journalism and media

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Investigating the Role of Artificial Intelligence to Measure Consumer Efficiency: The Use of Strategic Communication and Personalized Media Content

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Abstract: This study examines the relationships between strategic communication, personalized media content, AI, and consumer service efficiency in social marketing companies in Saudi Arabia. The study used a cluster sampling technique with a quantitative research design. The study targeted 498 responses via distributing the survey links on social media platforms. Using the SEM analysis in Smart PLS 4, this research tested the research hypotheses. The findings showed that strategic communication significantly improves personalized media content and consumer service efficiency, confirming its importance in business customer interactions and outcomes. Customized media content does not significantly improve consumer service efficiency, suggesting other mediating factors may be involved. AI mediates this relationship, bridging strategic inputs and service outcomes. AI boosts strategic communication and personalized content, improving consumer service efficiency. The results showed that AI fully mediates strategic communication and personalized media content into improved service efficiency, demonstrating its transformative potential in business communications and operations. The study shows that AI supports and improves digital marketing communication strategies. It is statistical evidence and confidence intervals that exclude zero, AI-enabled the application of personalized content and strategic directives to improve service efficiency in the mediation analysis.

Keywords: strategic communication; personalized media content; consumer service efficiency; AI; social media companies

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Citation: Binlibdah, Saud. 2024. Investigating the Role of Artificial Intelligence to Measure Consumer Efficiency: The Use of Strategic Communication and Personalized Media Content. *Journalism and Media* 5: 1142–1161. https://doi.org/10.3390/journalmedia5030073

Academic Editors: Rashid Mehmood and João Canavilhas

Received: 14 June 2024
Revised: 28 July 2024
Accepted: 30 July 2024
Published: 21 August 2024

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1. Introduction

The use of strategic communication and personalized media content to improve customer service in the Saudi Arabian market has greatly influenced the evolution of e-commerce in the digital age. Al-Jehani et al. (2021) examine how AI-assisted social media marketing affects Saudi Arabian SMEs and how AI improves business management through targeted intelligent marketing. Alqahtani and Alqahtani (2022) examine AI techniques in e-commerce and how they could improve consumer interactions and business processes in Saudi Arabia. AlGosaibi et al. (2020) propose an intelligent framework to improve service quality in government organizations, showing how AI can improve service delivery and customer satisfaction through smart, adaptive communication. Al-Baity (2023) proposes a comprehensive framework that highlights AI's transformative impact on digital finance, highlighting its role in improving customer interactions and service efficiency through advanced analytics and personalized content.

Personalization is crucial in email marketing and health campaigns to improve relevance and impact by tailoring content to individual traits (Dijkstra 2008; Pfiffelmann et al. 2020; Upadhyaya 2024). Personalization is the incorporation of recognizable personal aspects into content (Al-Jehani et al. 2021). It can include personally identifying information, past behaviors, or group characteristics such as gender. Marketing often uses cue-based personalization, such as a consumer's name or location, to draw attention and improve message relevance (Hawkins et al. 2008). Some studies show that such strategies increase consumer engagement (Maslowska et al. 2016). while others note potential negative reactions, primarily when privacy concerns are raised. AI-enabled personalization has advanced and become more subtle (Boerman et al. 2017). AI role in personalization, especially in consumer service and strategic communication, is a promising area of research for efficiency and engagement (Cheng and Jiang 2022; Huang and Rust 2021a, 2021b). Strategic communication using AI involves planning and implementing communication methods and tools to achieve organizational goals. This involves using AI to analyze, optimize, and implement communication strategies to improve engagement, understanding, and effectiveness across platforms and audiences. The goal is to streamline, personalize, and improve communications using AI.

Despite extensive research on personalization, strategic communication's effects on personalized media content are still unclear. Strategic communication, which involves an organization using communication to achieve its mission (Coombs 2015), shapes personalized content. However, strategic communication and personalization in digital and social media contexts should be studied more. Previous studies have focused on the direct effects of personalization cues (Pfiffelmann et al. 2020) without addressing how strategic communication strategies affect personalization. The digital age expects immediate and personalized responses, so consumer service efficiency—the effectiveness and promptness of service delivery (Gursoy et al. 2019)—is crucial. AI-driven personalization improves service efficiency and customer satisfaction (Bag et al. 2022; Buhalis and Moldavska 2022), but little is known about how it affects media content perception. The impact of consumer service efficiency on the reception and effectiveness of personalized media content needs further study to understand AI potential to improve consumer experiences fully.

Another research gap is how AI mediates strategic communication, consumer service efficiency, and personalized media content. AI can analyze massive amounts of data and create personalized content (Ameen et al. 2022; Hawkins et al. 2008). The mechanisms by which AI improves strategic communication and personalization or service efficiency and personalization are unclear. This mediating role can illuminate how AI can optimize personalization strategies. Since the personalization-privacy paradox shows the conflict between personalization benefits and privacy concerns (Awad and Krishnan 2006), strategic communication and service efficiency may help mitigate privacy concerns when using AI for personalization. Data show that privacy concerns can reduce the effectiveness of personalized advertising (Gurau et al. 2003), but ways to address these concerns through better communication and service delivery are scarce.

Finally, AI's personalization effects need further study. Many overlook AI's ethical and practical implications despite its potential to improve personalized media content (Huang and Rust 2021a; Mustak et al. 2021). Sustainable and consumer-friendly personalization strategies that balance technological capabilities with user expectations and privacy rights must address these issues. Based on the research gaps and problem statement, the study offers the following research objectives:

1. To examine the effect of strategic communication on consumer service efficiency;
2. To investigate the effect of personalized media content on consumer service efficiency;
3. To explore the mediating role of artificial intelligence between strategic communication, personalized media content and consumer service efficiency.

2. Literature Review

2.1. What Is Personalized Media Content?

Social media marketing and campaigns have extensively studied personalization. Dijkstra (2008, p. 768) defines personalization as "incorporating recognizable aspects of a person in the content information." Personal details such as a person's name or picture, past behaviors such as websites visited or movies watched, or group characteristics such as gender may be considered. These traits describe many people, but their combination may identify one person (Basri 2020). Social media marketing often uses cue-based personalization to include a consumer's name, employer, or town in the header or body. This approach keeps the persuasive message generic for all recipients and adds personal cues to grab attention (Hawkins et al. 2008).

Research shows that people process information with their names (Tacikowski and Nowicka 2010) and pay more attention to first-name ads than non-personalized ads (Bang and Wojdynski 2016). Despite being less noticeable or visited, Pfiffelmann et al. (2020) found that personalized ads capture more frequent and prolonged visual attention. Cue-based personalization may also increase self-referencing and heuristic or central processing (De Keyzer et al. 2015). This personalization enhances message development (Maslowska et al. 2016). Many studies have used cue-based personalization (Sahni 2016), but some studies have shown no effect or even negative effects.

Other studies indicate that personalization has limited benefits. Maslowska et al. (2011) found that personalization improves communication evaluations, not behaviors. Negative effects may result from involvement and relevance (Kalyanaraman and Sundar 2006). Simola et al. (2013) found that personalized ads on social media, which consumers use for information and socializing, disrupt these experiences and cause negative reactions. The recipient may perceive the message as personalized, which may increase persuasion knowledge and decrease effectiveness (Pfiffelmann et al. 2020). Personalized ads can be seen as intrusive in social spaces, significantly when personal information is misused or collected without consent (Aguirre et al. 2015; De Keyzer et al. 2015; Pfiffelmann et al. 2020). Increased privacy concerns may reduce the impact of personalized advertising (Gurau et al. 2003). The "*personalization-privacy paradox*" shows how delicate personalization strategies are (Awad and Krishnan 2006).

