JIMT: Jurnal Ilmu Manajemen Terapan
E-ISSN: 2686-4924
P-ISSN: 2686-5246
DINASTI REVIEW
https://dinastirev.org/JIMT dinasti.info@gmail.com +62 811 7404 455
DOI: https://doi.org/10.38035/jimt.v7i4

The Impact of AI Personalization on Customer Engagement on TikTok: The Role of Trust, Perceived Usefulness, and Usage Intention

Britney Marchsyela Alchotib[1], Grace Vernanda[2], Muhammad Izzas Ferdiansyah[3], Kevin Suryaatmaja[4]
[1]Binus Business School, Jakarta Pusat, Indonesia, britney.alchotib@binus.ac.id
[2]Binus Business School, Jakarta Pusat, Indonesia, gracevernanda@binus.ac.id
[3]Binus Business School, Jakarta Pusat, Indonesia, muhammad.ferdiansyah004@binus.ac.id
[4]Binus Business School, Jakarta Pusat, Indonesia, kevin.suryaatmaja@binus.ac.id

Corresponding Author: britney.alchotib@binus.ac.id[1]

Abstrak: *Di tengah pesatnya integrasi kecerdasan buatan (AI) dalam media sosial, penelitian ini bertujuan menganalisis pengaruh personalisasi berbasis AI terhadap customer engagement pada TikTok dengan memasukkan trust, perceived usefulness, dan usage intention sebagai variabel mediasi. Penelitian ini menggunakan kerangka Stimulus–Organism–Response (SOR) dengan data yang dikumpulkan dari 238 pengguna TikTok di Indonesia berusia 18–34 tahun. Analisis data dilakukan menggunakan Structural Equation Modeling (SEM). Hasil penelitian menunjukkan bahwa personalisasi AI berpengaruh positif dan signifikan terhadap trust, perceived usefulness, dan usage intention. Ketiga variabel tersebut juga terbukti berpengaruh signifikan terhadap customer engagement. Hasil uji mediasi menunjukkan bahwa trust dan usage intention memediasi secara penuh hubungan antara personalisasi AI dan customer engagement, sedangkan perceived usefulness berperan sebagai mediator parsial. Selain itu, hasil Multi-Group Analysis (MGA) menunjukkan tidak adanya perbedaan signifikan berdasarkan gender dan tingkat pendidikan.Penelitian ini menegaskan bahwa dalam lingkungan digital yang cepat seperti TikTok, trust dan niat penggunaan memiliki peran yang lebih dominan dibandingkan nilai fungsional dalam mendorong keterlibatan pengguna.*

Kata Kunci: *Personalisasi AI, Customer Engagement, TikTok, Model SOR*

Abstract: Amid the rapid integration of artificial intelligence (AI) in social media, this study examines the effect of AI-driven personalization on customer engagement on TikTok, with trust, perceived usefulness, and usage intention as mediating variables. Using the Stimulus–Organism–Response (SOR) framework, data were collected from 238 Indonesian users aged 18–34 and analyzed using Structural Equation Modeling (SEM). The results show that AI personalization has significant positive effects on trust, perceived usefulness, and usage intention. These variables, in turn, significantly influence customer engagement. Mediation analysis indicates that trust and usage intention fully mediate the relationship between AI personalization and engagement, while perceived usefulness acts as a partial mediator.

Furthermore, Multi-Group Analysis (MGA) reveals no significant differences across gender and education, indicating model consistency across demographic groups. This study highlights that in fast-paced platforms like TikTok, trust and behavioral intention play a more critical role than functional value in driving engagement. Practically, the findings emphasize the need for platforms to enhance transparency and user control alongside algorithmic sophistication.

Keyword: AI Personalization, Customer Engagement, TikTok, SOR Model

INTRODUCTION

In today's digital era, social media has become deeply embedded in daily life. In Indonesia alone, approximately 143 million users actively engage with platforms such as TikTok, Instagram, Facebook, and X, which function as spaces for communication, information exchange, and digital content consumption (Kemp, 2025). The rapid advancement of technology has further accelerated this growth, particularly through the integration of Artificial Intelligence (AI) into social media systems. AI has become a key tool for managing and analyzing large-scale user data, enabling platforms to deliver personalized, relevant, and engaging experiences tailored to individual users (Varsha et al., 2021). Recent studies highlight that TikTok's algorithm adopts a hybrid approach by combining collaborative filtering and content-based techniques, supported by advanced machine learning models to predict user preferences (Zhou, 2024; Kang & Lou, 2022). As one of the fastest-growing social media platforms, TikTok extensively utilizes AI to curate its For You Page (FYP), which presents content that aligns closely with each user's interests. Through continuous analysis of billions of video interactions, TikTok's algorithm dynamically adapts to user behavior to enhance engagement and prolong platform usage (Matusin et al., 2023).

