

1SYED MUHAMMAD OMER, 2SHANZAY SHAHID, 3SYEDA TOOBA SALEEM, 4DR. SARA SOHAIB

¹Student

Institute of Business Management, Karachi
BBA Honors
Std_30259@iobm.edu.pk

²Student

Bahria University Karachi

BS-SCM

02-116202-021@student.bahria.edu.pk

³Lecturer

Bahria University Karachi Syedatoobasaleem.bukc@bahria.edu.pk

⁴Assistant Professor Bahria University Karachi sarasohaib.bukc@bahria.edu.pk

Abstract

This research aims to explore the influence of AI-driven tools on brand recall using established theoretical frameworks. Understanding this impact can empower businesses to enhance customer interactions, build stronger brand relationships, and ultimately boost overall performance. Employing a positivist research philosophy and quantitative design, this study seeks to validate hypotheses with data from 201 respondents, while recognizing the potential for respondent bias. Evaluating variables like customer trust and brand image poses challenges due to their subjective nature. This research provides valuable insights for businesses looking to optimize AI technology deployment, offering recommendations to enhance marketing efforts and improve customer service through AI agents such as chatbots and virtual assistants. Continued monitoring and improvement of AI agents are crucial, and future research may consider qualitative approaches like interviews and explore the impact of electronic word-of-mouth (e-WOM) on social media marketing efforts.

Key Terms: Brand Recall, AI-Powered Agents, Business Performance.

1.1. INTRODUCTION

Artificial Intelligence (AI) refers to the simulation of human intelligence processes by machines, specifically computer systems. It involves the development of computer programs and algorithms that can perform tasks that typically require human intelligence, such as problem-solving, learning from experience, recognizing patterns, understanding natural language, and making decisions.

Al encompasses a wide range of techniques and approaches, including machine learning, deep learning, natural language processing, computer vision, and more. These technologies enable Al systems to process large amounts of data, identify patterns and trends, and make predictions or decisions based on the information they have learned.

The primary objective of this essay is to conduct a comprehensive examination of the existing literature concerning the impact of AI-enabled agents on brand recall, elucidating their roles and applications within marketing contexts. This research endeavor seeks to harmonize the advancements



in artificial intelligence with the intricate processes of brand networking, with the ultimate aim of achieving marketing objectives. Furthermore, it aims to construct a framework that delineates the potential of AI-enabled agents and their influence on brand recall.

In making choices about the most suitable AI technologies for specific branding processes, individuals such as managers, senior executives, policymakers, and decision-makers will derive valuable insights from this study. Furthermore, this analysis holds promise for future research endeavors across various marketing disciplines, offering a blueprint for how artificial intelligence has transformed the branding landscape in recent years. Given the continuous evolution of artificial intelligence, the voluminous data it generates has emerged as a pivotal resource for future corporate success.

As a result of the relentless advancement of artificial intelligence, the digital era has seen the ascendancy of massive data as the foremost asset for corporate prosperity. This transformation is exemplified by the web-based entertainment industry and e-commerce websites, both of which leverage AI-driven strategies to expand their customer bases and promote the sale of branded products (Chen, 2019). Industry experts and scholars have posited that AI is rapidly gaining momentum through its utilization in extensive data analysis, AI-driven virtual entertainment assessments, algorithmic innovations, navigation systems, simulation modeling, and other methodologies employed to enhance brand visibility in the global market (Singh et al., 2019; Syam and Sharma, 2018). Consequently, artificial intelligence is profoundly reshaping brand preferences, marketing strategies, and customer attitudes.

1.2. Problem Statement

Providing exceptional customer service is crucial for building and maintaining a strong brand image. However, many companies struggle to consistently deliver high-quality service. Al-enabled chatbots have emerged as a potential solution, offering a scalable and cost-effective way to handle customer inquiries and support. Nevertheless, the effectiveness of chatbots in improving customer support and brand recall remains unclear, and little attention has been given to the role of customer trust and brand image in this context. This study aims to address this gap by investigating the influence of Alpowered chatbots on brand recall, with customer service as an intermediary factor, and considering the moderating effects of customer trust and brand image on this relationship.

1.3. Research Objectives

The research objectives associated with the research model include:

- 1. Investigate the influence of AI-enabled agents on brand recall.
- 2. Examine how brand image and customer trust affect customer service quality and brand recall.
- 3. Explore the impact of Al-enabled agents on customer service.
- 4. Determine the impact of increased utilization of AI-enabled agents on consumer decision-making processes.
- 5. Assess whether the use of AI-enabled agents enhances customer service and increases brand recall.
- 6. Measure the influence of Al-enabled agents on consumer decision-making and purchasing behavior.

