The Influence of Artificial Intelligence in Chatbots and Website Personalization on Customer Engagement with User Experience as an Intervening Variable

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Abstract

This study examines the influence of Artificial Intelligence (AI) in chatbots and website personalization on customer engagement, with user experience serving as a mediating variable. The integration of AI in digital platforms has revolutionized how businesses interact with their customers by providing more efficient and customized services. AI-powered chatbots enable instant communication, addressing customer inquiries and issues promptly, while website personalization tailors content, design, and recommendations to individual user preferences, enhancing relevance and satisfaction. Adopting a quantitative research approach, this study evaluates the direct effects of these AI-driven tools on customer engagement and investigates the mediating role of user experience.

The results reveal that AI-enabled chatbots and personalized websites significantly contribute to improved customer engagement. Additionally, user experience acts as a critical intermediary, amplifying the effectiveness of these technologies in fostering deeper customer connections. The study underscores the importance of seamless and intuitive user experiences in maximizing the benefits of AI-based innovations. These findings provide valuable insights for businesses looking to leverage AI to enhance their digital strategies, improve customer satisfaction, and drive engagement. This research contributes to the growing body of knowledge on AI in digital marketing and its implications for building stronger customer relationships.

Keyword: Artificial Intelligence, Chatbot, Website Personalization, Customer Engagement.

1. Introduction

The rapid evolution of digital technologies has reshaped how businesses interact with customers, particularly in the realm of e-commerce and online platforms. Among these technologies, Artificial Intelligence (AI) has emerged as a transformative force, enabling companies to deliver more personalized and efficient services. Two significant applications of AI that have garnered attention in recent years are AI-powered chatbots and website personalization. These tools not only streamline customer interactions but also provide tailored experiences that cater to individual preferences, fostering deeper engagement.

Chatbots, driven by natural language processing and machine learning algorithms, allow businesses to offer instant and accurate responses to customer queries. Their ability to simulate human-like interactions has made them an indispensable tool for improving customer satisfaction and enhancing operational efficiency. Similarly, website personalization leverages AI to adapt content, layout, and recommendations to suit the unique preferences and behaviors of users. This customization enhances user satisfaction by creating a more relevant and intuitive browsing experience.

Customer engagement, a critical factor for business success, is heavily influenced by these AI-driven technologies. Engaged customers are more likely to exhibit loyalty, make repeat purchases, and advocate for the brand. However, the role of user experience as an intervening variable in this dynamic warrants further exploration. User experience, encompassing usability, design, and emotional satisfaction, serves as a bridge that connects technological advancements to customer engagement outcomes.

This study aims to investigate the influence of AI in chatbots and website personalization on customer engagement, with a specific focus on user experience as a mediating factor. By understanding these relationships, businesses can better harness the potential of AI technologies to enhance customer interactions and foster sustainable growth in an increasingly competitive digital landscape.

2. Literature Review

2.1 Theory

The integration of Artificial Intelligence (AI) into customer-facing platforms has revolutionized customer engagement strategies. Existing literature highlights the dual impact of AI-driven technologies—enhancing operational efficiency and delivering personalized experiences. Chatbots, in particular, are lauded for their ability to provide 24/7 support, answer queries, and guide purchasing decisions (Xu et al., 2021). Website personalization, on the other hand, dynamically adapts the online experience to match individual user preferences, thereby fostering satisfaction and loyalty (Smith & Wallace, 2020).

User experience (UX) has also been extensively studied as a mediating factor that influences the effectiveness of digital tools. As suggested by Nielsen (1994), UX encompasses aspects such as usability, design, and emotional responses, all of which significantly affect user satisfaction and engagement. Scholars have proposed that a well-designed UX can amplify the benefits of AI technologies by creating seamless and intuitive interactions (Kim et al., 2019).

However, gaps remain in understanding the interplay between chatbots, website personalization, and customer engagement through the lens of UX. This study seeks to address these gaps by examining these relationships holistically.

