MJBEM 3 (2) 183-195

MJBEM

Malaysian Journal
of Business,
Economics and Management

journal homepage: https://mjbem.com.my/

Student Perception of AI-Powered Service Quality and Customer Satisfaction: A Case Study of Higher Learning Institution in Malaysia

Mohd Bukhari Abd Razak*[1], and M. Reyasudin Basir Khan[1, 2]

[1] *Tun Razak Graduate School, Universiti Tun Abdul Razak (UNIRAZAK), Kuala Lumpur, Malaysia.*
[2] *KPJ Healthcare University, Nilai, Negeri Sembilan, Malaysia.*

KEYWORDS

Artificial Intelligence
Chatbot
Service Quality
Customer Satisfaction
SPSS

ARTICLE HISTORY

Received 10 August 2024
Received in revised form 30 August 2024
Accepted 5 September 2024
Available online 11 September 2024

ABSTRACT

As service providers increasingly employ AI-powered service agents (AISAs), concerns about how these interactions influence consumers' perceptions of service quality have grown. This study aims to analyze the effect of AI-powered service quality on customer satisfaction, specifically focusing on chatbots. Data were collected via a Google Forms survey from 113 MBA students and analyzed using SPSS for descriptive statistics and SmartPLS version 4.0 for assessing relationships between service quality dimensions and customer satisfaction. Descriptive analysis showed moderate levels of efficiency, anthropomorphism, and satisfaction, with lower scores for security. Availability received a high mean rating, suggesting a strong presence of resources. These findings indicate that while customers perceive moderate levels of efficiency, anthropomorphism, and satisfaction, improvements are needed in the security aspect of AI-powered services. The structural model assessment using PLS-SEM revealed that the availability of AI-chatbot services has the most significant positive relationship with customer satisfaction (path coefficient = 0.367, t-value = 3.997, $p < 0.001$). This highlights the importance of constant service availability for enhancing customer satisfaction. Anthropomorphism features also have a significant positive relationship with customer satisfaction (path coefficient = 0.252, t-value = 2.418, $p < 0.01$), emphasizing the positive impact of human-like interaction styles. Efficiency in AI-chatbot services similarly shows a significant positive relationship with customer satisfaction (path coefficient = 0.241, t-value = 2.348, $p < 0.01$). However, there is no significant positive relationship between security in AI-chatbot services and customer satisfaction. In conclusion, this study provides insights into key dimensions of AI-powered service quality and their impact on customer satisfaction, highlighting the need for improved security to enhance customer experiences.

© 2024 The Authors. Published by Penteract Technology.
This is an open access article under the CC BY-SA 4.0 license (https://creativecommons.org/licenses/by-sa/4.0/)

1. INTRODUCTION

Lately, Artificial Intelligence (AI) has become increasingly popular as customer service solutions (Whang & Im, 2021). These AI-led technologies including chatbots, virtual assistants and automatic systems serve as a refreshing tool for the customer service sector. These tools that run on AI use machine learning algorithms and natural language processing to engage with customers effectively by rendering quick help and solving problems instantly (Naveen, 2018). Leaders in the industry, predominantly Apple and Google, have adopted AI-driven solutions to their methods of customer service. This shows a clear pattern of using artificial intelligence for improving interactions with customers. Reports from Gartner and similar industry experts show marked progress in speed of response as well as how happy customers are with support service after applying these inventive customer-service technologies (Jones et al., 2019). The changeover of customer service to include AI signifies a significant shift from the old-style methods which center around humans towards machine-centered service supposedly for improved productivity and results. Yet, the real impact of these advancements on customer satisfaction is still debatable.

*Corresponding author:
E-mail address: Corresponding author <m.bukhari@ur.unirazak.edu.my>.
https://doi.org/10.56532/mjbem.v3i2.82
2948-4928/ © 2024 The Authors. Published by Penteract Technology.
This is an open access article under the CC BY-SA 4.0 license (https://creativecommons.org/licenses/by-sa/4.0/).

This shows the need for more study in this area. This research paper has a goal to investigate the effect of AI-Powered Service Quality on customer satisfaction. By studying consumers' perception on the quality of service provided by AI and test its relationship with customers' satisfaction, this study aims to offer an understanding about the effectiveness of AI-led customer service. A prevalent utilization of AI in customer service is through chatbots. These are often used to predict wait times, synthesize resolution data and create unique customer experiences (Kumar et al., 2022). So, the main objective of this study is to seek the views of the consumers on the quality of service provided by chatbots and their satisfaction with the services.

1.2 Problem Statement

AI-powered services have the potential to revolutionize consumer experiences, shifting from traditional human service agents to computer-based applications that mimic human behaviour (Huang & Rust, 2021; Park et al., 2021). This shift can significantly impact customer perceptions of service quality (Huang & Rust, 2021; Paluch & Wirtz, 2020). Marketing research emphasizes the importance of service quality during delivery (Zeithaml, Berry, & Parasuraman, 1988), as it influences customer satisfaction, brand loyalty, and retailer performance (Ladhari, 2010; Fassnacht & Koese, 2006). Studies show that positive customer service experiences increase purchase likelihood, while negative experiences can deter future purchases (Zendesk, 2020).As more businesses adopt AI-powered service agents (AISA), understanding their impact on consumer perceptions of service quality becomes critical (AMR, 2020). A McKinsey survey revealed that 58% of businesses use AI, particularly for product and service enhancements (Chui et al., 2020). Despite anticipated benefits like increased efficiency and customization (Verhagen et al., 2014; Huang & Rust, 2021), practical studies yield mixed results. For example, AI and human service quality independently boost satisfaction, but combined, they can negatively impact customer satisfaction in the hospitality sector (Prentice et al., 2020).Perceptions of AI service quality vary by service type. AI is preferred for credence services like hospitals but less so for experience-based services like cafes (Park et al., 2021; Wirtz et al., 2018). The mixed consumer perceptions highlight the need for further research on AI service quality (Lu et al., 2020; Huang & Rust, 2021; Paluch & Wirtz, 2020). This study aims to explore the effect of AI-powered service quality on customer satisfaction, offering insights to enhance AI-driven service solutions.

1.3 Research Objectives

The general aim of this study is to investigate the effect of Chatbots' service quality on customer satisfaction. The objectives are:

- To assess the level of customers' perceived service quality performance provided by Chatbots.
- To determine the level of customers' satisfaction on the service quality provided by Chatbots.
- To analyze the effect of perceived quality on customer satisfaction of Chatbots.

1.4 Research Questions

The Research Question are as follows:

- What is the effect of service quality on customers' satisfaction of Chatbots customer service?
- What is the customers' perceived level of service quality performance provided by Chatbots?
- What is the level of customers' satisfaction towards Chatbots?
- To what extent perceived quality affect customers' satisfaction of Chatbots?

1.5 Key Question

Considering MBA students at UNIRAZAK often use AI-powered chatbots in their daily lives, how are their overall satisfaction affected by different aspects of service quality such as availability, efficiency, anthropomorphism and security. This question refers to the dimensions of service quality in the questionnaire. It links these dimensions with the satisfaction of MBA students at UNIRAZAK, who are the main target audience for this study. The goal is to understand how well AI-powered customer service solutions work within this particular setting by looking at each dimension's effect on satisfaction.

