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Failure of Information Disclosure about Medical Artificial Intelligence and Patients' Acceptance during COVID-19: the Mediating Effect of Trust

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Abstract

Based on innovation diffusion theory and self-determination theory, this study examines the interactions of undisclosed medical AI information on patients' acceptance of medical AI, discusses the mediating role of trust between them, and demonstrates the moderating mechanism of big five personality traits though analyzing 249 valid questionnaires. These questionnaires were conducted in China when COVID-19 broke out. The results indicate that the failure of information disclosure about medical AI has a significantly negative impact on patients' acceptance of medical AI, and patients' trust in medical AI plays a mediating role. The personality of openness to experience in big five personality traits negatively moderates the relationship between undisclosed medical AI information and patients' trust in medical AI. This study provides a significant reference value for the influence mechanism of undisclosed medical AI information on patients' acceptability, which could offer practical guidance for medical institutions to apply AI system.

Keywords

Failure of information disclosure about medical AI; patients' trust in medical AI; patients' acceptance of medical AI; big five personality traits.

1. Introduction

Medical Artificial Intelligence (AI) refers to the applications achieving a series of functions such as auxiliary diagnosis, disease risk prediction and triage, hospital & healthcare management through intelligent algorithms including machine learning, representation learning and deep learning (He et al., 2019) [1]. At the beginning of 2020, people all over the world are focusing on the sudden outbreak of COVID-19. Medical AI has played an important role in the fight against the pandemic. Especially in China, more than 20 AI robots have been put into use in hundreds of hospitals across the country. Mature applications mainly focus on intelligent imaging, intelligent pathology and intelligent decision-making (Krittanawong, 2018) [2]. In fact, AI robots with different functions have already been put into use in the world before the pandemic. For instance, the Watson robot of International Business Machines (IBM), which can diagnose heart disease through algorithms (Matthew, 2017) [3]; SkinVision (Haenssle et al., 2018) [4], which is an application with high accuracy of skin cancer diagnosis; A chat robot, which provides medical advice to the public for the Britain's National Health

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Service(Steve, 2017) [5]. They play an important role in medical image analysis, disease diagnosis and medical workload saving. According to the forecast from International Data Corporation (IDC), the global medical artificial intelligence application market value is expected to exceed $25 billion in 2025, accounting for about one-fifth of the total value of AI applications, on the premise of continuous growth of user demand.

Although the factors of high accuracy, low cost, medical workload saving, non-contact diagnosis and treatment are conducive to improve people's acceptance of AI (Hamilton et al., 2019) [6], patients' acceptance of medical AI is not ideal at present. A study conducted in the UK found that even if the data show that the accuracy of AI diagnosis is higher than that of human doctors, the vast majority of patients still preferred human doctors for diagnosis and treatment (Longoni et al., 2019) [7]. Prior research has explored how factors such as the accuracy, cost efficiency and scalability of medical AI influence patients' acceptance (Longoni et al., 2019) [7]. Although some progress has been made in these aspects, patients still have doubts about the use of AI in the process of diagnosis and treatment. In particular, there is a lack of research on whether and when to disclose medical AI information to patients in the process of diagnosis and treatment. In this research, we explored the impact of disclosure on patients' AI acceptance. Although information disclosure is an important factor of patients' satisfaction with medical services in the process of medical treatment (Maguire et al., 2016) [8], some institutions do not disclose medical AI information for the sake of doctor-patient relationship (Hamilton et al., 2019) [6]and ethics (fast & Horvitz, 2016) [9]. In addition, prior studies have explored that AI's high accuracy (Hamilton et al., 2019) [6], cost efficiency (Longoni et al., 2019) [7], and different application scenarios (Liling et al., 2019) [10] either positively or negatively affect patients' acceptance. However, it ignores the influence of individual differences of medical AI users, such as personality traits, behavioral preferences and other factors on the acceptance of medical AI. In this research, we state that individual characteristics of patients, such as personality traits, will affect their acceptance of medical AI.

This research makes innovative contributions to the disclosure of information in medical AI industry. Firstly, as the first article to explore the impact of medical AI information disclosure on AI acceptance, this research expands the research scope of Longoni (2019) [7] study, in which states that the accuracy, cost efficiency and extendibility of medical AI are the important influencing factors of AI acceptance. This research also discusses whether the disclosure of medical AI information affects the patients' acceptance of medical AI. Secondly, this research finds out information disclosure as the psychological mechanism taking effect through trust. According to innovation resistance model, this research explores that whether disclose medical AI information causes patients to have different perceived risks and then determines their trust in medical AI. Thirdly, our research extends the influence of individual characteristics on trust and acceptance in the field of medical AI, and shows that different personality traits to a certain extent can predict the preference of different patients using AI when they face the same information disclosure.