Customer engagement refers to the level of users' interaction, involvement, and emotional attachment to a platform or brand (Chen et al., 2022). On social media platforms such as TikTok, high engagement is associated with increased usage intensity, as users are more likely to return when they are emotionally and behaviorally connected (Huang & Rust, 2021). In this context, AI-driven personalization plays a pivotal role by delivering tailored content that aligns with individual user preferences, thereby enhancing relevance and user experience (Davenport et al., 2020). When users perceive the content as useful and relevant, their engagement tends to increase, leading to more dynamic and sustained interactions (Chen et al., 2022). Perceived usefulness acts as a key mediating variable, reflecting the extent to which users believe that personalized content provides value and meets their needs (Davenport et al., 2020). In the case of TikTok's For You Page (FYP), the perceived value of recommendations strengthens the relationship between AI personalization and customer engagement, resulting in higher satisfaction and longer platform interaction (Chen et al., 2022).

In addition, usage intention defined as the user's willingness to continue using the platform plays an equally important role, as engagement cannot be sustained without consistent behavioral commitment. However, the effectiveness of AI personalization is also influenced by user trust. Trust becomes a critical mediating factor, particularly in environments where AI systems collect and process personal data. Transparency in AI processes is essential to foster trust and ensure that users perceive the system as fair and ethical (Molina & Sundar, 2022). Conversely, a lack of understanding regarding how recommendations are generated may lead to perceptions of reduced control and privacy concerns, which can negatively affect trust (Chen et al., 2022). Therefore, it is essential to examine how AI personalization influences customer engagement on TikTok through the mediating roles of perceived usefulness, usage intention, and trust. In recent years, AI-driven personalization has become a core feature of many social media platforms, including TikTok. This technology enables platforms to deliver content customized to each user's preferences and behavior, with the goal of enhancing engagement and satisfaction (Huang & Rust, 2021).

However, empirical findings on AI personalization remain inconsistent, particularly regarding how psychological factors interact in shaping customer engagement. Teepapal (2025) found that although AI personalization significantly enhances trust and perceived usefulness, it does not directly influence customer engagement, as engagement emerges through these mediating variables. This challenges the assumption that personalization alone is sufficient to sustain user involvement and suggests that its effectiveness depends on users' cognitive and emotional responses (Ameen et al., 2021). In addition, usage intention—defined as an individual's willingness to continue interacting with a platform—has been widely recognized as a key behavioral predictor in AI-based systems (Adawiyah et al., 2024), yet its mediating role in the relationship between AI personalization and customer engagement remains underexplored. Prior studies using the Stimulus–Organism–Response (SOR) framework also indicate that factors such as privacy concerns may not directly reduce engagement, while trust may function as a moderating or intervening variable (Teepapal, 2025). Nevertheless, limited research has simultaneously examined the combined roles of perceived usefulness, trust, and usage intention within the context of short-form video platforms such as TikTok. Therefore, this study aims to address this gap by investigating the extent to which AI personalization influences customer engagement through these mediating variables using the SOR framework.

Based on the preceding discussion, this study aims to examine the effect of AI personalization on customer engagement on TikTok by analyzing its direct and indirect relationships through key psychological variables. Specifically, this research seeks to analyze the influence of AI personalization on trust, perceived usefulness, and usage intention, as well as the effect of these variables on customer engagement. Furthermore, this study aims to investigate the mediating roles of trust, perceived usefulness, and usage intention in the relationship between AI personalization and customer engagement. Despite its contributions, this study has several limitations. The research focuses exclusively on TikTok users in Indonesia, which may limit the generalizability of the findings due to differences in cultural, behavioral, and regulatory contexts across regions. In addition, while this study incorporates trust, perceived usefulness, and usage intention as mediating variables, other potentially relevant factors such as perceived privacy risk and perceived control are not included. Future research is therefore encouraged to integrate these variables to provide a more comprehensive understanding of user responses to AI personalization. Moreover, since this study is limited to a single platform, the findings may not be directly applicable to other platforms with different algorithmic systems and user characteristics, such as Instagram Reels or YouTube Shorts.