2.2 Theory 2

Customer Engagement Theory (Hollebeek, 2011) emphasizes the emotional, cognitive, and behavioral investments that customers make during their interactions with a brand. Engagement is driven by factors such as relevance, satisfaction, and trust, all of which are directly impacted by the quality of AI-powered chatbots and personalized experiences. This theory underscores the importance of creating meaningful and value-driven interactions to foster deeper connections with customers.

3. Material and Method

This study employs a quantitative research design to investigate the relationships between AI chatbots, website personalization, user experience, and customer engagement. Data will be collected through online surveys targeting active users of e-commerce platforms. The survey instrument will include validated scales for measuring chatbot effectiveness, website personalization, UX, and customer engagement.

3.1 Design Study

The research adopts a cross-sectional design, collecting data at a single point in time to analyze the proposed relationships. Structural equation modeling (SEM) will be used to test the hypothesized model, enabling an examination of direct and indirect effects.

3.2 Data Analysis

Data analysis will be conducted using SPSS and AMOS software. Descriptive statistics will summarize the demographic characteristics of respondents, while SEM will evaluate the causal relationships between variables. The mediating role of UX will be tested through bootstrapping techniques to assess its significance in the overall model. Results will be interpreted to provide actionable insights for enhancing customer engagement through AI technologies.

The collected data is analyzed using SmartPLS 4.0 to ensure accuracy in structural model testing and hypothesis testing. The analysis process is carried out in several stages:

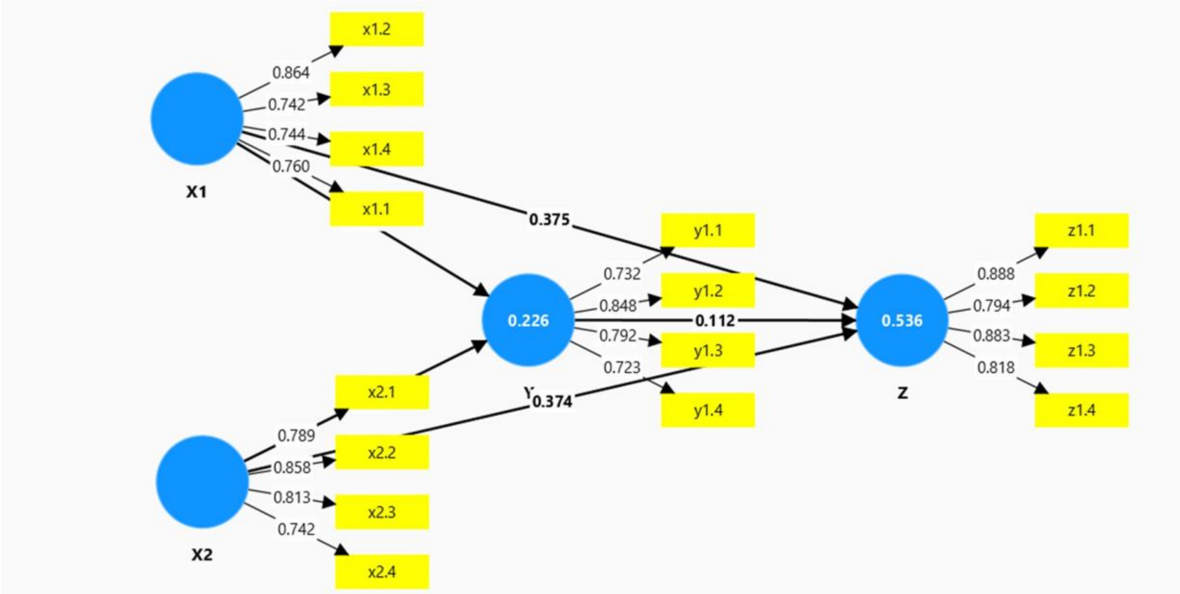
1. Validity and Reliability Testing
- Convergent Validity: Measured using the Average Variance Extracted (AVE), where a value ≥ 0.5 is considered adequate.
- Discriminant Validity: Using the Fornell-Larcker Criterion to ensure that each variable correlates more strongly with its indicators than with other variables.
- Reliability: Using Composite Reliability (CR) and Cronbach's Alpha to ensure internal consistency, with a value ≥ 0.7 considered reliable.