While cue-based personalization uses simple elements such as demographics or past behaviors, it can backfire, especially when privacy concerns arise. More advanced personalization strategies, such as trait-based personalization, have garnered attention for their use in recent political campaigns. This method, called microtargeting (Pfiffelmann et al. 2020) or online behavioral advertising (Boerman et al. 2017), subtly tailors messages to recipient characteristics.

2.2. Role of Technologies in Social Media Marketing

Companies use Facebook, Snapchat, and Twitter for social media marketing. Their choice depends on the audience and marketing strategy. Chen and Lee (2018) examined Snapchat's role in youth-targeted social media marketing. Snapchat is an intimate, casual, and dynamic platform for information, socialization, and entertainment, according to their findings. The study found that young consumers like Snapchat, which affects their purchase intentions and brand perceptions of Snapchat-advertised products. In addition, Tafesse and Wien (2018) examined company-advertising strategies. Transformational, which associates the brand with positive psychological traits; informational, which clearly communicates product or service details; and interactional, which encourages customer interaction through social media advertising. Interactive brand posts were more engaging than informative ones (Kusumasondjaja 2018). The study found that Twitter worked best for informative content, Facebook for interactive entertainment, and Instagram for informative entertainment posts. Interactive posts with mixed appeals received the most Facebook and Instagram engagement, while informative messages received the least (Kusumasondjaja 2018).

Content marketing is essential for marketing communications, and some research suggests that emotional messaging influences consumer behavior. Hutchins and Rodriguez (2018) examined eleven B2B companies' content marketing and found that using emotions can boost brand equity and competitiveness. According to Ang et al. (2018), consumers view livestreaming as more authentic, increasing their search and subscription intentions. A scenario-based experiment with 462 participants used social impact theory to reach this conclusion. Advertisers need social media message characteristics. Hwang et al. (2018) applied motivation theory to tourism and found that argument completeness, relevance, flexibility, timeliness, and source credibility increase user satisfaction, which influences their intention to return to websites and buy tourism products. Seo et al. (2020) found that message structure—interactivity, formality, and immediacy—significantly impacts consumer behavior, including brand attitudes, corporate trust, and purchase intentions. Companies face many challenges when creating social media marketing strategies. Parsons and Lepkowska-White (2018) proposed a framework to help managers market via social media.

2.3. Media Richness Theory

Media Richness Theory (MRT) states how AI can enrich media interactions, making it relevant to the study of AI in media personalization (Dennis and Kinney 1998). MRT founders Daft and Lengel (Hutchins and Rodriguez 2018) argue that richer media provide immediate feedback, multiple cues, personalization, and language variety, which are essential for effective communication. AI can improve media richness and communication by tailoring content to individual preferences (Daft and Lengel 1986). Studies have found that AI-enabled personalized content matches MRT principles. Dennis and Kinney (1998) found that feedback- and customization-rich media improve user engagement and understanding. This personalized approach makes content more relevant and engaging, improving user satisfaction and communication (Dennis and Kinney 1998).

AI in strategic communication enriches interactions by making them more dynamic and interactive. Carlson and Zmud (1999) found that real-time user input makes interactive media richer and more effective. AI-powered tools can adjust content and make personalized recommendations in real time, improving communication. These real-time adaptations and responses to user needs align with MRT emphasis on immediacy and feedback, making it applicable to AI-driven personalized media content (Carlson and Zmud 1999). AI also improves media richness and consumer service efficiency. According to Kock (2004), richer media helps customers understand and resolve issues faster, improving service efficiency. AI can reduce customer service time by providing personalized responses and solutions. AI-enhanced media richness allows for more nuanced and effective consumer communication, improving efficiency. Therefore, MRT provides a solid theoretical foundation for understanding how AI can improve media personalization and consumer service efficiency (Kock 2004).

2.4. Strategic Communication and Personalized Media Content

Strategic communication helps create and deliver personalized media content for consumer engagement. For example, Schivinski et al. (2016) found that strategically tailoring brand-related social media content to audience preferences and expectations increases consumer engagement. This suggests that strategic communication-produced personalized media content can boost user engagement and satisfaction. Coombs (2015) also emphasizes strategic communication during crises, showing how well-crafted messages can change public opinion. This suggests that strategic communication improves media personalization by tailoring messages to individual users.

AI enhances strategic communication's impact on personalized media content. Basri (2020) finds that AI-assisted social media marketing improves SME performance by creating more personalized and engaging content. Bag et al. (2022) discuss how AI technologies personalize the digital customer journey to increase user engagement and conversion. Effective media personalization requires real-time adjustments and personalized interactions, which AI can provide. A systematic review of strategic AI use by Borges et al. (2020) shows that AI can personalize and respond to digital communication. In hospitality, AI-driven voice assistants improve customer service by providing personalized responses based on user data, according to Buhalis and Moldavska (2022). AI-supported strategic communication personalizes media content to meet users' needs and preferences, improving their experience and engagement. Thus, a research hypothesis is proposed:

H1. *Strategic communication has a significant impact on personalized media content.*

2.5. Strategic Communication and Consumer Service Efficiency

Strategic communication helps companies improve customer service by facilitating clear, effective, and timely interactions. For example, Coombs (2015) shows how well-structured and transparent crisis communication can reduce damage and maintain customer trust. Consumer efficiency refers to the degree to which consumers can achieve their desired outcomes with minimal effort, time, and resources (Gursoy et al. 2019; Maslowska et al. 2016). Optimizing consumer decision-making, using information effectively, and integrating consumer activities into daily routines improves satisfaction and reduces cognitive load. In daily consumer interactions, strategic communication ensures accurate and prompt responses to customer queries, improving service efficiency. When combined with strategic communication practices, AI-enhanced communication enhances customer experience and service efficiency (Daqar and Smoudy 2019). AI personalized and immediate responses boost strategic communication's impact on consumer service efficiency. Gursoy et al. (2019) examined consumer acceptance of AI devices in service delivery and found that AI handles routine inquiries, freeing up human agents to handle more complex issues. Strategic communication guides this division of labor to streamline and improve customer service. Huang and Rust (2021a) discuss a marketing AI strategic framework, noting that AI-scaled personalized communication enhances service quality and efficiency. Thus, AI in strategic communication improves customer service by streamlining interactions.

AI in communication improves customer engagement and satisfaction. Chan-Olmsted (2019) examined media industry AI adoptions and found that chatbots and personalized messaging improve consumer engagement by providing timely and relevant information. Nguyen and Malik (2021) found that AI-enabled knowledge sharing enhances service quality. Effective strategic communication optimizes tools to provide consistent, high-quality service, increasing consumer service efficiency. Communication improves consumer service efficiency, according to empirical evidence from various industries. By providing personalized and efficient service, predictive modeling and AI-driven customer support can increase customer loyalty (Patel and Trivedi 2020). Song et al. (2022) found that AI-powered communication improves response times and service quality, increasing customer satisfaction. These studies emphasize the importance of strategic communication in using AI to improve service processes and efficiency.

