THE ROLE OF INTERACTION QUALITY IN USE OF AI-BASED VOICE-ASSISTANT SYSTEMS - EVIDENCE FROM FINLAND.

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Abstract

This study focuses on the influence of interaction quality on users' intention to use AI-based voice assistance systems (VAS). The study is conducted in Finland and reveals users' behaviors toward AI-based VAS utilization. The researcher conducted empirical testing to understand the impact of information quality and system quality on interactions with an intention to use AI-based VAS.

The research design was quantitative survey-based research, and primary data through self-administrated surveys was collected from Finland. Item response theory was utilized to determine the population of the study, and the researcher received 100 fully filled responses. The data was analyzed using partial least square (PLS) regression software. PLS was used for structural equation modeling (SEM) and for advanced analysis (i.e., model testing).

The findings of the study show that system quality and information quality are positively and strongly related to the interaction quality of AI-based VAS. In addition, the results indicated that consumers were more likely to use AI-based VAS when the interaction quality is higher.

The current research has both practical and theoretical implications. From a theoretical perspective, the research adds to the IS (Information System) success model and the existing debate on user interactions with technology. From a managerial point of view, the researcher concludes that technology developers and innovators should enhance the quality of information and systems of AI-based VAS so that people can interact with AI-based VAS more effectively. The limitations and future research of the study are discussed at the end of the thesis.

Keywords:
Interaction Quality, Information Quality, System Quality, Artificial Intelligence (AI), AI-based Voice Assistance System (VAS), Information System Success Model.

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1. INTRODUCTION

Artificial intelligence (AI) is known as the demonstration of intelligence by machines. The term AI was invented by John McCarthy in 1956 during an academic conference (Kurzweil, R., 1985). However, journey towards understanding the intelligence nature of the machines began before that in 1950. Several scientists, including Alan Turing, an English mathematician and computer scientist, tested the machine's ability to mimic human actions (A. M. Turing, 2007). According to Nasirian et al. (2017), the interaction of humans with computers has a traditional term relationship. Humans are able to set up machines that can copy interaction styles as well as the behavior of humans. The basic interest in artificial intelligence revolved around determining if a computer system can display intelligence that can copy human behaviors. Researchers have studied intelligence for different capabilities such as communication, problem-solving techniques, processing of natural language, and learning capabilities (Chen et al., 2018). AI provides a wide range that can be utilized in medical diagnosis, automatic vehicles, image recognition, marketing, conversations, and voice assistants.

According to Polyakov et al. (2018), AI systems utilize technology's processing power and suggest recommendations based on specific criteria. Online business is the best example where AI algorithms recommend particular services or products based on customer interactions. Meanwhile, other studies have analyzed whether computing machinery, equipped with the competencies of natural language, can mimic and understand human language (Wang et al., 2022). Currently, systems related to artificial intelligence are emerging, and they have the opportunity to bring aggressive change in the ways organizations, individuals, and societies interact.

The latest interest in digital assessment systems is based on artificial intelligence in information systems. A significant part of this interest comes from the development of technologies that can communicate and interact with humans on a daily basis (i.e., smart devices). Smart devices are electronic devices that have the potential to connect with humans and with other devices. According to Keerthana et al. (2020), such devices are generally called voice assistant systems (VAS), voice-based AI devices, or AI-based VAS. Such systems are becoming crucial elements of individual lives and can transform the ways in which an organization operates. Google Assistant on Android services, Siri on Apple devices, and Amazon Alexa on Amazon devices are the perfect examples of voice assistant systems or voice assistant devices (VAD). Operating such devices or systems requires a specific keyword to activate the devices. When the device activates, it performs based on users' verbal requests and commands (Yan et al., 2022). Interaction is considered the main element of AI research, which is the core mechanism of human communication (Lee et al. 2021). However, AI interaction that leads to improved utilization of systems, based on artificial intelligence, has not been well-researched in past studies.

By using quality measures, this study examines an information system success model (ISSM) for AI-based VAS adoption. Based on the information system success model (ISSM), proposed by Delone and McLean (1992), smart devices rely on traditional quality success factors, which include system quality, information quality, and interaction quality. Information quality, system quality, service quality, intention to use, user satisfaction, and net welfare are the six dimensions of the ISSM (Petter et al., 2008). AI-based VAS relies heavily on communication, and the quality of interaction depends on the systems' quality and the information quality provided. AI is designed to communicate with users similarly to an online human. The impact of AI's information quality and its system will only be evaluated with the help of interaction quality. Furthermore, in the context of voice assistants, the lack of confidence among users in their interaction's outcome (i.e., the interaction's quality), if poor, is considered a major obstacle in achieving deep trust in an AI-based system. For this purpose, this research focuses on the system and information quality of AI-based VAS that improves the interaction quality.

Figure 1. Interaction between human & AI-based VAS

1.1 Research gap:

The previous studies related to AI-based VAS devices lack attention to determining the quality factors of the system (Al Shamsi et al., 2022). Quality factors are such important elements when using AI-based VAS. However, previous studies have failed to address these variables. The study conducted by Polyakov et al. (2018) provided a demonstration of system quality; however, the study was unable to provide the role of interaction for analyzing a user's intention. Likewise, the study conducted by Komiak and Ilyas (2010) found the impact of information quality on user intention. However, the role of interaction quality was missing. Given the lack of research on this topic, the current study aims to fill this gap by examining the combine impact of information quality and system quality on the interaction quality in the use of AI-based VAS in Finland.

1.1.1 Research objectives:

The research objectives of the current study are as follows:

1. To examine the relationship between the information quality and interaction quality of AI-based VAS.
2. To determine the relationship between the system quality and interaction quality of AI-based VAS.
3. To determine the relationship between the interaction quality and the intention of the user to use AI-based VAS.

1.2 Research questions:

The following are the research questions of the current study:

1. What is the relationship between the information quality and interaction quality of AI-based VAS?
2. What is the relationship between the system quality and interaction quality of AI-based VAS?
3. What is the relationship between the interaction quality of the VAS and the intention to use AI-based VAS?

1.2.1 Scope of the research

The current research is focused on the quality factors used in AI-based VAS. This research includes the system and information quality of AI-based VAS and aims to determine its impact on interaction quality. However, based on the nature and time limit of the research, the following study does not include any secondary elements of AI-based VAS (i.e., performance factor, credibility factor, and accuracy factor).

1.3 Structure of the research:

Figure 2 below represents the structure of the research. The study starts with the introduction as the background of the research and defines the objectives and research questions. The theoretical framework defines the study variables and a detailed description of the methods used in this research. Data collected is provided in the data and methodology chapter. Finally, the conclusion of the research appears after data analysis.

Figure 2. Structure of the study

2. THEORETICAL FRAMEWORK

The following chapter includes the past studies conducted on the study variables. With the help of past research reviews, the current chapter establishes the theoretical and conceptual framework model for the study.

2.1 Voice assistant system and AI-based VAS

A voice assistant system is a digital system that utilizes language processing algorithms, voice recognition, and voice synthesis to respond to specific voice commands by providing relevant information as requested by the users. The voice assistant system provides relevant information by listening for keywords and filtering out ambient noise. McLean et al. (2021) stated that such systems are completely based on software programming and can be integrated into most devices. Some assistants are designed specifically for single device applications. Amazon Alexa wall clock is a real life example of a voice assistant system. Today, many devices, such as smart speakers, computers, and cell phones, have the feature of voice assistant systems. At the other extreme of functionality, AI-based voice assistants are the operating system that can identify human voices and address them via integrated voices. According to Mclean and Osei-Frimpong (2021), the AI-based VAS collects audio from the microphone, converts it into text, and sends that text through Google Text to Speech, a conversational AI tool that uses commands to interpret and receive directives. With the implementation of this technology, devices can respond and interact with human questions in natural language.