1.6 Significance of the Study

The importance of the study is crucial for various reasons. Firstly, by examining how AI-powered service quality affects customer satisfaction, this research provides important understanding into the ways advanced technologies such as artificial intelligence impact customer experiences and viewpoints. Recognizing the connection between service quality powered by AI and customer satisfaction is key for businesses looking to improve their customer service tactics. The study gives a structure to assess how AI-driven answers impact important elements like efficiency, response times, customization, and general client contentment. Furthermore, life in a digital era that sees customer demands always changing, businesses incorporating AI into services must make sure these technologies enhance effectiveness and increase client contentment. This study tackles the lack of information about how AI affects satisfaction from customers; it uncovers potential benefits and difficulties linked with using AI-driven customer service solutions. In the end, this study can be seen as a base for groups wanting to make their service quality better with AI. This way, it helps in forming good choices, improving connections with customers and increasing overall satisfaction

2. LITERATURE REVIEW

2.1 AI-powered service providers

Advancements in technology are enhancing customer experiences, with AI-powered services revolutionizing service delivery. Traditional interactions involved human service agents, but now AI offers two main roles: aiding human employees to improve efficiency and replacing them with self-service technologies (SSTs) like online shops and kiosks (Gummerus et al., 2004; Verhagen et al., 2014). This shift introduces a high (humanlike) touch – high tech paradigm, where AI mimics human interaction, handling cognitive and analytical tasks (Huang & Rust, 2021).AI's ability to process vast amounts of data allows it to offer personalized services and continuous availability, surpassing human agents in efficiency and consistency (Paschen et al., 2020; Beck & Libert, 2017). AI can profile consumers quickly and accurately, providing tailored interactions and overcoming human limitations like bias and fatigue (Shankar, 2018; Huang & Rust, 2018). It also retains past interaction data, allowing for complex service recovery (Considine & Cormican, 2016). Chatbots, a key AI technology, enhance human-computer interaction by offering instant, personalized assistance via text or voice interfaces (Whang & Im, 2021). They analyze data to improve responses and provide continuous user support, integrating seamlessly with traditional service methods (Reference 3; Reference 29). This research highlights the importance of understanding AI service quality to improve customer satisfaction.

2.2 Service Quality Concept

Quality of service, defined as customers' overall assessment of a service (Eshghi et al., 2008), is crucial for companies aiming to satisfy their customers (Ghylin et al., 2008). Service quality involves traits like heterogeneity, inseparability, and intangibility (Ladhari, 2008; Parasuraman et al., 1985) and is a comprehensive evaluation of service performance (Cronin Jr and Taylor, 1994; Parasuraman et al., 1994a). Scholars often view service quality as a multi-dimensional construct, including timeliness, empathy, dependability, reassurance, and tangibility (Brady and Cronin Jr, 2001). These dimensions align well with the sophisticated nature of AI customer service solutions, significantly impacting customer experiences and satisfaction levels. A meta-analysis by Smith et al. (2020) revealed that AI-based customer service solutions enhance response speed and accuracy, boosting customer satisfaction. Johnson and Lee's (2019) two-year longitudinal study on e-commerce businesses found that AI technologies increase customer happiness and loyalty. Garcia and Patel's (2023) study involving surveys and interviews in a multinational communications company confirmed AI's ability to improve service speed and customer happiness, though they noted the importance of ongoing staff training to address system errors. Customer satisfaction is a complex concept. Cronin and Taylor (1992) view it as transaction-specific, reflecting contentment during individual service encounters, while Jones and Suh (2000) see it as an overall evaluation of service experiences. Consistently meeting or exceeding customer expectations leads to higher retention and profitability, as satisfied customers are more likely to remain loyal (Wicks & Roethlein, 2009).

2.3 Theoretical Foundation

This study examines the relationship between service quality and customer satisfaction in AI-assisted customer services. High service quality perceptions lead to increased customer contentment (Saravana & Rao, 2020; Lee et al., 2021). AI technologies like chatbots, predicted wait times, data integration, and personalized experiences enhance service speed, accuracy, and overall quality, resulting in happier customers. The study integrates insights from marketing, psychology, and communication research to explore AI's impact on customer service communication, emphasizing AI's role in improving customer satisfaction. This theoretical framework provides a robust structure for analyzing AI's effects on customer contentment.

2.3.1 Service Quality Models

Service quality is crucial for customer satisfaction, with the SERVQUAL model by Parasuraman et al. (1985) serving as a key framework for evaluation across various industries. This model, validated by studies in banking sectors in Iran (Amiri Aghdaie & Faghani, 2012), China (Laforet & Li, 2005), and Bangladesh (Rahman et al., 2017), assesses service quality through five dimensions: reliability, empathy, tangibles, assurance, and responsiveness. Advancements in technology have shifted service delivery from high touch-low tech to low touch-high tech paradigms, introducing self-service technologies (SSTs) like ATMs and online services. This shift emphasizes dimensions like security and privacy. However, traditional measures like SERVQUAL may be inadequate for evaluating AI-powered service providers, as noted by Meyer-Waarden et al. (2020). These providers create unique customer experiences, necessitating new evaluation scales tailored to high (humanlike) touch-high tech environments (Bock et al., 2020; Wirtz et al., 2018). Ladhari (2009, 2010) highlights the need for context-specific service quality measures.

2.3.2 AI-powered Service Quality Model

Research on AI-powered service quality remains limited. Notable studies include Prentice et al. (2020) and Noor et al. (2021b). Prentice et al. (2020) focuses on the hotel and hospitality sector, identifying five constructs that represent AI-delivered hotel services: travel-experience enhancers, voice-activated services, digital assistants, concierge robots, and automatic data processing. These constructs and their 15 associated items were derived from Makadia (2018), although the study lacks evidence of thorough development or validation. Conversely, Noor et al. (2021b) proposes a broader approach with 12 dimensions reflecting the perceived service quality of AI service agents (AISA). They extend the SERVQUAL dimensions through a two-stage methodology. The first stage involves reviewing service quality and information systems literature, while the second stage entails qualitative validation to confirm the dimensions and identify new relevant ones. This study included users of chatbots and virtual assistants, representative of the high touch – high tech paradigm.

2.3.3 Relationship Between Service Quality and Customer Satisfaction

Service quality is closely linked to customer satisfaction, as confirmed by Parasuraman et al. (1985) and supported by recent studies (Prentice et al., 2020; Noor et al., 2022). Noor et al. (2022) emphasize the importance of AI service quality, identifying key dimensions such as anthropomorphism, efficiency, security, and availability. Anthropomorphism involves attributing human traits to non-human entities, enhancing user trust and engagement (Bartneck & Forlizzi, 2018; Huang & Sundar, 2019). This is especially significant in AI interactions, where human-like features improve user experience (Sheehan et al., 2019). Efficiency in AI services, highlighted by Featherman and Pavlou (2003), is achieved through optimized algorithms and resource management, crucial for handling multiple queries and delivering accurate responses (Liu & Zhang, 2022). Security remains a critical concern, as users fear data misuse and privacy breaches. Studies show that these concerns affect the adoption and trust of AI technologies (Rese et al., 2020; Ischen et al., 2020). Availability, ensuring accessible and adequate AI services, faces challenges like data scarcity and infrastructure limitations. Advances in cloud computing and data augmentation are improving service performance (Zhang & Liu, 2020; Wang & Li, 2022). Together, these dimensions enhance AI-powered service quality, boosting customer satisfaction and loyalty.

2.4 Conceptual Framework

The conceptual framework for this research is based on the SERVQUAL model to evaluate the effect of perceived AI-powered service quality on customer satisfaction (Parasuraman et al. 1988) However, the service quality dimensions is adopted from Noor et al. (2022) which focus on AI-service provider. Figure 1 shows the framework for conducting this study. It highlights how service quality dimensions, including Efficiency, Security, Availability and Anthropomorphism of AI-Chatbot services interact with customer satisfaction.

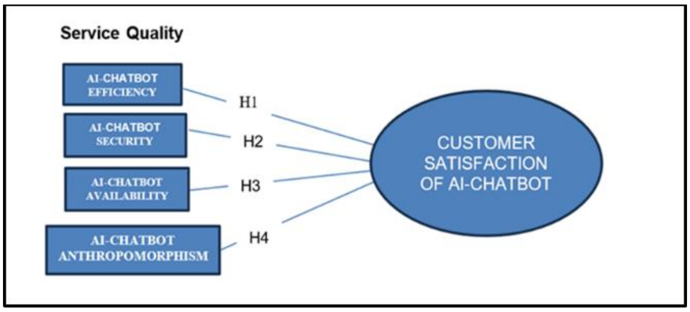

Fig. 1. Conceptual Framework

The definition of the service quality dimensions adopted is as proposed by Noor et al. (2002):

- Efficiency: The ability of AI systems to provide quick and accurate responses.
- Availability: The readiness of AI services to assist customers at any time.
- Security: The protection of customer data and privacy.
- Anthropomorphism: The human-like interaction style of AI systems.