1.4 Significance of the Study

This research holds paramount importance in advancing knowledge and addressing real-world problems. Its potential impact extends to individuals, organizations, and societies, fostering progress and positive change. By leveraging AI-enabled agents, marketers and advertisers can enhance brand recall through personalized and relevant marketing messages, ultimately leading to increased engagement, brand loyalty, and higher sales. Additionally, these agents offer consumers a tailored shopping experience, leveraging AI algorithms to provide product recommendations and valuable advice. This approach not only improves customer service but also serves as a valuable data source for researchers studying consumer behavior and marketing trends. Furthermore, AI-enabled agents



can streamline purchasing decisions, promoting efficiency and sustainability by reducing waste. This study can also empower businesses to gain a competitive edge by identifying effective AI agent strategies for enhancing brand recall, thereby increasing market share and driving innovation in the marketing and advertising domain.

LITERATURE REVIEW

2.1 Focus of the Study

The central focus of this study is on brand recall, which is the ability of customers to remember and identify a brand based on factors such as the product category, meeting their expectations, and prior interactions with the brand. Several studies have explored this concept from various angles. For instance, Memon et al. (2016) emphasized the importance of customers' ability to recall a brand when provided with a relevant cue. Abrar et al. (2018) found that augmented reality, particularly when customers are familiar with social media platforms, significantly influences consumer brand engagement and purchase intent. Brand recall is crucial as it reflects the extent to which individuals can remember past interactions and communications with a brand through advertisements or other touchpoints (Prashar et al., 2012).

Khurram et al. (2018) delved into the role of brand recall and recognition in actual purchase decisions, highlighting that brand memory plays a pivotal role in driving real purchases. The ability of customers to recall brand information at the time of purchase, known as brand knowledge, influences their choices and encourages repeat purchases (Lin 2013; Thomas and Williams 2013). Wang et al. (2018) also noted that brand recall is enhanced when associated with positive emotions or memories, highlighting the impact of emotions on brand recall.

Furthermore, this study explores the emerging role of chatbots in e-commerce and e-services, as investigated by Misischia et al. (2022). Their research focuses on the functional aspects of chatbots that lead to improvements in service quality. While there has been substantial research on the effects of brand recall on various aspects such as purchase intention (Memon B et al. 2016), actual purchases (Khurram M et al. 2016), and consumer buying behavior (Trevedi M. et al. 2013), limited information is available regarding the direct impact of customer support on brand recall.

2.2 Effect of Al-Enabled Chatbot on Brand Recall

Recent research has explored the potential of AI-powered agents in measuring brand recall. Studies by Sun et al. (2020), Wu et al. (2021), Liu et al. (2021), and Garg et al. (2021) indicate that AI agents can accurately identify brands that participants have encountered before. Sun et al. (2020) reported an overall accuracy rate of 83% for AI chatbots in brand identification. However, these studies also highlight certain limitations. Liu et al. (2021) found that the accuracy of AI models could be influenced by factors such as the type of stimuli used and participants' cognitive load, while Garg et al. (2021) pointed out the need for more diverse training data and the potential for bias.

2.3 Effects of Artificial Intelligence on Customer Service

The advancement of technology, including chatbots, has transformed the customer service landscape. Chatbots have proven to be effective in reducing customer wait times and organizational labor costs (Ostrom et al., 2019; Turel and Connelly, 2013; Xu, 2016). Organizations are increasingly adopting artificial intelligence to enhance operational efficiency (Huang and Rust, 2018; Wirtz et al., 2018) and improve customer engagement (Urban and Gaffurini 2018). Xiao and Kumar (2019) note that AI is being embraced across various industries, including education, finance, healthcare, retail, and transportation, to provide end-to-end solutions for customer service rather than just as a means of interaction within an organization's customer support system.

2.4 Effects of Customer Service on Brand Recall

The integration of AI in organizations can lead to improved customer engagement, which in turn enhances brand image. Customer engagement encompasses various activities related to brand-



related content, including responding to firm-produced content, commenting, sharing, and generating user-generated content across virtual platforms (Barger and Pektier, 2017). Customer engagement is valuable to organizations as it directly or indirectly contributes to their performance, impacting sales through direct purchase and influencing the organization through feedback, opinions, and ideas about products and services (Pansari and Kumar, 2017).