METHOD

This study adopts the Stimulus–Organism–Response (SOR) framework, originally introduced by Woodworth (1929) and further developed by Mehrabian and Russell (1974), to examine how external stimuli influence individuals' internal states and subsequent behavioral responses. Within this framework, AI personalization is conceptualized as the stimulus, while trust, perceived usefulness, and usage intention represent organism variables that mediate the relationship toward customer engagement as the response. The SOR model has been widely applied in digital and AI-driven contexts to explain how technological stimuli shape cognitive and emotional reactions, ultimately influencing user behavior (Gao & Liu, 2023; Gligorea et al., 2023; Wang et al., 2025)

This research employs a quantitative approach to analyze causal relationships among variables using numerical data and statistical techniques. Data were collected through a self-administered online survey distributed via Google Forms. The study focuses on active TikTok users in Indonesia aged 18–34, representing the dominant user segment. A non-probability purposive sampling method was applied due to the absence of a comprehensive sampling frame. A total of 238 valid responses were obtained, exceeding the recommended minimum sample size for Structural Equation Modeling (SEM), thereby ensuring robustness and stability of the analysis (Hair et al., 2021; Kock & Hadaya, 2018).

All variables were measured using a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5). The constructs include AI Personalization, Trust, Perceived Usefulness, Usage Intention, and Customer Engagement, adapted from established prior studies. The research design follows a cross-sectional approach, capturing user perceptions at a single point in time, and is conducted in a non-contrived setting to reflect real user experiences. Data analysis was performed using Structural Equation Modeling (SEM). The evaluation process consists of three stages: measurement model (outer model), structural model (inner model), and hypothesis testing. Convergent validity was assessed using factor loadings (≥ 0.70) and Average Variance Extracted (AVE ≥ 0.50), while reliability was evaluated through Cronbach's Alpha and Composite Reliability (≥ 0.70). The structural model was assessed using path coefficients, coefficient of determination (R^2), and effect size (f^2), while hypothesis testing was based on t-statistics (≥ 1.645) and p-values (≤ 0.05).

RESULTS AND DISCUSSION

There are 6 questions regarding the demographics of the research respondents which include gender, age, occupation, length of time using TikTok, frequency of using TikTok, and average duration of using TikTok per day. To make it easier to read the data from these questions, a summary of the demographics of the respondents is attached in the table below:

Table 1. Respondents' Demographic Information Summary

Question	Information		
	Option	**Number**	**Percentage**
Gender	Male	9	39.5%
	Female	144	60.5%
Age	18-24 years old	58	24.5%
	25-29 years old	143	60.3%
	30-34 years old	33	13.9%
	>35 years old	3	1.3%
Work	Student	6	2.5%
	University Student	56	23.6%
	Employee	103	43.5%
	Entrepreneur	72	23.6%
Length of time using TikTok	< 6 months	13	5.5%
	6 months - 1 year	23	9.7%
	1 - 2 years	91	38.6%
	>2 years	109	46.2%
Frequency of TikTok usage	Every day	199	84%
	Several times a week	19	8%
	Once a week	15	6.3%
	Rarely	4	1.7%
Average daily usage duration of TikTok	<30 minutes	3	1.3%
	30 minutes - 1 hour	19	8%
	1 - 2 hours	98	41.2%
	>2 hours	118	49.6%

From the questionnaire that has been distributed, there are 238 total respondents who have answered all the questions. 60.5% of all respondents are women. In terms of age, it can be seen that the age group that most often uses TikTok is the age of 25-29 at 60.3% of all respondents, followed by the age group of 18-24 years with a percentage of 24.5% of the total respondents. This shows that most TikTok users are in the young adult group. In terms of occupation, the majority of TikTok users are workers (43.3%) and entrepreneurs (30.3%). It can also be seen that most TikTok users have been using the platform for more than a year and with very frequent frequency. This shows that TikTok already has a strong user base. The use of TikTok in the daily lives of respondents is also very significant because almost 90% of all respondents use TikTok for more than two hours per day.

