Research Journal in Advanced Humanities

https://doi.org/10.58256/pbhpzq64

RJAH

Open Access

Check for updates

RESEARCH ARTICLE

Section: *Culture, Media and Film*

Work decently: AI-driven marketing strategies for a competitive edge in tourism

Karam Zaki[1,2], Abdelrahman A. A. Abdelghani[3*], Hebatallah A. M. Ahmed[3], Tagreed Abdelfadel[4,5], Entesar Abusalim[4], Khalda Ahmed[6], Alaa E. Abuzaid[6] & Ahmed K. Elnagar[7]

[1]Shaqra University, Saudi Arabia
[2]Fayoum University, Egypt
[3]Prince Sattam Bin Abdulaziz University,Al-kharj, Saudi Arabia
[4]Taibah University, Saudi Arabia
[5]Umdurman University, Sudan
[6]Qassim University, Saudi Arabia
[7]Suez Canal University, Egypt
*Correspondence: a.abdelghani@psau.edu.sa

ABSTRACT

Artificial intelligence-driven marketing (AIM) is emerging as a vital instrument for securing competitive advantage (CA) by enabling personalized customer interactions in the dynamic hospitality and tourism sectors. In Saudi Arabia, AIM techniques offer significant potential to attract and retain customers, underscoring the sector's importance. However, research on AIM's influence on tourists' decision-making (DM), guest engagement (GE), and satisfaction in this context remains in its early stages. This study investigates how AIM strategies shape tourists' DM processes, comparing the impacts of social media platforms and hospitality e-commerce channels on GE and guest loyalty (GL). Data was collected via a structured questionnaire using convenience sampling, resulting in 323 valid responses from tourists across Riyadh, Jeddah, and Madinah. Analysis using partial least squares structural equation modeling (PLS-SEM) revealed that AIM significantly influences DM, GE, and CA. Notably, personalized interactions on social media platforms markedly enhance GL, emphasizing the need for tailored AIM strategies. This research enriches the limited literature on AIM in the Saudi hospitality sector and introduces an innovative model integrating AIM, social media engagement, and personalization strategies, providing valuable insights for both researchers and practitioners.

KEYWORDS: AI Marketing, competitive advantage, guest engagement, Saudi Arabia, tourism and hospitality industry, tourist decision-making

Research Journal in Advanced Humanities

Volume 6, Issue 1, 2025
ISSN: 2708-5945 (Print)
ISSN: 2708-5953 (Online)

ARTICLE HISTORY

Submitted: **20 January 2025**
Accepted: **11 March 2025**
Published: 12 **April 2025**

HOW TO CITE

Zaki, K. ., Abdelghani , A. A. A. ., Ahmed, H. A. M. ., Abdelfadel, T. ., Abusalim, E. ., Ahmed , K. ., Abuzaid, A. E. ., & Elnagar, A. K. . . (2025). Work decently: AI-driven marketing strategies for a competitive edge in tourism. *Research Journal in Advanced Humanities,* 6(1). https://doi.org/10.58256/pbhpzq64

Published in Nairobi, Kenya by Royallite Global, an imprint of Royallite Publishers Limited

1. Introduction

Tourism plays a pivotal role in generating foreign currency revenues, making the hospitality industry a cornerstone of economic development. Given the hotel sector's integral contribution to tourism, optimizing operations through innovative technological interventions is essential (Elnagar and Derbali, 2020; Zaki and Elnagar, 2025). One of the most transformative developments reshaping business landscapes is digital transformation, with artificial intelligence-driven marketing (AIM) emerging as a critical driver of change. While AI has permeated various functional areas within organizations, its profound impact on marketing has been particularly pronounced (Kshetri et al., 2024). AIM are revolutionizing contemporary advertising, enhancing decision-making (DM) processes, and integrating automation to deliver faster and more effective marketing outcomes (Chintalapati and Pandey, 2022).

Recent studies underscore AI's potential to perform marketing tasks with human-like intelligence, augmenting DM efficiency and optimizing customer engagement (Vlačić et al., 2021). AIM enables businesses to analyze vast datasets, personalize customer interactions, and enhance predictive analytics to refine marketing strategies (Jain and Aggarwal, 2020). Despite its transformative potential, the application of AIM remains underexplored, particularly in publicly accessible research. While some enterprises have made significant strides in AI adoption, these advancements are often proprietary, serving as a source of CA (Stone et al., 2020). The fundamental aim is not to replace human DM in marketing but to establish a synergistic AI-human framework that enhances precision, speed, and strategic insight.

AIM analytics capabilities offer firms a sustainable CA by enabling real-time market sensing, data-driven DM, and strategic agility (Hossain et al., 2022) . AIM and big data analytics, surpasses traditional marketing approaches in processing structured and unstructured data with greater accuracy and efficiency (Kumar, 2021). The ability of AI to simulate human-like interactions and interpret consumer sentiments has led to the rise of AIM as a business differentiator. By leveraging AI algorithms, firms can extract actionable insights from extensive datasets, facilitating the creation of targeted advertising campaigns, product innovation, and enhanced customer experience (Fischer, 2024).

Moreover, AIM strategies enhance long-term business competitiveness by fostering customer-centric approaches (Zaki et al.,2025). AI-powered tools offer personalized recommendations based on behavioral analysis and consumer preferences, increasing guest engagement (GE), guest loyalty(GL) , and lifetime value (Adesoga et al., 2024) . In Saudi Arabia, AI and big data are reshaping market dynamics, influencing customer satisfaction and marketing effectiveness. Advanced AI-driven analytics enable firms to implement precise targeting, optimize marketing investments, and improve customer retention rates. Chatbots and AI-powered systems further enhance consumer interactions, fostering real-time engagement and higher brand loyalty (Alhumaid and Alotaibi, 2025).

Saudi Arabia is positioning itself as a global leader in AI adoption through strategic investments and national initiatives. The Saudi Data and AI Authority (SDAIA) spearheads efforts to integrate AI across key sectors, including tourism, with a focus on data-driven DM. The National Strategy for Data and AI emphasizes AI adoption in governance, healthcare, energy, education, and transportation while fostering innovation through policies, research, and investments. Recognized among the top 15 countries globally for AI expertise, Saudi Arabia seeks to leverage AI to enhance economic diversification and elevate the tourism industry (Alotaibi, 2024).

Aligned with Saudi Vision 2030, AI-powered innovations are revolutionizing religious tourism and overall tourist experiences. Studies have demonstrated the role of digital transformation in enhancing visitor satisfaction through AI-driven applications Aljuwaiber and Elnagar (2022). AI systems can analyze guest preferences and feedback, providing invaluable insights for tourism businesses. Such capabilities align with Saudi Arabia's goal of harnessing emerging technologies to drive tourism growth (Alzahrani et al., 2025) . Several studies have examined AI's impact on marketing innovation and performance in Saudi Arabia and Egypt's hospitality industries (Alnasser et al., 2024). While these studies highlight AI's role in enhancing creativity and marketing effectiveness, they predominantly focus on AI's merits rather than its strategic implementation in marketing.

Despite the growing discourse on AI adoption in the Saudi hospitality sector, a critical research gap remains. Most existing studies emphasize AI's role in enhancing operational efficiency and service innovation, yet limited attention has been given to the integration of AI in marketing strategies and its impact on competitive performance. For instance, prior research has focused on AI-powered recommendation systems and automation (Ahmed, 2024; Aljizawi's 2024), but there remains a dearth of empirical studies examining AI's influence on digital marketing tactics, GE, and strategic brand positioning within the Saudi hospitality sector.

This study aims to bridge these gaps by examining the interplay between AIM, CA, trust, and GL. Furthermore, it explores the mediating roles of DM and GE, distinguishing itself from prior research by incorporating trust as a key moderating factor. A novel contribution of this study is the exploration of three mediating variables, providing a comprehensive framework for understanding AI-driven marketing's transformative potential in the hospitality industry.

2. Literature review

2.1 Theoretical underpinnings

The variables of AIM strategies, GE, DM process, GL, trust, and CA are all explained in this study using the Social Exchange Theory (SET) and Resource-Based View (RBV) theories. The SET is an excellent framework for understanding AIM strategy since it emphasizes the mutual connections between companies (or marketers) and visitors (or consumers). The cost-benefit exchange concept holds that people or groups make decisions based on what would maximize advantages and minimize downsides, which is the foundation of SET, according to Chernyak-Hai and Rabenu (2018) suggest that interactions or exchanges among colleagues can cultivate a shared sense of responsibility and motivation to respond constructively, as supported by Harden et al., (2018). From the perspective of the Resource-Based View (RBV) of the firm, diverse market positions emerge from the effective utilization of unique, valuable, and rare organizational resources that are difficult to replicate or diminish, enabling companies to sustain a CA (Varadarajan, 2020). Miller (2019) explains that the RBV framework is grounded in the idea that firms possess heterogeneous and immobile resources. This view conceptualizes a business as a bundle of assets, capabilities, or practices that create value and are challenging for competitors to imitate due to mechanisms that preserve the firm's competitive edge in the market.