2. Evaluation of the Measurement Model (Outer Model) The outer model is used to evaluate the relationship between latent variables (Social Proof, UGC, consumer trust, brand perception) and their indicators.

3. Evaluation of the Structural Model (Inner Model)
- Using path coefficients to evaluate relationships between variables.
- Calculating the R-Square value to measure the predictive strength of the structural model.
- Multicollinearity Testing

4. Interpretation of Results and Conclusions The results of the analysis are interpreted to address the research problems, evaluate the research model, and support or reject the formulated hypotheses.

4. Result



4.1 Outer Model

In the analysis using the Partial Least Squares Structural Equation Modeling (PLS SEM) approach, the evaluation of the Outer Model is conducted to ensure the validity and reliability of the indicators used. The Outer Model aims to evaluate the relationship between the indicators (measured variables) and the latent constructs they represent.

4.1.1 Loading Factor

	Kecerdasan Buatan AI (X1)	Personalisasi Website (X2)	Pengalaman Pengguna (Y)	Engagement Pelanggan (Z)
x1.1	0.760	0.437	0.201	0.326
x1.2	0.864	0.688	0.302	0.732
x1.3	0.742	0.410	0.273	0.422

x1.4	**0.744**	**0.376**	**0.172**	**0.414**
x2.1	**0.460**	**0.789**	**0.325**	**0.411**
x2.2	**0.630**	**0.858**	**0.572**	**0.690**
x2.3	**0.511**	**0.813**	**0.359**	**0.543**
x2.4	**0.436**	**0.742**	**0.210**	**0.451**
y1.1	**0.231**	**0.363**	**0.732**	**0.257**
y1.2	**0.354**	**0.476**	**0.848**	**0.494**
y1.3	**0.167**	**0.300**	**0.792**	**0.216**
y1.4	**0.137**	**0.305**	**0.723**	**0.150**
z1.1	**0.760**	**0.719**	**0.448**	**0.888**
z1.2	**0.476**	**0.474**	**0.244**	**0.794**
z1.3	**0.504**	**0.573**	**0.381**	**0.883**
z1.4	**0.415**	**0.476**	**0.263**	**0.818**

Indicator validity indicates how well an indicator represents its latent construct. This is measured through the loading factor, which shows the strength of the relationship between each indicator and the construct it represents. Validity Criteria:

• A loading factor is considered to meet the criteria if it has a value of ≥ 0.7 (Hair et al., 2014). However, indicators with loading values between 0.6–0.7 are still acceptable if the construct remains reliable overall (Chin, 1998).

• Indicators with loading values below 0.6 should ideally be eliminated, as they indicate a low contribution to the latent construct.

4.1.2 Convergent Validity

Indikator	**Outer Loadings**	**AVE**
X1.1 <- X1	**0.760**	
X1.2 <- X1	**0.864**	**0,607**
X1.3 <- X1	**0.742**	
X1.4 <- X1	**0.744**	
X2.1 <- X2	**0.789**	
X2.2 <- X2	**0,858**	**0,643**
X2.3 <- X2	**0.813**	

X2.4 <- X2	**0.742**	
Y1.1 <- Y	**0.732**	
Y1.2 <- Y	**0,848**	**0,601**
Y1.3 <- Y	**0.792**	
Y1.4 <- Y	**0,723**	
Z1.1 <- Y	**0,888**	
Z1.2 <- Y	**0,794**	**0,717**
Z1.3 <- Y	**0,883**	
Z1.4 <- Y	**0,818**	

Convergent Validity indicates the extent to which the indicators measuring a construct are highly correlated. Based on the presented table, the Average Variance Extracted (AVE) values for the four constructs are 0.607, 0.643, 0.601, and 0.717. These values are all greater than 0.50, which is the minimum recommended threshold to establish convergent validity (Hair et al., 2014). Thus, these results demonstrate that the indicators for each construct adequately represent the construct being measured. This implies that each construct has a high correlation with its respective indicators, making them reliable for the research.