Strategic communication encourages proactive consumer service that anticipates and resolves issues before they escalate. Wamba-Taguimdje et al. (2020) note that strategic communication improves firm performance, including customer service efficiency, in AI-based transformation projects. Marti et al. (2024) suggest that AI in online customer communities can anticipate and resolve customer issues, improving service efficiency. Thus, a research hypothesis is proposed:

H2. *Strategic communication has a significant impact on consumer service efficiency.*

2.6. Personalized Media Content and Consumer Service Efficiency

Customized media content improves consumer service efficiency by meeting consumer needs and preferences. For example, Schivinski et al. (2016) developed and validated a scale to measure consumer engagement with brand-related social media content, finding that personalized and relevant content increases engagement. Engagement increases customer service efficiency because customers who feel understood and valued are more likely to have their needs met quickly. Gorla et al. (2010) found that high-quality, personalized information systems improve organizational service quality and customer service. AI helps create and deliver personalized media content, improving consumer service. Chatterjee and Bhattacharjee (2020) used structural equation modeling to analyze higher education AI adoption, highlighting AI's ability to personalize content and enhance learning outcomes. Ameen et al. (2022) advanced creativity in marketing and AI theory by showing that AI-driven personalization strategies improve consumer engagement and service efficiency.

Strategic communication using AI, personalized media content, and consumer service efficiency are linked by AI ability to tailor interactions to user data and preferences, improving relevance and engagement (Pfiffelmann et al. 2020). AI-driven personalization improves customer service by tailoring content to consumer behaviors and needs (Bang and Wojdynski 2016; De Keyzer et al. 2015). In addition, Maslowska et al. (2011) found that personalized AI communications improve efficiency by predicting and responding to consumer queries faster and more accurately. These capabilities strategically support organizational goals to improve customer service. AI-based marketing studies show that personalized media content improves customer service. Babatunde et al. (2024) found that AI-driven personalized content boosts consumer satisfaction and loyalty. Bag et al. (2022) showed how AI technologies personalize the customer journey to increase engagement, conversion, and service efficiency. The hospitality and service industries demonstrate how personalized media content improves service efficiency. Buhalis and Moldavska (2022) found that AI-driven voice assistants improve customer service by providing timely and relevant responses. This is consistent with Nguyen and Malik (2021), who found that AI-facilitated knowledge sharing enhances service quality, especially when content is personalized to customer needs.

Strategic AI integration in personalized media content creation improves consumer experiences and service efficiency. Kolasani (2023) mentioned how natural language processing and large language models improve customer service and hyper-personalization. Kshetri et al. (2024) found that AI-generated personalized content boosts consumer engagement and service efficiency in marketing. Thus, a research hypothesis is proposed:

H3. *Personalized media content has a significant impact on consumer service efficiency.*

2.7. Mediating Role of Artificial Intelligence between Strategic Communication and Consumer Service Efficiency

AI mediates strategic communication, improving consumer service efficiency. Media Richness Theory states that richer communication media reduce ambiguity and improve understanding (Dennis and Kinney 1998). AI technologies enhance consumer media by providing personalized, real-time, and contextually relevant communication. Chatterjee and Bhattacharjee (2020) found that AI adoption in higher education improves communication personalization and effectiveness, improving outcomes. Strategic AI in communication improves service efficiency by providing timely and relevant customer-specific responses. Buhalis and Moldavska (2022) noted that AI-driven voice assistants improved hospitality customer service through personalized interactions. This suggests that AI can mediate strategic communication and consumer service efficiency by enabling more personalized and responsive interactions. Bag et al. (2022) found that AI technologies improve service efficiency by customizing customer journeys to user preferences, increasing user engagement and conversion.

High-quality information systems deliver accurate and relevant information to customers, improving service quality, according to Gorla et al. (2010). AI systems can analyze massive amounts of data and generate insights, making strategic communication accurate and contextually relevant. Patel and Trivedi (2020) agreed, arguing that AI-driven customer support using predictive modeling and natural language processing boosts customer loyalty by providing efficient and personalized service. AI also mediates strategic communication into actionable insights that improve service efficiency. Babatunde et al. (2024) found that AI-driven personalized content boosts consumer satisfaction and loyalty. Wamba-Taguimdje et al. (2020) found that AI-based transformation projects boost firm performance, including customer service. AI improves consumer interactions by turning strategic communication into personalized and actionable content, mediating the relationship between communication strategies and service outcomes.

Finally, AI provides real-time feedback and adapts communication strategies to consumer behavior, strengthening its mediating role. Personalized and interactive brand-related social media content increases consumer engagement (2016). Through continuous consumer behavior analysis and communication strategy adjustments, AI technologies enable personalization and interactivity. According to Nguyen and Malik (2021), AI-enhanced knowledge sharing improves service quality, so real-time adaptability is essential for efficient and effective consumer service. Thus, a research hypothesis is proposed:

H4. *Artificial intelligence significantly mediates the relationship between strategic communication and consumer service efficiency.*

2.8. Mediating Role of Artificial Intelligence between Personalized Media Content and Consumer Service Efficiency

Media Richness Theory states that richer media can better convey complex and ambiguous messages (Dennis and Kinney 1998). AI provides personalized, real-time, contextually relevant communication and enriches media. Schivinski et al. (2016) found that personalized media content increases consumer engagement, suggesting that AI can make content more relevant and timely. By providing customized responses to customer needs, AI-generated personalized media content improves service efficiency. Buhalis and Moldavska (2022) noted that AI-driven voice assistants improved hospitality customer service through personalized interactions. Babatunde et al. (2024) found that AI-driven personalized content boosts consumer satisfaction and loyalty. AI facilitates more relevant and efficient interactions between personalized media content and consumer service efficiency, according to these studies.

AI improves the quality and consistency of personalized media content, which enhances consumer service. High-quality information systems deliver accurate and relevant information to customers, improving service quality (2010). AI systems can analyze massive amounts of data and generate insights, ensuring accurate and contextually relevant personalized content. Patel and Trivedi (2020) found that AI-driven customer support using predictive modeling and natural language processing boosts customer loyalty by providing efficient and personalized service. Bag et al. (2022) found that AI technologies personalized customer journeys to increase user engagement and conversion, improving service efficiency. According to Wamba-Taguimdje et al. (2020), AI-based transformation projects boost firm performance, including customer service efficiency. AI makes consumer interactions more efficient and effective by turning personalized media content into actionable and relevant interactions, mediating the relationship between personalized content and service outcomes.

Finally, AI real-time feedback and content strategy adaptation to consumer behavior strengthens its mediating role. Nguyen and Malik (2021) showed that AI-enhanced knowledge sharing improves service quality, especially when personalized to customer needs. This adaptability is essential for efficient and effective consumer service because AI can continuously analyze consumer behavior and adjust content strategies. Thus, the study proposed a research hypothesis:

H5. *Artificial intelligence significantly mediates the relationship between personalized media content and consumer service efficiency.*

After an in-depth literature justification, the study developed the conceptual model (see Figure 1).

