output SmartPLS 4 Version 4.1.0.2, 2024
*Note: Mean absolute error (MAE); Root mean squared error (RMSE); Linear regression model (LM)

Based on the RMSE Table, several metrics are used to evaluate the predictive performance of the model, especially in the comparison between PLS-SEM (Partial Least Squares Structural Equation Modeling) and Linear Regression (LM). These metrics include Q^2 predict, RMSE (Root Mean Squared Error), and MAE (Mean Absolute Error), each serving a specific purpose in assessing how well the model predicts the data. Q^2 predict measures the predictive relevance of the model, with values greater than 0 indicating that the model can effectively explain the variation in the data. In the table, higher Q^2 values for each indicator indicate that the PLS-SEM model has better predictive relevance. RMSE, on the other hand, measures the error between the predicted values and the actual values in the same units as the predicted variable. Lower RMSE values indicate better model fit. For example, for indicator Y1.1, the RMSE for PLS-SEM is 0.444, which is slightly better than the RMSE value of 0.450 for the LM model, indicating that the PLS-SEM model provides a more accurate prediction. MAE measures the average absolute error between the predicted values and the actual values, providing the average error size without emphasizing large differences. For indicator Y1.2, the MAE for PLS-SEM is 0.301, which is lower compared to the MAE of 0.255 for the LM model, indicating that PLS-SEM provides more accurate average predictions. Overall, RMSE provides an overview of prediction error in the same units as the data, MAE measures the average size of absolute error, and Q^2 predict evaluates the model's ability to generate accurate predictions. Based on these metrics, PLS-SEM shows better performance compared to linear regression in terms of prediction accuracy and relevance. Lower RMSE and MAE values, along with higher Q^2 values, reflect better predictive performance. In other words, PLS-SEM is more suitable for better predictive analysis, especially in the context of complex structural models with multiple variables.

Supports all evaluations of the structural model. Next is the Goodness of Fit Index (GoF Index) which is an evaluation of the entire model which is an evaluation of the measurement model and structural model.

Table 6. Index Goodness of Fit (GoF) Index Model Structural

Variable	R-square	R-square adjusted	$\sqrt{Gof}$
Y1_(Customer Citizenship Behavior)	0.737	0.734	0.7355
Y2_(Business Performance)	0.711	0.699	0.7053

Sumber: Output SmartPLS "(PLS-SEM algorithm)" 4 Version 4.1.0.2, 2024

Based on table 5, the GoF index can only be calculated from a reflective measurement model, namely the root of multiplying the geometric average communality by the average R square (Yamin, 2023). Communality is the square of the loading factor. According to Wetzels et al (2009), the interpretation of the GoF index values is 0.1 (low), 0.25 (medium) and 0.36 (high). For example, the calculation results show that the GoF value of model Y1 is √(0.737 x 0,.734) = 0.7355 including the high GoF category (Yamin, 2023). Furthermore, GoF Y2 of 0.7053 is also in the high category. This indicates that the measurement and structural models are both very suitable. Aside from that, you can see that the suggested Standardized Root Mean Square Residual (SRMR) is less than 0.08, while Karin Schermelleh et al. (2003) said that SRMR between 0.08 and 0.10 is still acceptable (Yamin, 2023). So, the SRMR value in this study is based on the values of Saturated model = 0.086 and Estimated model = 0.087 (output algorithm), indicating that the model constructed matches the actual data since it is between 0.08 and 0.10, or less than 0.10. Evaluation is also important to prove that PLS-SEM is capable of detecting goodness of fit. However, this evaluation is not considered the main reference (Hair et al., 2019), as the focus of PLS-SEM is on prediction and theory testing rather than just model fit.

The t-statistic value between the independent and dependent variables, as well as the Path Coefficient output variable, may be used to determine the predictive model's relevance in testing the structural model. Bootstrapping SmartPLS 4 Version 4.1.0.2 in Table 7 and Figure 1.