2.5 The Effect of Brand Image on Brand Recall

Brand image reflects consumers' perceptions of a brand's products, values, and qualities, shaped by marketing communications, user experiences, and social influences (Lee et al., 2011). A strong brand image, characterized by positive and lasting impressions, increases the likelihood of brand recall and purchase (Riezebos, 2003). Customer trust is closely linked to brand image, as it is based on the belief that a brand can consistently fulfill its commitments (Sidershmukh et al., 2002). Maintaining a strong brand image ensures that a brand is easily remembered and recalled by customers, leading to higher chances of purchase. Trust and brand image have not been directly examined as mediators influencing brand recall in previous research.

2.6 The Effect of Customer Trust on Brand Recall

Trust plays a pivotal role in building relationships between customers and businesses, and it has been extensively studied across various contexts, including online retailing, brand relationships, online communities, fan pages in virtual entertainment, online shopping behavior, and Al-mediated interactions (Morgan and Chase, 1994; Elbeltagi and Agag 2016; Wang, Wang, and Liu, 2016; Zhang, Bilgihan, Kandampull and Lu 2018; Akrout and Nagy, 2018; Rehman, Bhatti, Mohamed, and Ayoup, 2019; Wang, Tajvidi, Lin, and Hajli, 2019). Trust is essential in maintaining customer control over their data and influencing factors such as convenience and service quality in Al use (Siau and Wang, 2018; Ferrario, Loi, and Vigan, 2019; Ameen N. 2021).

THEORETICAL FRAMEWORK

Brand Equity Theory

Brand equity has been a pivotal concept in marketing since the 1980s, and its significance has continued to grow for cultural organizations, as highlighted by Trunfio (2019). Two influential models, developed by Aaker and Keller, serve as the cornerstone for numerous studies on customer-based brand equity (CBBE), as noted by Lim (2014). While Aaker and Keller had slightly different perspectives on brand equity, they both fundamentally defined it from a consumer standpoint, as emphasized by Camarero (2010). Brand equity is commonly perceived as having multiple dimensions, as discussed by Yoo (2000). According to Aaker, it comprises brand awareness, brand association, perceived quality, brand loyalty, and other exclusive assets like patents and registered trademarks (Suijin B., 2020).

Brand awareness encompasses two critical aspects: a consumer's ability to recognize, recall, and connect with a brand through its name, logo, or symbol (referred to as memory depth of brand awareness), and the breadth of situations where the brand comes to mind in the context of purchase and consumption (breadth of brand awareness) (Suijin B., 2020). Strong, positive, and distinctive brand associations are also crucial for enhancing brand equity. Another component of brand equity is brand association, closely tied to consumers' memories of a brand, serving as the foundation for purchase decisions (Hoeffler, 2002). Brand image, which depends on positive and distinctive brand associations, is a central focus of many studies exploring brand association (Chi, 2020). Empirical research has consistently shown that brand loyalty is positively influenced by brand equity. Brands receiving more favorable reactions, such as higher levels of brand association, awareness, preference, and familiarity, are more likely to possess strong brand equity (Suijin B., 2020).

Technology Acceptance Model: Al-Enabled Customer Experience

The term "customer experience" encompasses the overall impressions and interactions a customer encounters with a retailer (Oh, Teo, and Sambamurthy, 2012; Verhoef et al., 2009). Previous research