AIM offers businesses a comprehensive and valuable way to maximize the effectiveness of data-driven marketing strategies and get the highest level of success (Gabelaia, 2024). Companies employ AI-powered marketing to give customers personalized, relevant content that enhances their experience. In exchange, businesses receive valuable data on the preferences and behaviour of their customers, which they may use to further their AI strategies. In the travel and hospitality industry, customers engage with AI systems because they feel they are getting value in return—a concept known as reciprocity—and businesses' customized services can be seen as a benefit the company offers. The theory SET was utilized by Rather and Hollebeek (2019) to explain the variable in their study on the impacts of brand identification, satisfaction, commitment, and trust on consumer GL toward four- and five-star hotels. Based on the same theory, our inquiry likewise uses the two essential factors in that study: trust and GL. The effects of the core characteristics of consumer engagement—enthusiasm, attention, absorption, interaction, and identification—on GL and psychological commitment in the hotel sector were examined in another study by Rather and Hollebeek (2019) using SET. These factors are investigated considering the SET theory, which holds that clients are more likely to remain loyal to a brand if they feel they frequently interact with it and receive value (via personalized experiences, deals, or special incentives). Trust is the cornerstone of this engagement; customers need to believe that the company will continue to provide value in the future. The DM framework is determined by the diverse consumer engagement described by Alvarez-Milán et al. (2018) using the SET theory. Varadarajan (2020) emphasizes that customer-based resources, which fall under the broader category of a firm's market-based resources, are increasingly recognized as critical potential sources of CA in today's dynamic, data-driven digital market environment. Using a range of ideas, especially RBV, he attempted to explain a market resources-based perspective on strategy, CA, and performance in this study. Lastly, this study also uses the theories of SET and RBV to explain the mediating role of the variables (GE, DM).

2.2 Effects of AIM Strategies

AI technology has given marketers access to ground-breaking instruments and perspectives, enabling previously unheard-of levels of effectiveness, personalized service, and strategic campaign DM. According to Kumar et al.

(2024), AI in marketing is synonymous with accuracy because it enables marketers to tailor their marketing campaigns to clients' needs and taste preferences, resulting in more meaningful and fruitful partnerships. The use of AI in DM platforms increases transparency and aids companies in comprehending the requirements and preferences of their target audience, claim (Rabby et al., 2021). DM systems' AI capabilities are incorporated into live chat using chatbots, which interact with customers quickly and logically, answering their questions. Zed et al. (2024) investigated how AI-driven personalization tactics affected the GL of online shoppers and discovered a strong positive correlation between the two. This research lends credence to the idea that tailored experiences enhance GL, repurchase intent, and psychological bond. According to a study by Sharma et al. from 2021, using machine learning techniques could revolutionize targeted advertising and provide advertisers with a practical toolkit for targeting their audience with unprecedented accuracy. Among the six clusters, AI for DM was identified as a prominent emerging cluster by Labib's (2024) bibliometric analysis. However, these results prompt us to formulate the following research hypotheses:

H1: AIM strategies significantly influence GE.
H2: AIM strategies significantly influence DM Process.
H3: AIM strategies significantly influence GL.
H4: AIM strategies significantly influence CA.

2.3 Relationship between the variables

Although brand loyalty has been proven to be significantly influenced by consumer interaction, Li et al. (2020) revealed no correlation between the two. Chen et al. (2021) states that the hotel and tourism business needs to focus on client interaction. Service organizations should focus on and ensure smooth service quality for client satisfaction, even if it is university providing services to students and staffs (Derbali and Elnagar, 2020). Client satisfaction is most affected by consumer expectations, and GL is considered an essential component, according to a study by (Nobar and Rostamzadeh, 2018). Customer expectations positively impact GL. GL also predicts brand value in the hotel and tourism sectors significantly (Elnagar and Derbali, 2020). Strengthening the region where they have better resources may give businesses a competitive edge. Zhang et al. (2018) found that the cost of consumer product screening and the caliber of the DM process significantly impacts GL. They clarified that there is a positive correlation between self-reference and DM process quality and a negative correlation between dishonesty and information overload. The following theories are formulated because several factors have been observed to influence one another:

H5: GE significantly influences GL.
H6: DM Process significantly influences GL.
H7: GL significantly influences CA.

2.4 Mediating Role of GE and DM

Based on Chen et al. (2022), customer engagement (CE) mediates the association between GL and trust. AI may have an unfavorable moderating influence on the connection between host trust and CE and between CE and GL. According to a different study by Sofi et al. (2025), visitor engagement moderates the complex link between GL and satisfaction. Low levels of guest involvement lessen the beneficial influence of satisfaction on GL, whereas high levels of engagement improve it. Furthermore, a study by Prentice et al. (2020) demonstrated that AI preference significantly changes the quality and enjoyment of information. In considering these findings, the following ideas are formulated to ascertain the mediating role of GE and the DM process:

H8: GE mediates the relationship between AIM strategies and GL.
H9: DM mediates the relationship between AIM strategies and GL.
H10a: GE mediates the relationship between AIM strategies and GL towards CA.
H10b: DM Process mediates the relationship between AIM strategies and GL towards CA.

2.5 Moderating Role of Trust

Trust is a crucial element in both online and offline interactions, and a substantial positive correlation was found between customer trust and GE and GL (Chen et al., 2022). Businesses can enhance positive, tailored customer experiences and foster trust in digital platforms by combining AI and DM technology with human-generated data (Rabby et al., 2021). Li et al. (2020) discovered that brand loyalty and confidence in the brand fully mediated the relationship between client engagement and brand loyalty. Khaliq et al. (2022) found that mutual trust adversely regulated the link between AI and robotics awareness and turnover intention. The relationship between GL, perceived security, product diversity, and on-time delivery was mediated by trust in Mofokeng's 2023) study. Nonetheless, these results aid in the development of the following hypotheses:

H11a: The association between AIM strategies and CA is moderated by Trust.
H11b: The association between AIM strategies and DM Process is moderated by Trust.
H11c: The association between AIM strategies and GL is moderated by Trust.
H11d: The association between AIM strategies and GE is moderated by Trust.

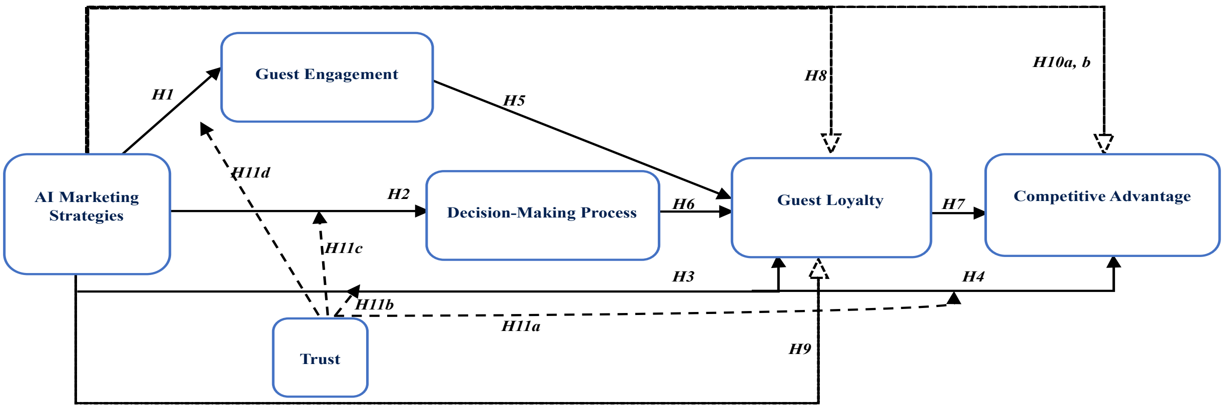

Figure 1. Conceptual framework.