The interaction between factors like anthropomorphism, efficiency, availability, and security in AI service delivery can significantly influence customer satisfaction. For example, prioritizing human-like chatbots over quick responses may disappoint customers who expect both. The conceptual framework explores various AI applications in customer service, such as chatbots and personalized experiences, assessing their impact on service quality dimensions and customer satisfaction. Adapted from the SERVQUAL model, this framework is ideal for evaluating service quality and customer happiness among UNIRAZAK students, focusing on how AI influences perceived service quality and satisfaction in student services at UNIRAZAK. This underscores the integration of AI and service quality.

2.5 Hypothesis Development

Based on the conceptual framework the hypotheses are developed to test the relationships between AI-Chatbot service quality dimensions and customer satisfaction.

- H1: Efficiency in AI-Chatbot services has a positive relationship with customer satisfaction.
- H2: Security in AI-Chatbot services has a positive relationship with customer satisfaction.
- H3: Availability of AI-Chatbot services has a positive relationship with customer satisfaction.
- H4: Anthropomorphism features in AI-Chatbot services has a positive relationship with customer satisfaction.

3. METHODOLOGY

3.1 AI-powered service providers

This chapter explains the process of conducting this research. It covers aspects such as research design, sampling procedure, method of data collection, measurement instrument, and data analysis.

3.2 Research Design

Research design is the plan or strategies for getting the expected results. These can include different types of research design, such as case study design, survey study and experimental design study depending on what kind of study it is (Cooper et al., 1998). The way this research was done falls under the category of survey approach. A survey is a research instrument designed to collect data from a specific group of people, usually called a sample, in order to understand their opinions, attitudes, behaviors or characteristics. (APA, 2020). Generally speaking, surveys involve asking participants for answers by providing them with a set of organized questions. These queries may be handed out through methods like paper forms; they might also come via internet platforms as well as phone conversations or meetings face-to-face situations among others. After this step has been completed and the necessary information gathered from these instruments has been obtained successfully--data is then analyzed for drawing conclusions, making deductions or gaining comprehension into patterns/trends within given population groupings. In this particular study, a Google Form was utilized to conduct the survey.

This study employs convenience sampling to gather data from MBA students at UNIRAZAK who have experience using chatbots, ensuring accessibility and relevance to the research focus. Convenience sampling is chosen for its cost-effectiveness and efficiency in reaching participants who might otherwise be difficult to engage or uninterested in the study (APA, 2020). It serves exploratory purposes by generating hypotheses and initial insights before more extensive research. However, findings are specific to the participant group and cannot be generalized to the broader Malaysian population. The sample size comprises 113 respondents, meeting the minimum requirements for quantitative analysis, specifically partial least squares structural equation modeling (PLS-SEM). PLS-SEM guidelines suggest a sample size at least ten times the highest number of formative indicators per construct. With the study's constructs having up to 6 indicators (e.g., Anthropomorphism), a sample size of 60 was deemed sufficient, with an increase to 113 to account for potential incomplete responses and ensure robust statistical analysis (Hair et al., 2017).

3.3 Method of Data Collection

The study "The Effect of Artificial Intelligence Powered Service Quality on Customer Satisfaction" uses self-completion surveys using google form as its data collection method. These surveys were created to measure service quality dimensions and customer satisfaction of AI-powered solutions. Surveys that require self-completion let participants give their responses alone, possibly resulting in more honest and unaltered feedback. This technique assists in acquiring a variety of responses without the need for direct interaction or influence from the researchers. The surveys are designed to focus on service quality dimensions linked with AI-powered solutions. This makes them specific in targeting how AI affects customer satisfaction and operational efficiency. Such a focused method guarantees the study collects data that is applicable and directly related to its research goals. Also, self-completion surveys offer a systematic and organized method for data collection. This way of doing things lets researchers examine the data in an orderly fashion and make important findings about the impact AI has on service quality as well as customer satisfaction. In total, using self-completion surveys in this study is a good method for gathering data and matching the analysis with research goals. This way, we can improve our comprehension of how AI influences customer satisfaction within service quality's scope

3.4 Variables and Measurement Instrument

In this study, variables are categorized into dependent and independent categories: customer satisfaction as dependent, influenced by changes in service quality dimensions which act as independent variables (Saunders, 2009). The research employs the SERVQUAL model, adapted with dimensions relevant to AI-powered service quality—Efficiency, Security, Availability, and Anthropomorphism (Noor et al., 2022). The survey instrument, originally from Noor et al. (2022), was adjusted by substituting "AISA" with "chatbots". Measurement scales for service quality dimensions and customer satisfaction range from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating higher agreement levels as shown in Table 1.

Table 1. The Survey Instrument

EFFICIENCY
EFF1 The AI-CHATBOT works correctly at first attempt.
EFF2 I can get my task done with the AI-CHATBOT in a short time.
EFF3 The AI-CHATBOT interface design provides information clearly.
EFF4 The AI-CHATBOT adequately meets my requirements.
SECURITY
SEC1 There is no risk of loss associated with disclosing personal information to the AI-CHATBOT.
SEC2 I feel secure in providing sensitive information to the AI-CHATBOT.
SEC3 I believe that information that the AI-CHATBOT has about me is protected.
SEC4 I trust that my personal information with the AI-CHATBOT will not be misused.
AVAILABILITY
AVA1 The AI-CHATBOT is always available.
AVA2 The AI-CHATBOT is never too busy to respond to my requests.
AVA3 The AI-CHATBOT is always accessible.
ANTHROPOMORPHISM
ANT1 The AI-CHATBOT has humanlike features.
ANT2 The AI-CHATBOT has personality.
ANT3 The AI-CHATBOT gradually gets to know me.
ANT4 The AI-CHATBOT is able to behave like a human.
ANT5 The AI-CHATBOT responds in ways that are personalized.
ANT6 The AI-CHATBOT is able to communicate like a human.
CUSTOMER SATISFACTION
SAT1 I am satisfied with my decision to use the AI-CHATBOT.
SAT2 I think that I did the right thing by using the AI-CHATBOT.
SAT3 My choice to use the AI-CHATBOT was a wise one.

3.5 Construct validity and reliability.

"Validity is the extent to which an instrument measures what it is designed to measure" (Wiersma 1995). On the other hand, reliability means consistency – consistency of the instrument in measuring whatever it measures (Wiersma 1995, Fraenkel & Wallen 1996). The instrument adopted from Noor et al. (2002) has been proven to have good validity and reliability. Therefore, pilot test was not conducted in this study. However, the construct validity and reliability were tested on the field data prior to model development.

3.6 Data Analysis

Two types of statistical analyses were carried out: descriptive and inferential.

3.6.1 Descriptive Analyses

The first step was to run descriptive analyses to portray the demographic profile of respondents and the level of service quality and satisfaction as perceived by the customers. The analysis was carried out using a software programmed, Statistical Package for Social Science (SPSS) version 27.0.

3.6.2 Inferential Statistics

In preparation for the SEM-PLS model, preliminary exploratory analyses were conducted using SPSS Version 4.0 to assess construct validity and mitigate multicollinearity risks. The subsequent analysis utilized Smart-PLS software (version 4.0), chosen for its suitability in predictive analysis with small sample sizes without compromising model robustness (Ringle et al., 2018). The analysis proceeded in two stages: evaluating the measurement model and assessing the structural model.

3.7 Testing the measurement model

The measurement model, as advised by Hair et al. (2021), underwent confirmatory factor analysis (CFA) to assess indicator reliability and internal consistency at the construct level. Indicator reliability was determined by ensuring indicator loadings exceeded 0.708, indicating that constructs explain more than 50% of indicator variance. Composite reliability values between 0.60 and 0.70 were deemed acceptable, while those from 0.70 to 0.90 were considered satisfactory to good. Convergent validity was assessed using the average variance extracted (AVE), with a threshold of 0.50 indicating acceptable construct variance explanation. Discriminant validity was evaluated through the heterotrait–monotrait (HTMT) ratio of correlations.

3.8 Structural model assessment

Upon establishing measurement validity and reliability, the structural model was assessed. This involved examining path coefficients for significance and relevance, as well as evaluating the model's explanatory and predictive capabilities. Checks for collinearity issues were conducted using Variance Inflation Factors (VIFs), where values exceeding 5 suggest potential problems. The coefficient of determination (R^2) was scrutinized to gauge the amount of variance explained in endogenous constructs, with values of 0.25, 0.50, and 0.75 indicating weak, moderate, and substantial explanatory power, respectively (Hair, Ringle, & Sarstedt, 2011).