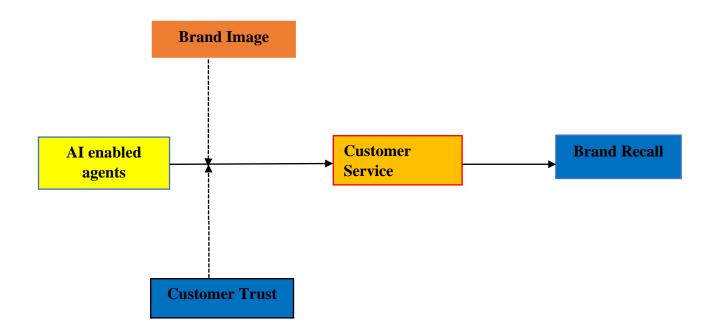
`````````

has identified four aspects of customer experience: mental, social, sensory, and personal dimensions (Ladhari, Souiden, and Dufour, 2017). Mental aspects refer to higher cognitive functions, including intelligence, memory, language, problem-solving, and decision-making (American Psychological Association, 2016). As per Keiningham et al. (2017), mental characteristics of a customer experience include attributes like usefulness, speed, and accessibility of a service. Moreover, prior research has emphasized the emotional aspects of customer support, which are often intricate in nature.

According to Metropolitan and Gaffurini (2018), artificial intelligence (AI) can help organizations stay up-to-date with the latest technology trends and enhance customer engagement activities, ultimately leading to improved brand perception. AI has significantly benefited companies in marketing by enhancing customer engagement. Recent studies have indicated that trust-building is essential for the adoption, continued advancement, and innovation of AI technology (Siau and Wang, 2018). Previous research has also demonstrated that consumers are more likely to establish long-term relationships with brands they trust (Keiningham et al., 2017). While earlier studies have shown a positive connection between customer experience and brand trust, this relationship also holds true for subsequent interactions after customers have undergone the initial experience and developed trust (Njamfa, 2018).

Al-related technologies are employed in Al marketing to aid in the collection, analysis, and interpretation of data related to target consumers and economic trends that could impact marketing strategies. All is frequently used in marketing areas where speed is of the essence (Paschen et al., 2019). Consequently, consumers are more inclined to purchase products associated with a positive brand image. Brands with a favorable reputation are easier to remember compared to those with a negative image, according to Adenan et al. (2018).

2.3 Conceptual Framework





3. METHODOLOGY

In our research, we have employed a research framework based on positivism, which seeks to obtain objective results by testing hypotheses experimentally and deriving logical or numerical evidence from statistical analysis. This approach is chosen to ensure the rigor of our investigation. We have also adopted a Deductive Research Approach, moving from general concepts to specific ones, and utilized a quantitative research design to assess cause-and-effect relationships between variables.

To collect primary data, we designed an online questionnaire aimed at gathering firsthand information from users who have interacted with Al-enabled service agents across different platforms. The survey primarily targeted an urban population in Pakistan with experience in online retail and the use of Al-powered chatbots for assistance. Respondents included individuals working for Al organizations and those who have used Al chatbots from various brands. The questionnaire employed a Likert scale (ranging from 1 - strongly disagree to 5 - strongly agree) to measure the research variables, following the approach of Chen and Paulraj (2004).

Regarding our sampling method, we opted for non-Probability sampling, as we did not have access to a complete list of our target population. Specifically, we used Purposive or judgmental sampling, where specific individuals or groups were manually selected to gather information that could not be obtained through other means (Maxwell, 1996). We collected 250 responses from the online questionnaire distributed via Google Forms, out of a calculated sample size of 300 generated by google through online survey form.

For data analysis, we employed Partial Least Squares Structural Equation Modeling (PLS-SEM), a robust multivariate analysis technique suitable for complex and non-normally distributed data. This technique involves two main phases: measurement model estimation and structural model estimation.

4. RESULTS AND DISCUSSION

4.1 Demographic Profile of Respondents

The demographic profile of our dataset reveals that the majority of respondents were male (61%), with females comprising 39% of the sample. Age-wise, 6% fell into the 15-20 age group, 19% were in the 21-25 age range, 39% belonged to the 26-30 age category, 24% were in the 31-35 range, and 11% were 36 years and older.