Table 7. Structural Model Estimation Results

Construct	Original sample (O)	T statistics (|O/STDEV|)	P values	2.50%	97.50%
X1_(Customer_Experience) → Y1_(Customer Citizenship _Behavior)	0.266	3.506	0.000	0.132	0.426
X2_(Brand_Commitment) → Y1_(Customer Citizenship Behavior)	0.702	11.275	0.000	0.560	0.800
X1_(Customer Experience) → Y2_(Business Performance)	0.255	2.602	0.009	0.061	0.444
X2_(Brand_Commitment) → Y2_(Business_Performance)	0.281	2.484	0.013	0.072	0.520
Y1_(Customer Citizenship_Behavior) → Y2_(Business Performance)	0.396	3.274	0.001	0.152	0.628
M_(Artificial_Intelligence) x X2_(Brand_Commitment) → Y2_(Business _Performance)	0.049	0.691	0.490	-0.127	0.140
M_(Artificial_Intelligence) x X1_(Customer_Experience) → Y2_(Business _Performance)	-0.104	1.206	0.228	-0.208	0.112

Source: Output SmartPLS "(PLS-SEM bootstrapping)" 4 Version 4.1.0.2, 2024

Based on the results of the structural model testing presented in Table 7, several significant relationships provide valuable insights into the influence between variables. Customer experience (X1) has a positive and significant effect on customer citizenship behavior (Y1), with a t-statistic value of 3.506, which is much greater than the t-table value of 1.971, and a p-value of 0.000, which is smaller than 0.05. This indicates that the relationship between customer experience and customer citizenship behavior is statistically significant. In other words, positive customer experiences have a significant impact on their tendency to engage in citizenship behaviors, such as recommending the company to others or voluntarily taking actions that support the company. This strengthens hypothesis H1, which suggests that customer experience contributes to the enhancement of customer citizenship behavior. Additionally, brand commitment (X2) also has a very significant positive effect on customer citizenship behavior (Y1). With a very high t-statistic of 11.275 and a p-value of 0.000, this relationship is strong and significant. This shows that the higher the level of customer commitment to the brand, the more likely they are to exhibit citizenship behaviors that support the brand. These results reinforce hypothesis H2, indicating that brand commitment significantly contributes to increased customer citizenship behavior. On the other hand, customer experience also has a positive and significant effect on business performance (Y2). With a t-statistic of 2.602 and a p-value of 0.009, this relationship is significant, meaning that hypothesis H3, which states that customer experience influences business performance, is accepted. This indicates that the better the customer experience, the better the company's business performance. It shows that a positive customer experience can enhance customer loyalty and satisfaction, which in turn drives improved business performance.

Brand commitment (X2) also shows a positive influence on business performance (Y2), with a t-statistic of 2.484 and a p-value of 0.013. This means that customer commitment to the brand significantly contributes to business performance. The stronger the brand commitment from customers, the higher the business performance a company can achieve. Thus, hypothesis H4 is well-supported, indicating the importance of brand commitment in improving organizational performance. Customer citizenship behavior (Y1) also has a positive effect on business performance (Y2), with a t-statistic of 3.274 and a p-value of 0.001, showing that this relationship is highly significant. This indicates that positive customer behaviors, such as recommending the brand or acting as brand advocates, directly contribute to improving business performance. These results support hypothesis H5, which suggests that customer citizenship behavior can enhance business performance.

However, the results of testing artificial intelligence (AI) as a moderating variable yield different findings. AI does not serve as a significant moderator in the relationship between brand commitment and business performance, with a t-statistic of 0.691 and a p-value of 0.490, which is greater than 0.05. Similarly, AI does not have a significant moderating effect in the relationship between customer experience and business performance, with a t-statistic of 1.206 and a p-value of 0.228. This indicates that, within the context of this model, AI does not significantly moderate the influence of brand commitment and customer experience on business performance. Overall, the results indicate that customer experience, brand commitment, and customer citizenship behavior have significant and positive effects on business performance, while the role of artificial intelligence as a moderator does not show significant results. This provides the understanding that customer-related factors, such as experience and brand commitment, play a more important role in improving business performance than technological factors like AI in this model.

The structural model test results in table 6 above can also be illustrated in the image below.