3. Materials and Methods

3.1 Measurement scale

The measures used in this research were adopted from previous validated measurement scale. The AIM scale, comprising five items (AIM1–AIM5), was adapted from Abrokwah-Larbi and Awuku-Larbi (2024), who examined the role of AI in marketing within SMEs in emerging economies. For GE and TR, five items each (GE1–GE5 and TR1–TR5) were adapted from Li et al. (2020), who explored the relationship between CE, brand loyalty, and trust in tourism social media contexts. The GL construct was measured using four items (GL1–GL4), adapted from So et al. (2016), who investigated the role of CE in building GL to tourism brands. The DM construct was assessed using six items (DM1–DM6), adapted from O'Connor (1995). Finally, CA construct was assessed using six items (CA1–CA6), adapted from Cao et al. (2019), who studied the link between information processing capability, and CA.

3.2 Sampling procedure

Data were collected through a structured questionnaire using a convenience sampling approach, yielding 323 valid responses from tourists and guests across various hospitality establishments in Saudi Arabia, including Riyadh, Jeddah, and Madinah. The target participants for this study were tourists and guests who had recently stayed at these establishments. The survey was conducted from October 2024 to January 2025, with participants required to complete the questionnaire independently to ensure the accuracy and reliability of the data collected. To facilitate the data collection process, the research team established direct communication with the management of the hospitality establishments, who assisted in distributing the questionnaires to their guests. The questionnaire was distributed evenly among the participants, with 500 questionnaires disseminated. By the cut-off date, 323 valid responses were received, resulting in a response rate of 64.6%, serving as this study's sample size. This sample size is considered adequate for conducting PLS-SEM analysis, similar approaches are also found in previous studies (Elshaer et al., 2024, 2024; Khalifa et al., 2025; Zaki et al., 2025; Zaki and Elnagar, 2025). According to the 10× rule proposed by Hair et al. (2019), the minimum sample size for PLS-SEM should be at least ten times the number of variables in the study. In this research, the model consists of 6 latent dimensions with 31 reflective variables, requiring a minimum sample size 310. With a sample size of 323, the study significantly exceeds this requirement. Additionally, the sample size aligns with the recommendations of Hair et al. (2019) and Kock (2015), who suggest that a minimum sample size of 100 is sufficient for achieving reliable results in SEM analysis. A larger sample size also allows for applying advanced data analysis techniques, such as SEM, to explore the relationships among the variables under investigation thoroughly.

To ensure the consistency of responses, a t-test was conducted to examine variations in average responses among participants who completed the questionnaire at different times. The results indicated no significant differences in means, confirming no notable deviations in reactions based on the timing of survey completion. The survey included 31 primary and three demographic questions about gender, age, and education level. Participants were informed about the study's objectives and assured of their privacy and voluntary participation. They were also informed about their right to withdraw from the survey. The majority of questions were closed-ended, with follow-up phone calls made to encourage participation. To ensure that the research variables were clear, a pilot test was conducted with a group of 15 tourists, who all agreed that they understood the questions and variables.

The questionnaire was divided into two sections. The first section included a cover letter detailing the purpose of the study, providing contact information, and highlighting the characteristics of the tourism and hospitality establishments. The second section aimed to capture participants' perspectives on key constructs such as AIM strategies, GE, DM Process, GL, CA, and Trust, using a five-point Likert-type scale ranging from 5 (strongly agree) to 1 (strongly disagree).

4. Results

4.1 Demographic analysis

The respondent profile comprises 323 male participants (61.6%) and female (38.4%). In terms of age distribution, the largest group falls within the 31–40 years range (45.8%), followed by 21–30 years (29.1%), 41–50 years (15.5%), and above 50 years (9.6%). Regarding education levels, most respondents hold a bachelor's degree (81.7%), while 14.9% have a master's degree or higher, and a small percentage (3.4%) possess a diploma degree.

Table 1. Respondents' profiles.

Category	n	%
Gender		
Male	199	61.6
Female	124	38.4
Age		
21 – 30 years	94	29.1
31 – 40 years	148	45.8
41 – 50 years	50	15.5
Above 50 years	31	9.6
Education Level		
Diploma degree	11	3.4
Bachelor degree	264	81.7
Master's degree and Higher	48	14.9

4.2 Descriptive analysis

The descriptive statistics for the constructs revealed that GL (M = 4.050, SD = 0.967) had the highest mean value, indicating that guests exhibited strong GL toward the hospitality establishments. This was closely followed by CA (M = 4.010, SD = 0.840) and DM (M = 3.955, SD = 0.964), suggesting that participants also highly rated these constructs. On the other hand, TR (M = 2.233, SD = 0.941) had the lowest mean value, indicating that participants perceived a lack of trust in the context of the studied variables. The skewness and kurtosis values for all constructs fell within the acceptable range, confirming that the data were normally distributed and suitable for further analysis.

Table 2. Summary statistics (N =323).

Constructs	Mean	SD	Skewness	Std. Error	Kurtosis	Std. Error
AIM strategies	3.768	.937	-1.256	.136	1.211	.271
GE	3.848	.905	-.921	.136	.714	.271
DM Process	3.955	.964	-1.700	.136	2.708	.271
GL	4.050	.967	-1.719	.136	2.709	.271
CA	4.010	.840	-1.963	.136	3.984	.271
Trust	2.233	.941	1.190	.136	1.402	.271

4.3 Multicollinearity test

Multicollinearity, or a high level of correlation among the independent variables, can adversely affect the interpretability of the results. Therefore, assessing and addressing multicollinearity issues is essential before proceeding with model testing. The results of the multicollinearity test, as shown in Table 3, indicate that both criteria—tolerance and variance inflation factor (VIF)—yielded acceptable values. Specifically, tolerance values should be above 0.10, and VIF values should be below 5 (Hair et al., 2019). In this study, all constructs met these thresholds, with tolerance values ranging from 0.297 to 0.550 and VIF values ranging from 1.819 to 3.369.

Table 3. Multicollinearity test

Constructs	Tolerance	VIF
AIM strategies	.475	2.104
GE	.550	1.819
DM Process	.297	3.369
Trust	.374	2.674

4.4 Structural Equation Modelling

4.4.1 Measurement Model Analysis

The measurement model was tested for construct reliability, convergent, and discriminant validity. As shown in Table 4, all constructs had acceptable reliability, with Cronbach's alpha (CA) and composite reliability (CR) values exceeding the recommended threshold of 0.70 (Hair et al. 2019). Convergent validity was established because all factor loadings (FL) were greater than 0.70, and the average variance extracted (AVE) for each construct exceeded the minimum criterion of 0.50 (Hair et al., 2019). These findings show that the measurement model meets the reliability and validity requirements, ensuring that the constructs are internally consistent and adequately explain the variance in their respective indicators.

Table 4. Summary of measurement model analysis.

Constructs	Items	FL	CA	CR	AVE
AIM (**AIM**)	AIM1: AIM in the Saudi hospitality helps to accurately predict customer needs.	0.903	0.927	0.945	0.774
	AIM2: AIM supports the marketing promotion through the elimination of human errors.	0.885			
	AIM3: AIM enables the hotel to interact with internet users through the application of analyzed data.	0.803			
	AIM4: AIM is important to the collaborative DM process.	0.909			
	AIM5: AIM enables the hotel to personalize its marketing activities to individual customers.	0.894			
Competitive advantage (**CA**)	CA1: The hotel is more effective than the competitors.	0.804	0.928	0.943	0.735
	CA2: The hotel has increasing sales compared to the competitors.	0.835			
	CA3: The hotel has increasing revenue compared to the competitors.	0.886			
	CA4: The hotel has generated greater profit compared to the competitors.	0.883			
	CA5: The hotel can provide products at a lower cost compared to the competitors.	0.889			
	CA6: The hotel can provide services at a lower cost compared to the competitors.	0.845			
Decision making (**DM**)	DM1: I feel confident that I can Get the facts about the benefits of each choice.	0.921	0.952	0.962	0.807
	DM2: I feel confident that I can Get the facts about the risks and side effects of each choice.	0.880			
	DM3: I feel confident that I can Understand the information enough to be able to make a choice.	0.880			
	DM4: I feel confident that I can Ask questions without feeling dumb.	0.908			
	DM5: I feel confident that I can Express my concerns about each choice.	0.902			
	DM6: I feel confident that I can Figure out the choice that best suits me.	0.898			
Guest Engagement (**GE**)	GE1: When someone praises this hotel, it feels like a personal compliment.	0.921	0.946	0.959	0.822
	GE2: Anything related to this hotel grabs my attention.	0.914			
	GE3: When I am interacting with the hotel, I forget everything else around me.	0.900			
	GE4: In general, I like to get involved in hotel community discussions.	0.917			
	GE5: I often participate in activities of the hotel community.	0.881			
Guest Loyalty (**GL**)	GL1: If available, I will stay in the hotel the next time I travel.	0.924	0.930	0.950	0.826
	GL2: I intend to keep staying with this hotel.	0.909			
	GL3: I am committed to this hotel.	0.899			
	GL4: I would be willing to pay a higher price for this hotel over other hotels.	0.902			