In terms of education, 1% held diplomas, 57% had completed their undergraduate degrees, 7% had finished high school, and 34% had completed postgraduate studies. Regarding income, 36% of respondents reported earning more than 100,000 PKR, while 28% fell within the income bracket of 50,000 to 100,000 PKR. Furthermore, 46% of respondents used AI-enabled agents on a monthly basis, with 40% using them primarily for obtaining product information and 33% utilizing them for customer service support.

Demographics	Category	Frequency	Percentage
Gender	Female	79	39%
	Male	122	61%
Age	15-20	13	6%
	21-25	38	19%
	26-30	78	39%
	31-35	49	24%
	36 & above	23	11%
Education	Diploma	3	1%
	Graduation	115	57%



	High School	15	7%
	Post Graduation	68	34%
Marital Status	Married	79	39%
	Single	122	61%
Income Range	25000 PKR - 50,000 PKR	20	10%
	50,000 PKR - 100,000 PKR	57	28%
	Less than 25,000 PKR	4	2%
	More than 100,000 PKR	73	36%
	others	47	23%
Frequency of usage of Al	Daily	38	19%
enabled agents Monthly		93	46%
	Weekly	58	29%
	Yearly	12	6%
Purpose of usage of Al	Customer service support	67	33%
enabled agents	Product information	80	40%
	Technical Support	51	25%
	Others	2	1%

4.2. Skewness & Kurtosis:

Construct	Items	Excess kurtosis	Skewness	p value
	AIG1	4.686	-1.478	0
	AIG2	3.198	-1.267	0
Service Experience Al Enabled agent	AIG3	2.13	-1.14	0
	AIG4	0.245	-0.508	0
	AIG5	0.862	-0.697	0
	CT1	1.799	-0.994	0
	CT2	0.174	-0.563	0
Customer Trust	CT3	1.074	-0.711	0
	CT4	0.65	-0.603	0
	CT5	0.198	-0.396	0
	BI1	1.555	-0.814	0
	BI2	1.322	-0.608	0
BRAND IMAGE	BI3	1.258	-0.837	0
BRAND IMAGE	BI4	0.141	-0.501	0
	BI5	1.324	-0.921	0
	BI6	-0.026	-0.413	0
	CS1	-0.747	-0.242	0
	CS2	-0.781	-0.24	0
CUSTOMER SERVICE	CS3	-0.692	-0.135	0
	CS4	-0.939	-0.252	0
	CS5	-0.066	-0.604	0
	BR1	1.052	-0.565	0
BRAND RECALL	BR2	0.477	-0.666	0
DIVARID RECALL	BR3	0.541	-0.496	0
	BR4	0.424	-0.781	0

	ATB1	0.318	-0.387	0
	ATB2	0.184	-0.32	0
	ATB3	-0.16	-0.285	0
Attitudes towards Color Blue	ATB4	0.298	-0.187	0
	ATB5	0.996	-0.661	0
	ATB6	0.268	-0.468	0
	ATB7	0.867	-0.881	0

The findings presented in Table 4.2 demonstrate that the majority of skewness and kurtosis statistics fall within the typical range of -3 to +3. This suggests that the sample distributions conform to the normal distribution and are within an acceptable range, indicating a lack of significant skewness. However, it is noteworthy that the kurtosis values for items one and two within Construct 1 (specifically, the Service Experience of Al-Enabled Agents) exceed the -3 to +3 range, signifying substantial non-normality. Consequently, a non-parametric approach is employed for testing and analysis in light of these observations.

4.3. Outer Loadings, Average Variance Extracted and Composite, reliability

Construct	Items	Outer Loading	Composite reliability (rho_c)	Average variance extracted (AVE)
	AIG1	0.779	0.848	0.529
	AIG2	0.73		
Service Experience	AIG3	0.7		
Al Enabled agent	AIG4	0.712		
	AIG5	0.711		
	BI1	0.517	0.868	0.528
	BI2	0.726		
BRAND IMAGE	BI3	0.715		
DRAND IMAGE	BI4	0.817		
	BI5	0.728		
	BI6	0.814		
	BR1	0.868	0.876	0.64
BRAND RECALL	BR2	0.792		
DRAND RECALL	BR3	0.777		
	BR4	0.759		
	CS1	0.877	0.927	0.717
CUSTOMER	CS2	0.882		
SERVICE	CS3	0.873		
SLICVICE	CS4	0.824		
	CS5	0.775		
	CT1	0.659	0.826	0.494
	CT2	0.641		
Customer Trust	CT3	0.842		
	CT4	0.813		
	CT5	0.506		

Table 4.4 presents the results for composite reliability, both rho a and c, as well as convergent validity measured by average variance extracted (AVE). These values have been computed using PLS-SEM software. The composite reliability values fall within an acceptable range, indicating that the constructs are reliable and can be trusted for analysis. Additionally, the AVE exceeds the threshold of >0.5, which suggests that the questions used in the study are pertinent to the construct being examined and contribute positively to its measurement.



4.4. Multivariate Normality

	В	Z	P-value
Skewness	420.7045	14093.60237	0
Kurtosis	1636.5206	25.53565	0

In Table 4.3, we've examined data normality using Mardia's Test, which assesses skewness and kurtosis in a multivariate context. A reported p-value of 0 indicates that the observed multivariate skewness and kurtosis statistics are highly improbable if we assume the null hypothesis of multivariate normality, as suggested by Mardia in 1970. However, the obtained p-value does not meet the established threshold of >0.05, as mentioned in the study by Wulandari et al. in 2021. This discrepancy indicates that our data does not adhere to a normal distribution. Therefore, our decision to employ SMART PLS, a method tailored for non-parametric analyses, is well-founded.

4.5 Significance & Relevance

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics	CI		P values	Decision
					5.00%	95.00%		
Direct Effect								
BI -> CS	0.324	0.319	0.081	4.003	0.184	0.452	0.00	Supported
CS -> BR	0.171	0.191	0.085	2.01	0.08	0.317	0.022	Supported