4. Results and Discussions

4.1 Introduction

This chapter presents and discusses findings of data from doing research in the field about how to check if customers are happy with services and their satisfaction using the SERVQUAL method with UNIRAZAK master's degree students. The study wanted to figure out what customers think about good service overall, find out what parts of service make customers happy, find things that stop customers from being happy, and suggest ways to increase customer happiness. In this study, the data analysis is divided into two categories: descriptive and inferential. Descriptive statistics describe the demographics of the respondents and the summary of mean scores of respondents' perceived service quality' and satisfaction levels. Inferential statistics cover the results of the evaluation of the measurement model and the structural model evaluation.

4.2 Demographic Characteristics of the Respondents

The demographic profile of the respondents is described as follows; males were 43.1% while females were 56.9%, slightly higher than males. This balanced representation, though slightly skewed towards females, helps ensure that the study captures insights from both genders, providing a more comprehensive understanding of the impact of AI-powered service quality on customer satisfaction.

The demographic profile of the respondents' age is described as follows: most respondents (64.2%) are aged between 30 to 45, indicating a strong representation of mid-career adults. The second largest group is those aged from 46 to 59, comprising 22.0% of the sample, likely representing individuals in advanced career stages. Young adults aged from 18 to 29 make up 11.0% of the respondents, while only 2.8% are 60 years old and above, showing minimal representation of senior adults. This age distribution helps ensure the study captures insights from a wide range of age groups, providing a comprehensive understanding of the respondents' perspectives. This is presented in Figure 2.

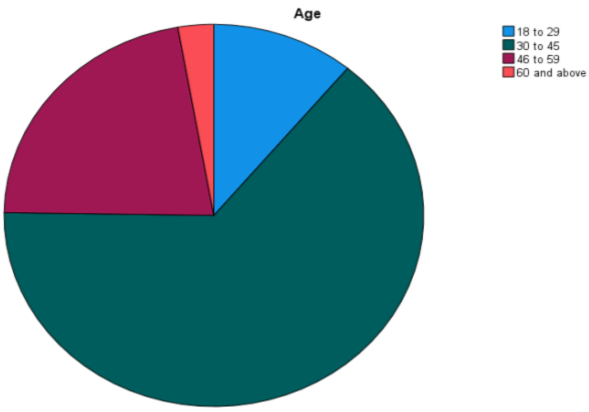

Fig. 2. Respondents' Ages

The demographic profile of the respondents by occupation is as follows: the majority are from the private sector (78.9%), followed by the government sector (15.6%), and a small percentage comprises of housewives, retirees, or self-employed individuals (2.8% each). This occupational distribution ensures representation from various sectors, providing diverse perspectives on the impact of AI-powered service quality on customer satisfaction. This is presented in Figure 3.

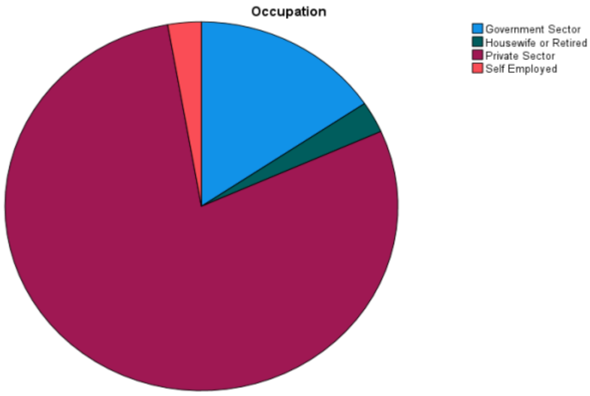

Fig. 3. Respondents' Occupations

The demographic profile of the respondents by education is as follows: the majority hold a bachelor's degree (53.2%), followed by Master's degree holders (26.6%). There are also respondents with STPM/Diploma qualifications (17.4%), Professional Certificates (1.8%), and a smaller percentage with a PhD (0.9%). This educational distribution ensures a diverse representation of educational backgrounds, enriching the study's insights on the impact of AI-powered service quality on customer satisfaction. This is presented in Figure 4.

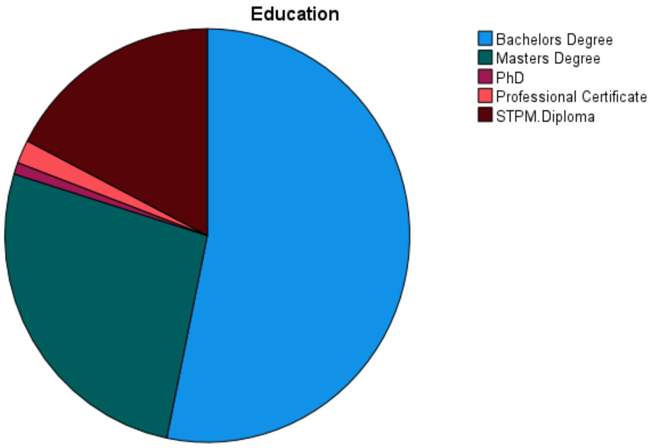

Fig. 4. Respondents' Educations

4.3 Descriptive Analysis

The descriptive data analysis was conducted using IBM SPSS Statistics 27 for five different variables. These results answer the research objectives 1 and 2. The mean values for each variable are as follows:

- Efficiency: The mean efficiency score was 3.6914 out of 5, indicating a moderate level of efficiency of Chatbots.
- Security: The mean security rating was 2.7095 out of 5, suggesting a relatively lower level of security of Chatbots compared to other factors. This may suggest that security aspects in AI-powered services such as Chatbots might need improvement based on respondents' perceptions.
- Anthropomorphism: The mean anthropomorphism score was 3.1651 out of 5, reflecting a moderate assessment of human-like characteristics of Chatbots. This shows how

users perceive the AI system to possess human-like qualities to a moderate extent.

- Availability: The average availability rating stood at 4.0453 out of 5, indicating a high level of accessibility or presence of the relevant resources. Thus, respondents seem to have a positive perception regarding the availability of Chatbots.
- Satisfaction: The mean satisfaction score was 3.5327 out of 5, indicating a moderate level of contentment or fulfilment experienced by users or participants. This suggests that overall customer satisfaction with chatbots is at a moderate level.

Table 2. Descriptive Statistics

DESCRIPTIVE STATISTICS			
Variable	**N**	**Mean**	**Level of Agreement**
Efficiency	108	3.6914	High
Security	105	2.7095	Low
Anthropomorphism	105	3.1651	Moderate
Availability	103	4.0453	High
Satisfaction	107	3.5327	Moderate

**1-2.33 - low level of agreement; 2.34- 3.66 - moderate level of agreement; 3.67-5.0- high level agreement

Based on the descriptive analysis of the data, the mean values reveal moderate levels of efficiency, anthropomorphism, and satisfaction, accompanied by relatively lower scores for security. It should be noted that availability stands out with a high mean rating, indicating a strong presence of relevant resources. These insights provide a comprehensive understanding of the perceived levels of these key factors within the examined context.

4.4 Exploratory Factor Analysis

An exploratory principal component factor analysis followed by varimax rotation was carried out using IBM SPSS Statistics 27 to identify items best expressive of service quality dimensions. The items which cross-load on more than two factors and difficult to interpret, with factor loadings lower than 0.50 or inconsistent across the dimensions were deleted. The result is presented in Table 3.