Trust (TR)	TR1: I believe that the hotel is concerned about my interest.	0.927	0.950	0.962	0.834
	TR2: I feel that the hotel is trustworthy.	0.916			
	TR3: I have confidence in the products and services of the hotel.	0.922			
	TR4: I feel that the hotel has the ability to provide good products.	0.907			
	TR5: I feel that the hotel has the ability to provide good services.	0.892			

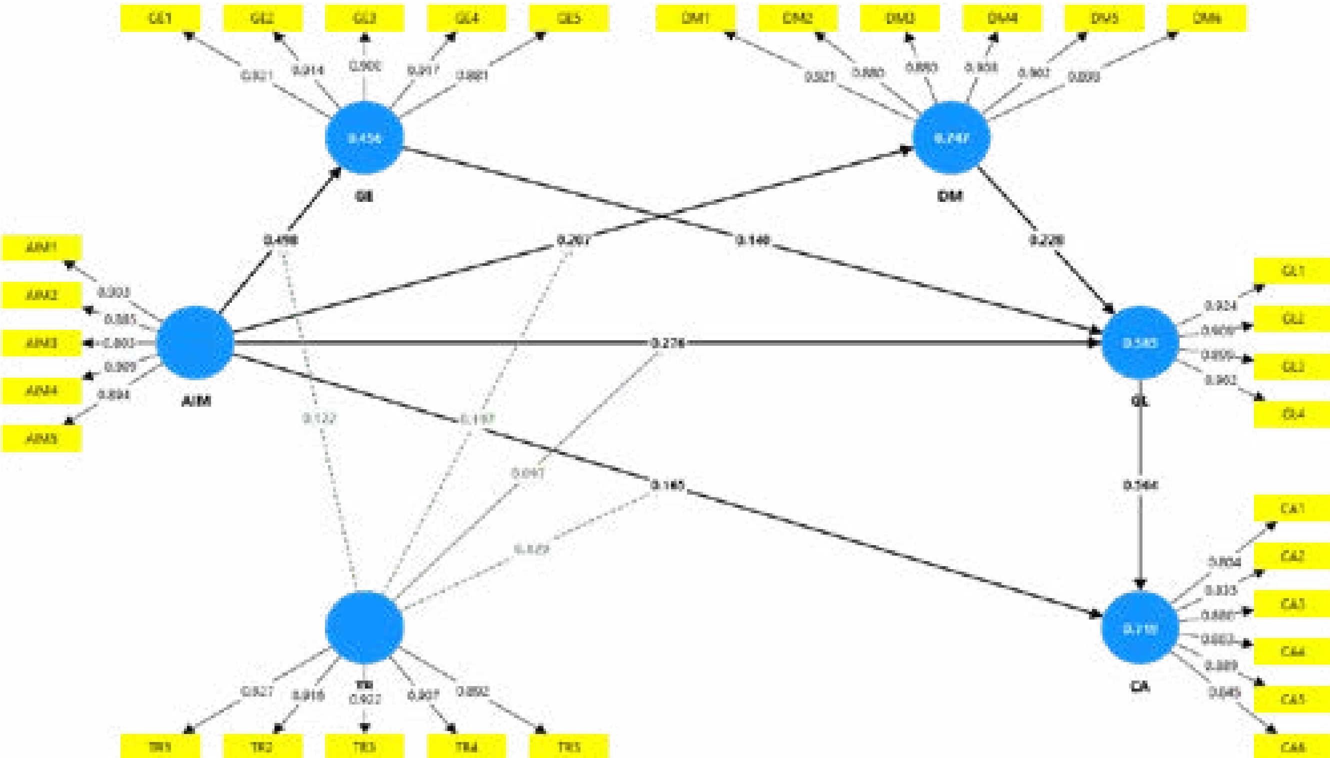

Figure 2. Estimated model diagram

The Heterotrait-Monotrait (HTMT) ratio was used to assess discriminant validity, which ensures that constructs differ from one another. As shown in Table 5, all HTMT values fell below the 0.85 threshold (Hair et al., 2019), indicating that the constructs are empirically distinct and do not overlap significantly. For instance, the highest HTMT value observed was 0.875 between CA and GL, which is still within the acceptable range. Similarly, the relationships between TR and other constructs, such as DM (HTMT = 0.832) and GL (HTMT = 0.641), further confirm the discriminant validity of the model.

Table 5. Results of HTMT.

Constructs	AIM	CA	DM	GE	GL	TR
AIM						
CA	0.714					
DM	0.682	0.728				
GE	0.684	0.583	0.594			
GL	0.707	0.875	0.731	0.616		
TR	0.569	0.617	0.832	0.485	0.641	

4.4.2 Structural Model Analysis

The structural model was investigated following the measurement model's reliability and validity tests. SmartPLS version 4 employed a bootstrapping method with 5000 sub-samples (Ringle et al., 2024). The R-square values for the structural model constructs were calculated to determine the independent variables' explanatory power. The findings show that CA had an R-square value of 0.719, DM had an R-square value of 0.747, GE had an R-square value of 0.456, and GL had an R-square value of 0.585. These results indicate that independent constructs accounted for a significant portion of the variance in the dependent constructs, with DM and CA providing strong explanatory power.

Table 6. Summary of structural model results (Direct effects).

Hypotheses	Beta	T statistics	P values	Decision
H1: AIM -> GE	0.498	6.599	0.000	Supported
H2: AIM -> DM	0.207	5.004	0.000	Supported
H3: AIM -> GL	0.276	4.072	0.000	Supported
H4: AIM -> CA	0.165	2.441	0.015	Supported
H5: GE -> GL	0.140	2.147	0.032	Supported
H6: DM -> GL	0.228	2.614	0.009	Supported
H7: GL -> CA	0.564	8.255	0.000	Supported

The structural model was evaluated by analyzing path coefficients, t-statistics, p-values, and hypothesis testing results, as shown in Table 6. The findings revealed that AIM had a significant positive influence on GE (**β** = 0.498, p < 0.001), DM (**β** = 0.207, p < 0.001), GL (**β** = 0.276, p < 0.001), and CA (**β** = 0.165, p < 0.05). Furthermore, GE positively influenced GL (**β** = 0.140, p < 0.05), while DM also had a significant positive effect on GL (**β** = 0.228, p < 0.01). Additionally, GL was found to impact CA strongly (**β** = 0.564, p < 0.001).

Table 7. Results of the Mediating Effects.

Hypotheses	Beta	T statistics	P values	Decision
H8. AIM -> GE -> GL	0.069	1.981	0.048	Supported
H9. AIM -> DM -> GL	0.047	2.103	0.035	Supported
H10a. AIM -> GE -> GL -> CA	0.039	1.842	0.066	Rejected
H10b. AIM -> DM -> GL -> CA	0.027	1.960	0.049	Supported

The mediating effects were examined in Table 7, confirming that both GE and DM significantly mediated the relationship between AIM and GL (H8: **β** = 0.069, p < 0.05; H9: **β** = 0.047, p < 0.05). However, the sequential mediation effect of AIM → GE → GL → CA was not statistically significant (**β** = 0.039, p = 0.066), leading to the rejection of H10a. In contrast, AIM → DM → GL → CA showed a significant mediation effect (**β** = 0.027, p < 0.05), supporting H10b.

Table 8. Results of the Moderating Effects.

Hypotheses	Beta	T statistics	*P* values	Decision
H11a: TR x AIM -> CA	0.129	3.902	0.000	Supported
H11b: TR x AIM -> DM	0.197	7.174	0.000	Supported
H11c: TR x AIM -> GL	0.097	2.050	0.040	Supported
H11d: TR x AIM -> GE	0.122	2.820	0.005	Supported

The moderating effects, as presented in Table 8, demonstrated that TR significantly moderated the relationships between AIM and CA (**β** = 0.129, p < 0.001), AIM and DM (**β** = 0.197, p < 0.001), AIM and GL (**β** = 0.097, p < 0.05), and AIM and GE (**β** = 0.122, p < 0.01). These findings indicate that TR strengthens the relationships between AIM and the respective dependent variables, reinforcing the robustness of the proposed structural model.