CT -> CS	0.147	0.162	0.073	2.003	0.044	0.285	0.023	Supported
AIG-> CS	0.09	0.101	0.075	1.191	-0.021	0.225	0.117	Not Supported
Mediation Effect								
BI -> CS -> BR	0.055	0.061	0.033	1.689	0.012	0.108	0.046	Supported
Moderation Effect								
CT x AIG-> CS	-0.005	-0.015	0.066	0.077	-0.12	0.091	0.469	Not Supported
BI x AIG-> CS	-0.011	0	0.084	0.127	-0.152	0.119	0.449	Not Supported

Table 4.7 presents the criteria for evaluating different paths in our analysis. To be considered statistically significant, a path's p-value (P) should be less than 0.05, and the corresponding T-statistic value should exceed 1.645. We observed that the p-value meets this criterion for all paths, except for those involving moderation constructs. This suggests that our path model does not provide support for the involvement of moderators in our model.



4.8 Coefficient of Determination (R-square and Adjusted R-square values):

	R-square	R-square adjusted
BR	0.029	0.024
CS	0.226	0.206

In Table 4.8, we are presented with R-squared and adjusted R-squared values, which are indicators of how well our model explains the variation in the dependent variables. R-squared values range from 0 to 1, with 0.75 being considered substantial, 0.50 moderate, and 0.25 weak. In our analysis, we find that the R-squared value for Brand Recall is 0.029, and for Customer Service, it is 0.226. These values indicate that our model's ability to account for the variability in these dependent variables is quite weak.

5 CONCLUSION

5.1 Contribution

This research paper offers valuable insights for businesses seeking to optimize their utilization of AI technology to enhance customer experiences and ultimately boost organizational performance. It sheds light on the influence of AI-powered agents on customer decision-making and provides strategies for enhancing marketing efforts. Through the use of AI-driven recommendation systems, companies can provide personalized product suggestions, resulting in more effective targeting and increased customer satisfaction. The integration of AI-powered chatbots also improves customer service by offering round-the-clock support, real-time assistance, and personalized recommendations, thereby facilitating quicker problem resolution.

The study underscores the significance of establishing trust and transparency in AI technology to enhance a brand's image. A positive association between AI and a brand can lead to greater brand recall and customer loyalty. Additionally, the research underscores how AI-enabled agents simplify the customer decision-making process. By offering tailored recommendations based on customer preferences, businesses can empower customers to make informed choices, bolstering their confidence in their decisions. Overall, this research equips businesses with valuable insights into how AI impacts customer decision-making, enabling them to remain competitive, enhance customer experiences, and subsequently improve their organizational performance.

5.2 Limitations:

It's important to acknowledge certain limitations when interpreting our research findings. Firstly, our study relies on data collected in Karachi, Pakistan, which may limit the generalizability of our results to other regions or cultural contexts. Thus, caution should be exercised when applying these findings to businesses operating in different geographic areas. Furthermore, our research primarily focuses on the role of AI-enabled agents in customer decision-making and brand recall, without extensively examining other potential influencing factors such as pricing, product quality, or customer service. Future research should delve into the interplay between AI technology and these additional variables for a more comprehensive understanding of their combined effects. Lastly, as with any technology-related research, there is the possibility of technical issues or limitations in AI systems themselves, which could impact the results and practical implications. Ongoing advancements and updates in AI technology may also render some of our findings less relevant over time. While our research offers valuable insights, these limitations should be kept in mind when applying our findings in real-world business contexts.

5.3 Recommendations:

Our study, validated using Smart PLSSEM, revealed that both moderators, Brand Image and Customer Trust, did not appear to play significant roles between Service by AI and Customer Service. Future