2.2 Information system success model

To determine the success of an information system, multiple elements can be implemented for measuring effectiveness. The information systems success model (also known as the IS success model or the Delone and McLean IS success model) is a concept in the field of information systems (IS) that attempts to provide a full picture of the factors that contribute to IS success by describing the interconnections between six key metrics (Cho et al., 2015). First developed by Ephraim R. McLean and William H. DeLone in 1992, the idea was revised by the same authors a decade later in light of critiques made by other academic researchers. The IS success model is widely acknowledged as a seminal contribution to the field of information systems research and has been cited in thousands of scholarly works.

The information system success model is a primary theory employed in the current research, which demonstrates that information and system quality impact user satisfaction and intention at both organizational and individual levels (Mardiana et al., 2015).

2.2.1 Dimensions of IS Success Model

Net system benefits, user satisfaction, intention to use/use intents, service quality, system quality, and information quality are the six fundamental criteria of IS success that are defined and described in the information systems success model.

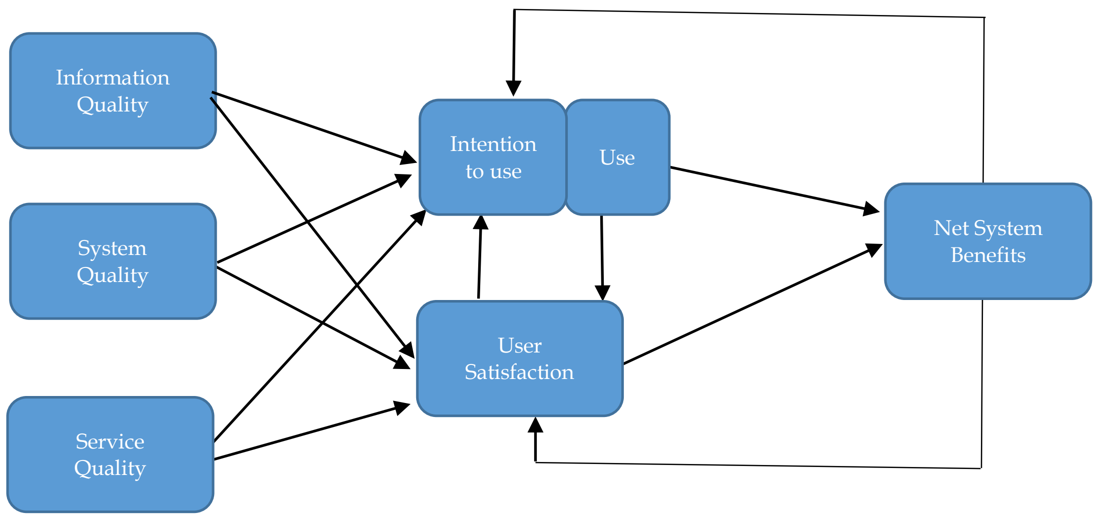

Figure 3. Updated information systems success model (DeLone & McLean 2002, 2003)

One of the most crucial considerations in any information system analysis is the quality of the data that the system can store, disseminate, or generate (Cho et al., 2015). The amount of the benefit that a user and an organization derive from a system is directly proportional to the degree to which the organization and the user are pleased with the system and the degree to which the user and the organization wish to make use of the system.

When assessing the worth of an IS solution, one common metric is its overall quality, much like information quality (Jaafreh, 2017). Mediating correlations between the dimensions of user satisfaction and usage intention suggest that system quality indirectly affects the amount to which the system can offer users advantages. When assessing the overall quality of the information system, researchers typically review the quality of service that an information system can provide alongside the information quality and the system quality (Cho et al., 2015). The level of service provided has a direct effect on how users intend to make use of the system as well as their overall level of satisfaction with it. These factors, in turn, affect the overall advantages delivered by the system.

Both the actual use and the intention to use an information system are well-established concepts in the information systems literature. According to the IS success model, service quality, system quality, and information quality all play a role in how people use and plan to utilize information systems (Jaafreh, 2017). It is hypothesized that a user's intention with the information system will shape how they plan to use it. The use of the system is closely related to the net advantages it may deliver, which in turn is affected by user satisfaction.

The level of satisfaction that a system's users feel toward the system has a direct bearing on the overall value the system provides (Mardiana et al., 2015). The degree to which a user is pleased or satisfied with the information system is referred to as "satisfaction," and the impact that the information system has on satisfaction is thought to have a causal relationship. The value of an information system to its users or the underlying organization is heavily influenced by the net benefit that the system can give. Using the system and having a positive experience with the system both play a role in the IS success model's calculation of net system benefits (Mardiana et al., 2015). The benefits of a system are hypothesized to have independent effects on user happiness and retention rates.

2.3 Quality factors in the adoption of AI-based VAS

According to Pal et al. (2020), there are different models that elaborate on the use and adoption of systems; however, for the current study, the researcher used the success model of information system by DeLone and McLean (1992). The success model of an information system argues that the information quality and system quality affect the intention of the user to use and adopt a system.

System quality refers to the aspects of functionality, reliability, and flexibility of the system in terms of its usage (Pal et al., 2020). Meanwhile, information quality is defined as the aspects of timelessness, completeness, and accuracy of the data (Pal et al., 2020). According to Gupta et al. (2020), the information system success model has been applied and extended in multiple contexts and then later adopted by quality measures such as the quality of the services for their initial framework. Service quality defines the elements of provided services that support a system. Lahoual and Frejus (2019) indicated that it is important to define the information system based on the services provided by VAS. In other words, if the focus of the information system is on a specific system, then information quality and system quality take superiority over the factors of service quality. In the current research, the objective of the study is not to evaluate the information system departments or customer support factors of the voice assistant system because the research operates under the assumption that service quality is not suitable for this purpose. The current study includes the factor of interaction quality to measure the quality system of the AI-based VAS. The purpose of designing the AI-based VAS is to address the commands of users and the interaction between AI-based VAS and users. Therefore, the following research has added the factor of interaction quality, which is crucial in the voice assistant system's context.

2.3.1 System quality

Mayer et al. (2020) stated that the system quality includes features like ease of learning, ease of use, and user-friendliness. Furthermore, if a system is easy to use, then it is likely that the learners will use it more frequently as it increases the positive impact on user intention.

2.3.2 Information quality

Information quality is the quality of the content related to the information system (Mayer et al., 2020). Pal et al. (2019) stated that there are five main elements of information quality, which further include accuracy, completeness, consistency, and timeliness. The quality of the information leads to an increase in the accuracy and usefulness of the system. Therefore, improved data quality in any system leads to better decision-making in an organization and eventually contributes to the success of the organization in different ways. The quality of the information is subjective and can vary among users, but the degree of the quality plays a key role in increasing its objectivity (Klein et al., 2020).

2.3.3 Intention to use

The acceptance of technology includes one's willingness to employ technology for a task that has been designed to support given task (Kondratova & Emond, 2020). The intention to use improved significantly when the quality factors of a device were improved and based on the effective installation of the latest technology.

2.4 Hypothesis development and research model

The section discusses the development of the hypotheses and the research model of the study. Using references from past studies, this section presents a discussion of each variable and the details of the current study's hypotheses.

2.4.1 System quality on interaction quality (H1)

Verma (2021) assessed the system quality of intelligent voice assistant systems' impact on the interaction quality with the user. According to the study, interaction quality can be determined by different factors of an information system, which include service quality and content quality. However, the study considered system quality as the most important dimension of an information system for determining the interaction quality. Using a questionnaire, Verma collected data from individuals who use the virtual assistant system frequently. Moreover, the researcher used structural equation modeling to assess the impact of system quality on interaction quality. According to the study outcomes, the system quality has a positive and significant impact on the interaction quality of VAS.

