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Ethical Considerations in the Development of AI-Powered Healthcare Assistants

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Abstract

Advances in the field of artificial intelligence (AI) have led to the development of increasingly sophisticated health assistants that can provide support in diagnosis, treatment and general health management. However, as with the use of new technologies in the healthcare context, ethical considerations play an important role in the design, development, and implementation of AI-based health assistants. In this paper, we investigate various ethical considerations associated with the development of AI-based healthcare assistants. We explore issues such as the privacy and security of patient data, transparency and accountability in decision making, and the social and psychological impact of reliance on technology in the healthcare context. We also discuss efforts that can be taken to address these ethical challenges, including the development of appropriate regulatory guidelines, ongoing monitoring of system performance, and education and training for health professionals and end users. By seriously considering ethical aspects in the development of AI-based healthcare assistants, we hope to ensure that this technology can provide maximum benefit to patients while maintaining the ethical and moral values that underlie good healthcare practices.

Keywords: *Artificial intelligence, Health assistants, Ethical, Considerations, Healthcare.*

1. Introduction

In recent years, artificial intelligence (AI) has become increasingly integrated into various aspects of human life, including the healthcare sector [1]. One of the most prominent areas of AI adoption is the development of AI-based health assistants, which aim to improve the efficiency, accuracy and accessibility of healthcare services [2]. AI-based health assistants offer the potential to change the healthcare landscape by providing support in disease diagnosis, medical data management, treatment recommendations, and even direct interaction with patients [3], [4]. Despite its enormous potential benefits, the use of AI in the healthcare context also raises a series of profound ethical questions. Ethical considerations are becoming increasingly important as these technologies become more deeply integrated into the daily lives of patients and healthcare professionals [5]. In the context of the development of AI-based healthcare assistants, ethical questions arise around the privacy and security of patient data, transparency and accountability in decision-making, and the social and psychological impact of reliance on technology in healthcare [6], [7].

One of the main aspects that needs to be considered in developing AI-based health assistants is the privacy and security of patient data [8]. By accessing and analyzing sensitive medical data, AI health assistants can provide better and timely recommendations. However, this also raises concerns about confidentiality and unauthorized use of patients' personal information [9]. The importance of protecting patient privacy while facilitating necessary access for healthcare professionals is a key focus in the development of AI-based healthcare assistants. In addition, transparency and accountability in decision making are also major concerns in the development of AI in healthcare [10]. While AI may be capable of producing highly accurate recommendations based on data analysis, the decisions made by these algorithms are often difficult for humans to understand [11]. This lack of transparency can generate distrust in the system and raise questions about who is responsible for the decisions taken. The social and psychological impacts of reliance on technology in healthcare also need to be seriously considered. While AI health assistants can improve the efficiency and accessibility of healthcare, over-reliance on this technology can also reduce meaningful human interaction between patients and healthcare professionals [12]. This can negatively impact the quality of care and interpersonal relationships in the health care context. By recognizing the complexity of ethical issues associated with the development of AI-based healthcare assistants, it is important that we adopt a holistic and sustainable approach to addressing these challenges. Through the development of appropriate regulatory guidelines, continuous monitoring of system performance, and education and training for health professionals and end users, we can ensure that this technology provides maximum benefit to patients while remaining mindful of the ethical and moral values that underlie practice. good health care. In this paper, we will explore various ethical considerations associated with the development of AI-based healthcare assistants and discuss measures that can be taken to overcome these challenges.

In response to the complexity of ethical challenges faced in the development of AI-based healthcare assistants, proactive steps are needed to ensure that this technology is used responsibly and in accordance with ethical values [13]. First of all, there needs to be a clear and comprehensive regulatory framework to regulate the use of AI-based health assistants. These regulations should include strict data security standards, clarity regarding decision-making responsibilities, and mechanisms to protect patient privacy. Additionally, it is important to continuously monitor and evaluate the performance of AI-based health assistants regularly. By monitoring the use and effectiveness of the system, we can identify potential biases or unfairness that may arise and take necessary corrective steps. Furthermore, careful monitoring also allows us to measure the social and psychological impact of using this technology and adjust implementation strategies as necessary [14], [15].