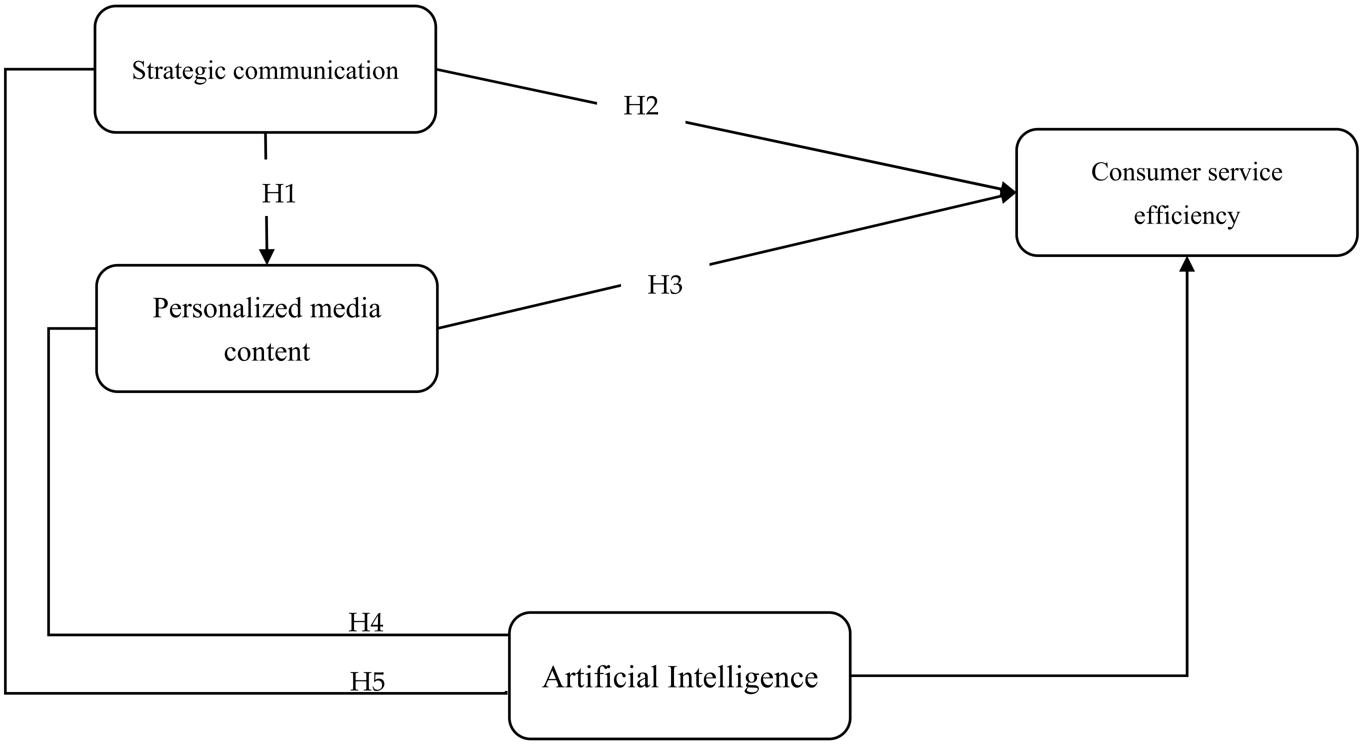

Figure 1. Conceptual framework.

3. Research Methodology

3.1. Research Design

Quantitative methods let researchers measure variables and analyze relationships statistically. Chatterjee and Bhattacharjee (2020) emphasize that quantitative analysis, including structural equation modeling, can accurately and reproducibly examine complex relationships and test hypotheses. Surveys collect large amounts of data from diverse respondents, improving generalizability. This study collected quantitative data on consumer perceptions and experiences using a survey method, providing statistically significant insights into AI-enhanced strategic communications and personalized content. Surveys allow diverse audiences to provide direct feedback, ensuring that data reflects a wide range of consumer interactions and preferences. This cost-effective and efficient method allows rapid data collection and analysis across Saudi Arabia's e-commerce demographics. Survey questionnaires (Appendix A) help quantify consumer perceptions, attitudes, and behaviors. Schivinski et al. (2016) showed that surveys measure consumer engagement with brand-related social media content. Surveys are ideal for collecting self-reported user experiences and satisfaction data to determine how AI-mediated personalized content affects service efficiency. Gorla et al. (2010) recommend surveys for assessing information system quality and organizational outcomes. Thus, a quantitative research design with survey questionnaires (Appendix A) allows for a structured and efficient test of the study's hypotheses and meaningful conclusions about AI's mediating role in improving personalized media content and consumer service efficiency.

3.2. Data Collection Procedures

The data for this study were gathered through an online survey distributed via social media platforms such as Facebook, LinkedIn, Twitter, and WhatsApp. Initially, the survey instrument, which included quartiles to capture the responses, was uploaded to Google Drive. This Google Drive survey has a shareable link that allows for easy access and distribution across various social media channels. The survey targeted Saudi consumers who are active social media users and buy and share stories online.

To ensure a diverse and representative sample, the study used a cluster sampling technique. The target population was divided into three age groups: 18–30 years, 31–45 years, and 46 years or older. This clustering method was chosen to capture potential differences in social media usage and purchasing behavior between age groups (Singh and Masuku 2014). Each cluster was represented equally in survey responses, resulting in balanced data for analysis. The study aimed to collect responses from the 18–30 years cluster, 31–45 years cluster, and the 46 years and older cluster.

The survey link was distributed on 1 January 2024, and responses were collected over a month, ending on 31 January 2024. Throughout this time, the survey link was actively shared and promoted on Facebook, LinkedIn, Twitter, and WhatsApp to reach a large portion of the target population. Periodic reminders and follow-up messages were sent to encourage participation and ensure that each cluster's response targets were met. The use of multiple social media platforms contributed to a broad reach and diverse set of respondents.

After the survey ended on 31 January 2024, the collected data were reviewed to ensure completeness and accuracy. Each cluster received the required number of responses, from the 18–30 age group, 31–45 age group, and 46+ age group. The total number of samples was 498 but the study collected and ensured 367 valid responses. The data were then cleaned and prepared for analysis, with any missing or duplicate responses removed to ensure data integrity. This thorough data collection process resulted in a robust and representative dataset for investigating the mediating role of artificial intelligence in the relationship between personalized media content and consumer service efficiency.

3.3. Measurement Scales

The study used a variety of measurement scales to evaluate the constructs of personalized media content, strategic communication, and service efficiency, adapting items from previous research to ensure reliability and validity. Schivinski et al. (2016) provided 17 items for measuring personalized media content. These items were divided into three categories: consumption (5), contributions (6), and creation (6). This comprehensive scale measures consumer engagement with personalized media content through various modes of interaction, such as passive consumption, active contributions, and content creation.

Additionally, Curtis et al. (2004) developed 12 items to assess strategic communication. These items were created to evaluate the effectiveness of communication strategies used by organizations, with a focus on clarity, responsiveness, and relevance. Service efficiency was measured using 6 items from the study of Gorla et al. (2010). Additionally, the study adapted 8 items of AI adoption from the study of Chatterjee and Bhattacharjee (2020). These items evaluated various aspects of service quality, such as system efficiency, data accuracy, and overall service performance. By adapting these well-validated scales, the study ensures that the measurement instruments are both reliable and valid, providing solid data for examining the relationships between personalized media content, strategic communication, and service efficiency.