In another study, Klein et al. (2020) measured the experience quality of a voice assistant system by different dimensions of information system. The authors stated that experience quality and interaction quality both are the same terminologies used for different types of virtual assistants. Hence both of these qualities are similar to each other and can be determined by different dimensions of the information system. The researchers collected data by distributing a questionnaire survey among users of the different virtual assistant systems. The results of the study indicated that system quality is positively and significantly related to the interaction quality of the virtual assistant system.

Moreover, Dzida et al. (2018) evaluated the factors of information system quality which improve the interaction quality of interactive systems. The study considered three dimensions of service quality, which included information quality, system quality, and content quality of an interactive system. According to the researchers, these dimensions could help in determining the interaction quality of such interactive systems. The study also collected primary data from 117 users of interactive assistants and measured the interaction quality of interactive systems with the help of information quality, system quality, and content quality. The results of the study suggested that of all the tested dimensions of service quality, system quality was the most significant dimension that impacted the interaction quality of the system.

Based on the literature review, the following hypothesis is proposed:

H1: System quality is positively and significantly related to interaction quality.

2.4.2 Information quality on interaction quality (H2)

In a study assessing the relationship between information quality and interaction quality of news-related queries on the Alexa voice assistant, Dambanemuya and Diakopolous (2021) found that interaction quality is the most significant factor and may be the critical element for measuring the success of overall information system. The researchers conducted a quantitative study for the statistical examination of information quality in terms of improving the interaction quality of virtual assistant systems. They employed the partial least square method in their data analysis, and the results indicated that information quality is the most dominant factor that impacts interaction quality positively and significantly.

Likewise, Maedche et al. (2021) examined the quality factors of AI-based digital assistants. The objective of the study was to highlight those quality factors that have a significant impact on interaction quality. The study enlisted system quality, content quality, information quality, and service quality for examining the interaction quality of digital assistants. Interaction quality reflected the quality of interactivity of digital assistants with users. The researchers conducted a survey to collect statistical data for reflecting on the statistical significance of the relationship between quality factors and interaction quality. The outcomes of the study suggested that information quality is positively linked with interaction quality. Hence, the researchers recommended that information quality must be improved to increase the interaction quality of digital assistants.

Therefore based on past studies, this hypothesis is proposed:

H2: Information quality is positively and significantly related to interaction quality.

2.4.3 Interaction quality and user's intention (H3)

Lien et al. (2017) examined the role of interaction quality on user satisfaction and intention to use WeChat. WeChat is an e-communication platform for Chinese individuals, and its use is widespread among Chinese people. The purpose of the study was to determine the impact of interaction quality on user satisfaction and intention to use WeChat. The researchers applied structural equation modeling to evaluate the collected data, which was randomly accumulated from different cities in China. According to the main findings of the study, user intention is positively and significantly improved by the interaction quality of the system. Hence, the study verified that interaction quality is important for improving user satisfaction and intention.

Similarly, a study conducted by Zhao et al. (2012) aimed to assess the impact of service quality on the user's continuous intention and satisfaction towards mobile added services. The researchers explored the determinants of service quality that impact user satisfaction associated with the continuous intention to use mobile services. Service quality, user intention, and satisfaction were measured by different dimensions. The researchers proposed a model built on multidimensional variables for examining the collected data. One of the service quality determinants was interaction quality, which the researchers determined was significantly and positively related to user satisfaction. The improved user satisfaction in turn increased user intention to use the information system. The results of the study indicated that only interaction quality has a significant impact on user intention. On the other hand, other service quality factors were directly related to user satisfaction, which improved user intention to use the system.

Kreugel et al. (2022) also conducted a study on determining the role of interaction quality in adopting and using the intention of intelligent personal assistants (IPA). Over the last decade, IPA has been one of the systems that can respond to, understand, and process user requests. IPA is also one of the most beneficial virtual assistants that helps in different applications by, for instance, allowing users to schedule appointments, control home appliances, and check weather updates. The main objectives of the study were to understand the user intention to adopt IPA based on the interaction quality. The researchers collected data from college students that had some experience in using IPAs. The results of the study suggested that the interaction quality of IPAs has a significant impact on user intention to adopt virtual assistant systems.

Based on these studies, the following hypothesis is proposed:

H3: Interaction quality is positively and significantly related to the user's intention to use AI-based VAS.

2.5 Research model:

Figure 4 below depicts the research model of the current study. The model visually represents the aim of the study, which is to examine the impact of system quality and information quality on interaction quality. The model also depicts that interaction quality directly influences the intention to use AI-based VAS.

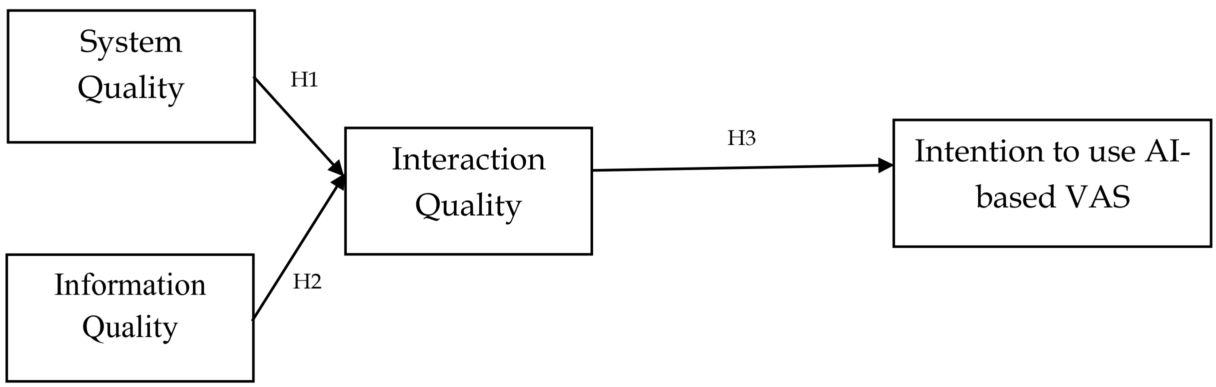

Figure 4. Conceptual model of the study

3. METHODOLOGY

This chapter of the study presents the methodologies and approaches employed to conduct this research. It includes data collection and data analysis to acquire the results, which are then used for processing and concluding the study.

3.1 Quantitative research

The current research is quantitative in nature. Thus, several processes are involved in analyzing data and interpreting results. The research approach adopted for this study is deductive as it requires hypothesis testing. A key purpose of applying this method is to enable a researcher to analyze the research hypotheses (i.e., accept or reject them). A research design is a next step after developing a research approach. According to Jackson (2015), a precise research design is essential for getting the desired results according to the research objectives and questions.

As part of this study, a cross-sectional design is also utilized to work on an explanatory research design. Studying multiple variables simultaneously allows the researcher to examine the results of their research. Mohajan (2018) described it as a form of observational research that estimates variables at a given point in time based on the collection of information. Creswell and Creswell (2018) contended that finding an effective research approach is key to completing the study accurately. Research design is driven by the nature of the topic. Data collected for this purpose are all numerical. Therefore, quantitative research is appropriate for this study. Using this method enabled the researcher to examine the relationship between the variables and conclude accurate and credible results.

There are several types of research, including explanatory, exploratory, review based, descriptive, and so on. A researcher's choice of research design is largely determined by the topic of the study, so this study is carried out using an explanatory method. Researchers can use this approach to get to the core of the problem quickly and accurately (Mohajan, 2018).