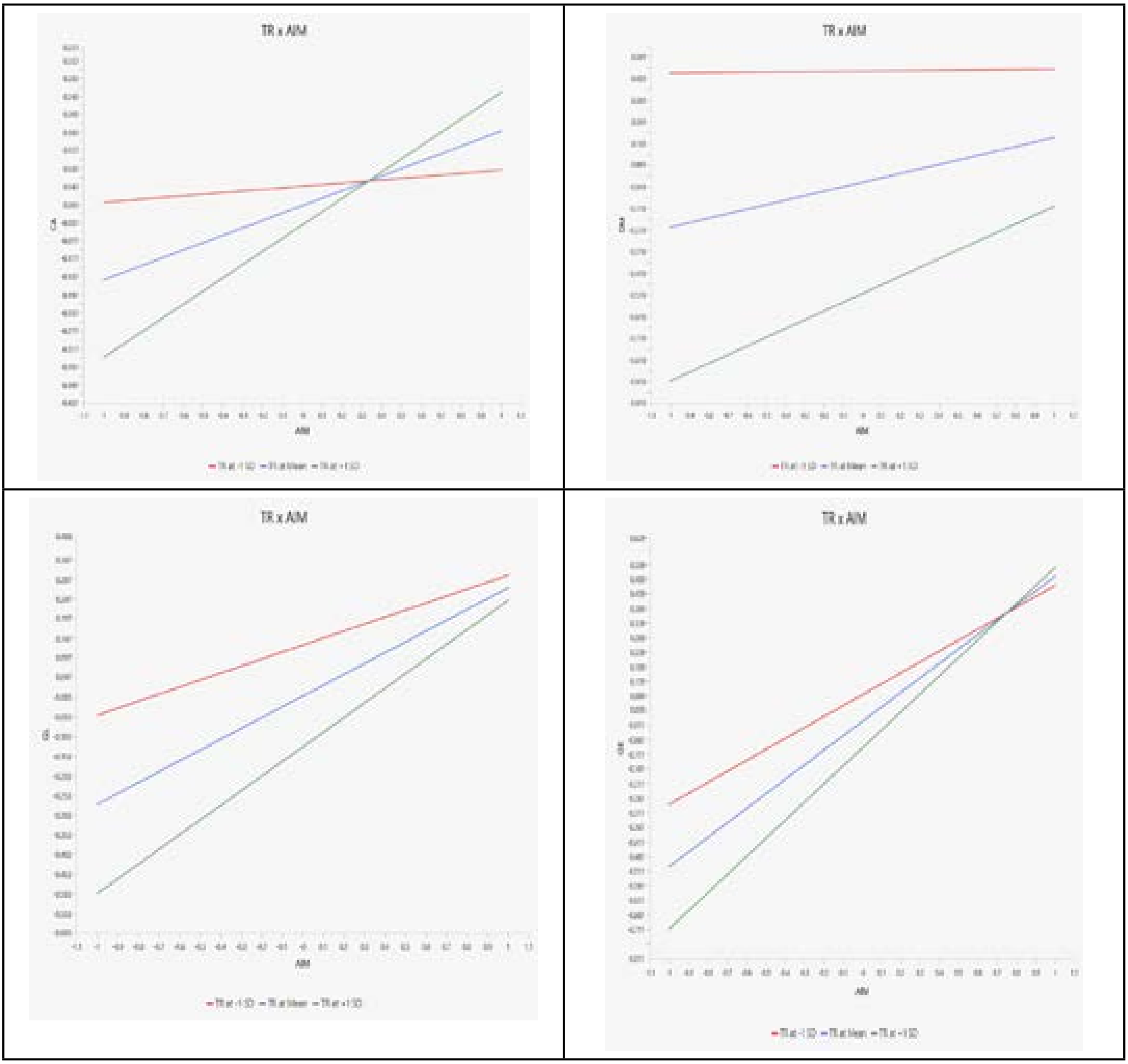

Figure 3. Graphical presentation of moderating effects

5. Discussion

The integration of AI and big data is reshaping the dynamics of the Saudi market by significantly enhancing advertising strategies and client satisfaction. By leveraging precise prospect targeting, tailored marketing, and sophisticated analytics, these technologies enable businesses to achieve a higher return on marketing investments, boost customer acquisition and retention, and optimize resource allocation. This study investigates the effects of AI-driven marketing strategies on tourist DM processes—with a focus on the comparative impact of social media and hospitality e-commerce channels on guest engagement (GE), satisfaction, and guest loyalty (GL) in Saudi Arabia's hospitality industry. Our model tests eleven hypotheses, incorporating GE and DM as mediators and trust as a moderator, with all hypotheses supported except for the mediating role of GE between AIM strategies and GL in driving CA.

Our findings confirm that AIM strategies exert a significant impact on GE, DM processes, GL, and ultimately CA, consistent with earlier research (Kumar et al., 2024; Sharma et al., 2021; Zed et al., 2024). Rane (2023) highlights the critical role of AI models and methods in boosting consumer engagement (CE) and satisfaction. By harnessing AI insights, businesses can tailor offerings to evolving consumer needs, thereby strengthening long-term customer connections and loyalty. A variety of advanced technologies—including big data analytics, machine learning, natural language processing, blockchain, augmented/virtual reality, the Internet of Things, cloud computing, social media listening, sentiment analysis, and gamification—provide companies with the tools to extract actionable insights, customize consumer experiences, and build trust, all of which contribute to sustained brand loyalty (Zamil et al., 2020). Furthermore, Abrokwah-Larbi and Awu-ku-Larbi (2024) note that AI-driven data collection and analysis can reveal previously unknown insights that empower SMEs to refine their DM, while Devarapalli (2022) emphasizes the growing academic and industry interest in AI for strategic marketing decisions. Zed et al. (2024) further support the positive link between AI-driven customization and GL, although Osakwe et al. (2022) caution that the overall success and CA depend on how organizations deploy their AI investments to build unique marketing competencies.

Our results also indicate that GE and effective DM processes are positively associated with GL. Active consumer participation in marketing communications creates added value that enhances brand satisfaction and loyalty. Customers engaging with a company's brand on social media report higher satisfaction levels, reinforcing the short-term positive relationship between consumer participation and brand loyalty. Studies have shown that customer interaction via social media significantly bolsters GL (Ajina, 2019), and research by Hapsari et al. (2020), Molinillo et al. (2020), and Zhang et al. (2021) supports a strong positive impact of customer involvement on GL. Zaid and Patwayati (2021) found that interaction and engagement directly boost customer happiness and GL, while customer experience indirectly influences these outcomes through consumer engagement. In the hotel industry, cognitive engagement has been shown to markedly enhance cognitive brand loyalty (Shin and Back, 2020), with additional evidence suggesting that customers' intentions to recommend platforms like Airbnb are clear indicators of GL (Sallaku and Vigolo, 2024; Widya Lelisa Army et al., 2024). Additionally, the DM process itself plays a crucial role in shaping customer perceptions, attitudes, intentions, and feedback, thereby influencing satisfaction and loyalty (Vo et al., 2022; Zhang et al., 2018; Redjeki et al., 2024).

The data further support that enhanced GL contributes directly to CA. Felix and Rembulan (2023) argue that measures such as improved online security, customized content, faster page loads, and live chat features can provide e-commerce companies with a competitive edge. Similarly, Edith Ebele Agu et al. (2024) emphasize the need for companies to integrate sustainability into their core strategies to maintain their CA amid shifting consumer demands. Al Karim et al. (2024) demonstrate that while mere client knowledge may not drive CA, a strong consumer focus coupled with robust technological capabilities—mediated by GL—is vital.

Our analysis reveals that while the mediating effect of GE is confirmed in most pathways, it is not significant between AIM strategies and CA. This nuanced finding suggests that while GE is crucial for enhancing overall engagement and loyalty, its role in directly mediating the impact of AIM on CA may be more complex. Riyanto et al. (2021) and others (Machmed Tun Ganyang, 2019; Alagarsamy et al., 2023) have shown that effective communication and employee engagement are essential to fostering a cohesive work environment, which in turn can influence overall organizational success. Furthermore, research by Sofi et al. (2025) indicates that visitor involvement moderates the relationship between satisfaction and GL, underscoring the need for deeper exploration of these mediating dynamics.

The mediation effect of the DM process is significant in our study. Boulesnane and Bouzidi (2013) underscore the importance of synthesizing diverse data streams to allocate resources effectively for strategic DM. Xu and Tracey (2015) further illustrate how DM self-efficacy mediates the relationship between various organizational factors and decision outcomes. Lastly, trust emerges as a critical moderator. Consistent with Zhou et al. (2022) and Li et al. (2020), trust significantly enhances the link between consumer engagement and brand loyalty. Tian et al. (2023) highlight that high levels of trust are linked to greater acceptance of digital innovations such as e-wallets, whereas Khaliq et al. (2022) note that mutual trust can modulate the effects of AI on operational outcomes. Integrating AI and DM technologies with human-generated data ultimately fosters more personalized consumer experiences and strengthens trust in digital platforms (Rabby et al., 2021).

