AI ADOPTION IN HEALTHCARE: TRUST AND PRIVACY CONCERNS

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ABSTRACT

This study aims to provide an empirical investigation of different factors that could affect AI adoption in healthcare. Since prior research has overlooked AI adoption in healthcare, especially in the Arab context, this research in progress can fill this untapped gap and develop a theoretical framework to evaluate the customer-concerned factors (i.e., trust and privacy concerns) across different healthcare services. Due to its good generalizability, a theory of planned behavior can fit well to the healthcare context and hence can provide an adequate theoretical lens to understand the phenomenon of AI adoption. This study can expand our knowledge of AI and highlight the importance of its role to reinforce the provided healthcare services as well as meet the pressing patients' needs for better quality.

KEYWORDS

AI, Theory of Planned Behavior, Adoption, Healthcare, Trust, Privacy

1. INTRODUCTION

Artificial intelligence (AI), with its ability to transform global economy and identify strategic necessities, is one of the most rapidly developing fields across various sectors. Prior research of AI has been conducted across various contexts such as identifying fault types and locations of power transmission lines (Hassan et al. 2017), detecting the consequences of cancer diseases (Kuboń et al. 2017), and increasing the efficiency of oil drilling (Hegde & Gray, 2017). AI, in essence, can effectively help in executing various human tasks, such as decision making, speech recognition, visual perception, and translation of languages (Dande & Samant, 2018).

As per McKinsey's report (2017), AI is composed of five technological areas; autonomous vehicles, natural language processing, computer vision, virtual agents, machine learning, and smart robotics. Machine learning is reported to receive the most investment among AI's areas with around 5-7 billion. This survey report, spanning 10 countries and 14 sectors, indicates that only 20% of the firms really adopt AI affiliated technologies in their business processes and 31% partially adopt, while 10% of these companies experiment and 40% contemplate. The firms of high tech, telecom, automotive, and financial sectors appear to be on a high AI adoption curve, whereas their counterparts of healthcare, education, travel sectors seem to be on a low AI adoption curve. Although AI in healthcare has become an essential tool, especially in diseases diagnosis, image recognition and interpretation, therapy recommendation, patient management, and telemedicine (Gorunescu, 2015), its adoption as indicated in McKinsey's report is lacking and needs further investigation to help understand its promising role across different healthcare services. This has been supported by Secinaro et al. (2021) who highlighted how emerging the use of AI in healthcare, which gives us a higher motivation to disclose to what extent AI can play a role in affecting health services, considering the patients' privacy and trust.

Healthcare organizations produce an enormous amount of data, which resides in different and uncoordinated repositories sources such as lab and imaging systems, electronic medical records, health-insurance claims, and physicians' notes. Besides this, the nature of such data makes it highly sensitive for access and disclosure and hence brings privacy with its regulatory issues to scene as well as trust. With such hurdles, AI has been less adopted in the healthcare industry. Accordingly, in this study, we incorporate privacy concerns (a cognitive factor) and trust (an emotional factor) into theory of planned behavior to explain healthcare's behavioral intention to adopt AI. By doing so, we aim to extend the explanatory power of theory planned behavior from a privacy perspective, while addressing its limited consideration of emotional factors. Hence, we would address the following research question; how trust and privacy concerns affect AI adoption in healthcare?

This paper contributes to theory and practice. Theoretically, this study would provide a better understanding for AI adoption and use in the healthcare sector and so could evaluate the market readiness and maturity especially in the Arab context. Second, it would to expand theoretical boundaries of theory of planned behavior by complementing it with privacy concerns and trust to provide more predictive power. Practically, the healthcare companies might be hesitant to move faster on adopting AI as they look for clear benefits of using this emerging technology. Therefore, this study can help those companies further understand the AI market and obtain different indications on how stable, profitable, and more importantly valuable to provide better services to their customers.

2. THEORETICAL BACKGROUND

2.1 Theory of Planned Behavior

Ajzen (1991) first introduced TPB that proposes the three elements of attitude, subjective norms, and perceived behavioral control and their impact on an individual's behavioral intention. Attitude refers to the extent to which an individual evaluates a specific behavior positively or negatively (Bergevoet et al. 2004). Subjective norms refer to the extent to which an individual performs or avoids a particular behavior according to the pressure of social circle. Perceived behavioral control refers to the extent to which an individual determines the level of difficulty to perform a specific behavior (Gird and Bagraim 2008).

Theory of planned behavior has been widely used in IS research. It has been regarded a very popular model because; 1) its capacity to provide a good explanation to people's social behavior (Ajzen 2011); and 2) its reliable generalizability across different disciplines, for instance, in education (Iakovleva et al. 2011; Pihie and Bagheri 2013), healthcare (Rashidian & Russell 2011; Sivell et al. 2013), consumer behaviors (Weisheng et al. 2014), mobile commerce (Mishra 2014), and entrepreneurship (Albashrawi and Alashoor, 2020).