2. Literature Review and Research Hypotheses

2.1 Failure of Information Disclosure

Information is usually regarded as a resource beneficial to consumers, which helps to improve the perceived value of products and services and reduce the perceived risk (Xu et al., 2017) [11]. Based on the research of Xu et al. (2020) [12], we define information disclosure as the behavior of providers to publicly disclose and publish product and service information. In addition, the basic requirements of information disclosure are integrity of the content, reliability of the information and timeliness of disclosure (Urquiza et al., 2014) [13] . As a result, consumers (patients) are not timely informed that they are treated by medical AI instead of medical staff, which not only aggresses consumers' right to know, but also violates the requirements of information disclosure.

Some researches regard that identity motivation is an important driving force of consumption, and AI may not be popular with consumers (Leung et al., 2018) [14]. When the identity of AI is not disclosed,

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consumers may face the risk of adverse selection. Prior research shows that before the conversation between the machine and the consumer, the disclosure of chat robot's identity will reduce the purchase rate by about 80%, and by adopting the strategy of delaying the disclosure time, the purchase intention of consumers can be improved, and the negative disclosure effect caused by the identity disclosure can be weakened (Luo, 2019) [15]. Moreover, A bill came into force on July 1, 2019 in California, USA, which requires that when using AI to communicate or interact with people for commercial or political purposes, it should not mislead people, and it must be disclosed that it is AI (Bertino et al., 2019) [16]. Thus, failure of information disclosure may not only lead to adverse selection of consumers, but also lead to ethical risks, and even face legal supervision.

2.2 Failure of Information Disclosure and Acceptance

With the rapid development of AI technology, researches on the acceptance of intelligent robots, driving assistance systems, and intelligent advertising systems have emerged one after another (Liang& Lee, 2017；Rahman et al., 2017) [17, 18]. However, there is a lack of empirical research on the usage behavior of medical AI, which is the most promising (Fan et al., 2018) [19]. Among the existing researches on medical AI, scholars has made some progress in the accuracy, cost efficiency and scalability of medical AI, but little is known about the acceptance and usage behavior characteristics of medical AI by doctors and patients (Israyelyan, 2017) [20]. However, doctors and patients are the end users of medical AI and directly or indirectly determine the adoption and implementation of AI (Longoni, 2019) [7]. Although the current researches on patients' medical AI usage behavior is very lacking, the previous related researches on medical information system and automation technology usage behavior can provide research clues for it. For example, existing studies have shown that people's preference for computer algorithms, information asymmetry, the weakness of automated machines in emotional services, and perceived risks have a certain impact on people's technology adoption behavior (Mathew, 2013; Hsieh, 2015) [21, 22].

According to the innovation diffusion theory, innovative ideas and technology spread among various members of the social system over time, and the whole innovation adoption process presents a normal distribution trend, including innovation adopters, innovation resisters, and slow neutrals (Park & Ryoo, 2013)[23]. As the terminal end of technology, consumers' acceptance or resistance to technology will ultimately affect its diffusion. Sheth (1981)[24] first proposed the concept of innovation resistance and defined it as consumers' resistance to innovation when innovation brings potential changes to satisfaction or conflicts with their belief structure. Heidenreich and spieth(2013)[25] divided innovation resistance into active innovation resistance (after the product evaluation) and passive innovation resistance (before the product evaluation) according to the time of occurrence. Prior studies have shown that functional barriers (including value advantage, technological complexity, usage habits, risks, etc.) and psychological barriers (including cultural and social habits, technological image or brand barriers, etc.) are the important factors leading to active innovation resistance, when users believe that the innovative technology or product attributes cannot fully meet their needs or cannot meet their expectations (active innovation resistance) (Talke & Heidenreich, 2014; Laukkanen,2016) [26, 27]. Unlike active innovation resistance, passive innovation resistance is mainly caused by individual resistance tendency towards changes and satisfaction with the current situation (Talke & Heidenreich, 2014) [26]

When the identity of medical AI is not disclosed in time, consumers feel "cheated", existing a trend of information asymmetry. Meanwhile, perceived risk is considered to play an increasingly important role in innovation resistance, and many studies on innovation diffusion also believe that the higher the perceived risk of innovation, the lower the willingness of consumers to adopt innovation (Setiawan et al., 2019) [28]. Failure to disclose information in time increases the uncertainty of consumers about innovative technology (Leung et al., 2018) [14], which will bring about perceived risks and inevitably generate anxiety, thus reducing their acceptance of medical AI. Based on the analysis above, hence, we hypothesize the following:

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Hypothesis 1 (H1). Failure of information disclosure about medical AI will be negatively related to patients' acceptance of medical AI.

2.3 The Mediating Role of Trust

In the construction of ethics about AI, trust is regarded as a core issue during the development of AI(IEEE，2016)[29]. Trust is considered to be a belief, an attitude intentionality (Hardjono，2014) [30]. In 2019, the European Commission issued Ethics Guidelines For Trustworthy AI to enhance people's trust in AI, which proposed that people's trust in AI should be discussed from both the technical and ethical dimensions, including the principles of initiative and supervision ability, security, privacy data management, transparency, inclusiveness, social well-being and accountability. Shariff et al.(2017)[31] believed that the lack of transparency in the decision-making process would make it difficult for people to predict the behavior of autonomous vehicles, thus reducing their trust in them. More and more literatures regard trust as a decision-making inspiration, helping people make cognitive judgments and decide whether to accept innovative technology(Huijts et al.，2012)[32]. Liu et al.(2018)[33] examined that trust can directly affect acceptance, or indirectly affect acceptance by weakening risk perception and improving benefit perception.

