Factors Influencing the Clinician's Intention to Use AI Systems in Healthcare: A Value-Based Approach

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Abstract

Healthcare systems worldwide are in rapid transition, moving from traditional, paper-based practices to computerized approaches to improve service delivery. Consequently, interest in AI applications within medicine has been growing exponentially. The benefits of adopting such technology in a data-driven healthcare environment have been readily studied. However, few studies have investigated whether these AI-based medical interventions would be valued and used by clinicians. Thus, this study aims to extend a value-based adoption model (VAM) within the North American healthcare context to assess the clinician's positive and negative views of AI and whether their perceptions of risks and benefits influence their intention to adopt the technology within their practice.

Keywords

Artificial Intelligence, Clinician Technology Acceptance, Value-Based Adoption Model, Perceived Risk, Perceived Benefits, Health Information Technology

Introduction

Healthcare systems worldwide are in rapid transition, moving from traditional, paper-based practices to computerized approaches to service delivery. As these trends in electronic health data collection continue to develop and converge, there are unprecedented opportunities to create and apply Artificial Intelligence (AI) algorithms in healthcare to analyze and interpret these massive datasets for screening, diagnosis, and prognostication (Topol, 2019). The field's rapidly advancing nature, regulatory demands, and commercial drive have created pressure to introduce AI into clinical practice as fast as possible (Leung, 2012). Therefore, despite many scientific publications related to this topic, research has failed to examine whether healthcare practitioners would readily accept and value these AI solutions. It is evident that AI will never be integrated into current practice without the voluntary cooperation from clinicians, as they often act as gatekeepers who can decide what is suitable for their practice and their patients (Laï et al., 2020). Given AI's limited adoption in clinical practice, we believe a series of technological, regulatory, and ethical concerns might be promoting hesitancy among clinicians. However, little is known about the perceived risk and benefits of using AI-based medical interventions from the clinician's perspective. Thus, this study aims to investigate the factors contributing to AI adoption intention within healthcare from the clinician's perspective and what concerns may influence their positive and negative views of the technology.

Research Model

Due to the sensitivity and novelty of AI, the intention to use AI-based devices in healthcare may require an alternative approach with more substantial prediction power than existing technology acceptance models. In their comparative study of technology acceptance models for AI, Sohn and Kwon (2020) found that traditional technology acceptance models were too broad and did not reflect the specific context of AI. The authors would conclude that the Value-Based Adoption Model (VAM) explained the acceptance of AI-based products better than other widely applied technology acceptance theories, including the TAM, UTAUT, and TPB. According to Kim et al. (2017), the VAM uses perceived sacrifices and benefits as two variables mediated through value to predict intentions to use technology. Using value-based considerations to predict adoption intention acknowledges the healthcare sector's unique nature compared to other less sensitive industries (Turja et al., 2020). For this reason, our study leverages a modified VAM developed by Esmaeilzadeh (2020), which assessed the value-based adoption intention for AI devices in healthcare from the patient's perspective. In line with the author's recommendation, there was a need to retest several hypotheses among a clinician sampling frame. Hence, our condensed model reflects the unique technological, regulatory, and ethical concerns clinicians consider when perceiving the associated risks of using AI. Such prominent concerns included the sparse number of randomized clinical trials to test the performance of AI systems, the lack of transparency of information flows within AI applications, the risk of inequity and discrimination introduced by algorithmic biases, and insufficient regulatory clarity (Nagendran et al., 2020). Other factors deemed less relevant to the clinician were dropped from the study to achieve a more parsimonious model. Expanding on the VAM, we will also explore an additional link between Perceived Mistrust and Perceived Benefits of AI to investigate trust's effect on formatting benefit perceptions. Figure 1 (below) presents this modified theoretical framework:

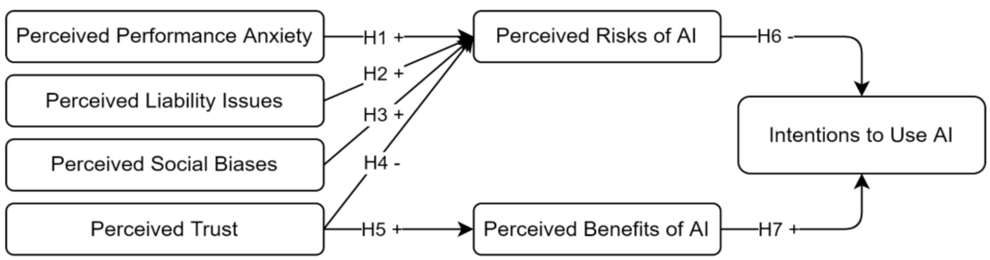

Figure 1 - Modified VAM Theoretical Framework

Perceived Performance Anxiety

Perceived performance anxiety refers to the clinician's perception of the likelihood that the system malfunctions or exhibits pervasive technological uncertainties (Kaplan & Haenlein, 2019). Zhang et al. (2021) found that poor performance or functional errors increased the patients' perceived risk when interfacing with the AI systems. Additionally, a study conducted by (Laï et al.,2020) found that physicians remained critical in the face of upcoming AI medical tools, as they are waiting for proof of efficiency in medical practice before adopting the new technologies. This skepticism may indicate that poor perceived performance demotes the intention to use AI by increasing one's perceived risk. Therefore:

H1: *Perceived performance anxiety will positively affect the clinician's perceived risks of AI-based tools.*

Perceived Liability Issues

Perceived liability issues can be defined as the extent to which an individual is concerned about the liabilities of using AI clinical tools (Laï et al., 2020). One study found that healthcare professionals had genuine concerns regarding the liability of these AI-based tools if they induced harm to a patient (Laï et al., 2020). From a physician's perspective, the utility of these AI-based interventions would be diminished if the safest way to use them from a liability viewpoint was as a confirmatory tool to support existing decision-making processes (Price et al., 2019). Seeing that their careers may be on the line if the AI makes a wrong decision, we believe that the clinician's degree of perceived liability will result in greater risk beliefs associated with healthcare AI. Therefore:

H2: *Perceived liability issues will positively affect the clinician's perceived risk of AI-based tools.*

Perceived Social Biases

Perceived social biases refer to how a person believes that data used in AI models may replicate and exacerbate health inequities in certain minority patient groups (Reddy et al., 2020). A recent study found that AI system architecture requires a more sophisticated structure to understand human moral values before being accepted (Edwards, 2019). Wiens et al. (2019) would demonstrate the importance of addressing these potential biases lurking in healthcare AI systems and indicated that it is a significant hurdle towards achieving acceptance from clinicians. While Esmaeilzadeh (2020) found that perceived social biases were insignificant in explaining the perceived risks from a patient-centred perspective, we expect clinicians to exhibit higher degrees of healthcare ethics. Accordingly, we believe these concerns about morally flawed practices will significantly contribute to clinicians' perceived AI risks. Therefore:

H3: *Perceived social biases will positively affect the clinician's perceived risk of AI-based tools.*

Perceived Trust

Perceived trust may be defined as the degree to which an individual believes the AI's recommendations are trustworthy (Reddy et al., 2020). When technology users express trusting beliefs and intentions towards technology, they may feel comfortable using it and are less likely to express apprehension (De Vries et al., 2003). It has also been demonstrated that human trust is critical to adopting AI systems, especially in high-critical contexts, such as healthcare (Larasati & De Liddo, 2019). Prior studies have highlighted that the lack of clinician trust in AI due to the black-box problem has been a significant barrier to adopting healthcare AI systems (Dhagarra et al., 2020; Tizhoosh & Pantanowitz, 2018). For this reason, we believe that higher trust beliefs toward AI should diminish the perceived risks of using the technology in healthcare. Therefore:

H4: *Perceived trust in AI will negatively affect the clinician's perceived risk of AI-based tools.*

Platt et al. (2019) also found that benefits and positive views of health information sharing were associated with system trust. In other words, if the clinician can trust the AI, we posit that this may enhance their perceived benefits of using the technology. Therefore:

H5: *Perceived trust in AI will positively affect the clinician's perceived benefit of AI-based tools.*

Perceived Risks

Perceived risks are defined as the general extent to which a clinician believes it would be risky to use AI-based tools in the healthcare sector (Bansal et al., 2010). Research has shown that risk perceptions related to a HIT system will reduce the affective utility attached to the technology and thus influence one's intention to use the technology in practice (Bansal et al., 2010). Specifically, the ambiguity regarding the safety and efficacy of AI in healthcare facilitates perceptions of risk and acts as a barrier to adopting the technology (Parikh et al., 2019). In other words, if the degree of uncertainty associated with using AI-based tools is high, clinicians are less likely to use or prescribe them in the future. We believe that higher risk perceptions of using AI-based devices in healthcare will exacerbate clinicians' intention to use AI. Therefore:

H6: *Perceived risks of AI will negatively affect clinician's behavioural intention to use AI-based tools.*

Perceived Benefits

Perceived benefits are defined as the general extent to which a clinician believes that AI-based tools can improve patient diagnostics and care planning (Lo et al., 2018). A systematic review of technology acceptance literature in healthcare found that perceived benefits encouraged behavioural intention in healthcare among clinicians, suggesting that one's belief mainly influences their intention to use a technology (AlQudah et al., 2021). Esmaeilzadeh (2020) demonstrates that perceived benefits from AIbased tools significantly increase the patient's intention to use AI technology in healthcare. In line with these studies, we believe that the greater beliefs that AI will benefit a clinician's healthcare delivery, the higher their intention to endorse and use the AI systems. Therefore:

H7: *Perceived benefits of AI will positively affect the clinician's behavioural intention to use AI-based tools.*

Methodology

We will conduct an online survey of North American clinicians through SurveyMonkey to test the hypothesized model. Before commencing the survey, participants will be asked to watch a short video characterizing the application of AI in radiology and clinical decision support systems to provide an overview of the technology's potential application in the field. By doing so, we aimed to give participants a better sense of AI's capabilities in healthcare to situate them in the study's context. A power calculation revealed that 129 participants were required to detect a medium effect size (f2 = 0.15). Each construct item will be measured on a five-point Likert scale, 1 being "strongly disagree" to 5 being "strongly agree." Face validity will be achieved by adjusting the instrument wording through consultation with an appropriate practitioner. After data has been collected, its quality will be visually assessed. Data will then be analyzed using partial least squares (PLS; Hair et al., 2011) to detect support for the hypotheses and reliability of the constructs in the theoretical models. Often used in MIS research (Ringle, 2012), PLS has been demonstrated to perform better in studies with smaller sample sizes (Wold, 1982) and provides added measurement assessment (Hair et al., 2011). A posthoc analysis will then be used to detect any patterns in the data that were not previously hypothesized.

Conclusion

This study aims to determine the relatively unexplored factors contributing to AI acceptance within healthcare from the clinicians' perspectives and what concerns may influence their positive and negative views of the technology. Currently, there is a shockingly scarce amount of research into the factors of AI acceptance from the clinician's perspective. Thus, this study aims to supplement the literature on technology acceptance among clinicians. Based on our literature review, this research will condense the value-based framework proposed by Esmaeilzadeh (2020) and explore a new negative link between perceived mistrust and perceived benefits. We believe that we have made the model more parsimonious, making future applications easier for researchers. This study will also retest the VAM in the North American healthcare context, which should help validate the theoretical framework for broader use in healthcare and other related service industries. Our study's findings could also guide healthcare AI developers in augmenting their offerings to increase value maximization and accelerate adoption.

REFERENCES

AlQudah, A. A., Al-Emran, M., and Shaalan, K. 2021. "Technology Acceptance in Healthcare: A Systematic Review," *Applied Sciences* (11:22), pp. 10537.

Bansal, G., Zahedi, F. Mariam, and Gefen, D. 2010. "The impact of personal dispositions on information sensitivity, privacy concern and trust in disclosing health information online," *Decision Support Systems* (49:2), pp. 138–150.

De Vries, P., Midden, C., and Bouwhuis, D. 2003. "The effects of errors on system trust, self-confidence, and the allocation of control in route planning," *International Journal of Human-Computer Studies* (58:6), pp. 719–735.

Dhagarra, D., Goswami, M., and Kumar, G. 2020. "Impact of Trust and Privacy Concerns on Technology Acceptance in Healthcare: An Indian Perspective," *International Journal of Medical Informatics* (141), pp. 104164.

Edwards, S. D. 2019. "The Heart Math coherence model: Implications and challenges for artificial intelligence and robotics," *AI & Society* (34:4), pp. 899–905.

Esmaeilzadeh, P. 2020. "Use of AI-based tools for healthcare purposes: A survey study from consumers' perspectives," *BMC Medical Informatics and Decision Making* (20:1)

Hair, J. F., Ringle, C. M., and Sarstedt, M. 2011. "PLS-SEM: Indeed a silver bullet," *Journal of Marketing Theory and Practice* (19:2), pp. 139–152.