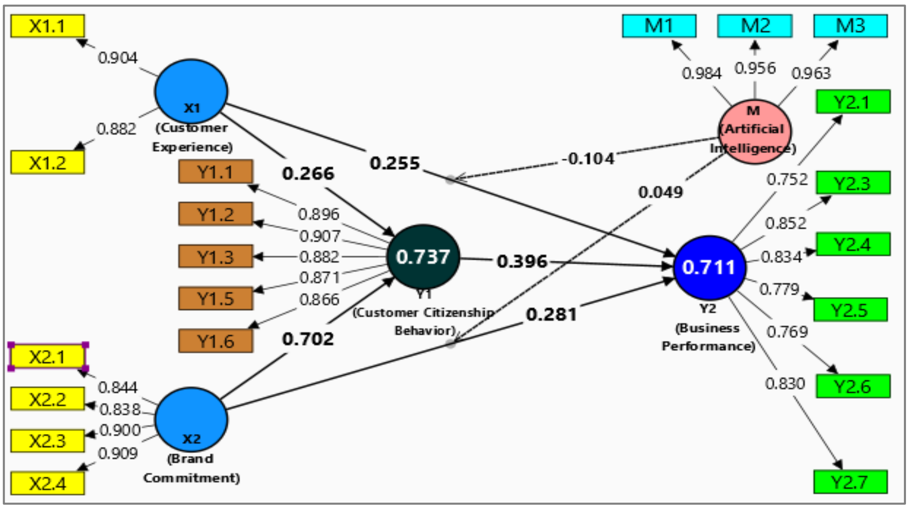

Figure 1. Output bootstrapping T-value and Path Coefficient, Second test
Source: Output SmartPLS 4 Version 4.1.0.2, 2024

Based on Figure 1, it shows various indicators that measure constructs in the model. X1 (Customer Experience) consists of indicator X1.1 with a loading factor of 0.904, indicating a very strong relationship, and X1.2 (0.882), which also shows a strong relationship, though slightly lower. X2 (Brand Commitment) has the strongest indicator, X2.4 (0.909), followed by X2.3 (0.900), and then X2.1 (0.844) and X2.2 (0.838). For Y1 (Customer Citizenship Behavior), indicator Y1.2 (0.907) shows the strongest relationship, followed by Y1.1 (0.896), while Y1.6 (0.866) has the lowest value but is still strong. In Y2 (Business Performance), indicators Y2.3 (0.852) and Y2.7 (0.830) show very strong relationships, while Y2.6 (0.769) is slightly lower. M (Artificial Intelligence) has indicator M1 (0.984) with a very strong relationship, followed by M3 (0.963) and M2 (0.956). Overall, these indicators show good convergent validity, with most loading factors above 0.8, indicating strong relationships between the indicators and their corresponding constructs.

The output of significant test parameters is based on the total effect table rather than the coefficient table, because the mediation effect is tested not only by the direct effect of the independent variable on the dependent variable, but also by the indirect effect between the independent variable and the dependent variable via the mediation variable. In other words, the mediation effect test may be found in the smar-pls output in the particular indirect effects table, as shown in table 8 below.

Table 8. Test of Mediation

Variable	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
X1_(Customer Experience) → Y1_(Customer Citizenship Behavior)) → Y2_(Business Performance)	0.105	0.047	2.219	0.027
X2 (Brand Commitment)) → Y1 (Customer Citizenship Behavior)) → Y2 (Business Performance)	0.278	0.088	3.176	0.002

Source: Output SmartPLS "(PLS-SEM bootstrapping)" 4 Version 4.1.0.2, 2024

Based on table 8 it shows that: (1) customer citizenship behavior significantly mediates the indirect influence of customer experience on business performance, because the T-statistic value (2.219) > t table (1.971) and the ρ-value of 0.027 is smaller than 0.05. This means that the sixth hypothesis (H6) is accepted;

and (2) brand commitment significantly mediates the indirect influence of product quality on business performance, because the T-statistic value (3.176) > t table (1.971) and the $\boldsymbol{\rho}$-value 0.002 is smaller than 0.05. This means that the sixth hypothesis (H7) is accepted. The next step is to determine the mediation between exogenous and endogenous variables "whether full mediation or partial mediation", so you need to use the formula: VAF = ($\boldsymbol{\rho}$12 . $\boldsymbol{\rho}$23) / $\boldsymbol{\rho}$12 . $\boldsymbol{\rho}$23 + $\boldsymbol{\rho}$13) (Hair et al., 2014).

Mediation in this study is important because it provides a deeper understanding of how customer experience and brand commitment influence business performance through customer citizenship behavior. The findings show that the impact of these two variables on business performance is indirect, mediated by customer behaviors such as recommendations and brand advocacy. This study contributes to the existing literature by introducing the mediation mechanism in the relationship between experience, brand commitment, and business performance, which has often been overlooked in previous research. This opens opportunities for further research on the role of customer citizenship behavior in improving business performance and company strategies.