Outer Model Testing

Reliability testing aims to assess the extent to which indicators in the research model can provide consistent results under various conditions and times. This reliability describes the consistency of the instrument in measuring a particular concept or variable (Adawiyah et al., 2024). In this study, reliability measurements were carried out by looking at Cronbach's Alpha and CR values. Meanwhile, convergent validity is used to evaluate the extent to which indicators can represent the measured construct accurately and consistently (Hair et al., 2021). The convergent validity test in this study was carried out by assessing the Factor Loading and AVE values.

Table 2. Outer Model Testing Result

Factors	Items			
	Cronbach's Alpha	Factor	AVE	Factor Loading
Trust	0.864	0.907	0.710	
I believe that content quality on TikTok is consistent, regardless of whether it's from popular or lesser-known creators.				0.877
I believe that the information presented by TikTok contents is generally reliable and unbiased.				0.831
TikTok ensures that recommended contents are trustworthy.				0.817
I believe TikTok takes steps to ensure that users comments and engagement (likes, shares, ratings) are authentic and not manipulated.				0.845
Perceived Usefulness	0.834	0.899	0.667	
TikTok helps me find the most relevant content for my interests.				0.834
Using TikTok improves my effectiveness in discovering engaging content.				0.825
I find TikTok useful for exploring content that matches what I like.				0.809
TikTok saves me time when I'm looking for enjoyable content.				0.799
Usage Intention	0.850	0.899	0.691	
I will continue using TikTok because its AI personalization helps me find content that suits me.				0.867
I would recommend TikTok to others because its personalized content improves the experience.				0.841
I will use TikTok regularly because I feel the personalized recommendations are useful.				0.826
I am willing to keep using TikTok because I understand and benefit from its personalized content.				0.789
Customer Engagement	0.877	0.916	0.731	
I feel genuinely interested when using TikTok.				0.898
I get deeply immersed when browsing personalized content on TikTok.				0.837
Time passes quickly when I use TikTok.				0.836
I feel absorbed in the experience when using TikTok.				0.847

The test results show that all indicators have Cronbach's Alpha and CR values above the minimum threshold of 0.6, which indicates that the measuring instrument used has adequate reliability. This finding confirms that all indicators consistently measure the intended construct and can be relied on for further analysis processes (Hair et al., 2021). In addition, based on the results of the factor loadings evaluation, all indicators have a value of ≥ 0.7, which indicates that the indicators are valid in measuring their respective constructs. The AVE value, which is also above the minimum threshold, supports the conclusion that each variable has been successfully constructed with valid and representative indicators (Adawiyah et al., 2024).

Path Coefficient

The path coefficient serves as an indicator to evaluate both the strength and direction of direct relationships between variables in a structural model. It quantitatively reflects the extent to which one variable affects another. A positive coefficient shows a direct (same direction) influence, while a negative coefficient reflects an inverse relationship. Values approaching one suggest a strong effect, whereas values near zero indicate a weak effect.

Table 3. Path Coefficient Result

Variable	AI Personalization	Perceived Usefulness	Trust	Usage Intention	Customer Engagement
AI Personalization		0.890	0.884	0.857	0.853
Perceived Usefulness					0.182
Trust					0.289
Usage Intention					0.487
Customer Engagement					

The table above presents the results of the path coefficient analysis in this study. The findings indicate that AI Personalization has a strong and positive influence on Perceived Usefulness (0.890), Trust (0.884), Usage Intention (0.857), and Customer Engagement (0.835). In terms of Customer Engagement specifically, AI Personalization and Usage Intention exert the strongest positive effects, while Trust (0.289) and Perceived Usefulness (0.182) demonstrate relatively weaker but still positive impacts. These findings provide deeper insight into the factors that influence user engagement in the context of using AI Personalization on TikTok.

R-Square

The R-Square value describes the proportion of variance of the dependent variable that can be explained by the independent variables in the structural model. The higher the R-Square value, the better the model's ability to explain the variable.