Kaplan, A., and Haenlein, M. 2019. "Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence," *Business Horizons* (62:1), pp. 15–25.

Kim, H.-W., Chan, H. C., and Gupta, S. 2007. "Value-based Adoption of Mobile Internet: An empirical investigation," *Decision Support Systems* 43(1), pp. 111–126.

Laï, M.-C., Brian, M., and Mamzer, M.-F. 2020. "Perceptions of artificial intelligence in healthcare: Findings from a qualitative survey study among actors in France," *Journal of Translational Medicine* (18:1), pp. 14.

Larasati, R., and De Liddo, A. 2019. "Building a Trustworthy Explainable AI in Healthcare," *INTERACT 2019/ 17th IFIP: International Conference of Human Computer Interaction.* in *Human-Computer Interaction – INTERACT 2019, D. Lamas, F. Loizides, L. Nacke, H. Petrie, M. Winckler, and P. Zaphiris (eds.),* Paphos, Cyprus. pp. 209-213

Leung, R. C. 2012. "Health information technology and dynamic capabilities," *Health Care Management Review* 37(1), pp. 43–53.

Lo, W. L. A., Lei, D., Li, L., Huang, D. F., and Tong, K.-F. 2018. "The Perceived Benefits of an Artificial Intelligence-Embedded Mobile App Implementing Evidence-Based Guidelines for the Self-Management of Chronic Neck and Back Pain: Observational Study," *JMIR MHealth and UHealth* (6:11), pp. e198.

Nagendran, M., Chen, Y., Lovejoy, C. A., Gordon, A. C., Komorowski, M., Harvey, H., Topol, E. J., Ioannidis, J. P. A., Collins, G. S., and Maruthappu, M. 2020. "Artificial intelligence versus clinicians: Systematic review of design, reporting standards, and claims of deep learning studies," *British Medical Journal* (368), pp. m689.

Parikh, R. B., Teeple, S., and Navathe, A. S. 2019. "Addressing Bias in Artificial Intelligence in Health Care," *Journal of the American Medical Association* (322:24), pp. 2377–2378.

Platt, J., Raj, M., and Kardia, S. L. R. 2019. "The public's trust and information brokers in health care, public health and research," *Journal of Health Organization and Management* (33:7/8), pp. 929–948.

Price, W. N., II, Gerke, S., and Cohen, I. G. 2019. "Potential Liability for Physicians Using Artificial Intelligence," *Journal of the American Medical Association* (322:18), pp. 1765–1766.

Reddy, S., Allan, S., Coghlan, S., and Cooper, P. 2020. "A governance model for the application of AI in health care," *Journal of the American Medical Informatics Association* (27:3), pp. 491–497.

Ringle, C.M., Sarstedt, M. and Straub, D.W., 2012. "Editor's Comments: A Critical Look at the Use of PLS-SEM in MIS Quarterly," *Management Information Systems Quarterly* (36:1), pp. 3-14

Sohn, K., & Kwon, O. 2020. "Technology acceptance theories and factors influencing artificial Intelligence-based intelligent products," *Telematics and Informatics* (47)

Tizhoosh, H. R., and Pantanowitz, L. 2018. "Artificial Intelligence and Digital Pathology: Challenges and Opportunities," *Journal of Pathology Informatics* (9), pp. 38.

Topol, E. J. 2019. "High-performance medicine: The convergence of human and artificial intelligence," *Nature Medicine* (25:1), pp. 44–56.

Turja, T., Aaltonen, I., Taipale, S., and Oksanen, A. 2020. "Robot acceptance model for care (RAM-care): A principled approach to the intention to use care robots," *Information & Management* (57:5)

Wiens, J., Saria, S., Sendak, M., Ghassemi, M., Liu, V. X., Doshi-Velez, F., and Jung, K. 2019. "Do no harm: A roadmap for responsible machine learning for health care," *Nature Medicine* (25:9), pp. 1337–1337.

Wold, H. 1982, "Soft modeling: the basic design and some extensions," in *Systems under Indirect Observation: Causality, Structure, Prediction*, Joreskog, K.G. and Wold, H. (eds.), North Holland, Amsterdam, pp. 1-54.

Zhang, Z., Genc, Y., Wang, D., Ahsen, M. E., and Fan, X. 2021. "Effect of AI Explanations on Human Perceptions of Patient-Facing AI-Powered Healthcare Systems," *Journal of Medical Systems* (45:6), pp. 64.