3.4. Data Analysis

The demographic analysis of the collected data was carried out using IBM SPSS version 22. This software is well-known for its powerful statistical capabilities and user-friendly interface, making it ideal for handling large datasets and performing descriptive statistics. SPSS made it easier to examine demographic variables such as age, gender, and social media usage patterns, resulting in a better understanding of the sample's characteristics. The literature strongly supports the use of SPSS for demographic analysis. Hair et al. (2021) emphasize effectiveness in descriptive and inferential statistical analysis, which ensures that demographic data are correctly summarized and presented.

The validity, reliability, and hypotheses were tested using Smart PLS 4. Smart PLS is an effective tool for partial least squares structural equation modeling (PLS-SEM), especially for complex models that include multiple constructs and indicators. The software's ability to deal with small to medium sample sizes, non-normal data distributions, and complex model structures makes it an excellent choice for this study. Sarstedt et al. (2020a) highlight the benefits of PLS-SEM in social science research, precisely its flexibility and robustness. Furthermore, Henseler et al. (2014) and Becker et al. (2014) show that Smart PLS is effective at evaluating both measurement and structural models, ensuring construct reliability and validity. The advanced features of the software enabled rigorous hypothesis testing, confirming artificial intelligence's role as a mediator in the relationship between personalized media content and consumer service efficiency.

4. Results

4.1. Demographic Analysis

Table 1 shows a demographic breakdown of a sample of 367 people. The gender distribution reveals a significant male dominance of 88.3% (324 males) versus 11.7% for females (43 females). In terms of age, the majority of participants are between 31 and 45 years old, accounting for 64.3% (236 individuals), followed by those aged 18 to 30 years, 25.9% (95 individuals), and a smaller proportion aged 46 and up, 9.8% (36 individuals). The purchasing experience varies, with the majority (42.2% or 155 individuals) having more than 6 years of experience, followed by those with 4–6 years at 31.6% (116 individuals), 1–3 years at 20.7% (76 individuals), and the least experienced group with less than 1 year at 5.4% (20 individuals). The educational level is predominantly high, with 66.5% (244 individuals) holding a Master's degree, followed by those with a Bachelor's degree at 19.1% (70 individuals), MS/PhD at 12.8% (47 individuals), and only a small fraction at O level at 1.6% (6 individuals). These findings show a demographic profile skewed towards male, middle-aged, highly educated individuals with extensive purchasing experience, indicating a potentially mature and professionally advanced sample.

Table 1. Demographic analysis.

Demographics	Sub-Categories	N	%
Gender	Male	324	88.3
	Female	43	11.7
Age	18–30 Years	95	25.9
	31–45 Years	236	64.3
	Over 46 Years	36	9.8
Buying Experience	Less than 1 Year	20	5.4
	1–3 Years	76	20.7
	4–6 Years	116	31.6
	More than 6 Years	155	42.2
Education	O level	6	1.6
	Bachelor's Degree	70	19.1
	Master's Degree	244	66.5
	MS/PhD	47	12.8

4.2. Assessing Measurement Model

The study runs an algorithm technique to assess the validity and reliability of the measurement constructs. For this purpose, the study used 5000 sub-samples in Smart PLS to create maximum iterations. According to Hair et al. (2021), the convergent validity and reliability assessment requires several statistical thresholds, i.e., factor loadings exceed 0.7 (see Figure 2), AVE exceeds 0.5, and Cronbach's alpha (α) and Composite reliability (CR) exceed 0.7 for convergent validity and reliability (Sarstedt et al. 2020a, 2020b; Henseler et al. 2014). A series of algorithms were performed to improve validity and reliability. Due to this, the study removed 8 items of strategic communication including SC1, SC6, SC7, SC8, SC9, SC10, SC11, and SC12, 12 items of personalized media content including PMC1, PMC2, PMC3, PMC4, PMC5, PMC6, PMC7, PMC8, PMC9, PMC10, PMC11, and PMC15, and 1 item of AI including AI1 had been deleted from the model due to lower factor loadings. Table 2 shows that the remaining items meet the thresholds, indicating robust model constructs.

All items under the scales—AI, consumer service efficiency, personalized media content, and strategic communication—have strong factor loadings, exceeding 0.7. This indicates good convergent validity because the items and constructs are strongly related. All scales have AVE values above 0.5, proving that the constructs can explain indicator variance. This is crucial to ensure that construct indicators accurately represent them.

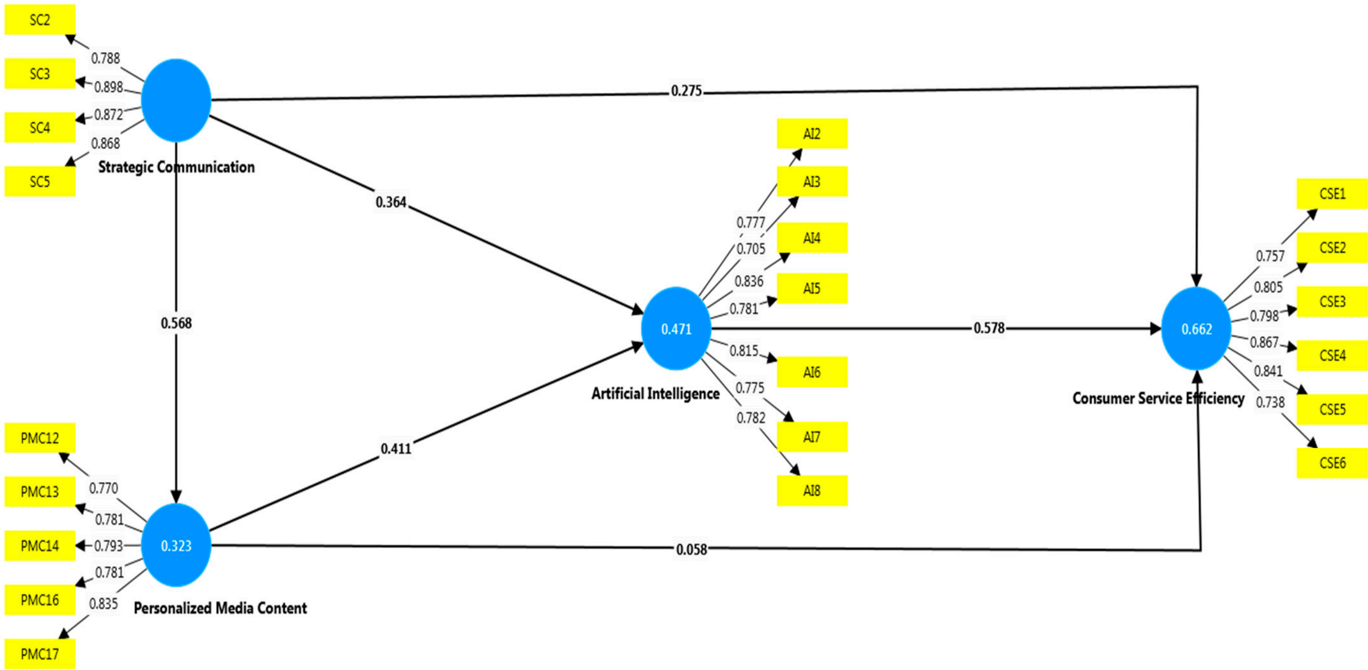

Figure 2. Confirmatory factor analysis.