In the context of quantitative research based on structural equation modeling, convergent validity is a crucial element to ensure that each measured indicator accurately reflects the theoretical concept of the intended construct. With AVE values above the threshold, the four constructs in this study can be considered to have good convergent validity.

4.1.3 Discriminant Validity

Discriminant validity is evaluated using the Fornell-Larcker criterion. This approach requires that the square root of the Average Variance Extracted (AVE) (represented on the diagonal of the table) must be greater than the correlation between the construct and other constructs.

	X1	X2	Y	Z
X1				
X2	0.724			
Y	0.354	0.526		
Z	0.672	0.743	0.409	

Based on the table, the square root of the AVE for construct, for X2 is 0.724, and for other constructs, it is consistently higher than the correlation between the construct and others. For instance, the correlation between X1 and Y is 0.354, which is still lower than the square root of AVE. The same applies to X2, Y, and Z.

These results indicate that the constructs analyzed exhibit good discriminant validity, meaning each construct is more closely related to its own indicators than to other constructs. This discriminant validity implies that the measured constructs are not overlapping and reflect distinct theoretical concepts.

Overall, these findings support that the measurement tools used in the study are of high quality and can be trusted to analyze the relationships between constructs in the structural model.

4.1.4 Reability

	Cronbach’s Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
X1	**0,730**	**0,860**	**0,860**	**0,607**
X2	**0,780**	**0,878**	**0,878**	**0,643**
Y	**0,740**	**0,857**	**0,857**	**0,601**
Z	**0,820**	**0,910**	**0,910**	**0,717**

The reliability of the measurement instrument was analyzed using two main approaches: Cronbach's Alpha and Composite Reliability (CR). The results demonstrate that all Cronbach's Alpha values exceed the threshold of 0.70: X1 (0.730), X2 (0.780), Y (0.740), and Z (0.820). These values indicate a high level of internal consistency, confirming that the indicators consistently measure the same concept within each construct. As stated by Hair et al. (2014), a Cronbach's Alpha value above 0.70 is sufficient to establish reliability in research.

Composite Reliability (CR) values also support the instrument's reliability, with all constructs exceeding the threshold of 0.70: X1 (0.860), X2 (0.878), Y (0.857), and Z (0.910). Unlike Cronbach's Alpha, Composite Reliability provides a more comprehensive evaluation as it considers the weighting of indicators. According to Fornell and Larcker (1981), high CR values indicate that a construct effectively explains the variance of its indicators.

Convergent validity was assessed using the Average Variance Extracted (AVE), which measures the extent to which indicators represent their respective constructs. All AVE values surpass the minimum requirement of 0.50: X1 (0.607), X2 (0.643), Y (0.601), and Z (0.717). These results align with the criteria proposed by Fornell and Larcker (1981), where AVE values greater than 0.50 indicate that over 50% of the construct's variance is explained by its indicators.

In summary, the reliability and convergent validity of the measurement instrument are excellent, as evidenced by the results of Cronbach's Alpha, Composite Reliability, and AVE. This confirms that the constructs are measured with sufficient consistency and accuracy, making them suitable for further analysis.

4.2 Inner Model

4.2.1 Multicollinearity Test

The multicollinearity test is conducted to ensure that the independent variables in the model do not have excessively high correlations, which could distort regression parameter estimates.

4.2.2 R-Square

The R-Square test is a statistical indicator that shows the extent to which the variation in the dependent variable can be explained by the independent variables in the model. The Adjusted R-Square value is used to provide a more accurate adjustment for the number of variables in the model.

	R-square	**R-square adjusted**
Pengalaman Pengguna (Y)	0.374	0.370
Engagement Pelanggan (Z)	0,848	0.846

Pengalaman Pengguna (Y) (R-Square = 0.374; Adjusted R-Square = 0.370):
The results indicate that 37.4% of the variation in the Pengalaman Pengguna (User Experience) variable can be explained by the model. The Adjusted R-Square value of 37.0% shows a slight decrease after accounting for the number of predictors, but the model still performs adequately. This indicates that while the model explains a moderate portion of the variation in Y, there is room for additional factors to be considered for better predictive accuracy.