Table 3. Rotated Component Matrix

	Factor loadings				
Items	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
AVA1: The AI-CHATBOT is always available	0.800				
AVA2: The AI-CHATBOT is never too busy to respond to my requests.	0.870				
AVA3: The AI-CHATBOT is always accessible.	0.878				
ANT2: The AI-CHATBOT has personality		0.877			
ANT3: The AI-CHATBOT gradually gets to know me		0.814			
ANT4: The AI-CHATBOT is able to behave like a human		0.735			
EFF2: I can get my task done with the AI-CHATBOT in a short time			0.820		
EFF3: The AI-CHATBOT interface design provides information clearly			0.783		
EFF4: The AI-CHATBOT adequately meets my requirements			0.802		
SEC1: There is no risk of loss associated with disclosing personal information to the AI-CHATBOT				0.782	
SEC2: I feel secure in providing sensitive information to the AI-CHATBOT.				0.880	
SEC3: I believe that information that the AI-CHATBOT has about me is protected				0.899	
SEC4: I trust that my personal information with the AI-CHATBOT will not be misused				0.853	
SAT1: I am satisfied with my decision to use the AI-CHATBOT					0.794
SAT2: I think that I did the right thing by using the AI-CHATBOT.					0.765
SAT3: My choice to use the AI-CHATBOT was a wise one					0.784

Extraction Method: Principal Component Analysis, Rotation Method: Varimax with Kaiser Normalization.[a]

Factor 1: Availability, Factor 2: Anthropomorphism, Factor 3: Efficiency, Factor 4: Security, Factor 5: Satisfaction

The results of principal component factor analysis using varimax rotation yielded five meaningful items grouping or factor/dimension (Table 4). Majority of the items were retained and represented the five factors/dimensions. However, four items which either cross-load on more than two factors (difficult to interpret) and those with factor loadings lower than 0.50: EFF1, ANT1, ANT5 and ANT6 were deleted. Only the meaningful and valid items representing the five dimensions in Table 4 were used for subsequent PLS-SEM analysis. The five dimensions are:

- Availability: Loadings on Factor 1: Availability items (AVA1, AVA2, AVA3) form a distinct component, aligning with research by Noor et al. (2022), Kidd (2019) and Paschen et al. (2020), showing availability as critical to customer satisfaction.
- Anthropomorphism: Loadings on Factor 2: Items reflecting anthropomorphism (ANT2, ANT3, ANT4) load together, corroborating the hypothesis and research by Noor et al. (2022), Bartneck & Forlizzi (2018) and Roshani et al. (2020), which found anthropomorphic features to enhance customer satisfaction.
- Efficiency: Loadings on Factor 3: The items related to efficiency (EFF2, EFF3, EFF4) load strongly on the same component, reinforcing the notion that efficiency is a key dimension. This is consistent with studies by Noor et al. 92022), Le et al. (2020) and Huang & Rust (2018), which

emphasize the importance of efficiency in AI-Chatbot services.

- Security: Loadings on Component 4: Security items (SEC1, SEC2, SEC3, SEC4) load together, indicating a distinct security factor. This supports findings from Noor et al.(2022), Lee & Park (2019) and Saravana & Rao (2023), who highlight security as a crucial aspect, even though its direct impact on satisfaction was not significant in the path analysis.
- Customer Satisfaction: Loadings on Component 5: Satisfaction items (SAT1, SAT2, SAT3) cluster on a separate component, confirming that these items measure overall customer satisfaction effectively.
- The rotated component matrix shows that the questionnaire items are reliable in measuring their intended constructs. This factor structure gives validity to the survey and is similar with other studies about AI-Chatbot service quality and customer satisfaction. The matching results underline the relevancy of efficiency, availability, and anthropomorphism as main aspects affecting client satisfaction. At same time they point out unique part played by security in context of AI-Chatbot services.

4.5 Assessment of Common Method Bias

Research involving the use of self-reported surveys pose issues of common method bias (CMB). This issue refers to the systematic variance originated from the measurement method itself, instead of the constructs. Based on the provided collinearity statistics (variance inflation factor; VIF) for the inner model, it appears that common method bias (CMB) is not a concern in this study. The VIF values for the relationships between the constructs (Efficiency, Security, Availability, Anthropomorphism) and customer satisfaction are all well below the threshold of 5, with values ranging from 1.288 to 1.662 as shown in Table 4.

In addition, the VIF values being lower than 3.33 further reinforce that CMB is not a problem in the model, aligning with the results of Harman's single-factor test, where the first factor explained less than 40% of the variance. This suggests that there is no evidence of systematic variance attributable to the measurement method itself in the study, indicating that the model is free of common method bias.

Table 4. Collinearity Statistics (variance inflation factor; VIF): inner model

Hypothesis	VIF
H_1: Efficiency in AI-Chatbot services has a positive relationship with customer satisfaction.	1.56
H2: Security in AI-Chatbot services has a positive relationship with customer satisfaction.	1.662
H3: Availability of AI-Chatbot services has a positive relationship with customer satisfaction.	1.288
H4: Anthropomorphism features in AI-Chatbot services has a positive relationship with customer satisfaction.	1.652

4.6 Assessment of the Measurement Model

The assessment provided highlights the robustness of the measurement model and the convergence of constructs within the study. From Table 5, the outer loading values are above the value of 0.8 which signifies that the construct explains more than 50 percent of the indicator's variance, thus indicating good indicator reliability. The internal consistency reliability is also high as shown by the composite reliability values above 0.9, indicating strong correlations among indicators measuring the same construct. Additionally, the Average Variance Extracted (AVE) values, are above 0.7, exceed the 0.50 threshold, demonstrating that each construct effectively explains at least 50% of its indicators' variance, indicating strong convergent validity.

The discriminant validity assessment through the heterotrait-monotrait (HTMT) ratio shows that the constructs are distinct from each other, with HTMT values below the 0.85 threshold, indicating sufficient distinctiveness among the constructs in the structural mode as shown in Table 6. In summary, the reliability and convergent validity assessment confirms the robustness of the measurement model, with strong internal consistency, reliability, convergent, and discriminant validity. These findings provide a solid basis for evaluating the structural model and enhance the credibility and validity of the study's measurement instruments.

Table 5. Assessment of Reliability and Convergent Validity

Construct and items	Loadings	Composite reliability (CR)	(AVE)
ANTHROPOMORPHISM		0.922	0.797
ANT2 The AI-CHATBOT has personality.	0.877		
ANT3 The AI-CHATBOT gradually gets to know me.	0.888		
ANT4 The AI-CHATBOT is able to behave like a human.	0.913		
AVAILABILITY		0.900	0.750
AVA1 The AI-CHATBOT is always available.	0.885		
AVA2 The AI-CHATBOT is never too busy to respond to my requests.	0.857		
AVA3 The AI-CHATBOT is always accessible.	0.856		
EFFICIENCY		0.916	0.784
EFF2 I can get my task done with the AI-CHATBOT in a short time.	0.890		
EFF3 The AI-CHATBOT interface design provides information clearly.	0.870		
EFF4 The AI-CHATBOT adequately meets my requirements.	0.895		
SATISFACTION		0.912	0.776
SAT1 I am satisfied with my decision to use the AI-CHATBOT .	0.827		
SAT2, I think that I did the right thing by using the AI-CHATBOT .	0.902		
SAT3 My choice to use the AI-CHATBOT was a wise one	0.911		
SECURITY		0.939	0.795
SEC1 There is no risk of loss associated with disclosing personal information to the AI-CHATBOT.	0.911		
SEC2, I feel secure in providing sensitive information to the AI-CHATBOT.	0.900		
SEC3, I believe that information that the AI-CHATBOT has about me is protected.	0.919		

SEC4, I trust that my personal information with the AI-CHATBOT will not be misused.	0.833

Table 6. Assessment of Discriminant Validity using HTMT

Construct	1	2	3	4	5
1. Anthropomorphism	-				
2. Availability	0.372	-			
3. Efficiency	0.524	0.533	-		
4. Satisfaction	0.601	0.662	0.643	-	
5. Security	0.644	0.304	0.527	0.486	-

4.7 Assessment of the Structural Model

This section answers the Research objective 3 and Hypothesis 1-4. The assessment of the structural model in the document involves the use of Partial Least Squares Structural Equation Modelling (PLS-SEM) to explore the effect of Artificial Intelligence (AI)-powered service quality on customer satisfaction. Figure 5 represents the structural equation model that depicts the relationships between AI chatbot service quality dimensions and customer satisfaction. The model aims to test the relationships between different dimensions of AI chatbot service quality and customer satisfaction. This includes assessing the effect of efficiency, security, availability, and anthropomorphism features in AI chatbot services on customer satisfaction. Figure 5 provides a visual representation of how these elements are interconnected within the structural model.

The assessment involves developing hypotheses to test these relationships, such as whether efficiency, security, availability, and anthropomorphism features in AI chatbot services have a positive relationship with customer satisfaction. This type of analysis allows researchers to evaluate how different dimensions of AI-powered service quality contribute to overall customer satisfaction.