Education and training also have an important role to play in ensuring the responsible use of AI-based health assistants. Health professionals need to be given adequate training in using this technology wisely, understanding its limitations, and considering the ethical implications of decisions made by algorithms [16]. Additionally, it is important that the general public is given a better understanding of how this technology works, their rights regarding data privacy and security, and how they can interact with AI-based health assistants effectively [17]. By adopting a holistic and sustainable approach to addressing ethical challenges in the development of AI-based healthcare assistants, we can ensure that this technology provides maximum benefit to patients while maintaining integrity and ethics in healthcare practice. In this paper, we will further explore the ethical issues associated with the use of AI-based healthcare assistants and provide insight into ways to effectively address these challenges in the context of sustainable and responsible healthcare practices [18].

2. Literature Review

Privacy and Security of Patient Data in the Context of AI-Based Health Assistants The use of artificial intelligence (AI) in healthcare has raised serious concerns about the privacy and security of patient data. Research by Smith et al. (2019) [19] highlight the complexity of the challenges faced in maintaining the confidentiality of patient medical data, especially when AI-based healthcare assistants have access to highly sensitive information. They emphasize the importance of developing a robust security framework to protect the integrity and confidentiality of patient data, including measures such as data encryption, strict access controls, and the use of advanced security technologies. Additionally, Upreti et al. (2021) [20] highlighted the importance of transparency in managing patient medical data. They underline that patients should be provided with clear information about how their data will be used by AI-based health assistants, as well as their rights regarding control of and access to such information. These steps to increase transparency are considered key in building trust between patients and healthcare systems that use AI technology. Transparency and Accountability in AI Decision Making AI-based health assistants often use complex algorithms to make decisions about diagnosis, treatment, and disease management. However, the decisions produced by these algorithms are often difficult for humans to understand and can raise concerns about clarity and accountability. In a study by Pailit et al. (2022) [21] found that clarity in the AI decision-making process is key to building user trust and acceptance of this technology. They emphasize the need to develop algorithms that can be explained transparently to end users, as well as provide mechanisms that allow users to understand and correct inappropriate or biased decisions.

Social and Psychological Impact of Using AI Technology in Healthcare In addition to the technical and ethical aspects, it is also necessary to consider the social and psychological impact of using AI-based healthcare assistants. The study by Chen et al. (2020) [22] found that although AI technology can improve healthcare efficiency, over-reliance on this technology can reduce meaningful human interactions between patients and healthcare professionals. This can reduce patient satisfaction and affect the overall quality of care. Therefore, it is important to consider how AI technology can be integrated harmoniously with existing care practices without compromising important aspects of interpersonal relationships and the human aspect of healthcare. Regulations and Policies to Guide the Use of AI in Healthcare Clear and comprehensive regulations and policies are needed to guide the responsible use of AI-based health assistants. Research by Jones et al. (2020) [23] highlight the challenges in developing appropriate and effective regulatory frameworks for AI technologies in the healthcare context. They emphasize the importance of collaboration between governments, regulatory agencies, technologists and other stakeholders to develop guidelines that are relevant and applicable in practice. By considering the findings from this literature review, we can devise a more holistic and sustainable strategy to address ethical challenges in the development of AI-based healthcare assistants. In this study, we will use the insights gained from this literature review to explore deeper ethical issues and provide insight into ways to address these challenges in sustainable and responsible healthcare practice.