Table 9. Effect Size Mediation

Model Structural	Statistik Upsilon (v) (β^2_{MX} $\beta^2_{YM\text{-}X}$)
X1 (**customer experience**) → Y1 (Customer Citizenship Behaviour) →Y2 (**Business performance**)	$(0.266)^2 \times (0.396)^2 = 0.011$
X2 (**brand commitment**) →Y1 (Customer Citizenship Behaviour) →Y2 (**Business performance**)	$(0.702)^2 \times (0.376)^2 = 0.287$

Source: Authors, 2024

Based on the findings of the Assess the variation accounted for (VAF) mediation test, it is possible to infer that customer experience and brand devotion have a considerable indirect impact on company performance through customer citizenship behavior, which falls into the partial mediation group. This is based on VAF values larger than or equal to 20%, but less than or equal to 80%. Table 9 shows how Y1 (customer citizenship behavior) strongly mediates the indirect impact of X1 (Customer Experience) on Y2 (business success) at the low class structural level. Y1 (customer citizenship behavior) has a substantial structural role in moderating the indirect impact of X2 (brand commitment) on (business success). The mediation levels are based on Cohen's view in Ogbeibu et al. (2020), which are 0.175 (high mediation influence), 0.075 (medium mediation influence), and 0.01. A low p-value (less than 0.05) provides strong evidence to support the hypothesis. This means that the likelihood of the observed relationship occurring by chance is very small, indicating a real and statistically significant relationship between the variables being tested. For example, the relationship between Customer Experience (X1) → Customer Citizenship Behavior (Y1) → Business Performance (Y2) has a t-statistic of 2.219 and a p-value of 0.027. This p-value, which is less than 0.05, indicates that this indirect effect is statistically significant. It supports the hypothesis that customer experience has a positive impact on business performance through customer citizenship behavior. Similarly, the relationship between Brand Commitment (X2) → Customer Citizenship Behavior (Y1) → Business Performance (Y2) has a t-statistic of 3.176 and a p-value of 0.002. This very low p-value further strengthens the argument that brand commitment has a significant indirect impact on business performance through customer citizenship behavior.

DISSCUSSION

The research findings show that there is a statistically significant relationship between customer experience and brand commitment on customer citizenship behavior. This is based on a probability value (p) smaller than 5%, which means that the identified relationship between these variables is significant. This indicates that both positive customer experience and the level of customer commitment to the brand have a substantial impact on customer citizenship behavior, which includes actions that support the company, such as leaving positive reviews, recommending products, or helping other customers. When customers are satisfied with the service or product they receive, they tend to be more actively engaged in supporting the company

(Siswadi et al., 2023; and Yuliantini et al., 2024). This may involve actions such as leaving positive reviews, recommending products to others, and helping other customers with questions or issues. This relationship suggests that improving customer experience not only benefits customer retention but also promotes positive behavior that supports the company's reputation and growth (Kim & Choi, 2016; Gao & Fan, 2021; and PhamThi & Ho, 2024). This means that positive customer experience consistently has a significant impact on customer citizenship behavior across various contexts and time periods. These findings reinforce the understanding that providing a satisfying and high-quality experience for customers can encourage them to engage in positive behaviors such as recommending products or services, giving constructive feedback, and helping other customers.