This study argues that the failure of information disclosure about medical AI decreases consumers' trust, which in turn reduces their acceptance of medical AI. When it comes to the relationship between innovation, risk and the speed of innovation diffusion, Mahajan (1990) [34] discussed that the higher the risk of innovation is, the slower the diffusion rate of innovation is, and the more consumers tend to adopt innovation resistance behavior. Transparency, a key factor in trusted AI, could reduce perceived risks and improve consumers' autonomy (Luo, 2019) [35]. However, failure of information disclosure about medical AI leads to information asymmetry between consumers and medical AI, which impairs transparency and further increases consumers' perceived risks. When the perceived risk of consumers increases and exceeds the specific tolerance level of potential adopters, it will lead to negative attitudes towards new products (Talke & Heidenreich, 2014) [26], which will weaken consumers' trust in medical AI, weaken their acceptance and trigger resistance to active innovation. We, therefore, hypothesize the following:

Hypothesis 2 (H2). Failure of information disclosure about medical AI will be negatively related to patients' trust of medical AI.

Hypothesis 3 (H3). Patients' trust of medical AI mediates the effect of Failure of information disclosure about medical AI on patients' acceptance of medical AI.

2.4 The Moderating Role of Big Five Personality Traits

The Self-Determination Theory (SDT) proposed by Deci can better explain the paradoxical effect that external behavior both promotes and weakens intrinsic motivation (Ning et al, 2019) [36]. According to this theory, when the external behavior damages the basic psychological needs of human beings, the internal motivation will be weakened, while the external behavior that provides the information supporting the ability will not weaken or even enhance the internal motivation (Deci & Ryan, 1985a) [37]. Human beings have three basic psychological needs, the need for competence, relevance, and autonomy (Deci & Ryan, 2000) [38]. Competency refers to the individual's competency demand in the activities they are engaged in. Autonomous refers to the individual's independent choice of activities. Relatedness refers to an individual's need to establish a mutual respect and dependence relationship with others. After years of development, SDT has formed a theoretical system of five sub-theories, including Basic Psychological Needs Theory (BPNT), Causality Orientation Theory (COT), Organismic Integration Theory (OIT), Cognitive Evaluation Theory (CET), and Goal Contents Theory (GCT) (Deci et al., 2001)[39].

According to COT, individuals have the tendency to create an environment conducive to self-determination and promote their own development (Deci & Ryan, 2008)[40]. Generally speaking, there are three levels of individual causal orientation, autonomous orientation, control orientation, and impersonal orientation. Autonomous orientation refers to the tendency of individuals to adjust

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and orient themselves to various environmental factors. Individuals with a high level of autonomous orientation tend to take on innovative and challenging tasks. Control orientation refers to the tendency of individuals to be controlled by instructions of people, and their behavior is easily influenced by external rewards. People with a high level of control orientation tend to be dependent on rewards or instructions from others, and value status, prestige and some external factors. Impersonal orientation refers to the individual's inability to control the consequences and intention of behaviors, which is related to the lack of conscious action (Deci & Ryan, 1985b)[41]. COT holds that the three orientations exist independently and play a role in the internalization of individual motivation together with environmental factors (Jian et al., 2010)[42]. In conclusion, SDT believes that environmental factors and individual causal orientation work together to promote the internalization of internal and external motivation by meeting the three psychological needs of autonomy, competence, and relatedness.

There are many factors that could predict trust, and personality trait is one of the important factors (Thielmann & Hilbig, 2014)[43]. Among the studies of personality traits, the Big Five Personality Model is the most widely accepted, studied, and recognized (Grucza & Goldberg, 2007). According to McCrae and Costa (1985)[44], the Big Five Personality Traits include extraversion, agreeableness, conscientiousness, openness to experience, and neuroticism.

Extraversion refers to the quantity and intensity of human interactions, and is characterized by boldness, decisiveness, and strong social skills. This dimension distinguishes the social, active, energetic person from the silent, serious, shy, quiet person (Costa & McCrae, 1991)[45]. The positive emotional component of extraversion will have a positive relationship with ethical concepts (Bratton & Strittmatter, 2013)[46]. In addition, personality traits can predict the response of trust (Zhao & Smillie, 2015)[47], and extraversion can positively predict the tendency of trust (Panyan, 2016)[48]. From the perspective of COT, those with high extraversion scores have stronger enthusiasm, initiative, higher self-orientation tendency, and are more willing to solve ethical problems encountered through communication and seeking help from others, like failing to disclose the information of medical AI, which weakens the negative effects such as the reduction of trust caused by the problems (Ching et al., 2014)[49]. Based on this, we propose Hypothesis 4:

Hypothesis 4 (H4). The relationship between failure of information disclosure and trust is moderated by extraversion such that a negative relationship is weaker when extraversion is higher rather than lower.