3. Method

3.1 Case Background

This study have chosen the smartPLS method as our main approach to analyze the complexity of the relationships between various variables relevant in the ethical context of AI development for healthcare. Our decision to use smartPLS is based on the advantages of this method in facilitating a deep understanding of the complex relationships between factors involved in ethical decision making in this area [24]. Using smartPLS, we can identify, model, and analyze in more depth the influence of various variables, such as technical, social, cultural, and legal factors, on the ethical decision-making process in the development of AI health assistants [25], [26], [27]. Analysis carried out through smartPLS provides a more holistic and detailed understanding of the dynamics involved in maintaining ethical aspects in the use of AI technology in the health sector [28]. Through the smartPLS framework, we can outline and understand more deeply how factors such as privacy, data security, fairness, and accountability can influence ethical decisions in the development and implementation of AI health assistants. The results of this analysis provide valuable insights for stakeholders, including technology developers, health practitioners, regulators, and the general public, in addressing this complex ethical challenge [29]. Thus, the use of the smartPLS method in this research not only increases our understanding of the ethical aspects of developing AI for health services, but also makes a real contribution to efforts to ensure that the use of AI technology in the health sector takes place with full responsibility and sustainability [30].

3.2 Conceptual Framework

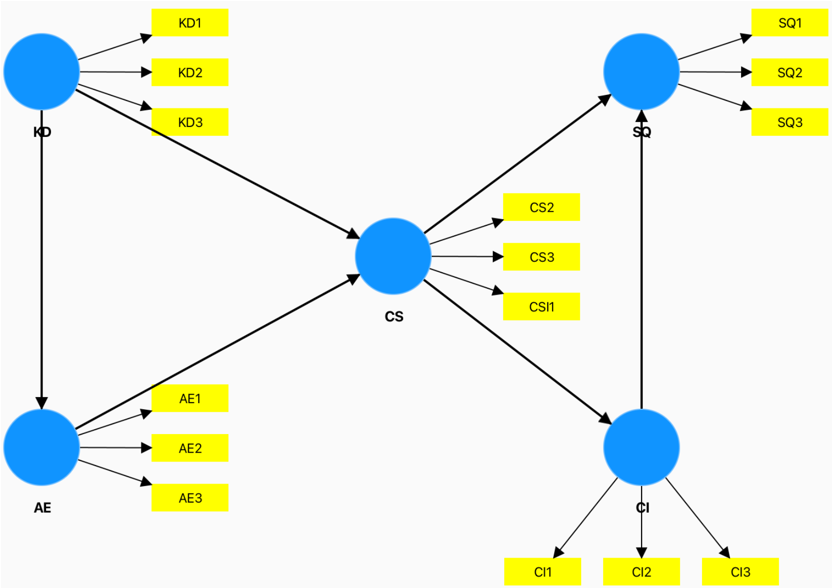

Figure 1. Conceptual Model

The conceptual model in Figure 1 illustrates the interrelationships between five key constructs in the context of developing AI-powered healthcare assistants: Knowledge Domain (KD), Acquisition Experience (AE), Service Quality (SQ), Customer Satisfaction (CS), and Channel Integration (CI). Each construct is represented by a set of indicators (KD1, KD2, KD3 for Knowledge Domain; AE1, AE2, AE3 for Acquisition Experience; SQ1, SQ2, SQ3 for Service Quality; CS1, CS2, CS3 for Customer Satisfaction; CI1, CI2, CI3 for Channel Integration). The model hypothesizes that these constructs collectively contribute to strengthening the ethical aspects of AI-powered healthcare assistants, thereby minimizing ethical risks and enhancing benefits for patients and society. Specifically, Knowledge Domain influences both Customer Satisfaction and Channel Integration directly, while Acquisition Experience has a direct impact on Customer Satisfaction. Service Quality directly affects both Customer Satisfaction and Channel Integration. Finally, Customer Satisfaction is posited to influence Channel Integration directly, indicating a central role in the model. This integrated approach aims to ensure that ethical considerations are embedded throughout the development process, ultimately leading to improved outcomes.