Furthermore, brand commitment will motivate customers to maintain the company's reputation because customers who have an emotional attachment or loyalty to a brand feel responsible for protecting and enhancing that brand's image. When customers are satisfied and connected with the brand, they tend to care more about how the brand is perceived by others. They will make efforts to maintain the company's reputation voluntarily, such as recommending products to others, giving positive feedback, or even defending the brand if there are criticisms or issues. This brand commitment creates a deeper sense of ownership and attachment, encouraging customers to act not only for their personal gain but also for the continuity and success of the brand they support. These findings are consistent with previous research (Shaari et al., 2012; Piehler, 2018; Putra et al., (2020) ; and Adileh & Cengel, 2021). Positive customer experiences often serve as a key driver for customers to develop brand commitment. When customers receive a satisfying experience whether from product quality, responsive customer service, or enjoyable interactions with the brand are more likely to feel valued and connected to the brand. This positive experience fosters higher loyalty and can motivate customers to continue supporting the brand over the long term, even when there are alternative options in the market. In other words, a positive experience enhances trust and satisfaction, which in turn strengthens brand commitment. This commitment is reflected in the decision to purchase a product, so service quality and brand should be considered to encourage purchasing decisions (Syarifuddin, 2022; and Koesworodjati & Fadillah, 2022). When customers feel emotionally attached to a brand, they tend to have higher expectations regarding the quality of products and services they receive. Customers with strong brand commitment are more patient and likely to give a second chance if there is an issue with the product or service, and they are more inclined to continue engaging with the brand. This commitment can create a sense of ownership of the brand, leading to a more positive experience because they feel part of the brand's journey and values. The study's findings indicate that, as the p-value is less than 5%, business performance behavior is significantly influenced by customer experience. Inferential statistics typically regard a p-value of less than 5% to be the threshold for rejecting the null hypothesis. This conclusion lends credence to the significance level of the investigation. Put differently, there is ample proof that the customer experience has a big influence on how well companies operate. In other words, these findings imply that there is a solid foundation in the examined data supporting the hypothesis that the relationship between customer experience and business performance is not random or the product of other unmeasured factors. This bolsters the claim that enhancing the client experience can directly improve. The findings support those of (Lee & Lee, 2022; Ningsih & Hurnis, 2023); and Suharto & Yuliansyah, 2023), which demonstrate that customer experience has a major impact on company performance.

Because the p-value is less than 5%, the research findings indicate that Band Commitment has a significant impact on company performance behavior. This graph demonstrates that there is a statistically significant likelihood that brand commitment actually contributes to higher business performance rather than the relationship between brand commitment and performance being the result of pure coincidence. Put another way, the presence of brand dedication is a significant aspect that affects the business outcomes of the organization. Other than that, the research findings align with other studies carried out by (Dam, 2020; and Cuong, 2020). Although brand commitment was not specifically examined in this earlier study, it did identify the impact of WOM and brand trust on company performance. The statement clarifies that earlier studies concentrated more on the impact of word-of-mouth (WOM) and brand trust on company success than they did on the concept of brand commitment. This indicates a deficiency in our knowledge of the precise ways in which brand commitment affects consumer behavior and company performance in the Indonesian setting. Stated differently, additional research on brand commitment in Indonesia is necessary to offer a more comprehensive and detailed understanding of consumer behavior and brand management in the regional market.

The research by Hu et al., (2020); and Sharif & Sidi Lemine (2021) provides important insights into the role of emotional brand attachment in driving customer citizenship behavior (OCB), although neither explicitly examines the direct relationship between OCB and business performance. Hu et al., (2020) highlight how emotional brand attachment can influence proactive customer behaviors, such as providing positive feedback, recommending the brand, or maintaining long-term loyalty to the brand. Meanwhile, Sharif & Sidi Lemine (2021) focus on the impact of emotional brand attachment on customer citizenship behavior, emphasizing that proactive customer behavior, reflected in OCB, can strengthen the relationship between the brand and customers. While both studies suggest that OCB can enhance the brand-customer relationship, neither links it directly to business performance as discussed in this study. This research affirms that customer citizenship behavior, through engagement, brand support, and loyalty, can significantly improve company performance. Therefore, although these studies contribute to understanding the influence of citizenship behavior on the brand, there is still a gap that needs to be further explored regarding the direct impact of OCB on business performance. Future research could delve deeper into how OCB affects specific aspects of company performance, such as sales, customer loyalty, or product innovation, particularly in different cultural or industrial contexts in Indonesia.

There is no moderating influence of artificial intelligence on the relationship between business performance and brand commitment. This claim suggests that the relationship between brand devotion and company performance is not moderated by artificial intelligence (AI). This implies that the relationship between brand devotion and company performance is unaffected by AI, either in terms of strength or direction. The ensuing statistical findings corroborate this: The t-table value of 1.971 is greater than the t-statistic, which is 0.691. This implies that the idea that AI has a major moderating influence is not supported by sufficient statistical evidence. The α (alpha) value of 0.05 is less than the significance value of 0.490. The observed differences are not statistically significant, according to this value. Put differently, these findings suggest that the existence of AI has no appreciable impact on the link between brand loyalty and company performance. Based on the t-statistic value of 1.206 < t-table = 1.971, it shows that artificial intelligence does not have a moderating influence on the relationship between customer experience and business performance. This means that, conceptually, the absence of AI's moderating role in the relationship between brand commitment and business performance suggests that AI does not affect the strength or direction of this relationship in the context of this research. This could be due to the limitations in the application of AI within the studied company, where AI has not been significantly implemented to influence this relationship. This contrasts with the findings of Faizal et al., (2024), which explain that although digitalization, including digital literacy, can influence company performance, there is a possibility that it could weaken performance if not managed properly. Furthermore, the relationship between brand commitment and business performance may be influenced by other more dominant factors, such as marketing strategies or product quality, making AI not appear as a significant moderating variable. Therefore, although AI has the potential to impact business performance, in this study, it did not provide a relevant effect on the relationship between brand commitment and business performance. This implies that advanced technologies like Artificial Intelligence (AI) require human resources (HR) with specialized competencies to optimize its use.