Table 4. R Square Result

Variable	R-Square
Perceived Usefulness	0.793
Trust	0.782
Usage Intention	0.735
Customer Engagement	0.843

Based on the results shown in the table, the R-Square value for Perceived Usefulness is 0.793, which means that 79.3% of the variation in Perceived Usefulness can be explained by AI Personalization. For Trust, the R-Square value reaches 0.782, which shows that 78.2% of the variation in Trust is also influenced by AI Personalization. While for Usage Intention it is 0.735, which means that 73.5% of the variation in Usage Intention can be explained by AI personalization. Meanwhile, Customer Engagement has the highest R-Square value of 0.843, which shows that 84.3% of the variation in Customer Engagement is explained by a combination of Perceived Usefulness, Trust, and Usage Intention. Overall, these values indicate that the model has high predictive ability and supports the theoretical relationship between variables in this study.

F-Square

F-Square is used to evaluate the effect size of each independent variable on the dependent variable by considering its unique contribution after accounting for other predictors in the model. Larger F-Square values indicate that the variable makes a more meaningful contribution to explaining the variance of the dependent construct.

Table 5. F-Square Result

Variable	AI Personalization	Perceived Usefulness	Trust	Usage Intention	Customer Engagement
AI Personalization		3.819	3.587	2.768	
Perceived Usefulness					0.034
Trust					0.117
Usage Intention					0.293
Customer Engagement					

Hypothesis Testing

Based on the PLS-SEM theory stated by Hair et al. (2021), for a one-tailed method analysis, a hypothesis is accepted when the significant value (P value) is less than or equal to 0.05, meaning the significance is above 95%, while the T statistics value has to be at least 1.645. One-tailed method analysis is used when the direction of the hypothesis is already known. From the analysis above, it can be concluded that:

Table 6. Hypothesis Testing Result

Relationship	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Result
AI Personalization -> Perceived Usefulness	0.890	0.889	0.018	48.426	0.000	Supported
AI Personalization -> Trust	0.884	0.883	0.023	37.871	0.000	Supported
AI Personalization -> Usage Intention	0.857	0.855	0.031	27.665	0.000	Supported
Perceived Usefulness -> Customer Engagement	0.182	0.188	0.094	1.942	0.026	Supported
Trust -> Customer Engagement	0.289	0.290	0.076	3.802	0.000	Supported
Usage Intention -> Customer Engagement	0.487	0.479	0.092	5.284	0.000	Supported
AI Personalization -> Usage Intention -> Customer Engagement	0.417	0.409	0.076	5.476	0.000	Supported
AI Personalization -> Trust -> Customer Engagement	0.256	0.257	0.069	3.732	0.000	Supported
AI Personalization -> Perceived Usefulness -> Customer Engagement	0.162	0.168	0.084	1.933	0.027	Supported

Discussion

AI Personalization has been shown to have a significant impact on Perceived Usefulness. When an AI system is able to provide content or services that suit customer needs, they tend to consider the system useful. This is in line with the research from Nagy & Hajdu (2021) which found that in the context of online shopping, personalization increases consumers' perceptions of the usefulness of the technology used. This shows that AI Personalization both improves the user experience and additionally strengthens the perception of the technology utilization. Users will be more likely to engage if trust is present between the users and the platform they are using. The outcome of this analysis matches the study of Teepapal (2025) and supports the hypothesis that the use of AI Personalization in TikTok in the form of For You Page in which users feel more comfortable in trusting the platform if they obtain personalized information that matches their interests. Likewise, research conducted by Choung et al. (2023) explains that trust is an important factor in the acceptance of AI-based technology. The study confirms that AI that provides relevant and customized experiences can create a sense of trust, especially when users feel that control and transparency remain in their interactions.

It is shown that AI Personalization has a significant impact towards users' usage intention. Supported by the previous hypothesis discussions, AI personalized contents are of higher use and trust to users. Users will most likely be exposed to those contents after consuming them continuously and feel the intent to use the platform for longer periods of time. This finding is supported by a study by Halim et al. (2022) on the AI personalized information in Indonesian Marketplace and how customers' usage intention is affected positively by it due to customers gaining more value and becoming more satisfied with the platform after receiving personalized offers. The findings indicate that perceived usefulness positively effecting customer engagement. This finding is in line with Teepapal (2025) who stated that perceived usefulness is an important factor in consumer behaviour related to AI personalization. In addition, research conducted by Marjerison et al. (2025) also shows that when users feel AI technology is useful, they will interact more as seen in the use of e-commerce chatbots in China. Likewise, research conducted by Nagy & Hajdu (2021) found that perceived usefulness increases satisfaction and digital engagement on an ongoing basis.