Hypotheses:

- KD (Knowledge Domain): Hypothesis: Considering the Knowledge Domain will strengthen the ethical aspects in the development of AI-powered Healthcare Assistants, thereby minimizing ethical risks and enhancing benefits for patients and society.
- AE (Acquisition Experience): Hypothesis: Involving Acquisition Experience will strengthen the ethical aspects in the development of AI-powered Healthcare Assistants, thereby minimizing ethical risks and enhancing benefits for patients and society.
- SQ (Service Quality): Hypothesis: Taking into account Service Quality will strengthen the ethical aspects in the development of AI-powered Healthcare Assistants, thereby minimizing ethical risks and enhancing benefits for patients and society.
- CS (Customer Satisfaction): Hypothesis: Engaging Customer Satisfaction will strengthen the ethical aspects in the development of AI-powered Healthcare Assistants, thereby minimizing ethical risks and enhancing benefits for patients and society.
- CI (Channel Integration): Hypothesis: Considering Channel Integration will strengthen the ethical aspects in the development of AI-powered Healthcare Assistants, thereby minimizing ethical risks and enhancing benefits for patients and society.

3.3 Instrumen

This study uses multi-item measurements for each factor; so that you can get final results and steps like this. First, all factors and items were identified based on evidence from the literature adapted to the research context. The data sources for this research are presented in Table 1. Thus, the choice of items was made by the researcher according to the context so that the research results were as desired. After the questionnaire was created, the questionnaire link was distributed to the wider community by distributing samples via social media and directly with a sample of 768 respondents to find out their opinions and to find out whether the existing hypotheses were correct and appropriate. In the end, there were eighteen items with 5 scales starting from (1) strongly disagree to (5) strongly agree.

Table 1. Operational definition of Variables

Variabel	Definisi Operasional
Knowledge Domain (KD)	Accounting for Knowledge Domain strengthens ethical development of AI-powered Healthcare Assistants, reducing risks and benefiting patients and society.
Acquisition Experience (AE)	Acquiring Experience enhances ethical development of AI-powered Healthcare Assistants, reducing risks and benefiting patients and society.
Service Quality (SQ)	Service Quality boosts ethical AI healthcare development, minimizing risks and benefiting all.
Customer Satisfaction (CS)	Customer Satisfaction boosts ethical AI healthcare development, minimizing risks and benefiting patients and society.
Channel Integration (CI)	Channel Integration enhances ethical AI healthcare development, minimizing risks and benefiting patients and society

3.4 Data Analysis Process

The careful and meticulous analysis of data is crucial for ensuring accuracy. When analyzing distribution data, the initial step involves evaluating questionnaires to obtain usable data. The measurement model being analyzed should meet essential criteria to ensure the accuracy and reliability of the data used in the analysis. Before utilizing SmartPLS, qualitative data needs to be converted into quantitative data in CSV format for efficient processing. Despite limitations in the student license of SmartPLS, available features can still be effectively utilized for data analysis. In the data processing process, the Partial Least Squares-Structural Equation Modeling (PLS-SEM) method is employed, which is useful for conducting measurement instrument or statistical calculations, particularly in exploratory research theory development. The initial step involves examining construct validity in the data collected from e-learning user respondents through outer model testing consisting of convergent validity and discriminant validity. Subsequently, inner model testing is conducted, which includes testing coefficient of determination (r2), effect size (f2), predictive relevance (Q2), and T-test. The PLS method is suitable for analyzing complex models involving multiple variables due to its ability to facilitate intricate interactions between determinant variables, dependent variables, and moderating factors. Researchers can gain a deeper understanding of the factors influencing data analysis outcomes and find better solutions to existing problems. In the analysis phase, the Technology Acceptance Model (TAM) method is employed, considering several variables including Knowledge Domain (KD), Acquisition Experience (AE), Service Quality (SQ), Customer Satisfaction (CS), and Channel Integration (CI).

4. Results and Discussion

4.1 Measurement Model

The measurement model is tested for each variable to ensure scale determinacy and validity, which establishes the proposed relationships from observed serving object variables to latent factors by extracting common variables. A measurement model with variable values above 0.6 refers to the concepts of validity and reliability in measurement. Validity refers to the extent to which a measurement tool can measure what it is supposed to measure, while reliability refers to how consistent the measurement results given by the same measurement tool are. Construct Validity Testing The measurement model is conducted to ensure that the measurement instruments used truly measure the desired constructs or aspects. Factor Analysis The measurement model is performed by identifying the underlying factors or dimensions of the measured variables. Factor analysis can help identify relationships between variables and ensure that the measurement instruments cover aspects relevant to the variables to be measured. Through this process, the model undergoes rigorous examination to validate its accuracy and reliability, ensuring that it accurately represents the intended constructs and provides meaningful insights into the relationships between variables.