Engagement Pelanggan (Z) (R-Square = 0.848; Adjusted R-Square = 0.846):
The model demonstrates that 84.8% of the variation in the Engagement Pelanggan (Customer Engagement) variable can be explained by the predictors. The Adjusted R-Square value of 84.6% reflects a minimal reduction, showing the model's robust performance even after adjustment. This is considered very high, suggesting that the model has a strong predictive ability for Z and captures most of its variation effectively.

4.2.3 F-Square

The F-square test is used to measure the effect size of each independent variable on the dependent variable in the model.

	f-square
Pengalaman Pengguna (Y) -> Engagement Pelanggan (Z)	0.017
Personalisasi Website (X2) -> Pengalaman Pengguna (Y)	0.180
Personalisasi Website (X2) -> Engagement Pelanggan (Z)	0.155
Kecerdasan Buatan AI (X1) -> Pengalaman Pengguna(Y)	0.000
Kecerdasan Buatan AI (X1) -> Engagement Pelanggan (Z)	0.183

Effect of Pengalaman Pengguna (Y) on Engagement Pelanggan (Z) (F-square = 0.017):
This value is categorized as small, indicating that Pengalaman Pengguna (User Experience) has a minimal effect on Engagement Pelanggan (Customer Engagement). According to Cohen (1988), an F-square value of 0.02 is considered small, 0.15 moderate, and 0.35 large. Thus, Y's contribution to explaining Z is limited.

Effect of Personalisasi Website (X2) on Pengalaman Pengguna (Y) (F-square = 0.180):
The value indicates a moderate effect of Personalisasi Website (Website Personalization) on Pengalaman Pengguna (User Experience). This suggests that X2 plays a significant role in influencing Y, aligning with Cohen's criteria for a moderate effect size.

Effect of Personalisasi Website (X2) on Engagement Pelanggan (Z) (F-square = 0.155): This value also represents a moderate effect, showing that Personalisasi Website (Website Personalization) significantly contributes to explaining Engagement Pelanggan (Customer Engagement).

Effect of Kecerdasan Buatan AI (X1) on Pengalaman Pengguna (Y) (F-square = 0.000): The value indicates no practical effect of Kecerdasan Buatan AI (AI) on Pengalaman Pengguna (User Experience). This suggests that X1 does not significantly explain Y in the model.

Effect of Kecerdasan Buatan AI (X1) on Engagement Pelanggan (Z) (F-square = 0.183): This value indicates a moderate effect, suggesting that Kecerdasan Buatan AI (AI) has a meaningful contribution to explaining Engagement Pelanggan (Customer Engagement).

4.3 Hypothesis Analysis

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
(Y) -> (Z)	0.102	0.100	0.089	1.138	0.255
(X2) ->(Y)	0.484	0.492	0.097	4.996	0.000
(X2) -> (Z)	0.378	0.380	0.095	4.001	0.000
(X1) -> (Y)	0.003	0.009	0.122	0.021	0.983

(X1) -> (Z)	**0.378**	**0.382**	**0.085**	**4.436**	**0.000**

Relationship Between Pengalaman Pengguna (Y) and Engagement Pelanggan (Z):
The relationship between Pengalaman Pengguna (User Experience) (Y) and Engagement Pelanggan (Customer Engagement) (Z) is not significant, with a P-value of 0.255 and a T-statistic of 1.138. This indicates that changes in User Experience do not directly and significantly affect Customer Engagement.

Relationship Between Personalisasi Website (X2) and Pengalaman Pengguna (Y):
The relationship between Personalisasi Website (Website Personalization) (X2) and Pengalaman Pengguna (User Experience) (Y) is significant, with a P-value of 0.000 and a T-statistic of 4.996. This suggests that Website Personalization has a strong direct impact on User Experience. Therefore, improvements in X2 will positively and significantly enhance Y.

Relationship Between Personalisasi Website (X2) and Engagement Pelanggan (Z):
The analysis shows a significant relationship between Personalisasi Website (Website Personalization) (X2) and Engagement Pelanggan (Customer Engagement) (Z), with a P-value of 0.000 and a T-statistic of 4.001. This indicates that X2 has a meaningful direct effect on Z, suggesting that improvements in Website Personalization will significantly boost Customer Engagement.