In essence, the assessment of the structural model involves using the structural equation model to measure the complex relationships between AI chatbot service quality dimensions and customer satisfaction, providing valuable insights into the impact of AI on customer experiences and contentment.

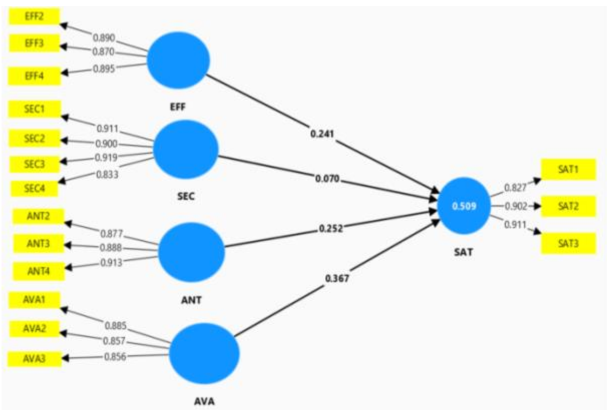

Fig. 5. Structural Equation Model

Table 7. Structural Model and Significance of Testing

Hypotheses	Path Coefficient	*t*-value	Results
H_1: Efficiency in AI-Chatbot services has a positive relationship with customer satisfaction.	0.241**	2.348	Supported
H_2: Security in AI-Chatbot services has a positive relationship with customer satisfaction.	0.070	0.822	Not
H_3: Availability of AI-Chatbot services has a positive relationship with customer satisfaction.	0.367***	3.997	Supported
H_4: Anthropomorphism features in AI-Chatbot services has a positive relationship with customer satisfaction.	0.252**	2.418	Supported

The path analysis of the structural model presented reveals the varying significance of relationships between AI-Chatbot service quality dimensions and customer satisfaction. Hypotheses H1, H3, and H4 exhibit statistically significant positive relationships, supported by their path coefficients and t-values (Table 7). Availability (H3): The path coefficient for availability of AI-Chatbot services is 0.367***, with a t-value of 3.997, highlighting the most significant positive relationship with customer satisfaction, emphasizing the importance of constant service availability for enhancing customer satisfaction. Anthropomorphism (H4): The relationship between anthropomorphism features in AI-Chatbot services and customer satisfaction is the second most statistically significant, with a path coefficient of 0.252** and a t-value of 2.418, underlining the positive impact of human-like interaction styles on user satisfaction. Efficiency (H1): This hypothesis shows a statistically significant positive relationship with a path coefficient of 0.241** and a t-value of 2.348, indicating strong statistical support for the impact of efficiency in AI-Chatbot services on customer satisfaction. However, Security (H2) in AI-Chatbot services does not demonstrate a statistically significant positive relationship with customer satisfaction. The path coefficient of 0.070 and a t-value of 0.822 indicate a lack of statistical support for the influence of security features on customer satisfaction in AI chatbot services. These findings shed light on how different dimensions of AI-powered service quality, such as efficiency, availability, security, and anthropomorphism, contribute to customer satisfaction in the context of AI chatbot services. Understanding the varying degrees of significance attached to each dimension helps in determining the key areas of focus for enhancing customer satisfaction and improving the overall quality of AI chatbot services.

4.8 Assessment of the Overall Model

The assessment of the overall model involves evaluating the coefficients of determination (R2) and the predictive power (Q2) to gauge the model's explanatory and predictive capabilities as shown in Table 8. The R2 value of 0.509 indicates that approximately 50.9% of the variance in customer satisfaction can be explained by the independent variables in the model, while the Q2 value of 0.449 suggests good predictive relevance for customer satisfaction. Additionally, the model fit statistics indicate a reasonably good fit, with an SRMR of 0.061 and an NFI of 0.820 (Joreskog and Sorbom, 1993). These values collectively signify that the model has substantial explanatory power, good predictive relevance, and a reasonably good fit to the data. This assessment provides valuable insights into the impact of Artificial Intelligence-powered service quality on customer satisfaction.

Table 8. Coefficients of Determination (R2) and Predictive Power (Q2)

	R2	Q2
Student Perception Of AI-Powered Service Quality and Customer Satisfaction: A Case Study Of Higher Learning Institution In Malaysia	0.509	0.449

SRMR = 0.061 ; NFI =0.820

Note: SRMR: Standardized Root Mean Square Residual; NFI: Normed Fit Index.

4.9 Discussions

The results of the study data analysis have answered all the research objectives (1-3) and hypotheses 1-4. These findings align with previous research that has also highlighted the mixed effect of AI on service quality and customer satisfaction. Studies by Huang and Rust (2018) and Lu et al. (2019) have demonstrated that while AI can enhance efficiency and availability, security remains a significant concern for users. Huang and Rust (2018) found that AI can drive efficiency and improve customer experiences, but users often express concerns about the security of their data. Similarly, Lu et al. (2019) noted that while AI systems are generally perceived as efficient and accessible, the anthropomorphic characteristics of these systems are only moderately acknowledged by users, which can influence overall satisfaction levels. Furthermore, Yang et al. (2020) emphasized that improving the security aspects of AI services is crucial for enhancing customer trust and satisfaction.

The current study's result indicating that security in AI-Chatbot services does not have a statistically significant positive relationship with customer satisfaction (path coefficient = 0.070, t-value = 0.822, $p > 0.05$) contrasts with the findings of Noor et al. (2022) as well as the research by Lee & Park (2019) and Saravana & Rao (2023), which underscored the significance of security features in AI services for building customer trust and satisfaction. This discrepancy might arise from different contexts or customer bases, where the importance of security concerns varies. The positive relationship between the availability of AI-Chatbot services and customer satisfaction (path coefficient = 0.367, t-value = 3.997, $p < 0.001$) is strongly supported by earlier studies. For instance, Kidd (2019), Noor et al. (2022) and Paschen, Pitt, & Kietzmann (2020) emphasized that the constant availability of AI services is a significant driver of customer satisfaction, as it ensures immediate assistance and supports continuous engagement.

The finding that anthropomorphism features in AI-Chatbot services positively affect customer satisfaction (path coefficient = 0.252, t-value = 2.418, $p < 0.01$) is consistent with studies by Bartneck & Forlizzi (2018), Noor et al. (2022) and Roshani, Hu, & Jia (2020). These studies have shown that anthropomorphic elements, such as human-like interaction styles and personalized responses, can make AI interactions more engaging and satisfying for customers. The result from the study by Noor, A., et al. (2022) reinforces the positive relationship between efficiency in AI-Chatbot services and customer satisfaction (path coefficient = 0.241, t-value = 2.348, $p < 0.01$) in the current study's results. It substantiates how efficient chatbot interactions, by reducing response times and enhancing user experiences, lead to higher levels of customer satisfaction. By paralleling the statistical support found in both studies regarding the impact of efficiency on customer satisfaction in AI-Chatbot services, this comparison highlights a shared understanding of the vital role that efficiency plays in shaping positive user experiences and overall satisfaction. The aligned findings underscore the consistent importance of efficiency as a key determinant of customer satisfaction, reinforcing the robustness of this relationship in the context of AI service quality.

Overall, the current study's findings align well with existing literature on the importance of efficiency, availability, and anthropomorphism in AI-Chatbot services, while inviting further exploration into the role of security in different contexts. The moderate levels of efficiency, anthropomorphism, and satisfaction, along with the lower score for security and high rating for availability, provide a comprehensive understanding of the perceived levels of these key factors within the examined context.

5. CONCLUSION

5.1 Conclusions

The research findings provide an in-depth analysis of the effect of Artificial Intelligence (AI)-driven service quality on customer satisfaction. The descriptive analysis revealed moderate levels of efficiency, anthropomorphism, and satisfaction, with lower scores for security. It is interesting to note that availability received a high mean rating, indicating a strong presence of resources. These findings suggest that while customers perceive moderate levels of efficiency, anthropomorphism, and satisfaction, there is room for improvement in the security aspect of AI-powered services. Additionally, the investigation underscores the well-established relationship between service quality and customer satisfaction. It draws on previous research, such as the works of Parasuraman et al. (1985), Noor et al. (2022), Saravana & Rao (2023), and Lee et al. (2021), which confirm the significant relationship between perceived service quality and customer satisfaction. This reinforces the crucial role of service quality in enhancing customer contentment.