Neuroticism is a negative emotional state, which reflects the instability of personal emotions and the ability to regulate emotions (Ariyabuddhiphongs & Marican, 2015)[50]. Jackson et al. (2002)[51] found that people with high neuroticism were more likely to report deception or form unethical cognition. It is found that there is a significant but negative relationship between neuroticism and moral ethics (Bratton & Strittmatter, 2013)[46]. In addition, emotional stability, as the opposite of neuroticism, is positively correlated with trust (Kaplan et al., 2015)[52], which is consistent with previous studies that neuroticism negatively predicts trust propensity (Evans & Revelle, 2008)[53]. In contrast to extraversion, individuals with high neuroticism scores have poor ability to regulate emotions, poor ability to bear pressure, unstable emotions, and are easy to put themselves into full of negative emotions (Judge et al., 1995)[54], with a higher level of impersonal orientation tendency, which enhances the negative effects brought by negative moral and ethical problems. We propose Hypothesis 5:

Hypothesis 5 (H5). The relationship between failure of information disclosure and trust is moderated by neuroticism such that a negative relationship is stronger when neuroticism is higher rather than lower.

Conscientiousness compares the organized, responsible, and prudent individual with the thoughtless, irresponsible, and careless ones. Individuals who score high on conscientiousness tend to be self-disciplined, have strong control, and be cautious in their actions (Costa & McCrae, 1991)[45]. The research of Bratton and Strittmatter (2013)[46] showed that individuals with high scores in

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conscientiousness are more likely to make ethical decisions. In addition, conscientiousness positively predicts the tendency of trust (Evans & Revelle, 2008)[53]. Based on COT, conscientiousness refers to the way we control, manage, and regulate our own impulses. Those who score high in conscientiousness have higher levels of autonomous orientation, which weaken the negative effects caused by failure of information disclosure about medical AI. Therefore, we propose the sixth hypothesis:

Hypothesis 6 (H6). The relationship between failure of information disclosure and trust is moderated by conscientiousness such that a negative relationship is weaker when conscientiousness is higher rather than lower.

Agreeableness is a prosocial trait that describes how people communicate with each other (Costa & McCrae, 1991)[45]. Agreeableness reflects the degree to which individuals attach importance to cooperation and harmony with others. Individuals with high agreeableness scores attach more importance to establishing mutual respect and connection between people and others (McCarthy et al., 2017)[55]. In addition, personality traits can predict patients' trust in doctors. Patients with higher agreeableness and emotional stability are easy to establish trust with doctors in the process of interactive diagnosis and treatment with doctors (Cousin & Mast, 2016)[56]. Relatedness refers to the need for individuals to establish a sense of mutual respect, mutual support and interdependence with others (Frielink et al., 2018)[57], and the failure to disclose the identity of real medical staff destroys the relatedness, thus enhancing its negative impacts. Therefore, hypothesis 7 is proposed as follows:

Hypothesis 7 (H7). The relationship between failure of information disclosure and trust is moderated by agreeableness such that a negative relationship is stronger when agreeableness is higher rather than lower.

Individuals with the personality trait of openness to experience have rich imagination and creativity. They are willing to accept new ideas and actively seek new ideas (Costa & McCrae, 1991)[45]. It distinguishes the creative, intelligent, open individual from the simple, superficial, unintelligent individual. Studies have shown that people with the personality trait of openness to experience are more likely to accept innovative technologies such as medical AI (Watjatrakul, 2016)[58]. Individuals with high score of openness to experience dare to break away from conventions and adopt new ideas and methods to solve problems when they encounter problems (Ching et al, 2014)[49]. According to COT, individuals who are willing to innovate, dare to take responsibility and seek challenging learning tasks tend to have high levels of autonomous orientation, which plays a role in the internalization of individual motivation and weakens the negative impacts of the decline in trust caused by failure of information disclosure. We, therefore, hypothesize the following:

Hypothesis 8 (H8). The relationship between failure of information disclosure and trust is moderated by openness to experience such that a negative relationship is weaker when openness to experience is higher rather than lower.

The theoretical model of this study is shown in Figure 1.

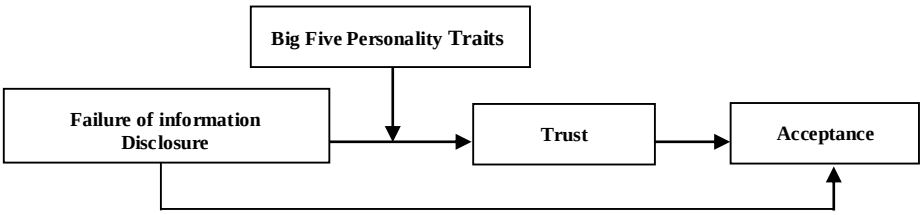

Figure 1. Hypothesized theoretical model.