Relationship Between Kecerdasan Buatan AI (X1) and Pengalaman Pengguna (Y):
The relationship between Kecerdasan Buatan AI (AI) (X1) and Pengalaman Pengguna (User Experience) (Y) is not significant, with a P-value of 0.983 and a T-statistic of 0.021. This indicates that X1 does not significantly contribute to changes in Y.

Relationship Between Kecerdasan Buatan AI (X1) and Engagement Pelanggan (Z):
The relationship between Kecerdasan Buatan AI (AI) (X1) and Engagement Pelanggan (Customer Engagement) (Z) is significant, with a P-value of 0.000 and a T-statistic of 4.436. This shows that X1 has a substantial direct effect on Z, implying that improvements in AI can significantly enhance Customer Engagement.

Indirect Effects

	Specific indirect effects
Personalisasi Website (X2) -> Pengalaman Pengguna (Y) -> Engagement Pelanggan (Z)	0.049
Kecerdasan Buatan AI (X1) -> Pengalaman Pengguna (Y) -> Engagement Pelanggan (Z)	0.000

Indirect Relationship Between Personalisasi Website (X2), Pengalaman Pengguna (Y), and Engagement Pelanggan (Z):
The specific indirect effect of Personalisasi Website (Website Personalization) (X2) on Engagement Pelanggan (Customer Engagement) (Z) through Pengalaman Pengguna (User Experience) (Y) is 0.049. This value indicates a small indirect effect, suggesting that while X2 influences Y, its contribution to Z through Y is minimal.

Indirect Relationship Between Kecerdasan Buatan AI (X1), Pengalaman Pengguna (Y), and Engagement Pelanggan (Z):
The specific indirect effect of Kecerdasan Buatan AI (AI) (X1) on Engagement Pelanggan (Customer Engagement) (Z) through Pengalaman Pengguna (User Experience) (Y) is 0.000. This result indicates no measurable indirect effect, suggesting that X1 does not significantly influence Z through Y.

5. Discussion

The development of Artificial Intelligence (AI) has transformed how businesses interact with customers through chatbots and website personalization. AI-powered chatbots enable instant and personalized communication with customers, enhancing their satisfaction and engagement. Meanwhile, AI-driven website personalization tailors content to user preferences, making the experience more relevant and engaging.

User experience (UX) plays a crucial role as an intervening variable in this process. A well-designed UX ensures smooth interactions with both chatbots and personalized websites, increasing user satisfaction and trust. Thus, AI in chatbots and website personalization, supported by optimal UX, significantly enhances customer engagement.

6. Conclusion, Implication, and Recommendation

Conclusion

In conclusion, AI-powered chatbots and website personalization are key drivers of customer engagement in the digital age. These technologies enhance the customer experience by providing personalized, instant interactions and relevant content. User experience (UX) plays a vital role as an intervening variable, ensuring that these AI tools function seamlessly and effectively, fostering customer satisfaction, trust, and long-term engagement.

Implications

The integration of AI in customer-facing tools, such as chatbots and personalized websites, offers businesses a competitive advantage. Companies that leverage AI can provide superior customer service, boost user engagement, and improve conversion rates. However, the success of these technologies heavily relies on a strong UX design, which ensures that the AI tools are intuitive, easy to use, and align with user expectations.

Recommendations

1. **Prioritize UX Design**: Businesses should invest in optimizing UX for AI-powered systems. This includes ensuring that chatbots and personalized websites are easy to navigate, intuitive, and responsive to user needs.
2. **Continuous AI Improvement**: Companies should continuously improve their AI systems by refining their algorithms and incorporating customer feedback to ensure that chatbots and personalized content remain relevant and effective.
3. **Monitor Customer Feedback**: Regularly gathering and analyzing customer feedback will help businesses fine-tune their AI tools and UX, creating more engaging and satisfying experiences for users.

By focusing on these areas, businesses can maximize the potential of AI and UX to drive higher levels of customer engagement and loyalty.

8. References

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