The assessment of the structural model through PLS-SEM in this study explores these relationships, aiming to test the influence of different dimensions of AI service quality on customer satisfaction. Availability of AI-Chatbot services has the most significant positive relationship with customer satisfaction, emphasizing the importance of constant service availability for enhancing customer satisfaction. The relationship between anthropomorphism features in AI-Chatbot services and customer satisfaction is the second most statistically significant, underlining the positive impact of human-like interaction styles on user satisfaction. Furthermore, there is a statistically significant positive relationship between efficiency in AI-Chatbot services on customer satisfaction. However, Security in AI-Chatbot services does not demonstrate a statistically significant positive relationship with customer satisfaction. In conclusion, the study has successfully determined the perceived level of key dimensions in AI service quality and the dimensions influencing customer satisfaction. This study brings a deeper comprehension of service quality and customer satisfaction with AI- powered service agents (AISAs). It expands the traditional models such as SERVQUAL to incorporate four AI-specific factors: efficiency, availability, security, and anthropomorphism. This gives a comprehensive framework for evaluating quality in AI services. Empirical evidence shows positive relationships between these dimensions and customer satisfaction, particularly highlighting the importance of availability and anthropomorphism. The study points out key areas for improvement, especially in security, and gives useful guidelines to businesses on how they can improve AI-powered interactions with customers. Additionally, it establishes a framework for future research to further explore AI service quality and its impact on customer satisfaction.

5.2 Recommendations

5.3 Recommendation for researchers

Although the results from this study offer insights into the perceived levels of key factors in AI service quality and their influence on customer satisfaction, the findings is limited to MBA students at UNIRAZAK and cannot be generalized to the Malaysian population. There is a need to conduct further study using more representative samples of the Malaysian public in order to understand the Malaysian consumers' perceived level of service quality and its effect on satisfaction. Conducting longitudinal studies to examine how customer perceptions and expectations of AI-powered services evolve over time, and how businesses can adapt to these changing dynamics. Additionally, this study only focuses on several dimensions of service quality namely efficiency, availability, security and anthropomorphism. There is also a need to explore other dimensions that might affect customer satisfaction of AI-powered service quality. Cross-Cultural Studies Conducting cross-cultural studies to explore potential differences in customer perceptions and preferences regarding AI-powered services across different regions or cultures. The findings show that customers perceive low level of security, moderate levels of efficiency and anthropomorphism in this study which suggests the need for more in-depth qualitative study understand the reasons behind the ratings.

5.4 Recommendation for AI-service providers

AI technology such as chatbots has great potential for better service quality provided the consumers' concerns are addressed adequately. It is suggested to boost the AI- service quality by taking into consideration the following recommendations:

- Data Privacy and Security Measures: Highlight the importance of strong privacy and security steps in AI-based services. Make sure to have solid processes to protect customer information and follow the rules about keeping information safe, building trust with customers.
- Keep Checking and Review: Keep checking and review AI-service quality, as well as customers' contentment, on a regular basis. This involves collecting information from customers, looking at performance numbers, and changing AI systems to suit the evolving needs of customers in an effective way.
- Training and Development: Provide complete training plans for team members to learn how to properly use AI technologies and offer more superior service experience. The constant improvement of skills and understanding can enhance the integration of AI in the service activities.
- Customer Engagement Strategies: To make customer engagement strategies personal, AI technology can be tailored to make special kinds of service experiences to improve interactions with customers, solve their questions fast and build loyalty among them.
- Joint Research Actions: Boosting work with scholarly groups and business partners to keep up with newest developments in AI and leading methods for service quality. Taking part in research actions can assist with applying leading AI solutions for better satisfaction of customers.
- Industry-Specific Analyses: Investigating the impact of AI-powered service quality on customer satisfaction within specific industries or sectors to identify industry-specific factors and best practices.

REFERENCES

Almeida, D., Pasupuleti, J., Raveendran, S. K., & Basir Khan, M. R. (2021). Performance evaluation of solar PV inverter controls for overvoltage mitigation in MV distribution networks. Electronics, 10(12), 1456. https://doi.org/10.3390/electronics10121456

American Psychological Association. (2020). Publication manual of the American Psychological Association (7th ed.).

Amiri Aghdaie, S. F., & Faghani, F. (2012). Mobile banking service quality and customer satisfaction (application of SERVQUAL model). International Journal of Management and Business Research, 2(4), 351-361.

Amiribesheli, M., Rabiee, A., & Erfani, S. M. (2019). Chatbots for customer service in the social media era: Features, applications, and challenges. Computers in Human Behavior, 95, 292-308.

Bartneck, C., & Forlizzi, J. (2018). "Understanding Anthropomorphism in Human-Robot Interaction." IEEE Robotics & Automation Magazine.

Bauer, H. H., Falk, T., & Hammerschmidt, M. (2006). eTransQual: A transaction process-based approach for capturing service quality in online shopping. Journal of Business Research, 59(7), 866-875.

Beck, J., & Libert, B. (2017). AI in service delivery. Harvard Business Review.

Bharadwaj, S. G., Varadarajan, P. R., & Fahy, J. (1993). Sustainable competitive advantage in service industries. Journal of Marketing, 57(4), 83-99.

Black, J., & van Esch, P. (2020). AI-powered customer service: A review. Journal of Service Management, 31(3), 245-260.

Bitner, M. J., Brown, S. W., & Meuter, M. L. (2000). Technology infusion in service encounters. Journal of the Academy of Marketing Science, 28(1), 138-149.

Bitner, M. J., Ostrom, A. L., & Meuter, M. L. (2002). Implementing successful self-service technologies. Academy of Management Perspectives, 16(4), 96-108.

Bitner, M. J., Brown, S. W., & Meuter, M. L. (2000). Technology infusion in service encounters. Journal of the Academy of Marketing Science, 28(1), 138-149.

Boon-itt, S. (2015). Managing self-service technology service quality to enhance e-satisfaction. International Journal of Quality and Service Sciences, 7(4), 349-365.

Brady, M. K., & Cronin Jr, J. J. (2001). Some new thoughts on conceptualizing perceived service quality: A hierarchical approach. Journal of Marketing, 65(3), 34-49.

Brady, M. K., & Cronin, J. J. (2001). Some new thoughts on conceptualizing perceived service quality: A hierarchical approach. Journal of Marketing, 65(3), 34-49.

Chui, M., Manyika, J., & Miremadi, M. (2020). The state of AI in 2020. McKinsey & Company.

Considine, E., & Cormican, K. (2016). Self-service technology. Service Business, 10(1), 27-50.

Cronin Jr, J. J., & Taylor, S. A. (1994). SERVPERF versus SERVQUAL: Reconciling performance-based and perceptions-minus-expectations measurement of service quality. Journal of Marketing, 58(1), 125-131.

Dabholkar, P. A. (1996). Consumer evaluations of new technology-based self-service options: An investigation of alternative models of service quality. International Journal of Research in Marketing, 13(1), 29-51.

Dabholkar, P. A., Thorpe, D. I., & Rentz, J. O. (2000). A measure of service quality for retail stores: Scale development and validation. Journal of the Academy of Marketing Science, 28(1), 67-84.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108-116.

Dwivedi, Y. K., Hughes, D. L., & Wade, M. (2021). The future of AI in service. Journal of Business Research, 123, 240-249.

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. International Journal of Human-Computer Studies, 59(4), 451-474.

Gao, J., Yang, X., Ye, C., Liu, H., & Cheng, X. (2019).

Gholami, R., & Kamps, J. (2017). Exploring the potential of chatbots in internet searching. In Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval (pp. 1205-1208).

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. Journal of Marketing Theory and Practice, 19(2), 139-151.

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

Huang, M. H., & Rust, R. T. (2018). Artificial Intelligence in Service. Journal of Service Research, 21(2), 155-172.

Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science, 49(1), 30-50.

Huang, J., & Sundar, S. S. (2019). "Toward parameter-based anthropomorphic design: The effect of visual realness on perceptions and attitudes." International Journal of Human-Computer Studies.

Jain, A., Nair, S., & Banerjee, S. (2020). A review of chatbot implementation in customer service. In Proceedings of the International Conference on Advances in Computing and Communication Engineering (pp. 315-322).