6. Theoretical and practical implications

Our study contributes a distinct perspective on the role of AI-driven customization in promoting visitor engagement and CA within the Saudi hospitality sector. By integrating social media interaction, AIM, and personalization tactics, we extend the scant literature on AIM in this region. Utilizing Social Exchange Theory

(SET) and the Resource-Based View (RBV) to validate our variables, our RBV-oriented framework effectively links the success of AIM techniques to CA. In line with RBV, the study demonstrates that investments in various AI technologies—used to analyze data, monitor client needs, and adapt strategies—are vital resources that can transform customer data into a strategic asset. Moreover, our empirical findings on the impact of AIM tactics on guest loyalty (GL) add to the literature, showing a direct, significant relationship between visitor engagement and GL, consistent with Self-Determination Theory (SDT). By harnessing Big Data, companies can extract actionable insights, identify patterns, and forecast trends to deliver personalized experiences that drive sustained customer satisfaction and loyalty (Zamil et al., 2020; Abrokwah-Larbi and Awu-ku-Larbi, 2024; Devarapalli, 2022).

To implement the recommendations from our study, we propose a comprehensive strategic action plan that calls on key stakeholders in the Saudi hospitality industry to act collaboratively. First, advanced AI algorithms and big data analytics should be deployed to enhance personalized customer interactions across digital and social media platforms. Marketing managers, social media managers, and digital transformation teams are responsible for this initiative, which should commence with a 3- to 6-month pilot phase and progress to full-scale implementation within 12 months. It is recommended that approximately 15–20% of the annual marketing budget be allocated for AI technology acquisition, analytics platforms, and relevant training (Fischer, 2024). Concurrently, data analytics teams—working in close coordination with marketing and IT departments—should leverage customer data to pinpoint behavioral trigger points and tailor marketing communications and offers. This initiative should be set up within 3 months, with continuous refinement over the following year through investments in advanced analytics software and specialized training programs. Furthermore, to optimize DM processes, DM managers, customer experience teams, and IT departments must integrate AI-driven insights into their operational planning by deploying interactive tools such as chatbots and instant messaging services. A pilot test for these solutions is advised for a period of 3 months, with full integration expected within 6–9 months, supported by allocated resources for technology integration and staff training. In addition, building trust in AIM systems is critical; therefore, brand managers, HR departments, and digital trust teams should implement trust-building measures—such as ensuring transparency in AI operations, securing digital infrastructure, and maintaining consistent service delivery—within a short-term timeframe of 1–3 months, with ongoing enhancements supported by regular customer service training and performance audits (Li et al., 2020; Khaliq et al., 2022). Finally, fostering innovation and employee engagement is essential to sustain these initiatives. HR managers and organizational leaders should integrate AI and DM technologies into daily operations by launching initial training programs within 6 months and scheduling periodic refreshers, with a dedicated portion of the HR development budget earmarked for this purpose. Collectively, these strategic actions are designed to enhance guest engagement, streamline DM processes, and ultimately secure a sustainable CA in the Saudi hospitality industry (Vo et al., 2022; Zhang et al., 2018; Zamil et al., 2020).

7. Conclusions and Study Limitations

AI and big data also affect the dynamics of the Saudi market. It has been shown that AI and big data improve advertising tactics and customer happiness. With a focus on the relative contributions of social media platforms and hospitality e-commerce channels to enhancing GE, satisfaction, and GL in Saudi Arabia's hospitality sector, the study aims to explore how AI-driven marketing strategies impact the DM processes of tourists. Eleven hypotheses are tested, including the moderating variable of trust and the mediating variables of visitor involvement and DM. The findings validate every hypothesis except for the mediation function of guest involvement between AIM techniques and GL toward CA. Although the study provides insightful information, it should be noted that it has many limitations. There is not enough information in the dataset to assess how social media usage affects Saudi Arabia's hotel industry's efforts to increase GL. However, a larger sample size might improve a future study's validity and capacity for generalization in this situation.

Furthermore, we could only interview the two managers due to time and resource limitations. As a result, qualitative research has also encountered limitations, and expanding the number of interviews might yield further insights into the banking industry. The emphasis goes beyond consumer behaviour, business management, and technology. Instead, the initiative encompasses uncharted territories that intersect various sectors. By developing a thorough model or theory that accurately captures the present state of AI system adoption in the marketing industry, it is feasible to clear the way for the future. For a more thorough understanding of satisfaction and engagement, future studies might examine the influence of organizational elements, such as service provider training or company culture, in designing AIM strategies. The factors of AIM techniques, such as database automation of marketing and digital buyer-seller interaction, were not considered in this study. Future studies should focus on how AIM techniques may evaluate consumer communications and data, including social media postings, to create messages that could improve CE.

Author Contributions: “Conceptualization, KZ, AA, HA, TA, EA, KA, A Abuzaid and AE; Data curation, AA, HA and KA; Formal analysis, TA and EA; Funding acquisition, AA; Investigation, A A, HA, EA, KA and Alaa Abuzaid; Methodology, HA, EA, Alaa Abuzaid and AE; Project administration, KZ; Resources, AA, HA, KA and Alaa Abuzaid; Software, TA and EA; Supervision, KZ; Validation, TA; Visualization, TA, AAbuzaid and AE; Writing – original draft, KZ, AA and AE; Writing – review & editing, KZ,HA and AE.

Funding: This study is supported via funding from Prince Sattam Bin Abdulaziz University, Saudi Arabia (Project number: PSAU/2025/R/1446).

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki.

Informed Consent Statement: Informed consent was obtained from all subjects involved in this study

Data Availability Statement: The information provided in this research can be obtained by contacting the corresponding author.

Acknowledgments: The Researchers would like to thank the Prince Sattam Bin Abdulaziz University, Saudi Arabia for financial support (PSAU/2025/R/1446).

Conflict of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

References

Abrokwah-Larbi, K., Awuku-Larbi, Y., 2024. The impact of artificial intelligence in marketing on the performance of business organizations: evidence from SMEs in an emerging economy. J. Entrep. Emerg. Econ. 16, 1090–1117. https://doi.org/10.1108/JEEE-07-2022-0207

Adesoga, T. o, Olaiya, O.P., Obani, O.Q., Orji, M.C.U., Orji, C.A., Olagunju, O.D., 2024. Leveraging AI for transformative business development: Strategies for market analysis, customer insights, and competitive intelligence. Int. J. Sci. Res. Arch. 12, 799–805. https://doi.org/10.30574/ijsra.2024.12.2.1291

Ahmed, S., 2024. Exploring the Influence of AI on Tourism Development Strategies in Saudi Arabia. Int. J. Sci. Res. 3, 291–314. https://doi.org/10.59992/IJSR.2024.v3n7p13

Ajina, A.S., 2019. The role of social media engagement in influencing customer loyalty in Saudi banking industry. Int. Rev. Manag. Mark. 9, 87–92. https://doi.org/10.32479/irmm.8060

Al Karim, R., Alam, M.M.D., Al Balushi, M.K., 2024. The nexus between CRM and competitive advantage: the mediating role of customer loyalty. Nankai Bus. Rev. Int. 15, 248–268. https://doi.org/10.1108/NBRI-04-2022-0040

Alagarsamy, S., Mehrolia, S., Aranha, R.H., 2023. The Mediating Effect of Employee Engagement: How Employee Psychological Empowerment Impacts the Employee Satisfaction? A Study of Maldivian Tourism Sector. Glob. Bus. Rev. 24, 768–786. https://doi.org/10.1177/0972150920915315

Alhumaid, M.M., Alotaibi, I.S., 2025. Artificial Intelligence, Big Data, and Their Impact on Improving Marketing Effectiveness and Customer Experience in the Retail Sector in the Kingdom of Saudi Arabia. Jazan Univ. J. Hum. Sci. 13, 224–240.

Aljizawi, J., 2024. Personalized Travel Recommendations and Marketing Automation for Saudi Arabia: Harnessing AI for Enhanced User Experience and Business Growth. Effat Univ. 1–43.