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3. The research methodology

3.1 The sample and data collection

In order to promote the positive role of medical AI in the COVID-19 prevention work, this study collected data by conducting a questionnaire survey in China from February to March 2020. After eliminating invalid questionnaires, 249 valid questionnaires were finally obtained. The demographic characteristics of this sample are as follows. Males accounted for 33.3%, and females for 66.7%. Their ages mainly concentrated between 21 and 30 years old. 44.1% of the respondents lived in the first-tier cities (Beijing, Shanghai, Guangzhou, etc.). Respondents who had equal or higher than high school education background accounted for 85.1%.

3.2 Measures

In this study, the translation/back-translation procedures were used to translate the original measures into Chinese ones to avoid misunderstandings and translation bias caused by language and cultural differences. At the same time, this study adapted the existing scales and experiments, and adopted mature measures to ensure its scientificity. All these items were measured by a 5-point Likert scale, in which "1 = strongly disagree; 5 = strongly agree". This research reversely processed some items in the questionnaire and reversely converted the scores during data analysis to make the respondents think deeply and reduce cognitive errors.

3.2.1 Failure of information disclosure

Luo et al.'s (2019)[15] experiment was adapted in this study， which contained 3 items. A typical item was "When you were not informed that you were diagnosed and treated by an AI robot instead of a doctor". In this study, the Cronbach's alpha was 0.792.

3.2.2 Trust

The scale was adapted from Nordheim et al. (2019)[59]、Corritore et al. (2003)[60] and Ho & MacDorman (2010)[61], and contained seven items. A sample item was "when I have a consistent perception of AI, I am willing to trust it". In this study, the Cronbach's α of the measure was 0.724.

3.2.3 Acceptance

This study adopted the high-frequency scene scale in the pre-survey conducted in February 2020, which contained 7 items. Typical items included "AI robots make online diagnosis and analyze medical cases". The Cronbach's α of the measure in this research was 0. 854.

3.2.4 Big five personality traits

Mengcheng et al.'s (2011)[62] forty-item scale was adopted in this study. Big Five personality traits includes extraversion, agreeableness, conscientiousness, openness to experience and neuroticism. There were 8 items in the measurement of extraversion. A typical item was "In lively gatherings, I often act proactively and play as much as I want". In this study, the Cronbach's α of the scale was 0.752. There were 8 items to measure agreeableness. Typical items of this scale included "I think most people are basically kind-hearted." In this study, the Cronbach's α of the scale was 0.711. There were 8 items in the measurement of conscientiousness. Sample items contained "Once the goal is determined, I will continue to work hard to achieve it". The Cronbach's α in this research was 0.778. There were 8 items to measure openness to experience. A sample item was "I am a person who has the courage to take risks and breaks through the convention". In this study, the Cronbach's α of the scale was 0.843. Measuring neuroticism had 8 items, typical items such as "I think most people are basically well-intentioned". In this study, the Cronbach's α was 0.827.

3.2.5 Control variables

We consider gender, age, education, profession, distinct, and annual household income, and modeled them as the control variables. The control variables were age (1 = age below 20 years old, 2 = age between 21 and 30, 3 = age between 31 and 40, 4 = age between 41 and 50, 5 = age between 51 and 60, and 6 = age over 60), gender, education (1 = junior high school and below, 2 = high school, 3 =

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junior college degree, 4 = bachelor degree, and 5 = master degree or above), profession (1 = students with medical or AI background, 2 = students without medical and AI background, 3 = medical staff who have been exposed to medical AI, 4 = medical staff who have not been exposed to medical AI, and 5 = others), distinct (1 = first-tier cities (Beijing, Shanghai, Guangzhou, etc.), 2 = second-tier cities (some provincial capitals, economically strong cities in the eastern region, etc.), and 3 = other prefecture-level cities and below).

4. Results

4.1 Confirmatory Factor Analysis

In this study, SPSS 22.0 software was used to test the reliability of failure of information disclosure about medical AI, patients' trust in medical AI, big five personality traits and patients' acceptance of medical AI. In addition, we adopted Amos 22.0 software to implement the confirmatory factor analysis on the discriminant validity of variables with structural equation. The CFA results in Table 1 indicated that compared with the other three models, the four-factor model fitted the data most satisfactorily ($\chi 2/df = 2.561$, RMSEA = 0.079, CFI = 0.906, ILI = 0.908, SRMR = 0.067). Moreover, the results showed that the factor load coefficients of each item in the four-factor model were greater than 0.5 (significant) and had good convergence validity.

Table 1. Results of CFA.

Models	Factors	2/ df (df)	RMSEA	CFI	IFI	SRMR
Tour-factor model	FOID;T;A;BFPT	2.561（84）	0.079	0.906	0.908	0.067
Three-factor model	FOID;T+A;BFPT	4.132（87）	0.142	0.808	0.805	0.076
Two-factor model	FOID+T+A;BFPT	6.710（89）	0.152	0.637	0.641	0.109
One-factor model	FOID+T+A+BFPT	9.010（90）	0.180	0.484	0.490	0.125

Note: N=249. FOID: failure of information disclosure; T: trust; BFPT: big five personality traits; A: acceptance; "+" represents two factors merged into one.