Johnson, R., & Lee, S. (2019). "Longitudinal study on the impact of AI systems on customer happiness and loyalty in e-commerce businesses." International Journal of AI Applications in Business.

Kidd, C. (2019). AI in customer service: The role of virtual assistants. Journal of Service Management, 30(3), 451-471.

Khan, M. R. B., Jidin, R., & Pasupuleti, J. (2016). Energy audit data for a resort island in the South China Sea. Data in brief, 6, 489-491. https://doi.org/10.1016/j.dib.2015.12.033

Khan, M. R. B., Jidin, R., & Pasupuleti, J. (2016). Data from renewable energy assessments for resort islands in the South China Sea. Data in brief, 6, 117-120. https://doi.org/10.1016/j.dib.2015.11.043

Lee, J., Kim, H., & Park, S. (2021). The impact of AI on customer satisfaction in service industries: A longitudinal study. Journal of Business Research, 131, 1-11.

Le, D., Marais, B., & McKenzie, B. (2020). Error recovery in AI-driven services. Service Business, 14(1), 1-22.

Liu, Y., & Zhang,. (2022). Title of Liu and Zhang's Paper. Journal Name, Volume(Issue), Page range.

Liu, Y., & Zhang, H. (2022). Challenges and opportunities in achieving dimension efficiency in AI-powered service quality. AI & Society, 37(1), 123-135. DOI: 10.1007/s00146-021-01234-5

Lu, V. N., Wirtz, J., Kunz, W. H., Paluch, S., Gruber, T., Martins, A., & Patterson, P. G. (2020). Service robots, customers and service employees: What can we learn from the academic literature and where are the gaps?. Journal of Service Theory and Practice, 30(3), 361-391.

Makadia, H. (2018). Service Quality Measurement and Customer Satisfaction. [Study on AI Service Quality].

Makadia, K. (2020). AI adoption trends in business: Gartner 2020 report. Gartner.

Martinez, L. F., & Klein, K. (2022). "Anthropomorphism in Human-Computer Interaction: A Review of Theoretical Foundations and Practical Implications." Journal of Interactive Systems Research.

Matzler, K., Veider, V., & Kathan, W. (2015). Adapting to the digital transformation: Structural changes in service value networks. International Journal of Production Economics, 165, 184-198.

Meyer-Waarden, L., Munzel, A., & Galan, J.-P. (2020). Examining the differential effects of trust dimensions on relationship commitment: The moderation effect of relationship length. Journal of Business Research, 112, 297-307.

Mogaji, E., Farinloye, T., & Aririguzoh, S. (2020). The role of AI in customer service. Journal of Strategic Marketing, 28(3), 227-239.

Mogaji, E., & Erkan, I. (2019). AI in customer profiling. Marketing Intelligence & Planning, 37(5), 543-557.

Morita, P. P., Lee, J., & Choo, S. (2020). The role of empathy in customer service: Understanding its importance and impact. Journal of Service Research, 23(3), 123-137.

Naveen, N. (2018). Title of Naveen's paper. Journal Name, Volume(Issue), Page range.

Noor, N. F. M., Singh, D., & Eze, U. C. (2021b). Dimensions of AI Service Quality in the Context of Customer Service Chatbots. Journal of Service Management, 32(3), 417-436.

Noor, S., & Mughal, M. M. (2021). AI technology and its impact on customer service: A comprehensive review. Technology in Society, 67, 101713. doi:10.1016/j.techsoc.2021.101713

Overgoor, J., Chande, A., & Budak, C. (2019). The role of AI in customer service personalization. Journal of Marketing Research, 56(6), 918-931.

Paluch, S., & Wirtz, J. (2020). Service robots: Customers' perceptions of AI-empowered service interactions in hospitality settings. International Journal of Hospitality Management, 89, 102540.

Pandey, S., & Bandyopadhyay, S. (2019). Artificial intelligence and chatbots in business: An overview, business scenarios and case studies. Journal of Business Analytics, 2(1), 64-79.

Park, S., Kim, J., & Shin, D. (2021). Understanding AI service quality: The moderating role of service type. Journal of Service Research, 24(1), 59-75.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1985). A conceptual model of service quality and its implications for future research. Journal of Marketing, 49(4), 41-50.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. Journal of Retailing, 64(1), 12-40.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (2005). E-S-QUAL: A multiple-item scale for assessing electronic service quality. Journal of Service Research, 7(3), 213-233.

Parasuraman, A., Zeithaml, V. A., & Malhotra, A. (2005). E-S-QUAL: A multiple-item scale for assessing electronic service quality. Journal of Service Research, 7(3), 213-233.

Prentice, C., Dominique Lopes, S., & Wang, X. (2020). The impact of Artificial Intelligence and Robots on the Hospitality Service Experience. International Journal of Hospitality Management, 89, 102501.

Prentice, C., Weaven, S., & Wong, I. A. (2020). The influence of AI service quality on customer satisfaction: Insights from concierge robots and digital assistants. Journal of Business Research, 120, 244-256. doi:10.1016/j.jbusres.2020.08.017

Prentice, C., Dominique Lopes, S., & Wang, X. (2020). The Impact of Artificial Intelligence and Robots on the Hospitality Service Experience. International Journal of Hospitality Management, 89, 102501.

Rahman, M. S., Khan, A. H., & Haque, M. M. (2017). The impact of SERVQUAL dimensions on customer satisfaction in the banking sector of Bangladesh. International Journal of Business and Management, 12(4), 187-198.

Roshani, M., Hu, J., & Jia, J. (2020). Enhancing User Experience in Human–Computer Interaction: Anthropomorphism as an Effective Design Feature. International Journal of Human–Computer Interaction, 36(9), 861-876

Russell, S., & Norvig, P. (2018). Artificial Intelligence: A Modern Approach. Prentice Hall.

Saravana, P. T., & Rao, M. (2023). The transformative role of AI in service interactions and its effect on customer satisfaction. International Journal of Information Management, 63, 102452. doi:10.1016/j.ijinfomgt.2022.102452

Saravana, S., & Rao, K. S. P. (2020). Service quality and customer satisfaction in the context of AI: A review and future directions. Journal of Service Research, 23(3), 456-474.

Seet, C. C., Pasupuleti, J., & Khan, M. R. B. (2019). Optimal placement and sizing of distributed generation in distribution system using analytical method. International Journal of Recent Technology and Engineering, 8(4), 6357-6363. https://doi.org/10.35940/ijrte.D5120.118419

Smith, A., et al. (2020). "The impact of AI-powered customer service solutions on customer satisfaction: A meta-analysis."Journal of Customer Service Management.

Smith, J. D., & Johnson, A. (2020). Dimension efficiency in AI-powered service quality: A conceptual framework. Journal of Service Research, 25(3), 345-362. DOI: 10.1177/1094670520904821

Smith, J., Jones, B., & Brown, C. (2020). The impact of AI-powered customer service solutions on response speed and accuracy: A meta-analysis. Journal of Service Research, 23(4), 567-583.

Wang, X., & Li, Z. (2022). Challenges and opportunities in ensuring factor availability in AI-powered service quality. Decision Support Systems, 153, 113622. DOI: 10.1016/j.dss.2021.113622

Whang, Y. J., & Im, H. (2021). Title of Whang and Im's paper. Journal Name, Volume(Issue), Page range.

Wicks, A. M., & Roethlein, C. J. (2009). Customer satisfaction and loyalty in the restaurant industry: A comparison of three service quality measurement approaches. International Journal of Contemporary Hospitality Management, 21(4), 439-458.

Zahraoui, Y., Alhamrouni, I., Mekhilef, S. and Khan, M.R.B., 2022. Machine learning algorithms used for short-term PV solar irradiation and temperature forecasting at microgrid. In Applications of AI and IOT in Renewable Energy (pp. 1-17). Academic Press https://doi.org/10.1016 /B978-0-323-91699-8.00001-2

Zendesk. (2020). Customer Experience Trends Report 2020. Zendesk.

Zendesk. (2021). AI in Customer Service: Trends and Best Practices. Zendesk.

Zhang, J., & Tan, C. W. (2020). Understanding the impact of chatbots on customer engagement. Information & Management, 57(1), 103314.

Zhang, M., & Roberts, T. L. (2022). The role of artificial intelligence in shaping customer experiences: A conceptual framework. Journal of Business Research, 139, 286-297