Trust as a variable significantly influences Customer Engagement, as users who have confidence in the AI system are more likely to interact actively through actions such as liking, commenting, or sharing content. Previous research conducted by Chen et al. (2022) supports this, by showing that trust has a significant positive relationship with customer engagement, suggesting that building and maintaining trust is essential for enhancing user interaction and loyalty. The higher the level of user's trust, the higher the engagement because users feel comfortable and safe using the system. Customer engagement is positively impacted by Usage Intention, as seen from the research above. The intent to use a platform derives from the conscious decision of users to interact with a platform, hence why it is proven that the usage intention a user has will increase the engagement a platform has. This result is supported by Corrêa et al. (2020), in their study of YouTube's usage intention and its impact on several factors, including customer engagement, where good sentiments for the contents being put up creates a positive engagement the platform has after new videos are uploaded.

The results of this study also show that Trust, Perceived Usefulness, and Usage Intention significantly mediate the relationship between AI Personalization and Customer Engagement. These results are in line with research conducted by Teepapal (2025) and Adawiyah et al. (2024), which show that AI personalization increases user trust in the system, and trust fully mediates the relationship between AI personalization and customer engagement. In addition, perceived usefulness has also been shown to be an important mediator because users who feel that personalized content is useful and relevant are more likely to interact with features on social media. Then, usage intention also acts as a mediator because the intention to use AI and AR-supported technology can encourage ongoing engagement.

CONCLUSION

This study investigates the impact of AI personalization on customer engagement in TikTok by testing nine hypotheses within the Stimulus–Organism–Response (SOR) framework. The findings demonstrate that AI personalization significantly enhances trust, perceived usefulness, and usage intention, all of which positively influence customer engagement. As seen from the result of the hypothesis testing, AI Personalization positively affects Trust, which also affects Customer Engagement, proving that the relationship between the variables exists positively. AI Personalization also positively affects Perceived Usefulness, which affects Customer Engagement positively as well. Another relationship has been proven to be true positively between AI Personalization, Perceived Usefulness and Customer Engagement. The last chain of relationships to be proven positively related are AI Personalization and Usage Intention, as well as Usage Intention and Customer Engagement. The analysis reveals that Trust plays an indirect role in linking AI Personalization with Customer Engagement, helping to clarify the research questions about how these variables are connected. Likewise, the analysis confirms that Perceived Usefulness and Usage Intention also act as mediators in the link between AI Personalization and Customer Engagement, with both variables exerting a positive mediating effect. These results highlight the evolving dynamics of user interaction with AI-driven platforms. While AI personalization successfully improves both trust and perceived usefulness, it is trust and usage intention that emerge as the strongest pathways to sustained engagement.

REFERENCES

Adawiyah, S. R., Purwandari, B., Eitiveni, I., & Purwaningsih, E. H. (2024). The Influence of AI and AR Technology in Personalized Recommendations on Customer Usage Intention: A Case Study of Cosmetic Products on Shopee. Applied Sciences, 14(13), 5786. https://doi.org/10.3390/app14135786

Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. Computers in Human Behavior, 114, 106548. https://doi.org/10.1016/j.chb.2020.106548

Asyraff, M. A., Hanafiah, M. H., Aminuddin, N., & Mahdzar, M. (2023). Adoption of the Stimulus-Organism-Response (S-O-R) Model in Hospitality and Tourism Research: Systematic Literature Review and Future Research Directions Adoption of the Stimulus-Organism-Response (S-O-R) model in hospitality and tourism research: Systematic literature review and future research directions. Asia-Pacific Journal of Innovation in Hospitality and Tourism (APJIHT), 12(1).

Bag, S., Srivastava, G., Bashir, M. M. Al, Kumari, S., Giannakis, M., & Chowdhury, A. H. (2022). Journey of customers in this digital era: Understanding the role of artificial intelligence technologies in user engagement and conversion. Benchmarking: An International Journal, 29(7), 2074–2098. https://doi.org/10.1108/BIJ-07-2021-0415

Bitrián, P., Buil, I., & Catalán, S. (2021). Enhancing user engagement: The role of gamification in mobile apps. Journal of Business Research, 132, 170–185. https://doi.org/10.1016/j.jbusres.2021.04.028

Bougie, Roger., & Sekaran, Uma. (2020). Research methods for business : a skill-building approach. John Wiley & Sons, Inc.