4.2 Descriptive Statistics

Failure of medical AI information disclosure negatively affected patients' acceptance of medical AI ($r = -0.207$, $P < 0.01$) and patients' trust in medical AI ($r = -0.273$, $P < 0.01$). Moreover, there was a significant positive correlation between patients' trust and acceptance of medical AI ($r=0.464$, $P < 0.01$). These results provide preliminary support for the hypotheses of direct relationship, mediating effect and moderating effect proposed in this study.

4.3 Hypotheses Testing

4.3.1. Direct Effect Hypothesis and Mediation Analyses

This study adopted the three-stage analysis method of Wen et al. (2014) [63] to test the mediating effect of patients' trust in medical AI. Based on the figures shown in Table 2, The results met the following three conditions. Firstly, as can be seen from M4, the failure of medical AI information disclosure negatively affected the patients' acceptance of medical AI ($\beta = -0.209$, $p < 0.01$), strongly supporting Hypothesis 1. Secondly, as shown in M2, the failure of medical AI information disclosure related strongly and negatively to patients' trust in medical AI ($\beta = -0.275$, $P < 0.01$), consistent with Hypothesis 2. At the same time, it can be seen from M5 that patients' trust in medical AI has a significant positive impact on patients' acceptance of medical AI ($\beta= 0.470$, $P < 0.01$). Thirdly, as shown in M6, after adding patients' trust in medical AI in M4, the negative impact of undisclosed medical AI information on the acceptance of medical AI is no longer significant ($\beta = -0.086$, $P > 0.05$), but the trust of patients in medical AI has a significant positive impact on patients' acceptance of medical AI ($\beta = 0.446$, $P < 0.01$), indicating that patients' trust in medical AI played a completely mediating role between failure of medical AI information disclosure and patients' acceptance of medical AI. Hypothesis 3 was verified.

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Table 2. The results of parameter estimates.

	Trust		Acceptance		Acceptance							
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
District	0.059	0.055	0.009	0.006	-0.019	-0.018	0.05	0.059	0.069	0.03	0.052	0.059
Gender	-0.037	-0.01	-0.047	-0.027	-0.03	-0.023	-0.001	-0.017	-0.002	-0.043	0.013	0.014
Age	-0.146	-0.133	-0.111	-0.101	-0.042	-0.041	-0.126	-0.128	-0.134	-0.155	-0.097	-0.127
Profession	0.027	0.028	0.074	0.074	0.061	0.062	0.038	0.021	0.022	0.053	0.045	0.04
Education	-0.046	-0.02	0.025	0.044	0.046	0.053	-0.018	-0.012	-0.031	-0.031	0.002	-0.014
Annual household income	0.12	0.125	-0.012	-0.008	-0.068	-0.064	0.106	0.125	0.1	0.09	0.082	0.088
Failure of information disclosure		-0.275**		-0.209**		-0.086	-0.278**	-0.261**	-0.271**	-0.334**	-0.207**	-0.243**
Trust					0.470**	0.446**						
Extraversion							0.092					
Failure of information disclosure×Extraversion							-0.002					
Neuroticism								0.036				
Failure of information disclosure×Neuroticism								-0.035				
Conscientiousness									0.185**			
Failure of information disclosure×Conscientiousness									-0.06			
Agreeableness										0.363**		
Failure of information disclosure×Agreeableness										0.047		
Openness to experience											0.168**	
Failure of information disclosure×Openness to experience											-0.177**	
R2	0.024	0.098	0.009	0.052	0.224	0.231	0.106	0.101	0.135	0.223	0.156	0.123
△R2	0.024	0.098	0.009	0.052	0.224	0.179	0.000	0.001	0.003	0.002	0.029	0.017
F	0.98	3.742**	0.35	1.871	9.993**	8.995**	3.150**	2.970**	4.136**	7.632**	4.925**	3.736**

Note: N=249; *p＜0.05，**p＜0.01.

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Additionally, according to the Hayes (2014), Bootstrap method was used for testing and repeated sampling was performed for 1000 times. The results showed that the magnitude of the mediating effect of patients' trust in medical AI was -0.083, and the 95% confidence interval was [-0.137, -0.038], excluding 0, indicating that the mediating effect of patients' trust in medical AI was significant, Hypothesis 3 was further supported.