3.1.1 Sampling process

The research population is determined by the respondents who have chosen to register their insights on the research topic. The selection of the research population is also influenced by the nature of the topic (Jackson, 2015). The research population of the study is the people who are oriented toward the usage of voice assistance technology devices in Finland. Following the work of Mohajan (2018), the non-probability sampling method is used because it takes less time and cost than probability sampling. Samples are collected using a non-probability sampling method based solely on the researcher's judgment. In a quantitative study, researchers can utilize observation techniques to conduct a study (Martin et al., 2018). An example of a non-probability sampling method is convenience sampling, in which survey respondents are selected primarily based on ease of access, and based on the reasoning that people available at the time can provide high quality information. Therefore, the researcher used the convenience sampling method in this study. Thus, 100 research participants were chosen as respondents. The dependent variable of the study is the intention of the user, whereas interaction quality, system quality, and information quality are taken as the independent variables.

3.2 Data collection method and practical implication

The method of data collection plays a vital role in determining the authenticity of the entire research project. To generate reliable and efficient results, researchers must gather reliable and efficient data. After a suitable approach and design are finalized, a good data collection method can ensure effective data collection. In order to determine whether collected data is reliable and efficient, researchers must collect data accurately (Martins et al., 2018). A primary data collection method is used in this study. The researcher used questionnaire in order to collect updated data independently of the respondent. This method allows accurate results, saves time, and increases the efficiency and credibility of the study.

3.3 The questionnaire

To collect the required data effectively, an efficient research instrument is essential. Surveys, interviews, and observations are viable options because primary data is collected in this study. The current research used questionnaires for data collection in accordance with the research objective, topic, and population (White & Marsh, 2006). The researcher adopted the survey instrument based on a Likert scale of 7 points from previous researches (Lee et al., 2022; Nasirian et al., 2017). In addition, irrelevant data was removed from the questionnaire in order to use it in accordance with the nature of the study and the variables used in current research.

Respondents were asked to fill out questionnaires based on previous research to comply with this decision. By using this method, the researcher could collect all the information necessary from the population sample. Respondents were first asked to consent to participate in this study to maintain the quality of their responses.

3.4 Data analysis technique

The methodology is critical to analyzing the collected data through various tools and models and is therefore the most important part of the study. Following the design in the work of Grünwald (2020), SPSS software was used for confirming the hypothesis; however, Smart PLS was used for the prediction of the result. Moreover, with regard to structural equation modeling, PLS regression has several advantages over covariance-based approaches. Therefore, to identify, condense, and evaluate the collected data, the researcher used Smart PLS statistical software to gauge the viability of the study.

3.5 Ethical consideration

The researcher has ensured that all the information of the research participants will remain confidential. To encourage people to participate in the research, no personal data, such as names or email addresses, has been collected. To ensure privacy, the researcher has only used the respondent's information to conduct research. Moreover, upon the request of the respondents, the researcher has an obligation to share the research outcomes with those respondents.

4. RESEARCH FINDINGS

The chapter discusses the data analysis section of the collected data. The researcher represents the demographic and respondent profile of the study along with the help of frequency analysis. Additionally, descriptive statistics for each variable are also presented in the current chapter. The reliability and regression analysis is used to reject or accept the research hypotheses of the current study.

4.1 Respondent profile

4.1.1 Gender:

As depicted in Figure 5 below, 56 percent of research participants were male, and 44 percent of research respondents were female in the current study.

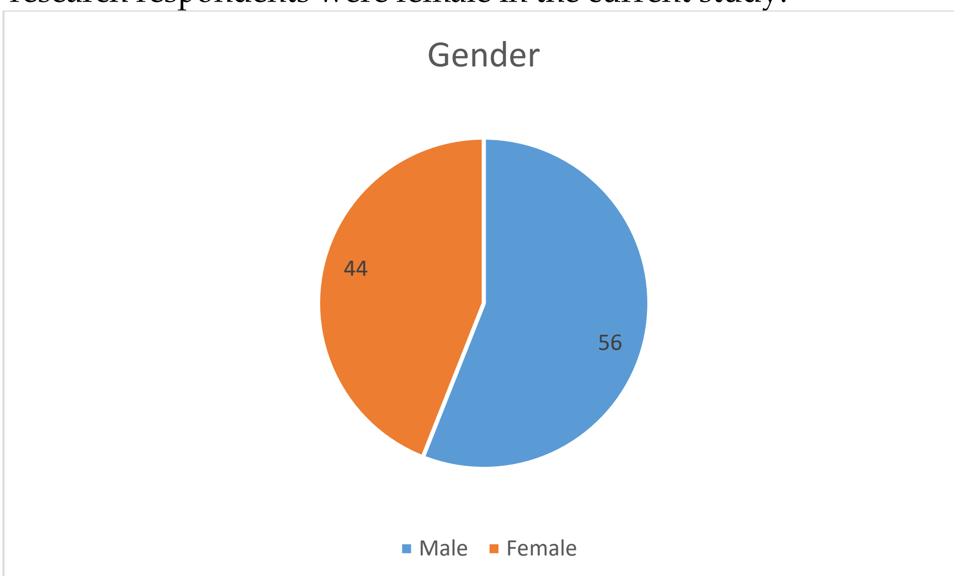

Figure 5. Gender frequency

4.1.2 Age:

Figure 6 displays the age group of respondents. As shown in the pie chart, most of the research respondents categorized themselves in the 23-27 age bracket. Almost 42 percent of research participants were from the age bracket of 23-27. Twenty-five percent of the research respondents categorized themselves in the age bracket of 18-22. Twenty-one percent of participants said that they are within the age bracket of 28-32, whereas 5 percent of research participants shared the age bracket of 33-37.

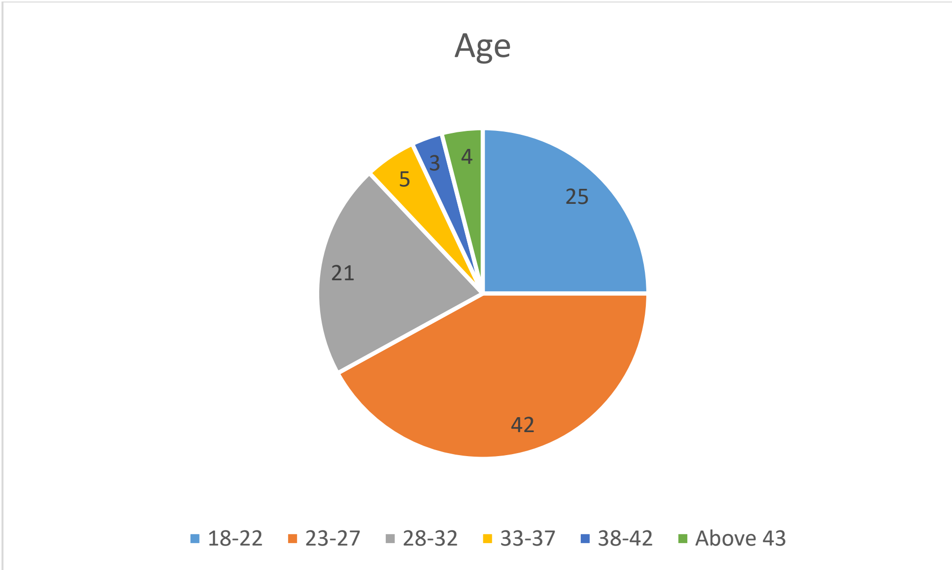

Figure 6. Age group

4.1.3 Number of AI-based VAS

Figure 7 depicts the number of AI-based voice assistant systems that respondents use. It shows 56 participants out of 100 have only one AI-based VAS, whereas 8 participants have more than one. However, 36 participants have no specific AI-based VAS.