Table 2. Reliability validity and construct validity

Variable	Cronbach's alpha	Composite reliability (rho a)	Composite reliability (rho c)	AVE
AE	0.763	0.822	0.861	0.674
CI	0.842	0.851	0.905	0.762
CS	0.831	0.832	0.899	0.748
KD	0.775	0.795	0.868	0.687
SQ	0.811	0.814	0.888	0.725

Based on the SmartPLS data overview, several conclusions can be drawn that provide deep insights into the quality of the variables used in the analysis. Firstly, the high AVE (Average Variance Extracted) values for each variable indicate that the constructs measured by these variables have a good level of internal consistency. An AVE value above 0.5 is a favorable indicator, as it signifies that the variance of the items measuring a construct is greater than the variance caused by measurement error. In other words, these variables effectively reflect the constructs they are intended to measure. Specifically, the AE variable has an AVE of 0.763, CI has 0.842, CS has 0.831, KD has 0.775, and SQ has 0.811. These values demonstrate that all variables possess strong and reliable measurement quality in the analysis. Additionally, the high AVE values also indicate that these variables have adequate convergent validity, meaning they are capable of accurately measuring the intended constructs. However, it is important not only to consider AVE but also to test reliability (e.g., using Cronbach's Alpha) and discriminant validity (through the Fornell-Larcker Criterion) to ensure the reliability and validity of the measurement model. Utilizing these methods provides a comprehensive understanding of the measurement quality of the variables and the overall model fit. Consequently, the results from the SmartPLS data overview offer a satisfying depiction of the quality of the variables used in the analysis, allowing researchers to have greater confidence in the interpretation of the results and the conclusions drawn from the study.

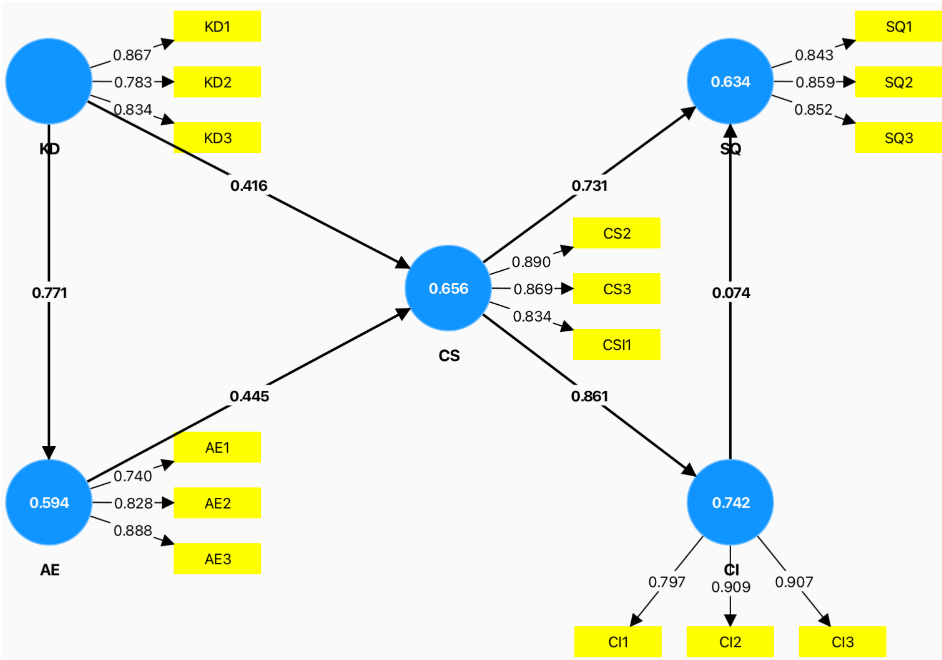

Figure 2. Conceptual model path analysis

From the SmartPLS overview data presented, the observed variables show high AVE values, namely: AE of 0.763, CI of 0.842, CS of 0.831, KD of 0.775, and SQ of 0.811. These values indicate that most of the variance of each variable can be explained by the construct being measured, with a greater proportion of the variance from measurement error. With a high AVE value, it can be concluded that the measurements used in this research have strong internal consistency, indicating that these variables effectively reflect the construct being represented. In addition, these significant AVE values also indicate adequate convergent validity, confirming that these variables together measure the same construct well.