4.3.2. Moderation Analyses

Hypothesis 4-8 pointed out that extraversion, neuroticism, conscientiousness, agreeableness and openness to experience in the big five personality traits can moderate the relationship between the failure of information disclosure about medical AI and patients' acceptance of medical AI. In this paper, we adopted hierarchical regression method used to test its moderation effect. Firstly, the demographic control variables were put into the regression equation. Secondly, the failure of information disclosure and extraversion, neuroticism, conscientiousness, agreeableness and openness to experience in the big five personality traits were respectively incorporated into the regression equation. Thirdly, the interaction terms (both terms are standardized to prevent collinearity) were put into the regression equation to investigate their influence. As shown in M7-11, the interaction terms of undisclosed medical AI information and extraversion, neuroticism, conscientiousness and agreeableness had no significant predictive effect on patients' trust in medical AI, while the interaction item of undisclosed medical AI information and openness to experience has a significant predictive effect on patients' trust in medical AI (β = -0177, $P < 0.01$). Hence, only Hypothesis 8 was verified. The interaction diagram in Figure 2 shows the moderating effect of openness to experience more clearly.

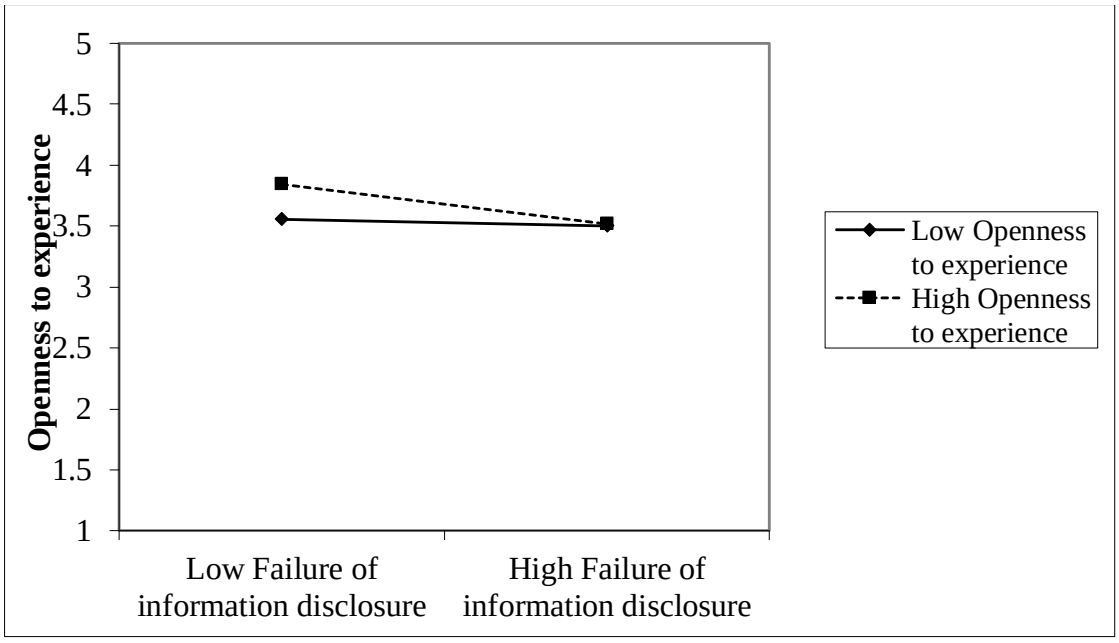

Figure 2. Interaction effect of failure of information disclosure and openness to experience on trust

5. Discussion and implications

5.1 Discussion

Based on the innovation resistance model and self-determination theory, this research takes the relationship between whether disclose the medical AI information and the acceptance of medical AI as the research topic, exploring the mediating role of patients' trust in medical AI and the moderating effect of big five personality traits. The results are as follows. Firstly, the failure of medical AI information disclosure has a significant negative impact on patients' acceptance of medical AI. The

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failure of information disclosure of medical AI information also has a significant negative impact on patients' trust in medical AI. Secondly, patients' trust in medical AI mediates the relationship between undisclosed medical AI information and patients' acceptance of medical AI. Thirdly, the openness to experience of the big five personality traits negatively moderates the relationship between undisclosed medical AI information and patients' trust in medical AI, that is, the higher the score of openness to experience, the weaker the negative effect of non-disclosure of medical AI information on patients' trust in medical AI.

5.2 Theoretical Contribution

Our research makes three main contributions to the literatures on AI acceptance. Firstly, this study enriches the research on the impact mechanism of information disclosure on AI technology acceptance. Previous studies on the influencing factors of AI technology acceptance mainly focused on the discussion of the accuracy, cost efficiency and scalability of medical AI (Longoni, 2019) [7], while previous studies paid little attention on the failure of information disclosure. There is a lack of empirical research on medical AI use behavior in the existing literature, which is the most potential behavior in the future (fan et al., 2017) [19]. This research is to study the impact of medical AI information disclosure on AI acceptance. The conclusion shows that the failure of information disclosure will directly affect and reduce patients' acceptance of medical AI. Meanwhile, the prior research on information disclosure focused on the audit information and concealment or incomplete information to consumers. We extend the problem whether disclose information to the field of medical AI. This is because different from other consumption situations, patients' decisions may have a huge impact on the results in the medical field, sometimes it is even life-threatening (Botti et al., 2009) [64]. Therefore, whether to disclose medical AI information is particularly important for patients to accept medical AI.