Table 2. Convergent validity and reliability.

Scales	Items	Factor Loadings	α	CR	AVE	Multi-Collinearity
Artificial Intelligence	AI2	0.777	0.894	0.917	0.612	1.889
	AI3	0.705				
	AI4	0.836				
	AI5	0.781				
	AI6	0.815				
	AI7	0.775				
	AI8	0.782				
Consumer Service Efficiency	CSE1	0.757	0.889	0.915	0.644	1.726
	CSE2	0.805				
	CSE3	0.798				
	CSE4	0.867				
	CSE5	0.841				
	CSE6	0.738				
Personalized Media Content	PMC12	0.770	0.851	0.894	0.628	1.476
	PMC13	0.781				
	PMC14	0.793				
	PMC16	0.781				
	PMC17	0.835				
Strategic Communication	SC2	0.788	0.879	0.917	0.735	1.000
	SC3	0.898				
	SC4	0.872				
	SC5	0.868				

In terms of reliability, α and CR values are strong for all constructs. α values range from 0.851 to 0.894, and CR values from 0.894 to 0.917. These metrics easily exceed recommended thresholds, indicating construct internal consistency and reliability. This high reliability indicates that constructs are consistent across items and reliable for SEM analysis. The low multi-collinearity values for all constructs shown in Table 2 indicate that there is no issue.

Assessing discriminant validity requires analyzing cross-loadings to ensure that each item correlates more strongly with its own construct than with any other model construct (Henseler et al. 2014). The loading of each item on its designated construct is greater than its loadings on other constructs, indicating discriminant validity (Sarstedt et al. 2020a, 2020b). Table 3 shows that all items follow this principle. These results support the construct framework and the reliability and validity of this SEM analysis by showing that the constructs are distinct and measure different aspects as intended. Discriminant validity improves the model's research and field application.

Table 3. Cross-loadings.

Items	Artificial Intelligence	Consumer Service Efficiency	Personalized Media Content	Strategic Communication
AI2	0.777	0.635	0.549	0.474
AI3	0.705	0.515	0.346	0.356
AI4	0.836	0.648	0.534	0.478
AI5	0.781	0.578	0.457	0.486
AI6	0.815	0.666	0.489	0.534
AI7	0.775	0.606	0.433	0.420
AI8	0.782	0.597	0.542	0.500
CSE1	0.521	0.757	0.429	0.499
CSE2	0.654	0.805	0.558	0.553
CSE3	0.620	0.798	0.437	0.537
CSE4	0.690	0.867	0.491	0.581
CSE5	0.678	0.841	0.490	0.520
CSE6	0.562	0.738	0.321	0.445
PMC12	0.453	0.424	0.770	0.448
PMC13	0.511	0.427	0.781	0.443
PMC14	0.447	0.449	0.793	0.461
PMC16	0.475	0.458	0.781	0.431
PMC17	0.552	0.501	0.835	0.468
SC2	0.506	0.510	0.459	0.788
SC3	0.490	0.548	0.483	0.898
SC4	0.498	0.582	0.479	0.872
SC5	0.550	0.595	0.524	0.868

Contemporary methods for assessing discriminant validity in SEM models use the Heterotrait-Monotrait (HTMT) ratio of correlations, with threshold values typically not exceeding 0.90 (Henseler et al. 2014; Sarstedt et al. 2020a). This method estimates the true correlation between constructs using the geometric mean of the average correlations among indicators of the same constructs. In Table 4, all construct pairs (artificial intelligence, consumer service efficiency, personalized media content, strategic communication) have HTMT values below 0.90, ranging from 0.651 to 0.866. No construct correlations exceed 0.90, indicating good discriminant validity. This suggests that the constructs are distinct enough to be reliable and valid in the SEM model. Results showing that constructs do not overlap significantly confirm their uniqueness and suitability for structural model analysis and interpretation.

Table 4. HTMT Ratio.

Constructs	Artificial Intelligence	Consumer Service Efficiency	Personalized Media Content	Strategic Communication
Artificial Intelligence				
Consumer Service Efficiency	0.866			
Personalized Media Content	0.700	0.651		
Strategic Communication	0.669	0.736	0.656	

4.3. Assessing Model Fitness

Table 5 shows how well the model explains and predicts AI, service efficiency, and personalized media content. R^2 values, which indicate how well the model explains dependent variable variance, are telling. Consumer service efficiency has the highest R-square value, 0.662, indicating that the model explains 66.2% of its variability. Following closely are artificial intelligence (0.471) and personalized media content (0.323). The model is well-specified with minimal overfitting because the adjusted R^2 values, which account for the number of predictors, are close to the R^2 values. Positive Q^2 predictive values (0.351, 0.422, and 0.315) indicate model relevance in predicting new data. These values show that the model fits the data well and can predict all three constructs, especially Consumer Service Efficiency, which has high explanatory and predictive power.

Table 5. R^2 and Q^2.

Constructs	R^2	R^2 Adjusted	Q^2 Predict
Artificial Intelligence	0.471	0.468	0.351
Consumer Service Efficiency	0.662	0.660	0.422
Personalized Media Content	0.323	0.321	0.315

4.4. Assessing Path Model

Table 6 shows how strategic communication and personalized media content affect outcomes. The analysis examines these direct effects' strength, significance, and practical effects on consumer service efficiency. Hypothesis H1 states that strategic communication affects personalized media. The analysis reveals a significant effect with a β value of 0.568, a high T-value of 12.868, and a p-value of 0.000. Not including zero in the confidence interval [0.479, 0.652] strengthens this effect. The large effect size (f^2 = 0.476) suggests that strategic communication is a strong predictor of how personalized media content is developed or used, emphasizing its importance in media content strategies. We accept Hypothesis H1.

Hypothesis H2 examines how strategic communication affects consumer service efficiency. It is supported by a significant β value of 0.275, T-value of 6.183, and p-value of 0.000. With a moderate effect size (f^2 = 0.130), the confidence interval [0.187, 0.362] supports the hypothesis. Strategic communication improves clarity, engagement, and service goal alignment, which may boost consumer service efficiency, so the study accepted hypothesis H2. Hypothesis H3 examines how personalized media content affects consumer service efficiency. Despite the expected positive effect, the analysis shows a β value of 0.058, a T-value of 1.302, and a non-significant p-value of 0.193. The confidence interval includes zero [−0.027, 0.150], and the effect size is negligible (f^2 = 0.006), suggesting that personalized media content does not affect consumer service efficiency. The model rejects Hypothesis H3, showing that while personalized media content is essential for engaging consumers, its direct effect on service efficiency may be less than expected or may require interaction with other factors not captured in this model.

Table 6. Direct effects.

No	Hypotheses Testing	β Value	T-Values	*p*-Values	Confidence Interval (C.I.) %	f^2	Decision
H1	Strategic Communication -> Personalized Media Content	0.568	12.868	0.000	[0.479, 0.652]	0.476	Accept
H2	Strategic Communication -> Consumer Service Efficiency	0.275	6.183	0.000	[0.187, 0.362]	0.130	Accept
H3	Personalized Media Content -> Consumer Service Efficiency	0.058	1.302	0.193	[−0.027, 0.150]	0.006	Reject

Strategic communication is crucial to personalizing media content and improving consumer service efficiency. However, the role of personalized media content in directly impacting service efficiency is unclear, suggesting further research or a reevaluation of media content in consumer service strategies.