Bryman, Alan., & Bell, Emma. (2015). Business research methods. Oxford University Press.

Chen, Y., Prentice, C., Weaven, S., & Hisao, A. (2022). The influence of customer trust and artificial intelligence on customer engagement and loyalty – The case of the home-sharing industry. Frontiers in Psychology, 13. https://doi.org/10.3389/fpsyg.2022.912339

Choung, H., David, P., & Ross, A. (2023). Trust in AI and Its Role in the Acceptance of AI Technologies. International Journal of Human–Computer Interaction, 39(9), 1727–1739. https://doi.org/10.1080/10447318.2022.2050543

Cohen, Jacob. (1988). Statistical power analysis for the behavioral sciences. Psychology Press, Taylor & Francis Group.

Corrêa, S. C. H., Soares, J. L., Christino, J. M. M., Gosling, M. de S., & Gonçalves, C. A. (2020). The influence of YouTubers on followers' use intention. Journal of Research in Interactive Marketing, 14(2), 173–194. https://doi.org/10.1108/JRIM-09-2019-0154

Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. Technological Forecasting and Social Change, 173, 121092. https://doi.org/10.1016/j.techfore.2021.121092

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48(1), 24–42. https://doi.org/10.1007/s11747-019-00696-0

Davis, F., Francis Gnanasekar, M. B., & Parayitam, S. (2021). Trust and product as moderators in online shopping behavior: evidence from India. South Asian Journal of Marketing, 2(1), 28–50. https://doi.org/10.1108/SAJM-02-2021-0017

Duarte, F. (2025). TikTok User Age, Gender, & Demographics (2025). Exploding Topics. https://explodingtopics.com/blog/tiktok-demographics

Gao, Y., & Liu, H. (2023). Artificial intelligence-enabled personalization in interactive marketing: a customer journey perspective. Journal of Research in Interactive Marketing, 17(5), 663–680. https://doi.org/10.1108/JRIM-01-2022-0023

Gligorea, I., Cioca, M., Oancea, R., Gorski, A.-T., Gorski, H., & Tudorache, P. (2023). Adaptive Learning Using Artificial Intelligence in e-Learning: A Literature Review. Education Sciences, 13(12), 1216. https://doi.org/10.3390/educsci13121216

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. Research Methods in Applied Linguistics, 1(3), 100027. https://doi.org/10.1016/j.rmal.2022.100027

Hair, J. F. ., Hult, G. T. M. ., Ringle, C. M. ., Sarstedt, Marko., Danks, N. P. ., & Ray, Soumya. (2021). Partial least squares structural equation modeling (PLS-SEM) using R : a workbook. Springer.

Halim, E., Buana, M. K., Hartono, H., Ferdianto, & Hebrard, M. (2022). Analysis of AI-enabled Service Quality and Personalization to Continuous Usage Intention. 2022 International Conference on Information Management and Technology (ICIMTech), 699–704. https://doi.org/10.1109/ICIMTech55957.2022.9915042

Hochreiter, V., Benedetto, C., & Loesch, M. (2023). The Stimulus-Organism-Response (S-O-R) Paradigm as a Guiding Principle in Environmental Psychology: Comparison of its Usage in Consumer Behavior and Organizational Culture and Leadership Theory. Journal of Entrepreneurship and Business Development, 3(1), 7–16. https://doi.org/10.18775/jebd.31.5001

Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science, 49(1), 30–50. https://doi.org/10.1007/s11747-020-00749-9

Kang, H., & Lou, C. (2022). AI agency vs. human agency: understanding human–AI interactions on TikTok and their implications for user engagement. Journal of Computer-Mediated Communication, 27(5). https://doi.org/10.1093/jcmc/zmac014

Kemp, S. (2025). DIGITAL 2025: INDONESIA. DATAREPORTAL. https://datareportal.com/reports/digital-2025-indonesia

Kock, N. (2015). Common Method Bias in PLS-SEM. International Journal of E-Collaboration, 11(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. Information Systems Journal, 28(1), 227–261. https://doi.org/10.1111/isj.12131

Kumar, M. M., Kesharwani, A., Gautam, V., & Sinha, P. (2022). Stimulus-Organism-Response (S-O-R) Model Application in Examining the Effectiveness of Public

Service Advertisements. INTERNATIONAL JOURNAL OF BUSINESS, 27(2), 2022. https://sanevax.org/media-