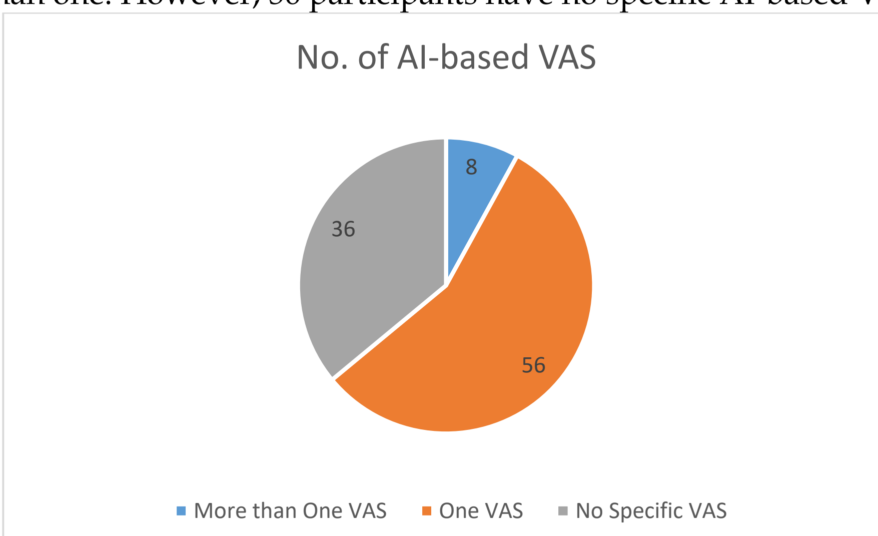

Figure 7. Number of AI-based VAS

4.1.4 AI-based VAS frequency

Figure 8 indicates the frequency of AI-based VAS usage in a month. According to the recorded responses, 77 percent of participants use it two to five times in a month, 15 percent of participants use it more than nine times in a month, and only 8 percent of participants use it six to nine times in a month.

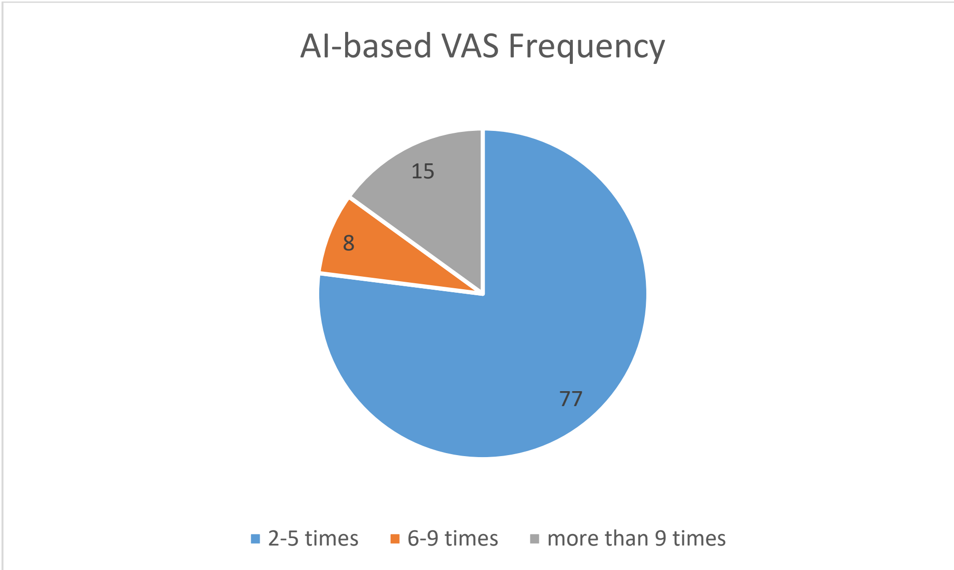

Figure 8. AI-based VAS Frequency

4.1.5 Hours for AI-based VAS

Figure 9 shows the number of hours respondents use an AI-based VAS in a month. Most of the participants use AI-based VAS for less than one hour. Some respondents use it for one to three hours, and very few respondents use it for more than five hours.

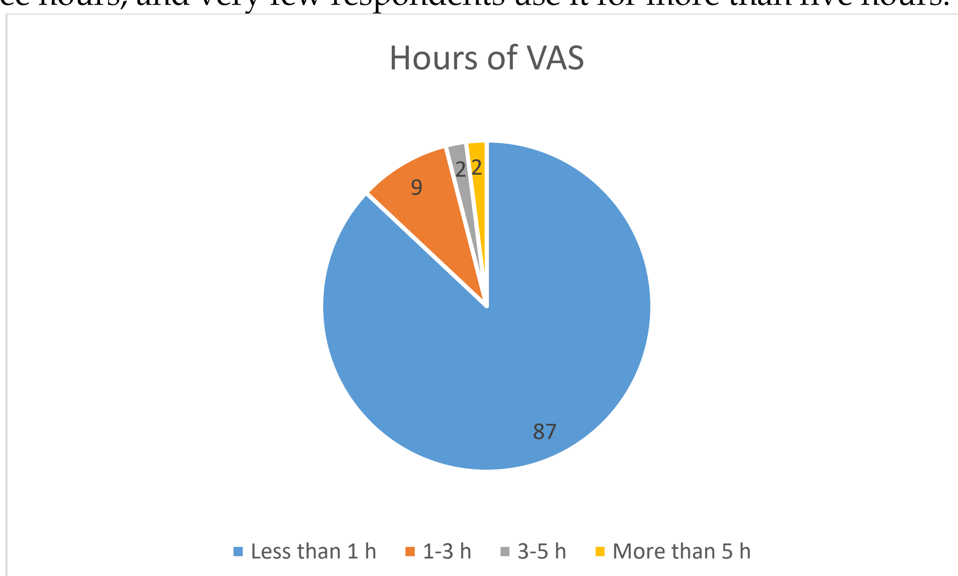

Figure 9. Hours for VAS

4.1.6 Main purpose of AI-based VAS

Figure 10 presents participants' reported primary purpose for their use of AI-based VAS. According to the data, 35 percent of research participants use such VAS for the convenience of speaking, 28 percent of research participants use it for the purpose of entertainment and fun, 22 percent of research participants use it to get faster results, and 15 percent of participants use AI-based VAS for other purposes.

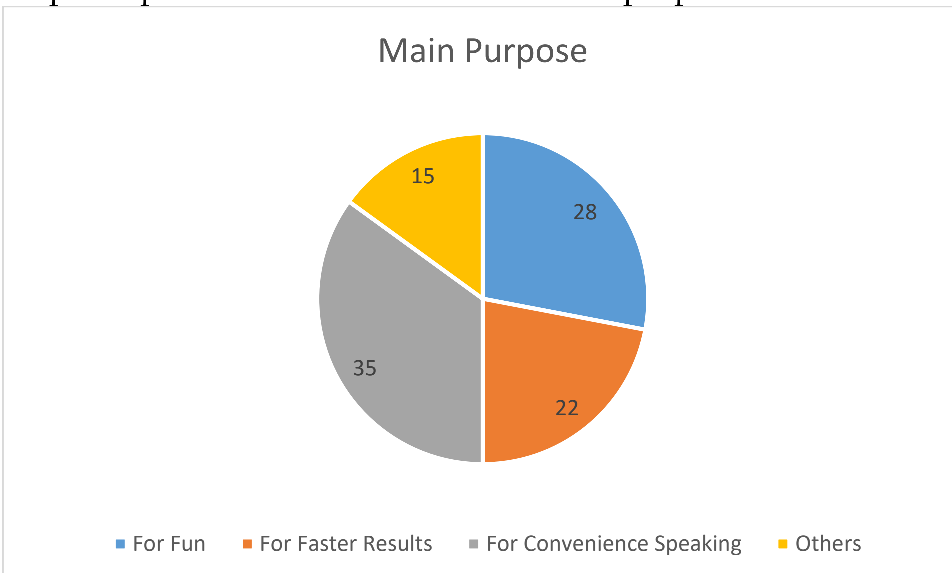

Figure 10. Main purpose of AI-based VAS

4.2 Frequency analysis

Frequency analysis is used to analyze the frequency of responses on the given scale. This section analyzes the frequency of each study variable and provides an overview of the recorded responses. In the given charts, SD represents "Strongly Disagree," MD represents "Moderately Disagree," SLD represents "Slightly Disagree," N represents "Neutral," SLA represents "Slightly Agree," MA represents "Moderately Agree," and SA represents "Strongly Agree."