Aljuwaiber, A., Elnagar, A.K., 2022. Predicting Pilgrim and Visitor Satisfaction Through Using Smartphone Applications at Holy Sites During Covid-19. Virtual Econ. 5, 91–108. https://doi.org/10.34021/ve.2022.05.03(5)

Alnasser, E.M., Alkhozaim, S.M., Alshiha, A.A., Al-Romeedy, B.S., 2024. The Impact of Artificial Intelligence on the Marketing Performance of Tourism and Hospitality Businesses: The Mediating Role of Marketing Innovation, in: Nadda, V., Tyagi, P.K., Singh, A., Singh, V. (Eds.), Advances in Hospitality, Tourism, and the Services Industry. IGI Global, pp. 375–396. https://doi.org/10.4018/979-8-3693-7909-7.ch019

Alotaibi, I.S., 2024. A theoretical exploration study of artificial intelligence applications in marketing within Saudi Arabia. Univ. Tabuk 4, 20–38.

Alvarez-Milán, A., Felix, R., Rauschnabel, P.A., Hinsch, C., 2018. Strategic customer engagement marketing: A decision making framework. J. Bus. Res. 92, 61–70. https://doi.org/10.1016/j.jbusres.2018.07.017

Alzahrani, A., Alshehri, A., Alamri, M., Alqithami, S., 2025. AI-Driven Innovations in Tourism: Developing a Hybrid Framework for the Saudi Tourism Sector. AI 6, 7. https://doi.org/10.3390/ai6010007

Boulesnane, S., Bouzidi, L., 2013. The mediating role of information technology in the decision-making context. J. Enterp. Inf. Manag. 26, 387–399. https://doi.org/10.1108/JEIM-01-2012-0001

Chen, S., Han, X., Bilgihan, A., Okumus, F., 2021. Customer engagement research in hospitality and tourism: a systematic review. J. Hosp. Mark. Manag. 30, 871–904. https://doi.org/10.1080/19368623.2021.1903644

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. Front. Psychol. 13, 912339. https://doi.org/10.3389/fpsyg.2022.912339

Chernyak-Hai, L., Rabenu, E., 2018. The New Era Workplace Relationships: Is Social Exchange Theory Still Relevant? Ind. Organ. Psychol. 11, 456–481. https://doi.org/10.1017/iop.2018.5

Chintalapati, S., Pandey, S.K., 2022. Artificial intelligence in marketing: A systematic literature review. Int. J. Mark. Res. 64, 38–68. https://doi.org/10.1177/14707853211018428

Derbali, A., Elnagar, A.K., 2020. Measuring Student and Staff Satisfaction with the University Facilities. Virtual Econ. 3, 25–52. https://doi.org/10.34021/ve.2020.03.03(2)

Devarapalli, S.P., 2022. Artificial intelligence in marketing 1–7.

Edith Ebele Agu, Toluwalase Vanessa Iyelolu, Courage Idemudia, Tochukwu Ignatius Ijomah, 2024. Exploring the relationship between sustainable business practices and increased brand loyalty. Int. J. Manag. Entrep. Res. 6, 2463–2475. https://doi.org/10.51594/ijmer.v6i8.1365

Elnagar, A., Derbali, A., 2020. The importance of tourism contributions in Egyptian economy. Int. J. Hosp. Tour. Stud. 1, 45–52. https://doi.org/10.31559/IJHTS2020.1.1.5

Elshaer, I.A., Azazz, A.M.S., Elsaadany, H.A.S., Elnagar, A.K., 2024. Social CRM Strategies: A Key Driver of Strategic Information Exchange Capabilities and Relationship Quality. Information 15, 329. https://doi.org/10.3390/info15060329

Felix, A., Rembulan, G.D., 2023. Analysis of Key Factors for Improved Customer Experience, Engagement, and Loyalty in the E-Commerce Industry in Indonesia. Aptisi Trans. Technopreneurship ATT 5, 196–208. https://doi.org/10.34306/att.v5i2sp.350

Fischer, T., 2024. Driving business growth through AI-driven customer insights: leveraging big data analytics for competitive advantage. J. Artif. Intell. Res. Appl. 41, 56–72.

Gabelaia, I., 2024. The Applicability of Artificial Intelligence Marketing for Creating Data-driven Marketing Strategies. J. Mark. Res. Case Stud. 1–11. https://doi.org/10.5171/2022.466404

Hair, J.F., Black, W.C., Babin, B.Y., Anderson, R.E., 2019. Multivariate data analysis, Eight Edition. ed. Springer International Publishing, Cengage.

Hapsari, R., Hussein, A.S., Handrito, R.P., 2020. Being Fair to Customers: A Strategy in Enhancing Customer Engagement and Loyalty in the Indonesia Mobile Telecommunication Industry. Serv. Mark. Q. 41, 49–67. https://doi.org/10.1080/15332969.2019.1707375

Harden, G., Boakye, K.G., Ryan, S., 2018. Turnover Intention of Technology Professionals: A Social Exchange Theory Perspective. J. Comput. Inf. Syst. 58, 291–300. https://doi.org/10.1080/08874417.2016.1236356

Hossain, M.A., Agnihotri, R., Rushan, M.R.I., Rahman, M.S., Sumi, S.F., 2022. Marketing analytics capability, artificial intelligence adoption, and firms' competitive advantage: Evidence from the manufacturing industry. Ind. Mark. Manag. 106, 240–255. https://doi.org/10.1016/j.indmarman.2022.08.017

Jain, P., Aggarwal, K., 2020. Transforming Marketing with Artificial Intelligence. https://doi.org/10.13140/RG.2.2.25848.67844

Khalifa, G.S.A., Elshaer, A.M., Hussain, K., Elnagar, A.K., 2025. What drives customers' participation behaviour? Unveiling the drivers of affective satisfaction and its impacts in the restaurant industry. J. Hosp. Tour. Insights 8, 612–636. https://doi.org/10.1108/JHTI-01-2024-0100

Khaliq, A., Waqas, A., Nisar, Q.A., Haider, S., Asghar, Z., 2022. Application of AI and robotics in hospitality sector: A resource gain and resource loss perspective. Technol. Soc. 68, 101807. https://doi.org/10.1016/j.techsoc.2021.101807

Kock, N., 2015. Common Method Bias in PLS-SEM: A Full Collinearity Assessment Approach. Int. J. E-Collab. 11, 1–10. https://doi.org/10.4018/ijec.2015100101

Kshetri, N., Dwivedi, Y.K., Davenport, T.H., Panteli, N., 2024. Generative artificial intelligence in marketing: Applications, opportunities, challenges, and research agenda. Int. J. Inf. Manag. 75, 102716. https://doi.org/10.1016/j.ijinfomgt.2023.102716

Kumar, A.B.R., 2021. AI-Based Digital Marketing Strategies—A Review, in: Smys, S., Balas, V.E., Kamel, K.A., Lafata, P. (Eds.), Inventive Computation and Information Technologies, Lecture Notes in Networks and Systems. Springer Nature Singapore, Singapore, pp. 957–969. https://doi.org/10.1007/978-981-33-4305-4_70

Kumar, V., Ashraf, A.R., Nadeem, W., 2024. AI-powered marketing: What, where, and how? Int. J. Inf. Manag. 77, 102783. https://doi.org/10.1016/j.ijinfomgt.2024.102783

Labib, E., 2024. Artificial intelligence in marketing: exploring current and future trends. Cogent Bus. Manag. 11, 2348728. https://doi.org/10.1080/23311975.2024.2348728

Li, M.-W., Teng, H.-Y., Chen, C.-Y., 2020. Unlocking the customer engagement-brand loyalty relationship in tourism social media: The roles of brand attachment and customer trust. J. Hosp. Tour. Manag. 44, 184–192. https://doi.org/10.1016/j.jhtm.2020.06.015

Machmed Tun Ganyang, G., 2019. The The Impact of Organization culture and Work Environment on Employee Engagement and It's Implication on Employee Performance of The Automotive Industry In Jakarta,