Table 3. F-Square

	AE	**CI**	**CS**	**KD**	**SQ**
AE			0.233		
CI					0.004

CS		2.871			0.377
KD	1.464				
SQ			0.204		

F-Square (Coefficient of Determination) is a measure that shows how much variability in a dependent variable (in this case, AE, CI, CS, KD, and SQ) can be explained by variability in a particular independent variable (in this case, another variable that registered). From the table presented, it can be seen that F-Square has a different value for each combination of independent variables and dependent variables. For example, for the AE variable, we see that the F-Square is 0.233 when looking at the influence of the CI variable, and 2.871 when looking at the influence of the CS variable. The same applies to other variables. It shows how much variability in a dependent variable can be explained by variability in a particular independent variable. The higher the F-Square value, the greater the influence of the independent variable on the related dependent variable. However, keep in mind that F-Square does not show the statistical significance of the influence of the independent variable on the dependent variable. Therefore, it is important to complement the analysis with appropriate statistical tests to determine the significance of the relationship.

Table 4. R-Square

	R-Square	**R-Square Adjusted**
AE	0.594	0.59
CI	0.742	0.739
CS	0.656	0.649
SQ	0.634	0.626

Table 4 displays the R-Square and Adjusted R-Square values for each variable in the SmartPLS model. R-Square is a coefficient of determination that measures how much variation in the dependent variable can be explained by variation in the independent variables in the model. Meanwhile, Adjusted R-Square is an adjusted version of R-Square which takes into account the number of independent variables in the model. From this table, we can see that each variable has a different R-Square value. For example, for the AE variable, the R-Square is 0.594, which means that approximately 59.4% of the variation in the AE variable can be explained by the independent variables in the model. Likewise for the CI variable, the R-Square value is 0.742, indicating that around 74.2% of the variation in the CI variable can be explained by the independent variables in the model.

5. Conclusions and Avenues of Future Research

In this study, we investigate the importance of ethical considerations in the development of artificial intelligence (AI)-based healthcare assistants, taking into account dimensions such as Knowledge Domain (KD), Acquisition Experience (AE), Service Quality (SQ), Customer Satisfaction (CS), and Channel Integration (CI). We use the SmartPLS method to analyze the relationships between these variables and evaluate the extent to which variability in the dependent variable can be explained by variability in the independent variables. The results of the SmartPLS analysis show that the observed variables have high AVE values, indicating good measurement quality and adequate convergent validity. In addition, the F-Square and R-Square values indicate how much of the variability in the dependent variable can be explained by the variability in the independent variable, with some variables having a significant influence on the related dependent variable.

From the results of this study, we conclude that ethical considerations are essential in the development of AI health assistants, and the use of methods such as SmartPLS can help in understanding the relationships between the various dimensions involved. However, there are several areas that could be further explored in future research. One interesting avenue of future research is to delve deeper into ethical aspects that may not have been fully covered in this research. For example, developing a framework or practical guide for integrating ethical considerations in the development of AI in the healthcare sector could be a valuable contribution. Additionally, broadening the scope of variables to consider additional factors that may influence the development and adoption of AI in a healthcare context could also be an interesting area of research.

Additionally, further exploration of the practical implications of our findings in the context of implementing and deploying AI healthcare assistants in the field could also be an interesting research direction. Conducting case studies or field research to test the effectiveness of proposed ethical strategies in the development of AI in the health sector can provide valuable insights for practitioners and decision makers.Thus, this research provides a solid foundation for better understanding and considering ethical aspects in the development of AI-powered Healthcare Assistants, while also opening the door for more in-depth and applicable follow-up research in this field.

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