4.2.1 Intention to use AI-based VAS

Figure 11 below indicates the composition of participant response for each question regarding the intention to use AI-based VAS. The results suggest that most people slightly agree with the statements asked of the participants in the questionnaire. The observed variables are used to extract the latent variable of participant intention to use AI-based VAS, and the bar chart below expresses the frequency of each option for each question.

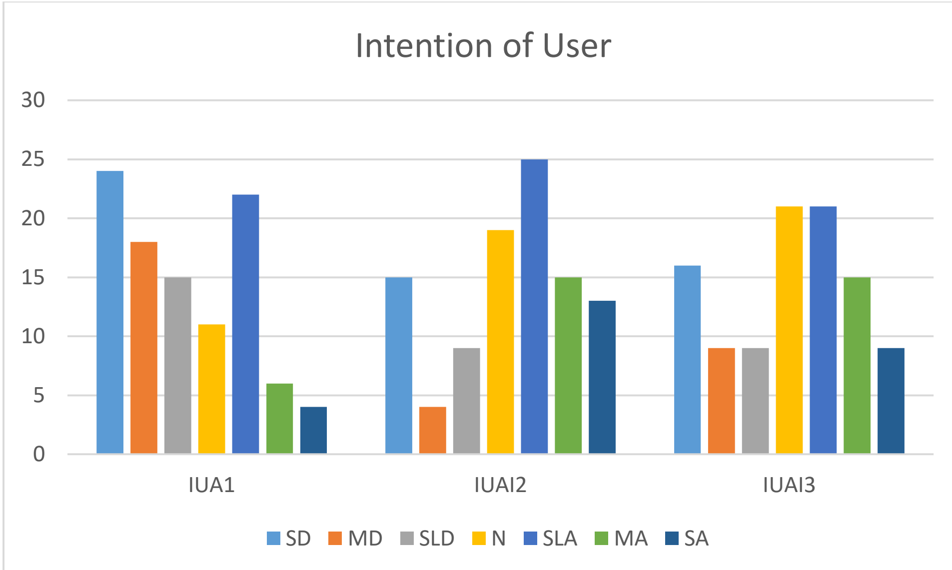

Figure 11. Frequency to use AI-based VAS

4.2.2 System quality

Figure 12 indicates the composition of participant responses for each question regarding the system quality. The results suggest most respondents slightly agree or moderately agree with the questionnaire statements on the topic of system quality. The three observed variables are used to extract the latent variable of system quality, and the bar chart expresses the frequency of each response for each question.

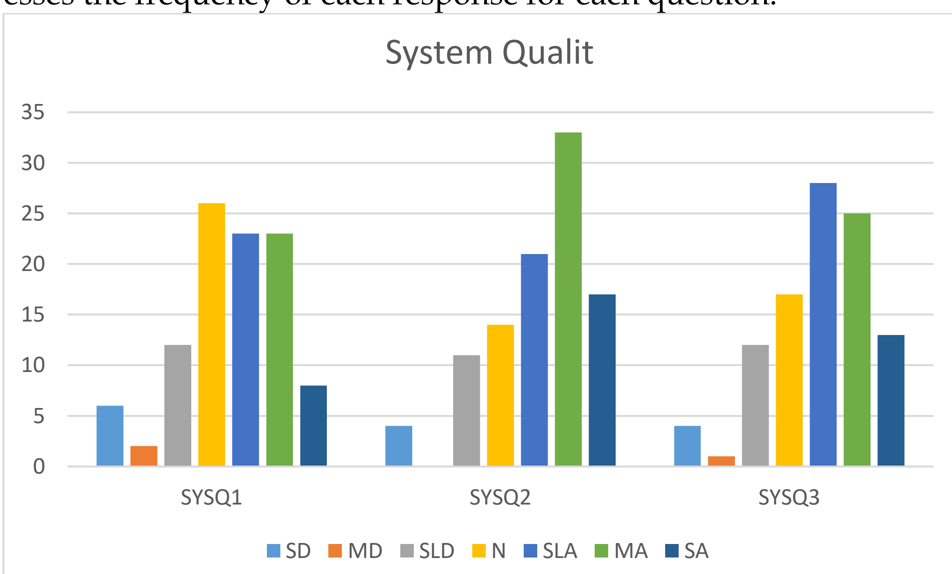

Figure 12. Frequency of system quality

4.2.3 Information quality

Figure 13 indicates the composition of participant responses for each question regarding information quality. The results suggest that most of respondents slightly agreed, moderately agreed, and were neutral on the questionnaire statements. The four observed variables were used to extract the latent variable of information quality, and the bar chart depicts the share of each choice for each question.

Figure 13. Frequency of information quality

4.2.4 Interaction quality

Figure 14 below indicates the composition of participant responses for each question regarding interaction quality. The results suggest that most respondents slightly agreed, moderately agreed, and were neutral on the statements in the questionnaire. The four observed variables were used to extract the latent variable of interaction quality, and the bar chart displays the share of each response for each question.

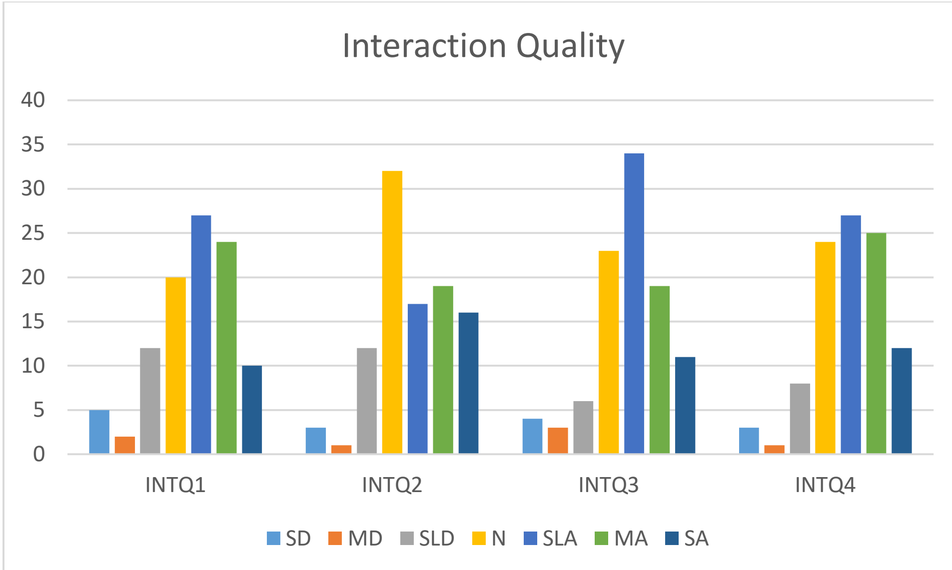

Figure 14. Frequency of Interaction quality

4.3 Reliability analysis

It is critical to examine whether the acquired data is consistent for further statistical analysis before proceeding with the data analysis. The reliability of the data is assessed with the use of reliability analysis. According to convention, Cronbach's alpha must be larger than 0.6 for the data to be credible. As a result, to be considered credible, the data collected must have a dependability of 60% or above. The data is invalid for further investigation for all the values that are lesser than 0.6. The table below shows that every variable has a Cronbach's alpha value greater than 0.6, which indicates that the data collected for the research is credible for further research.

Table 1. Reliability Analysis

Variables	**Item**	**Cronbach's Alpha**
Intention to use VAS	3	0.892
Information Quality	4	0.888
System Quality	3	0.824
Interaction Quality	4	0.907

4.4 Discriminant validity

Discriminant validity is established when the square root of the average variance extracted from each construct is more than the highest correlation of the construct as compared to the latent construct (Hair et al., 2012).