Secondly, we found a new pespective of psychological mechanism. The non-disclosure of medical AI information reduces the trust of consumers, and thus reduces their acceptance of medical AI. Prior studies have explored the application of medical AI in different medical scenarios and the importance of medical AI in decision-making (Liling et al., 2019) [10] will change the acceptance of medical AI by influencing patients' trust in medical AI. Liling et al. (2019) [10] proposed that patients' acceptance and trust in medical AI are complementary aspects. The higher the degree of trust, the higher the acceptance. On the basis of innovation resistance model, this research finds that for patients, using AI robots for medical activities is an innovative technology acceptance behavior, and the resulting perceived risk will change with the disclosure of medical AI information, which will determine the trust level of patients in medical AI, thus affecting whether patients accept medical AI. Meanwhile, this research complements the research of innovation resistance model in the medical field. Most of the existing literature discusses the application of innovation resistance model in consumer behavior, and this research focuses on the theoretical significance of innovation resistance in the medical industry. At present, the vast majority of research on consumer innovation resistance comes from west countries, and the relevant research combined with China's situation is rare, and mainly focuses on the impact of complex social network on innovation resistance (Zhu et al., 2017) [65]. This research supplements the localization research of innovation resistance.

Thirdly, this study found that different personality traits of patients have an impact on trust and acceptance of medical AI. Table 2 shows that only three dimensions are related to AI acceptance. They are conscientiousness, agreeableness and openness to experience. Meanwhile, patients' openness to experience can moderate the relationship between information disclosure and trust in the medical field. At present, it is difficult for AI to be accepted rapidly by patients in the medical field due to risk, ethics and other factors (Tang, 2019) [66]. However, patients with high scores of openness to experience have the characteristics of daring to create and accept new methods (Ching et al., 2014) [49], thus negatively moderating the negative correlation between the failure of information disclosure and the trust of AI. Although prior studies have confirmed that personality traits are the important factor in predicting trust (Thielmann & Hilberg, 2014) [43], our study extends it to the field

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of medical AI, and finds that according to different personality traits and behavioral styles, we can predict patients' preference to use AI when facing the same information disclosure. This suggests that the production and sales of medical AI should choose targeted information disclosure strategies according to different individual characteristics.

5.3 Practical Implications

From the perspective of practice, our research has three implications. Firstly, medical institutions should change their usual practice and actively disclose information about medical AI, so as to protect consumers' right to know and reduce relevant ethical risks, such as formulating procedures for disclosure of medical AI information and strengthening supervision on disclosure of medical AI information. In terms of specific measures, for example, medical institutions using medical AI should set up the process of communicating with patients to discuss whether to use medical AI for diagnosis and treatment, so as to reduce and eliminate information asymmetry and improve the overall trust level and acceptance of medical AI by patients.

Secondly, the public's trust in AI will provide strong support for the development of AI (Steffel et al., 2016) [67]. Medical institutions should attach importance to patients' trust in medical AI. Non-disclosure of medical AI identity information will negatively affect patients' trust in medical AI. Therefore, medical institutions should actively disclose information about medical AI. Meanwhile，the performance (such as trustworthiness, willfulness, reliability) and attributes (such as appearance and sound) of an AI system, as well as the different social and cultural situations people live in, may affect the establishment of human-technology trust (Williams et al., 2019) [68]. Therefore, from the perspective of intervention research, the factors influencing human-technology trust (such as performance / attribute, anthropomorphic characteristics, task characteristics, etc.) can be designed by people to improve the trust of medical AI, and provide beneficial practical guidance for the large-scale application of medical AI.

Finally, in view of the differences of consumers' personality traits, differentiated marketing strategies can be adopted, using the positive aspects of consumers' personality traits to control the negative aspects, and then marketing strategies can be designed to cultivate consumers with strong emotional connection. Specifically, for consumers with a high level of openness, they have certain creativity and imagination, so medical institutions can use the consumers with high level of openness to realize value co-creation, abandon the traditional view that consumers are only passive buyers, and should fully realize that consumers are more active participants and can jointly create value. For example, medical institutions can focus on cultivating consumers with a high level of openness to participate in the design, development and improvement of medical AI, and adopt their views.

5.4 Limitations and Future Directions

Despite these contributions discussed above, our research also has some limitations. Firstly, considering the differences between Chinese and Western cultures, our samples of this study are patients in mainland China, which cannot completely ensure the universality of the research results. Future researches could expand samples from different countries to further analyze and generalize our conclusions. Secondly, there are many variables to measure personality traits. This study only examined the moderating effect of the big five personality traits on the relationship between failure of information disclosure about medical AI and patients' trust in medical AI. Therefore, we suggest that we can focus on other variables related to personality traits, which will not only help to build a more complete theoretical framework, but also better guide the popularization and application of medical AI. Thirdly, although the sampling methods in this study are questionnaire survey and interview, there are still some limitations. Based on this study, future researchers are suggested to combine qualitative research with experimental research to further explore the relationship between undisclosed medical AI information and patients' acceptance of medical AI.

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