Marjerison, R. K., Dong, H., Kim, J.-M., Zheng, H., Zhang, Y., & Kuan, G. (2025). Understanding User Acceptance of AI-Driven Chatbots in China's E-Commerce: The Roles of Perceived Authenticity, Usefulness, and Risk. Systems, 13(2), 71. https://doi.org/10.3390/systems13020071

Matusin, I. O., Matusin, A. R., Nasution, C. F., & Irma, D. (2023). The Effect of Social Media Marketing on Consumer Engagement and Electronic Word-Of-Mouth. International Journal of Social Science and Human Research, 06(02). https://doi.org/10.47191/ijsshr/v6-i2-06

Mehrabian, A., & Russell, J. A. (1974). An Approach to Environmental Psychology. The MIT Press.

Molina, M. D., & Sundar, S. S. (2022). When AI moderates online content: effects of human collaboration and interactive transparency on user trust. Journal of Computer-Mediated Communication, 27(4). https://doi.org/10.1093/jcmc/zmac010

Nagy, S., & Hajdu, N. (2021). Consumer Acceptance of the Use of Artificial Intelligence in Online Shopping: Evidence From Hungary. Www.Amfiteatrueconomic.Ro, 23(56), 155. https://doi.org/10.24818/EA/2021/56/155

Pan, J., Ishak, N. A., & Qin, Y. (2024). The application of Moore's online learning interactions model in learning outcomes: The SOR (stimulus-organism-response) paradigm perspective. Heliyon, 10(7), e28505. https://doi.org/10.1016/j.heliyon.2024.e28505

Saunders, M. N. K. ., Lewis, Philip., & Thornhill, Adrian. (2023). Research methods for business students. Pearson.

Shang, Y., Rehman, H., Mehmood, K., Xu, A., Iftikhar, Y., Wang, Y., & Sharma, R. (2022). The Nexuses Between Social Media Marketing Activities and Consumers' Engagement Behaviour: A Two-Wave Time-Lagged Study. Frontiers in Psychology, 13. https://doi.org/10.3389/fpsyg.2022.811282

Sugiyono. (2018). METODE PENELITIAN KUANTITATIF. Alfabeta.

Sung, E. (Christine), Bae, S., Han, D.-I. D., & Kwon, O. (2021). Consumer engagement via interactive artificial intelligence and mixed reality. International Journal of Information Management, 60, 102382. https://doi.org/10.1016/j.ijinfomgt.2021.102382

Teepapal, T. (2025). AI-driven personalization: Unraveling consumer perceptions in social media engagement. Computers in Human Behavior, 165. https://doi.org/10.1016/j.chb.2024.108549

Varsha P. S., Akter, S., Kumar, A., Gochhait, S., & Patagundi, B. (2021). The Impact of Artificial Intelligence on Branding. Journal of Global Information Management, 29(4), 221–246. https://doi.org/10.4018/JGIM.20210701.oa10

Vindytia, M., & Balqiah, T. E. (2024). AI Marketing Impact on Consumer Behavior: An SOR Model Analysis of Online Food Delivery Services. Jurnal Dinamika Manajemen, 15(2), 215–228. https://doi.org/10.15294/jdm.v15i2.6758

Walters, W. H. (2021). Survey design, sampling, and significance testing: Key issues. The Journal of Academic Librarianship, 47(3), 102344. https://doi.org/10.1016/j.acalib.2021.102344

Wang, C., Ahmad, S. F., Bani Ahmad Ayassrah, A. Y. A., Awwad, E. M., Irshad, M., Ali, Y. A., Al-Razgan, M., Khan, Y., & Han, H. (2023). RETRACTED: An empirical evaluation of technology acceptance model for Artificial Intelligence in E-commerce. Heliyon, 9(8), e18349. https://doi.org/10.1016/j.heliyon.2023.e18349

Wang, W., Chen, Z., & Kuang, J. (2025). Artificial Intelligence-Driven Recommendations and Functional Food Purchases: Understanding Consumer Decision-Making. Foods, 14(6), 976. https://doi.org/10.3390/foods14060976

Zhou, R. (2024). Understanding the Impact of TikTok's Recommendation Algorithm on User Engagement. International Journal of Computer Science and Information Technology, 3(2), 201–208. https://doi.org/10.62051/ijcsit.v3n2.