Table 2. Discriminant validity

Variables	Information Quality	Intention to use VAS	Interaction Quality	System Quality
Information Quality	0.872			
Intention to use VAS	0.499	0.904		
Interaction Quality	0.749	0.546	0.892	
System Quality	0.764	0.333	0.692	0.858

4.5 Average variance extracted

To find the convergent validity, the average variance extracted (AVE) has been measured. The value of AVE above 0.5 shows that convergent validity is established (Kline, 2011).

Table 3. Average variance extracted

Variables	Average Variance Extracted (AVE)
Information Quality	0.760
Intention to use VAS	0.817
Interaction Quality	0.796
System Quality	0.735

Table 3 shows that all the variables have shown acceptable AVE values and the convergent validity of the variable is established.

4.6 Regression analysis

The multivariate link between the independent and dependent variables is highlighted through regression analysis. The extent to which a dependent variable is impacted by the independent variable can be explained by this regression analysis. Because it allows the statistical search results to be concluded in the research, regression analysis is very critical for the research.

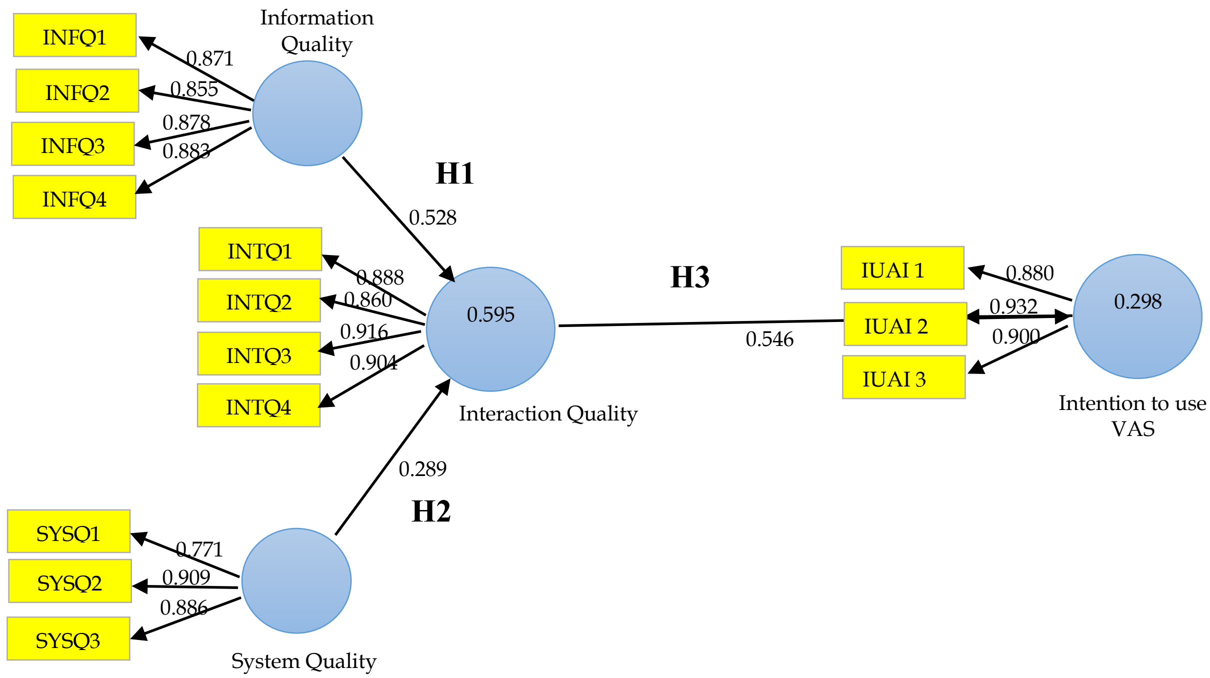

Figure 15. PLS for impact of SQ and IQ on interaction quality and interaction quality on IUAI

4.6.1.1 Model Summary

Figure 15 shows the estimations of multivariate regression analysis. The results of this study indicate that both information quality and system quality have a positive and direct impact on interaction quality. The path coefficient value of 0.528 shows that 1% increase in information quality causes 0.528% increase in interaction quality. Similarly, other path coefficient value of 0.289 represents that 1% increase in system quality causes a 0.289% increase in interaction quality. Moreover, the coefficient of correlation, as represented by the R value, is 0.771 (with the square root of R2 i.e. 0.595), indicates a strong positive correlation between the variables. The coefficient of determination, or R2 indicates that interaction quality is explained by 59.5% by information quality and system quality. This value also represents a good fit, as it is above 50%.

Additionally, the path coefficient value of 0.546 shows a direct and positive relationship between interaction quality and intention to use AI-based VAS. It also represents that 1% increase in interaction quality causes a 0.546% increase in intention to use AI-based VAS. Moreover, the R value of 0.545 (with the square root of R2 i.e. 0.298) demonstrates a good coefficient of correlation between the variables, and the R2 value of 0.298 indicates that intention to use AI-based VAS is explained by 29.8% by interaction quality.

Table 4 also shows the path coefficients and descriptive values for each variable construct. The path coefficient value of 0.289, as explained above, shows a positive impact on interaction quality where a 1% increase in system quality causes a 0.289% increase in interaction quality. The data is approximately normally distributed with a mean value of 0.286 and a standard deviation of 0.115. The p-value of 0.012 is <0.05, demonstrating a significant influence of system quality on interaction quality. Similarly, the path coefficient value of 0.528 against information quality shows a positive impact on interaction quality. A hypothetical 1% increase in information quality is associated with a 0.528% rise in interaction quality. The data is approximately normally distributed with a mean value of 0.532 and a standard deviation of 0.104. The p-value of 0.000 is <0.05, indicating a significant impact of information quality on interaction quality.

Additionally, the path coefficient value of 0.546 against interaction quality represents a positive effect on the intention to use VAS. For every 1% increase in interaction quality, intention to use VAS increases 0.546%. The data is normally distributed with a mean value of 0.548 and a standard deviation of 0.080. The p-value of 0.000 is <0.05, showing a significant influence of interaction quality on the intention to use VAS. Contrarily, the path coefficient value of 0.095 demonstrates a positive impact on interaction to use VAS.

Table 4. Model summary of system quality and information quality

Relationship	**Path coefficient**	**Sample Mean**	**Standard Deviation**	**T Statistics**	**P Value**
System Quality	0.289	0.286	0.115	2.521	0.012
Information Quality	0.528	0.532	0.104	5.073	0.000
Interaction Quality	0.546	0.548	0.080	6.859	0.000

4.7 Hypotheses summary

The following table depicts the hypotheses summary for the current study. The rejection and acceptance of study hypotheses are based on the significance values, which are less than 0.05. Based on that value threshold, three research hypotheses of the current study are accepted.

Table 5. Hypotheses summary table

S. No	Hypothesis Statement	Sig Value	Results
H1	System Quality has a positive and significant impact on interaction quality.	0.000	Accepted
H2	Information Quality has a positive and significant impact on interaction quality	0.000	Accepted
H3	Interaction Quality has a positive and significant impact on user's intention to use AI-based VAS.	0.000	Accepted

5. DISCUSSION

The following chapter discusses the statistical findings presented in the earlier chapter with respect to prior studies. Moreover, the research questions stated at the beginning of the research are also answered in this chapter. In addition to those discussions, the chapter also presents managerial implications and theoretical contributions. Furthermore, the chapter includes an evaluation of the study, along with suggestions, limitations, and future research guidance.