The research findings indicate that customer experience indirectly influences business performance through the mediating role of customer citizenship behavior. This underscores that customer experience, whether positive or negative, has a significant impact on business outcomes. Customer citizenship behavior, such as providing positive feedback, recommending products, or demonstrating long-term loyalty, has proven to be a crucial element in strengthening the effect of customer experience on business performance. Statistical analysis shows that this relationship is significant, with a T-statistic value of 2.219, exceeding the T-table value (1.971), and a significance level ($\boldsymbol{\rho}$-value) of 0.027, which is below 0.05. Furthermore, customer citizenship behavior also mediates the relationship between brand commitment and business performance, where active customer engagement in the form of product recommendations, participation in brand activities, or emotional loyalty enhances the positive impact of brand commitment on business outcomes. With a T-statistic value of 3.176, which is greater than the T-table value (1.971), this relationship is also statistically significant. These findings affirm that customer citizenship behavior not only connects customer experience and brand commitment to business performance but also serves as a strategic element in supporting overall business success. The practical implications of these findings are highly strategic for companies in managing customer experience and encouraging active customer behavior to create added value. Positive customer experiences should be managed holistically by ensuring quality at every customer touchpoint. Investments in technology, such as AI-based CRM systems, can help companies understand customer patterns and needs, enabling the personalization of relevant services. Additionally, companies can create channels to facilitate positive feedback, whether through digital platforms or loyalty programs, by offering incentives to encourage customer recommendations. Companies can further enhance customer engagement through value-based communities, such as events or social campaigns, which strengthen customers' sense of belonging to the brand. This engagement not only fosters loyalty but also motivates customers to actively participate in product innovation, for instance, through surveys or beta testing. Moreover, integrating customer experience strategies with brand commitment is essential to ensure consistency between the values perceived by customers and their experiences. These findings provide insights that customers can act as active brand ambassadors, where their roles in providing reviews, recommending products, and demonstrating long-term loyalty become strategic assets for companies to build sustainable competitive advantages.

CONCLUSION

The research results show that customer experience and brand commitment have a positive and significant impact on customer citizenship behavior and business performance. In addition, customer citizenship behavior also has a direct positive impact on business performance. The indirect effect of customer experience and brand commitment on business performance through customer citizenship behavior falls into the category of partial mediation. However, artificial intelligence (AI) does not function as a moderator in the relationship between customer experience or brand commitment and business performance. The practical implications of these findings highlight the importance of strategies to enhance personalized and relevant customer experiences through the use of technology such as in-depth data analysis, as well as employee training to strengthen interaction skills. Additionally, brand commitment can be reinforced through loyalty programs, continuous product innovation, and authentic brand communication. Although AI is not effective as a moderator, its integration remains relevant in supporting operational optimization, such as personalizing customer service and predictive analysis for strategic decision-making. Companies must continue to adapt to changing technology and market trends to stay competitive.

The failure of AI to function as a moderator in this study may be due to the lack of emotional elements in AI-based interactions, uneven technology adoption rates, or customer preferences for human interaction. However, AI could be more relevant in industries that heavily rely on big data and high personalization, such as e-commerce, financial services, or technology, where AI can be used to provide product recommendations, personalized solutions, or pattern detection based on data analysis. For future research, further exploration is needed on how AI can be effectively applied to enhance customer experience across various sectors. Potential research areas include examining customer perceptions of AI, the relationship between technology adoption levels and AI effectiveness, and how AI can be integrated with loyalty programs to strengthen customer commitment to the brand. This study also opens opportunities to investigate the factors influencing the success of AI in creating more personalized customer experiences, including interactions with other organizational elements such as product innovation and service differentiation.

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