Indonesia. Arch. Bus. Res. 7, 64–70. https://doi.org/10.14738/abr.79.6789
Miller, D., 2019. The Resource-Based View of the Firm, in: Oxford Research Encyclopedia of Business and Management. Oxford University Press. https://doi.org/10.1093/acrefore/9780190224851.013.4
Mofokeng, T.E., 2023. Antecedents of trust and customer loyalty in online shopping: The moderating effects of online shopping experience and e-shopping spending. Heliyon 9, e16182. https://doi.org/10.1016/j.heliyon.2023.e16182
Molinillo, S., Anaya-Sánchez, R., Liébana-Cabanillas, F., 2020. Analyzing the effect of social support and community factors on customer engagement and its impact on loyalty behaviors toward social commerce websites. Comput. Hum. Behav. 108, 105980. https://doi.org/10.1016/j.chb.2019.04.004
Nobar, H.B.K., Rostamzadeh, R., 2018. THE IMPACT OF CUSTOMER SATISFACTION, CUSTOMER EXPERIENCE AND CUSTOMER LOYALTY ON BRAND POWER: EMPIRICAL EVIDENCE FROM HOTEL INDUSTRY. J. Bus. Econ. Manag. 19, 417–430. https://doi.org/10.3846/jbem.2018.5678
O'Connor, A.M., 1995. User manual - Decision Self-Efficacy Scale. Ott. Hosp. Res. Inst.
Osakwe, J., Waiganjo, I.N., Tarzoor, T., Iyawa, G., Ujakpa, M., 2022. Determinants of Information Systems Resources for Business Organisations' Competitive Advantage: A Resource-Based View Approach, in: 2022 IST-Africa Conference (IST-Africa). Presented at the 2022 IST-Africa Conference (IST-Africa), IEEE, Ireland, pp. 1–8. https://doi.org/10.23919/IST-Africa56635.2022.9845670
Prentice, C., Weaven, S., Wong, I.A., 2020. Linking AI quality performance and customer engagement: The moderating effect of AI preference. Int. J. Hosp. Manag. 90, 102629. https://doi.org/10.1016/j.ijhm.2020.102629
Rabby, F., Chimhundu, R., Hassan, R., 2021. Artificial intelligence in digital marketing influences consumer behaviour: a review and theoretical foundation for future research. Acad. Mark. Stud. J. 25, 1–7.
Rane, N., 2023. Enhancing Customer Loyalty through Artificial Intelligence (AI), Internet of Things (IoT), and Big Data Technologies: Improving Customer Satisfaction, Engagement, Relationship, and Experience. SSRN Electron. J. https://doi.org/10.2139/ssrn.4616051
Rather, R.A., Hollebeek, L.D., 2019. Exploring and validating social identification and social exchange-based drivers of hospitality customer loyalty. Int. J. Contemp. Hosp. Manag. 31, 1432–1451. https://doi.org/10.1108/IJCHM-10-2017-0627
Redjeki, F., Amrita, N.D.A., Faisal, I., 2024. Implication of loyalty programme competition on customer decision making in the banking industry. J. Dev. Community Serv. 1, 1–16.
Riyanto, S., Endri, E., Herlisha, N., 2021. Effect of work motivation and job satisfaction on employee performance: Mediating role of employee engagement. Probl. Perspect. Manag. 19, 162–174. https://doi.org/10.21511/ppm.19(3).2021.14
Sallaku, R., Vigolo, V., 2024. Predicting customer loyalty to Airbnb using PLS-SEM: the role of authenticity, interactivity, involvement and customer engagement. TQM J. 36, 1346–1368. https://doi.org/10.1108/TQM-12-2021-0348
Sharma, A., Patel, N., Gupta, R., 2021. Enhancing ad targeting through AI-powered audience segmentation: Leveraging K-means clustering and random forest algorithms. Eur. Adv. AI J. 10.
Shin, M., Back, K.-J., 2020. Effect of Cognitive Engagement on the Development of Brand Love in a Hotel Context. J. Hosp. Tour. Res. 44, 328–350. https://doi.org/10.1177/1096348019890055
So, K.K.F., King, C., Sparks, B.A., Wang, Y., 2016. The Role of Customer Engagement in Building Consumer Loyalty to Tourism Brands. J. Travel Res. 55, 64–78. https://doi.org/10.1177/0047287514541008
Sofi, M.R., Bashir, I., Alshiha, A., Alnasser, E., Alkhozaim, S., 2025. Creating exceptional guest experiences: the role of engagement and relationship building in hospitality. J. Hosp. Tour. Insights 8, 891–914. https://doi.org/10.1108/JHTI-04-2024-0318
Stone, M., Aravopoulou, E., Ekinci, Y., Evans, G., Hobbs, M., Labib, A., Laughlin, P., Machtynger, J., Machtynger, L., 2020. Artificial intelligence (AI) in strategic marketing decision-making: a research agenda. Bottom Line 33, 183–200. https://doi.org/10.1108/BL-03-2020-0022
Tian, Y., Chan, T.J., Suki, N.M., Kasim, M.A., 2023. Moderating Role of Perceived Trust and Perceived Service Quality on Consumers' Use Behavior of Alipay e-wallet System: The Perspectives of Technology Acceptance Model and Theory of Planned Behavior. Hum. Behav. Emerg. Technol. 2023, 1–14. https://

doi.org/10.1155/2023/5276406

Varadarajan, R., 2020. Customer information resources advantage, marketing strategy and business performance: A market resources-based view. Ind. Mark. Manag. 89, 89–97. https://doi.org/10.1016/j.indmarman.2020.03.003

Vlačić, B., Corbo, L., Costa E Silva, S., Dabić, M., 2021. The evolving role of artificial intelligence in marketing: A review and research agenda. J. Bus. Res. 128, 187–203. https://doi.org/10.1016/j.jbusres.2021.01.055

Vo, N.T., Hung, V.V., Tuckova, Z., Pham, N.T., Nguyen, L.H.L., 2022. Guest Online Review: An Extraordinary Focus on Hotel Users' Satisfaction, Engagement, and Loyalty. J. Qual. Assur. Hosp. Tour. 23, 913–944. https://doi.org/10.1080/1528008X.2021.1920550

Widya Lelisa Army, Arif Nugroho, Sri Anita, Siti Sarah, 2024. The Customer Engagement Effect on Customer Loyalty (Case Study: Marketplace Retailer). J. Cahaya Mandalika ISSN 2721-4796 Online 5, 379–389. https://doi.org/10.36312/jcm.v5i1.2686

Xu, H., Tracey, T.J.G., 2015. Ambiguity Tolerance with Career Indecision: An Examination of the Mediation Effect of Career Decision-Making Self-Efficacy. J. Career Assess. 23, 519–532. https://doi.org/10.1177/1069072714553073

Zaid, S., Patwayati, P., 2021. Impact of Customer Experience and Customer Engagement on Satisfaction and Loyalty: A Case Study in Indonesia. J. Asian Finance Econ. Bus. 8, 983–992. https://doi.org/10.13106/JAFEB.2021.VOL8.NO4.0983

Zaki, K., Alhomaid, A., Ghareb, A., Shared, H., Raslan, A., Khalifa, G.S.A., Elnagar, A.K., 2025. Digital Synergy and Strategic Vision: Unlocking Sustainability-Oriented Innovation in Saudi SMEs. Adm. Sci. 15, 59. https://doi.org/10.3390/admsci15020059

Zaki, K., Elnagar, A.K., 2025. Unpacking talent management: a moderated mediation analysis of team dynamics and competitive performance in luxury hotels. Empl. Relat. Int. J. 47, 48–77. https://doi.org/10.1108/ER-02-2024-0114

Zaki, K., Alhomaid, A., & Shared, H. (2025). Leveraging Machine Learning to Analyze Influencer Credibility's Impact on Brand Admiration and Consumer Purchase Intent in Social Media Marketing. *Human Behavior and Emerging Technologies*, *2025*(1), 9959697. https://doi.org/10.1155/hbe2/9959697

Zamil, A.M.A., Adwan, A.A., Vasista, T.G., 2020. (2020). Enhancing Customer Loyalty with Market Basket Analysis Using Innovative Methods: A Python Implementation Approach. Int. J. Innov. 14, 1352–1368.

Zed, E.Z., Kartini, T.M., Purnamasari, P., 2024. The Power Of Personalization : Exploring The Impact Of Ai-Driven Marketing Strategies On Consumer Loyalty In E-Commerce. J. Ekon. 13, 1303–1314.

Zhang, C., Ma, S., Li, S., Singh, A., 2021. Effects of customer engagement behaviors on action loyalty: moderating roles of service failure and customization. Int. J. Contemp. Hosp. Manag. 33, 286–304. https://doi.org/10.1108/IJCHM-08-2019-0740

Zhang, H., Zhao, L., Gupta, S., 2018. The role of online product recommendations on customer decision making and loyalty in social shopping communities. Int. J. Inf. Manag. 38, 150–166. https://doi.org/10.1016/j.ijinfomgt.2017.07.006

Zhou, G., Gul, R., Tufail, M., 2022. Does Servant Leadership Stimulate Work Engagement? The Moderating Role of Trust in the Leader. Front. Psychol. 13, 925732. https://doi.org/10.3389/fpsyg.2022.925732