5.1 Theoretical Implications

The objective of the current research was to analyze the impact of system quality and information quality on the interaction quality of AI-based VAS devices. Therefore, the following primary research questions were tested:

1. *What is the relationship between the information quality and interaction quality of AI-based VAS?*
2. *What is the relationship between the system quality and interaction quality of AI-based VAS?*
3. *What is the relationship between the interaction quality of the Voice Assistant System and the intention to use AI-based VAS?*

The study results have revealed that the relationship between information quality and system quality with interaction quality is significant and positive. The research results are aligned with the findings of past studies (e.g., McLean & Osei Frimpong, 2019; Branham & Mukkath, 2019; Chen et al., 2018). The system quality of AI-based VAS is described as the stability, reliability, and suitability of the hardware and software, with the aspects of reliability, usage, understandability, adaptability, and functionality. Furthermore, since greater system quality levels are significantly related to increased frequency of actual usage, it is regarded as one of the pillars that influences user happiness and utilization. Around the world, many different forms of research have been conducted on the role of system quality in various technological applications, including AI-based VAS.

The study conducted by Komiak and Ilyas (2010) found that information quality has an insignificant impact on user intention. However, the study did not integrate the interaction quality. The current study analyzed the combined impact of system and information quality on the interaction quality of AI-based VAS devices.

Another result found in the current study is that the relationship between interaction quality and intention to use AI-based VAS has a positive and significant association. The research results are aligned with past studies (e.g., Lahoual & Frejus, 2019; Mayer et al., 2020; Pal et al., 2020). However, some studies found an insignificant relationship between interaction quality and intention to use AI-based VAS (e.g., Gupta et al., 2020; Ennis et al., 2017). The current research is significant for voice assistant technology manufacturers. The outcomes of the research enable tech organizations to identify the factors that impact customers' intent to use AI-based voice assistant systems. Moreover, the research will enable tech organizations in Finland to understand the quality factors that integrate into the voice assistant system (i.e., information quality, system quality, and interaction quality).

The last finding of the current research indicates that only interaction quality is enough to increase user intention to use AI-based VAS devices. Previously, human-computer interaction was believed to be solely based on human social responses (Shalini et al., 2019). However, the current study demonstrates that there are multiple factors that can stimulate human response when interacting with computers. The study reveals that information quality and system quality are two major factors that can improve social responses in the form of interaction quality. Moreover, it also confirms that information quality and system quality improve human interaction quality with technology. Additionally, the study establishes that interaction quality can be the sole source for improving the intention of the user to use such devices in Finland.

5.2 Managerial implications

The current research will be useful for AI technologists to improve the quality of AI-based VAS and other factors related to such systems. Additionally, it demonstrates how users seek the system quality, which can be improved for increasing the interaction quality and intention of the user to use the AI-based VAS. This study also helps policymakers to make policies based on information quality.

The findings of the study can be applied to the management of AI-based devices by understanding the needs of users. An AI device's design and the quality of such devices should align with human needs and societal goals as pillars for improvement. Research in areas of task technology and technology acceptance can lead to the development of AI-based devices that can be better fits for users. Moreover, it is important for the designers of AI-based VAS devices to incorporate advanced quality factors into the design of their devices, which can significantly improve user intention. The research outcomes demonstrate mainly the quality factors (i.e. information, system, and interaction quality) of AI-based devices, which are based on the design of such devices.

The study's findings can be used to develop services and products that are more attractive to users. Moreover, organizations must take interaction quality into account when designing products based on AI-based technology. VAS based on facial impressions and human faces can improve interaction quality by reducing the feeling of physical interaction with a machine.

Furthermore, the research results may be useful for developing better advertising and marketing plans. As a result of this study, marketing managers will have an increased understanding of customer perspectives and be able to decide which products are most valuable to their customers. Consequently, managers can improve sales by focusing their advertisements and marketing plans on user assessment criteria.

5.3 Limitation and future guide of the research:

The study has several limitations. The primary limitation of the current research is that the study outcomes can only be applied to the Finland consumer market. The research outcomes cannot be generalized globally. The scope of the research is limited to analyzing the user intention to use AI-based VAS devices. Moreover, only two quality elements of ISSM (i.e. system quality and information quality) are used in this research.

Future research can add other factors of the IS success model. Moreover, future research can design factors that may impact the user's intention to use AI-based VAS devices. The performance indicator of AI-based VAS devices, such as reliability, accuracy, and credibility of AI-based VAS devices, can also be used for a better understanding of such devices. Future research can also compare secondary studies, which are conducted in two different markets and analyze the quality factors of AI-based VAS devices that impact users’ intention to use the devices. The comparative studies may be able to demonstrate different factors that impact users’ intention to use AI-based VAS devices.

5.4 Conclusion

The current study has analyzed the impact of quality factors on the interaction and intention of users to use AI-based VAS. The study has reviewed past research on the same topic and identifies a research gap. This study adopts the conceptual framework from past studies that shows the relationship between each variable. In this study, a quantitative research method is used, and primary data is collected via questionnaire from 100 respondents living in Finland. The collected data is analyzed using SmartPLS with different statistical techniques. Each hypothesis of the current study is examined by regression analysis, which rejects and accepts the hypotheses for the current study. The outcomes of the research indicate that system quality and information quality of the AI-based VAS are positively and significantly related to interaction quality. The improved interaction quality then leads to the positive intention of the users to use such devices. Hence, the current study recommends that technology makers and innovators must improve the information quality and system quality of AI-based devices so that they can interact with humans more effectively. Moreover, designers, marketers, and managers can use the information in the research to design and build better products, marketing strategies, and customer perspectives. The more the devices interact with humans effectively, the more user intention to use AI-based devices will increase.

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APPENDICES

APPENDIX 1: Role of Interaction Quality in Use of AI-Based Voice Assistant Systems - Evidence from Finland.

People use artificial intelligence (AI)-based voice-assistant systems (VASs) (Apple Siri, Google Assistant, Amazon Alexa, and Microsoft Cortana) for a variety of reasons in their everyday lives. The purpose of this research is to understand the role of interaction quality in the use of AI-based VASs in Finland.

NOTE: This questionnaire does not gather personal information such as email addresses or names. The information gathered is solely for research purposes. It will be kept private and will not be shared with anyone else.

Gender
- ☐ Male
- ☐ Female

Age (in years)
- ☐ 18–22
- ☐ 23–27
- ☐ 28–32
- ☐ 33–37
- ☐ 38-42
- ☐ Above 43

No. of AI-based VASs in use
- ☐ More than one VAS
- ☐ One VAS
- ☐ No specific VAS

AI-based VAS use frequency (per month)
- ☐ 2-5 times
- ☐ 6-9 times
- ☐ More than 9 times

AI-based VAS use amount (per month)
- ☐ Less than 1h
- ☐ 1-3 h
- ☐ 3-5 h
- ☐ More than 5 h

Main purpose of AI-based VAS use
- ☐ For fun
- ☐ For getting faster results
- ☐ For convenience by speaking

☐ Others

Please tick appropriately

Strongly Disagree	Moderately Disagree	Slightly Disagree	Neutral	Slightly Agree	Moderately Agree	Strongly Agree
1	2	3	4	5	6	7

	Intention to use AI-based VAS (IUAI)	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1.	I presently intend to actually use VAS regularly for accomplishing my related tasks							
2.	I intend to use VAS in the near future							
3.	I intend to increase my use of VAS in the near future							
	Information quality (INFQ)	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1.	VAS provides me with information relevant to my needs							
2.	VAS provides me with sufficient information							
3.	VAS provides me with accurate information							
4.	VAS provides me with up-to-date information							
	System quality (SYSQ)	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1.	VAS quickly loads all the text and graphics							
2.	VAS is easy to use							
3.	VAS is easy to navigate							
	Interaction quality (INTQ)	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1.	VAS is able to help me							
2.	VAS is consistently courteous with me							
3.	VAS is competent in doing its job							
4.	VAS gives me prompt services							