research could explore Customer Trust as a mediator between Service by AI and Customer Service to measure the impact of customer trust in these services, which could be a valuable avenue for further investigation. Moreover, to address the limitation of generalizability, future research should consider collecting data from multiple cities or regions in Pakistan with a familiarity with AI-enabled agents and services. This would provide a more comprehensive understanding of the influence of AI-enabled agents on customer decision-making and brand recall across diverse cultural contexts. Given the rapid evolution of AI technology, researchers and businesses must stay up-to-date on the latest developments. Regular monitoring and evaluation of AI system performance and effectiveness are essential to ensure that practical implications derived from research findings remain relevant amid technological advancements.

5.4 Managerial Implications:

To effectively manage AI-enabled agents, clear performance goals should be established in alignment with the organization's objectives, focusing on key performance indicators such as accuracy, efficiency, response time, and customer satisfaction. Continual monitoring and evaluation of AI agent performance, data collection, trend analysis, and performance benchmarking are essential. Resources should be allocated for the ongoing retraining of AI models, involving new data, performance monitoring, and user feedback incorporation to enhance accuracy and relevance. Encouraging collaboration and feedback loops between human employees and AI agents can help identify performance gaps and refine AI algorithms. Establishing regular communication channels for insights from employees can further enhance performance.

Managers must prioritize understanding customer needs, preferences, and expectations through market research, customer data analysis, and feedback analysis. This understanding helps align AI agent capabilities with customer expectations, ensuring a personalized and engaging experience. User-friendly and intuitive interfaces for AI interactions contribute to a positive customer experience. Leveraging customer data, AI agents can provide personalized recommendations and tailored content, ultimately enhancing customer service and fostering stronger customer connections. Regular monitoring of customer sentiment through sentiment analysis, surveys, and social media monitoring helps identifies areas for improvement and emerging trends, allowing for targeted enhancements to customer service strategies.

REFERENCES

- [1] Ambolau, M. A., Kusumawati, A., & Mawardi, M. K. (2015). The influence of brand awareness and brand image on purchase decision. *Jurnal Administrasi Bisnis*, 2(2). https://tinyurl.com/spsu8xk3
- [2] Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. *Computers in Human Behavior*, 114, 106548. https://:doi:10.1016/j.chb.2020.106548
- [3] Bae, S., Jung, T. H., Moorhouse, N., Suh, M., & Kwon, O. (2020). The influence of mixed reality on satisfaction and brand loyalty in cultural heritage attractions: A brand equity perspective. Sustainability, 12(7), 2956. https://idoi:10.3390/su12072956
- [4] Baumann, C., Hamin, H., & Chong, A. (2015). The role of brand exposure and experience on brand recall—Product durables vis-à-vis FMCG. *Journal of Retailing and Consumer Services*, 23, 21-31. https://doi.org/10.1016/j.jretconser.2014.11.003
- [5] Bernarto, I., Berlianto, M. P., Meilani, Y. F. C. P., Masman, R. R., & Suryawan, I. N. (2020). The influence of brand awareness, brand image, and brand trust on brand loyalty. *Jurnal Manajemen*, 24(3), 412-426. https://doi.org/10.24912/jm.v24i3.676
- [6] Bilgin, Y. (2018). The effect of social media marketing activities on brand awareness, brand image and brand loyalty. *Business & management studies: an international journal*, 6(1), 128-148. https://doi.org/10.15295/bmij.v6i1.229
- [7] El Kedra, A. M., & Şener, D. U. (2020). The Mediating Role of Social Media and Customer Engagement in The Impact of Digital Content Marketing on Brand Awareness. *International Research Journal of Marketing & Economics*, 7(11), 1-11. https://tinyurl.com/3du885yd

- [8] Hamdani, N. A., Muladi, R., & Maulani, G. A. F. (2022). Digital Marketing Impact on Consumer Decision-Making Process. In 6th Global Conference on Business, Management, and Entrepreneurship (GCBME 2021) (pp. 153-158). Atlantis Press. https://idoi.org/10.2991/aebmr.k.220701.031
- [9] Han, S. H., Chen, C. H. S., & Lee, T. J. (2021). The interaction between individual cultural values and the cognitive and social processes of global restaurant brand equity. *International Journal of Hospitality Management*, 94, 102847. https://doi.org/10.1016/j.ijhm.2020.102847