Table 7 shows how AI mediates strategic communication, personalized media content, and consumer service efficiency (see Figure 3). This mediation analysis shows how AI mediates strategic initiatives into operational results. Hypothesis H4 examines whether AI mediates the relationship between personalized media content and consumer service efficiency. The β value for this pathway is 0.237, with a T-value of 6.778 and a 0.000 *p*-value. Without including zero, the confidence interval [0.173, 0.310] strongly supports mediation. Despite the lack of an effect size (f^2), AI significantly mediates this relationship, improving consumer service efficiency by integrating and applying insights from personalized media content. AI successfully implements personalized content strategies to improve service outcomes, supporting Hypothesis H4.

Table 7. Mediating effects.

No	Hypotheses Testing	β Value	T-Values	*p*-Values	Confidence Interval (C.I.) %	f^2	Decision
	Personalized media content -> Artificial intelligence	0.411	8.110	0.000	[0.315, 0.515]	0.216	-
	Strategic communication -> Artificial intelligence	0.364	6.679	0.000	[0.254, 0.467]	0.169	-
	Artificial intelligence -> Consumer service efficiency	0.578	13.070	0.000	[0.492, 0.666]	0.523	-
H4	Personalized media content -> Artificial intelligence -> Consumer service efficiency	0.237	6.778	0.000	[0.173, 0.310]	-	Accept
H5	Strategic communication -> Artificial intelligence -> Consumer service efficiency	0.210	5.672	0.000	[0.139, 0.286]	-	Accept

Hypothesis H5 examines how AI mediates strategic communication's effects on consumer service efficiency. The β value is 0.210, with a T-value of 5.672 and a *p*-value of 0.000. The confidence interval [0.139, 0.286] reinforces AI's mediating role. Strategic communication affects AI implementations, which improves consumer service efficiency. Results show that strategic communication directly affects AI and significantly improves consumer service operations through AI. We accept Hypothesis H5, emphasizing AI's crucial role in turning strategic communications into service efficiency gains.

Finally, AI mediates strategic communication and personalized media content to improve consumer service efficiency. These findings emphasize the importance of integrating advanced AI technologies to leverage strategic communications and personalized content for more efficient and effective service delivery. This integration leverages AI's analytical strengths and positions it as a key player in organizational strategic initiatives.

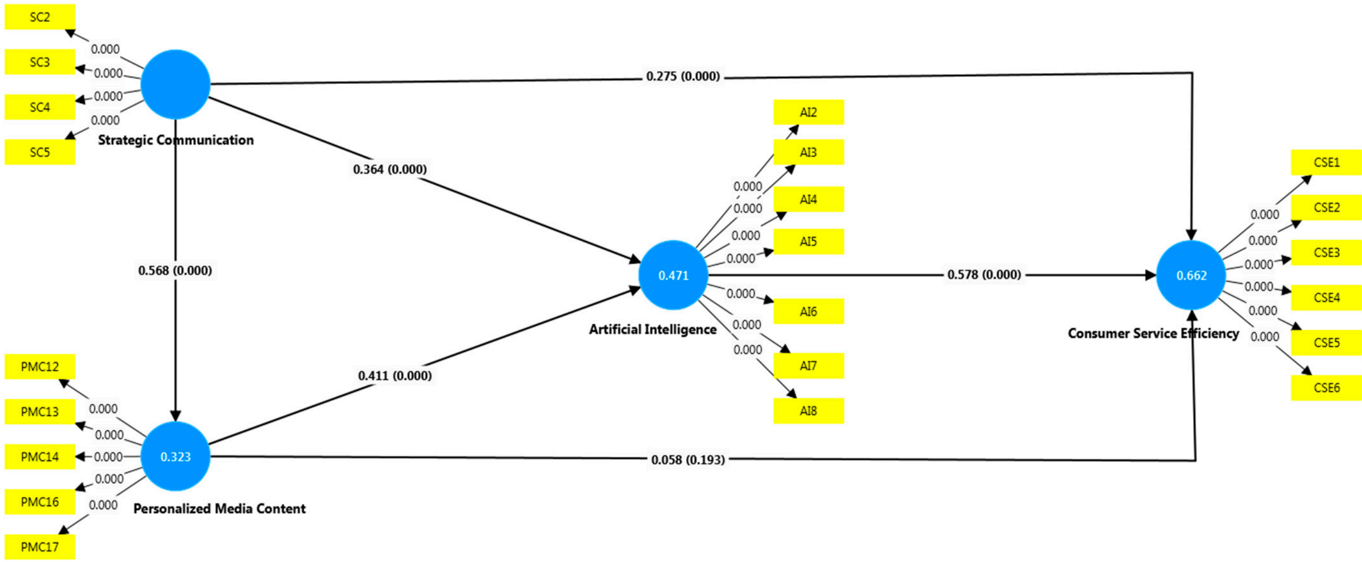

Figure 3. Structural equation modeling (SEM).

5. Discussion and Conclusions

The study is conducted in Saudi Arabia by targeting the social media marketing consumers who have shared evidence of how they perceive good efficiency via strategic communication, personalized media contents in the presence of AI as a mediator. The research respondents agreed that AI in consumer communications and personalized content management improves consumer service efficiency. This supports the literature that emphasizes AI's transformative role in personalizing user interactions and improving service delivery. Hawkins et al. (2008) and Dijkstra (2008) found that tailored communication in health-related contexts is psychologically effective, which is consistent with AI influence on optimizing personalized media content in this study.

The findings also support Pfiffelmann et al. (2020) and De Keyzer et al. (2015), which show that AI-enabled personalized advertising increases consumer engagement and response. AI ability to integrate complex consumer data and provide tailored interactions increases engagement and efficiency, as seen in the high predictive relevance (Q^2) for consumer service efficiency in this study. The high R^2 values for AI and consumer service efficiency support Ang et al.'s (2018) and Aguirre et al.'s (2015) findings that AI can navigate consumer preferences and improve service delivery through strategic communication. AI's mediating role between strategic communication and consumer service efficiency shows its ability to translate strategic inputs into improved service outputs.

In addition, Huang and Rust (2021a) and Gurau et al. (2003) also discuss the role of AI in marketing and service industries, which supports the current study's findings. Therefore, the research respondents agreed that AI has strategic value in predicting and adapting consumer behavior to optimize marketing and operations. High R^2 adjusted values indicate robust model specification and large effect sizes indicate practical significance. The consistency of the findings with prior research emphasizes the role of AI in personalizing and streamlining consumer services. The research respondents affirmed the strategic integration of AI in business processes as a tool for operational optimization and a competitive lever for consumer engagement and service excellence. These insights help explain AI operational and strategic effects across consumer interaction points, enabling its continued adoption and integration into modern business practices.

5.1. Theoretical Implications

This study advances the theoretical understanding of strategic communication, personalized media content, and AI's role in consumer service efficiency. The research shows how strategic messaging and effective communication protocols can directly affect service outcomes by carefully analyzing the impact of strategic communication on consumer service efficiency. This empirically shows that communication strategies cause operational efficiency in service delivery, supporting strategic communication theories. The findings support the theory that well-crafted communication strategies improve consumer service responsiveness and effectiveness, strengthening the case for communication as a core business strategy.