Nevertheless, of its wide use in literature, theory of planned behavior has been criticized for its limited capacity of explaining individuals' behavioral intention (Conner and Armitage 1998) as well as its deficiency to include an emotional factor (Rapaport and Orbell 2000). On the other hand, Sunarti et al. (2021) highlight how serious privacy concerns among patients when applying AI. In the same vein, Schwalbe and Wahl (2020) underline that the current research hasn't focused much on the ethical consideration (i.e., privacy) when using and deploying AI applications in healthcare. Hence, this study can expand the theoretical boundary of theory of planned behavior and provide further comprehension for AI adoption and use in healthcare.

2.2 Related Work and Potential Hypotheses

In the context of artificial intelligence and its affiliated areas, several scholars have investigated its adoption and usage in various industries. For instance, Rana et al. (2014) have developed a case study to show that providing accurate predictions and insights from data can significantly lead to adoption of machine learning for software defect predications. Moták et al. (2017) have used technology acceptance model and theory of planned behavior to examine the adoption of autonomous shuttle among college students. They have found that perceived usefulness, group norm, and experience significantly predict college students' intention toward the use of autonomous shuttle. Riek (2017) with her descriptive study of healthcare robotics has identified five major elements that stakeholders consider when deploying robotic agents in healthcare; safety and reliability, usability and accessibility, cost effectiveness, clinical effectiveness, and capability and function. Buckley et al. (2018) have investigated the intended use of automated vehicles using both technology acceptance model and theory of planned behavior through a simulated experimental drive and survey, and shown that theory of planned behavior's three pillars, perceived usefulness, and trust significantly determine the intention to use automated vehicles among US participants. Burlina et al. (2017) have used machine learning and deep learning to evaluate ultrasound for classification of myositis and illustrated their high accuracy in such classification. Machin et al. (2018) have described the use of AI's techniques like genetic algorithm and fuzzy logic in intelligent transportation systems especially across vehicle control, traffic control and predication, and road safety and accident prediction. Cosmin (2011) has described expert systems, special sensors, and robots and automatic systems as intelligent agents and their adoption in agriculture. Tan and Shao (2015) have predicted student potential dropout in e-learning using machine learning by examining personal characteristics and academic performance for students. Hassan et al. (2017) have employed machine learning to detect fault types and locations of power transmission lines to help in increasing reliability. Boyko et al. (2018) have suggested that machine learning especially survivalNet can be effective in detecting the consequences of cancer diseases.

Many other studies have used artificial intelligence techniques across different contexts, for example, in predicating consumers' preferences with organic food (Kuboń et al. 2017), shortening the behavioral diagnosis of autism (Wall et al. 2012), predicting pressure drops in rough pipes (Sahai et al. 2017), and increasing the efficiency of oil drilling for nearby wells (Hegde and Gray, 2017). It appears that many studies have been conducted in the domain of AI, though the literature lacks to reveal the big role of AI on healthcare and especially it further lacks to understand the AI adoption and use in the Arab context. Accordingly, we would develop hypotheses that evaluate the relationships between the three elements of theory of planned behavior, besides privacy concerns and trust, and AI adoption.

In the next research progress, we will develop a research model that provides underlying theoretical lens used to investigate the adoption of AI in healthcare and rationalizes the following hypotheses:

H1: Attitude is positively related to the adoption of AI
H2: Subjective norm is positively related to the adoption of AI
H3: Perceived behavioral control is positively related to the adoption of AI
H4: Trust is positively related to the adoption of AI
H5: Privacy concern is negatively related to the adoption of AI

3. RESEARCH METHOD AND CONCLUSION

In the next phase of our research, we will include a field survey to collect the study data and test the postulated relationships. All study variables will be adapted from well-established indicators from prior research to ensure better reliability, while will be measured using a 7-Point Likert Scale to ensure greater variance with 7 (strongly agree) and 1 (strongly disagree). By such, we can ensure better alignment of both construct and internal validity, though external validity may not be satisfied due to cross-sectional data of the survey. Although the study research design can establish a further empirical evidence of how TPB's factors are associated with AI adoption besides trust and privacy, future research should use a longitudinal research design to tackle the external validity. However, demographic variables will be collected to understand the study sample and control for their effect on the hypothesized relationships.

This research-in-progress work will use TPB as a theoretical lens and focus on revealing the influencing factors, in particular privacy concerns and trust, to streamline AI adoption in the healthcare sector. As such area has received a little attention in IS literature, this study can expand the existing knowledge of AI adoption and provide a ground where future studies can build on. Investigating the AI adoption in the Arab region can add a more layer of understating for this under-investigated context. In summary, this work will add a theoretical and practical value through extending the boundaries of TPB and addressing the market need by providing a better comprehension of this emerging phenomenon.

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