- [10] Husnain, M., & Toor, A. (2017). The impact of social network marketing on consumer purchase intention in Pakistan: Consumer engagement as a mediator. *Asian Journal of Business and Accounting*, 10(1), 167-199. https://tinyurl.com/7krfkdk7
- [11]Kato, T. (2021). Brand loyalty explained by concept recall: recognizing the significance of the brand concept compared to features. *Journal of Marketing Analytics*, 9(3), 185-198. https://doi.org/10.1057/s41270-021-00115-w
- [12]Khurram, M., Qadeer, F., & Sheeraz, M. (2018). The role of brand recall, brand recognition and price consciousness in understanding actual purchase. *Journal of Research in Social Sciences*, 6(2), 219-241. https://ssrn.com/abstract=3215875
- [13]Mafael, A., Raithel, S., & Hock, S. J. (2022). Managing customer satisfaction after a product recall: the joint role of remedy, brand equity, and severity. *Journal of the Academy of Marketing Science*, 50(1), 174-194. https://doi.org/10.1007/s11747-021-00802-1
- [14] Memon, B., Arif, H., & Aslam, M. F. (2016). Impact of brand recall on customer purchase intention. *Journal of Marketing and Consumer Research*, 25. https://ssrn.com/abstract=2913547
- [15] Merdiaty, N., & Aldrin, N. (2022). Effect of Brand Experience on Customer Engagement Through Quality Services of Online Sellers to Students in Bekasi. *Frontiers in Psychology*, 12, 6073. https://doi.org/10.3389/fpsyg.2021.801439
- [16] Misischia, C. V., Poecze, F., & Strauss, C. (2022). Chatbots in customer service: Their relevance and impact on service quality. *Procedia Computer Science*, 201, 421-428. https://doi.org/10.1016/j.procs.2022.03.055
- [17] Nordheim, C. B. (2018). Trust in chatbots for customer service-findings from a questionnaire study (Master's thesis). *UNIVERSITY OF OSLO*. https://tinyurl.com/y97344vf
- [18] Pham, L. T. M., Do, H. N., & Phung, T. M. (2016). The effect of brand equity and perceived value on customer revisit intention: a study in quick-service restaurants in Vietnam. *Acta Oeconomica Pragensia*, 24(5), 14-30. https://idoi.org/10.18267/j.aop.555
- [19]Pine, K., Young, B. M. (2016). Theories of Persuasion. Hayden, B., Rascon, N. *Introduction to Public Communication* (11.5). Indiana State University. https://tinyurl.com/5bj5bmw4
- [20]Pramudya, A. K., Sudiro, A., & Sunaryo, S. (2018). The role of customer trust in mediating influence of brand image and brand awareness of the purchase intention in airline tickets online. *Jurnal Aplikasi Manajemen*, 16(2), 224-233. http://dx.doi.org/10.21776/ub.jam.2018.016.02.05
- [21]Qiao, Y., Yin, X., & Xing, G. (2022). Impact of Perceived Product Value on Customer-Based Brand Equity: Marx's Theory-Value-Based Perspective. *Frontiers in Psychology*, 3727. https://doi.org/10.3389/fpsyg.2022.931064
- [22]Schreuder, H. T., Gregoire, T. G., & Weyer, J. P. (2001). For what applications can probability and non-probability sampling be used?. *Environmental Monitoring and Assessment*, 66, 281-291. https://doi.org/10.1023/A:1006316418865
- [23] Sitorus, T., & Yustisia, M. (2018). The influence of service quality and customer trust toward customer loyalty: the role of customer satisfaction. *International Journal for Quality Research*, 12(3), 639. https://idoi.org/10.18421/IJQR12.03-06
- [24] Taherdoost, H. (2016). Sampling methods in research methodology; how to choose a sampling technique for research. *International Journal of Academic Research in Management (IJARM)*, 5(2), 18-27. https://doi:10.2139/ssrn.3205035
- [25] Varsha, P. S., Akter, S., Kumar, A., Gochhait, S., & Patagundi, B. (2021). The impact of artificial intelligence on branding: a bibliometric analysis (1982-2019). *Journal of Global Information Management (JGIM*), 29(4), 221-246. https://:DOI:10.4018/JGIM.20210701.oa10



- [26] Vehovar, V., Toepoel, V., & Steinmetz, S. (2016). Non-probability sampling. Wolf, C., Joye, D., & Fu, Y. *The Sage handbook of survey methods*. (*Vol. 1*, pp. 329-45). Sage Publications. [Crossref], [Google Scholar]
- [27]Wang, W. C., Pestana, M. H., & Moutinho, L. (2018). The effect of emotions on brand recall by gender using voice emotion response with optimal data analysis. *Innovative Research Methodologies in Management: Volume II: Futures, Biometrics and Neuroscience Research*, 103-133. https://doi.org/10.1007/978-3-319-64400-4_5
- [28]Whang, J. B., Song, J. H., Lee, J. H., & Choi, B. (2022). Interacting with Chatbots: Message type and consumers' control. *Journal of Business Research*, 153, 309-318. https://doi.org/10.1016/j.jbusres.2022.08.012
- [29]Xu, Y., Shieh, C. H., van Esch, P., & Ling, I. L. (2020). Al customer service: Task complexity, problem-solving ability, and usage intention. *Australasian marketing journal*, 28(4), 189-199. https://doi.org/10.1016/j.ausmj.2020.03.005