Second, the study examined how personalized media content affects consumer service efficiency. This research contributes to the growing literature on digital marketing customization by showing how tailored content engages consumers and improves service delivery. The study suggests that strategic deployment of personalized content with advanced technological tools like AI may improve service efficiency. This observation highlights the conditional effectiveness of personalization, dependent on technological frameworks, in marketing and consumer behavior theories. The mediation of AI between strategic communication and personalized content is a major theoretical advance. The study fills a significant gap in the literature by showing that AI can use strategic communication and personalized content to improve consumer service efficiency. It portrays AI as a mediator that turns strategic inputs into service operations improvements. This finding adds nuance to AI in business process theories by showing how AI can bridge the gap between strategic intent and consumer satisfaction.

The analysis of strategic communication, personalized media content, and AI in service efficiency provides a solid foundation for future research. It expands the theoretical framework for how businesses can use AI to improve communication and content personalization. The research contributes to academic discourse and provides practical frameworks for businesses to optimize consumer engagement strategies in a digital marketplace by aligning theoretical concepts with empirical evidence.

5.2. Limitations and Future Directions

The study relies on a specific dataset and context, which may limit its generalizability across industries and cultures. Thus, the results may only be applicable to other sectors or global markets with further validation. The study also focused on AI as a mediator rather than other mediators or moderators that could affect strategic communication, personalized media content, and consumer service efficiency. Organizational culture, technology readiness, and consumer privacy concerns could affect the effectiveness of AI and personalized social media marketing strategies.

Future research should expand the study to include diverse industries and cross-cultural settings to improve robustness and applicability. Additionally, studying other mediators and moderators would help explain social media marketing and consumer engagement. Leadership styles and innovation capabilities may affect AI marketing strategy implementation, which researchers could study. Future studies could also examine how consumer privacy and data security perceptions affect AI-driven personalized marketing, which is becoming increasingly important in the digital age. These studies will fill the gaps in this study and advance the discussion on strategic AI and personalization to improve consumer relationships and business performance.

5.3. Conclusions

The hypotheses reveal how strategic communication, personalized media content, AI, and consumer service efficiency interact. Acceptance of H1 and H2 reveals significant direct effects of strategic communication on personalized media content ($\beta = 0.568$) and consumer service efficiency ($\beta = 0.275$), with significant effect sizes (f^2 values of 0.476 and 0.130). An insignificant t-value and a confidence interval straddling zero reject H3, which tested the direct effect of personalized media content on consumer service efficiency. The accepted mediated relationships in H4 and H5 involving artificial intelligence show that AI plays a crucial mediating role, enhancing the impact of both personalized media content and strategic communication on consumer service efficiency, with effect sizes demonstrating substantial leverage. These findings show that AI is crucial to optimizing communication strategies for organizational success.

Funding: This research received no external funding.

Institutional Review Board Statement: Due to the nature of the study and the absence of personal data utilization, in accordance with the laws of Saud Arabia, the study was deemed exempt from Ethics Committee approval at King Saud University.

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

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A Survey Questionnaire

Constructs	Items	Rating (1–5)
Personalized Media Content (Schivinski et al. 2016)	1. I read posts related to Brand X on social media.	[1] [2] [3] [4] [5]
	2. I read fan pages related to Brand X on social network sites.	[1] [2] [3] [4] [5]
	3. I watch pictures/graphics related to Brand X.	[1] [2] [3] [4] [5]
	4. I follow blogs related to Brand X.	[1] [2] [3] [4] [5]
	5. I follow Brand X on social network sites.	[1] [2] [3] [4] [5]
	6. I comment on videos related to Brand X.	[1] [2] [3] [4] [5]
	7. I comment on posts related to Brand X.	[1] [2] [3] [4] [5]
	8. I comment on pictures/graphics related to Brand X.	[1] [2] [3] [4] [5]
	9. I share posts related to Brand X.	[1] [2] [3] [4] [5]
	10. I "Like" pictures/graphics related to Brand X.	[1] [2] [3] [4] [5]
	11. I "Like" posts related to Brand X.	[1] [2] [3] [4] [5]
	12. I initiate posts related to Brand X on blogs.	[1] [2] [3] [4] [5]
	13. I initiate posts related to Brand X on social network sites.	[1] [2] [3] [4] [5]
	14. I post pictures/graphics related to Brand X.	[1] [2] [3] [4] [5]
	15. I post videos that show Brand X.	[1] [2] [3] [4] [5]
	16. I write posts related to Brand X on forums.	[1] [2] [3] [4] [5]
	17. I write reviews related to Brand X.	[1] [2] [3] [4] [5]
Strategic Communication (Curtis et al. 2004)	1. I read posts related to Brand X on social media.	[1] [2] [3] [4] [5]
	2. I look you in the eye when discussing your care.	[1] [2] [3] [4] [5]
	3. Including loved ones in treatment discussions is important.	[1] [2] [3] [4] [5]
	4. I ensure to answer all questions about your illness.	[1] [2] [3] [4] [5]
	5. Listening to what you have to say is crucial to me.	[1] [2] [3] [4] [5]
	6. I care about you as a person, not just as a patient.	[1] [2] [3] [4] [5]
	7. I give my full attention during our conversations.	[1] [2] [3] [4] [5]
	8. Talking about your feelings about getting sicker is part of our discussions.	[1] [2] [3] [4] [5]
	9. We discuss the details in case you get sicker.	[1] [2] [3] [4] [5]
	10. We discuss how long you have to live when necessary.	[1] [2] [3] [4] [5]
	11. Talking about what dying might be like is part of our conversation.	[1] [2] [3] [4] [5]
	12. Involving you in discussions about your care is fundamental.	[1] [2] [3] [4] [5]

Constructs	Items	Rating (1–5)
Consumer Service Efficiency (Gorla et al. 2010)	The company information systems apply modern technology effectively.	[1] [2] [3] [4] [5]
	The company information systems are well integrated.	[1] [2] [3] [4] [5]
	The company information systems are user-friendly.	[1] [2] [3] [4] [5]
	The company information systems have good documentation.	[1] [2] [3] [4] [5]
	The company information systems have a short response time for online inquiries.	[1] [2] [3] [4] [5]
	The company information systems have a short time lag between data input and output for batch processing.	[1] [2] [3] [4] [5]
AI Adoption (Chatterjee and Bhattacharjee 2020)	AI integration in social media marketing significantly contributes to societal progress.	[1] [2] [3] [4] [5]
	AI technologies in social media marketing help address societal challenges more effectively.	[1] [2] [3] [4] [5]
	AI facilitates more interactive and engaging learning experiences on social media platforms.	[1] [2] [3] [4] [5]
	The use of AI tools enhances student interaction with social media content.	[1] [2] [3] [4] [5]
	Implementing AI in social media marketing reduces overall marketing costs for consumers.	[1] [2] [3] [4] [5]
	AI adoption makes social media marketing more financially accessible to a broader range of consumers.	[1] [2] [3] [4] [5]
	AI technologies make learning activities on social media platforms more captivating and engaging.	[1] [2] [3] [4] [5]
	The incorporation of AI in marketing strategies increases consumer interest and participation in buying.	[1] [2] [3] [4] [5]

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