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Individual Decision Model for Using Technology of Health Crowdsensing in the Digital Era

Li Li, School of Computer and Information Engineering, Henan University, China
https://orcid.org/0000-0003-0765-5184

Xuliang Cai, YiHe (Shenzhou) Center of Life and Health Sciences, China

Xin He, International Joint Laboratory of Intelligent Network Theory and Key Technology, School of Software, Henan University, China*

Xi Yu, School of Computer and Information Engineering, Henan University, China

Haoran Li, School of Software, Henan University, China

Yanhong Liu, School of Software, Henan University, China

ABSTRACT

Digital transformation has brought about great social changes, and individuals are constantly facing the challenge of using emerging technologies. This article, for the first time, combines the diffusion of innovation theory and contract theory to build a decision model to solve the above challenge. The decision model is constructed according to the key factors that influence the individual decision process, including technological relative advantages, intrinsic motivation, risk-taking, use-cost, technological complexity, and compatibility. Through the analysis of the cost utility of each party in Health CrowdSensing technology, the question of whether individuals use the technology is transformed into the question of cost utility. In the experiments, the validity of the decision model is verified by numerical analysis. The decision model proposed in this article provides theoretical basis and experimental verification for further research on how an individual decides whether to use technology or not.

KEYWORDS

Contract Theory, Decision Making, Digital Transformation, Health CrowdSensing, Individual Behavior, Intelligence Extraction

INTRODUCTION

While the digital age brings many conveniences to people's life, it also makes people often be in the decision-making process of whether to use emerging technology. How individuals make appropriate decisions when facing technology to enjoy the convenience brought by technology has become a research hotspot. In health care domain, over 70% of health-care expenditures and 80% of mortality

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*Corresponding Author

are related to chronic diseases (Gerteis et al. 2014; Zhu et al.2022). Health Crowdsensing (HCS) technology (Guo et al. 2014; Ding et al. 2017; Liu et al. 2018; Tokosi et al. 2019), as a technology paradigm for providing various kinds of medical care to individuals or organizations, has become affordable and accessible to the general public due to its characteristics of high efficiency and low cost, even in resource-poor environments (Daniel et al. 2017).

Since 2010, there have been a number of advances in HCS technology (Kumar et al. 2020), including HealthKit (2019) and Googlefit (2019), which are used to create Apple and Google ecosystem-related services respectively. Researchers have also built HCS platforms, such as self-management interventions for schizophrenia users, digital diabetes coaches, and obesity prevention, to monitor and improve patient quality of life and stratify patients, enabling patients to adhere to medication, regulate mood, sleep normally, emergency patient monitoring, and socialize (Kalogiros et al. 2018; Ben-Zeev et al. 2013; Winterlich et al. 2016; Gao et al. 2009; Rabbi et al. 2011; Tabassum et al. 2022; Sharmila et al. 2020).

However, the study of Tokosi & Scholtz (2019) shows that the HCS technology is not widely used in the field of healthcare. Therefore, whether individuals are willing to use this technology becomes an urgent problem to be solved (Song et al. 2022).

The Diffusion of Innovation Theory (DIT) proposed by Rogers (2010) points out that the relative advantages, compatibility and complexity of technology have a profound impact on individual decision-making behavior (Yoo et al. 2021). Therefore, based on the Contract Theory, this article integrates the unique characteristics of HCS technology with DIT Theory, and constructs decision model by the key factors that affect individuals' use of technology. The key factors include technological relative advantages, intrinsic motivation, risk-taking, use-cost, technological complexity and compatibility. By analyzing the cost utility of individual involved in the use of HCS technology, the relationship between the key factors affecting individual decision making and the core needs of individual is extracted, and the decision problem is transformed into individual cost utility problem. The dynamic relationship between individual decision result and decision factors is deduced.

The main contributions of this article are as follows:

1. For the first time, the Diffusion of Innovation Theory and Contract Theory are combined to establish a decision model for whether individuals use technology or not in digital era, which is based on the self-disclosure and fair mechanism of Contract Theory.
2. Taking the Health Crowdsensing technology as a case study, the individual decision-making problem is transformed into a cost-effectiveness problem by extracting key factors such as the external factors that affect the individual's use of technology and the internal motivation of individual's demand for technology. Through the analysis of cost and utility, the dynamic relationship between single decision result and key factors is deduced.
3. In the experiments, according to the results of model optimization, numerical analysis was used to verify the difference of individual decision result when the values of key factors changed. The experimental results indicate the direction of further research to promote individuals to using technology.

The remainder of this paper is as follows. The second part reviews the relevant work. The third part introduces the system architecture and raises questions. The fourth part establishes the decision model and optimizes the model. The fifth part is the numerical analysis and related discussion. The sixth part points out the limitations and future research on the basis of summarizing the whole paper.

BACKGROUND

In recent years, the rapid improvement of communication and information technology, as well as the rapid popularization of smart terminals such as wearable devices and embedded medical devices, provide a material basis for the application of HCS technology. HCS technology collects in-depth data related to individual health through smart terminals carried by users, and uploads the collected data to the platform for intelligence extraction. On the one hand, the extracted intelligence is used to reduce the ecological heterogeneity of the generic diagnosis and treatment research, and on the other hand, the extracted intelligence is used to provide personalized diagnosis and treatment guidance to users. This technology collects a large amount of individual in-depth data in daily life, and carries out personalized health monitoring and immediate intervention (Mariakakis et al. 2019), which provides a solution for the treatment of most chronic diseases and personalized health diagnosis and treatment.

In the process of digital transformation, how do individuals decide whether to use HCS technology? The two representative research methods in traditional decision theory, standard paradigm and description paradigm, are very effective in interpreting empirical data, but cannot describe the decision process (Chen et al. 2016). Therefore, researchers have carried out a lot of researches on individual decision-making process.

Santos et al. (2019) and Agwa-Ejon et al. (2017) respectively studied the individual decision-making of commanders or experts. The former focused on the quality of decision-making, while the latter used big data and other information technologies to help experts make decisions. Entani (2020) proposed a method to derive individual decisions from a group of individual judgments based on the Analytic Hierarchy Process (AHP), the method emphasized the interrelationship among individual decisions in a group. Qi and Liu (2017) studied the individuals decision-making process in emergency and crisis. Zhang et al. (2013) studied the influence of culture on individual decision-making style. The decision-making style is defined as a consumer's mental orientation toward making choices for product purchasing. Lin (2020), Chen et al. (2017) and Peters (2011) respectively studied the influence of transaction data (especial the usefulness of reviews), information search and the video content of dynamic digital menu board in e-commerce on individual decision-making of consumers. Jia et al. (2016), Pasek and Zbigniew (2006) respectively investigated the role of environmental factors and predefined rules in individual decision making, which could improve people management or optimize product delivery in software projects. Chen and Yang (2021) analyzed the impact of digital inclusive finance on farmers' entrepreneurial decisions based on the advantages of digital technology. Li and Hu (2017) proposed a new consumption and investment decision model to discuss the relationship between consumption goals and consumption and investment behaviors. Based on the Prospect Theory, Li et al. (2007) studied people's different attitudes to risk under uncertain conditions, indicating that individual decision-making was not only driven by expected utility, but also influenced by a variety of psychological factors. Shi et al. (1991) proposed a modeling method for human decision-making process under the condition of complete information, which is based on game theory and relevant cognitive psychology research results. Acquisti and Grossklags (2005) stated that consumers often lack sufficient information to make privacy-sensitive decisions in individual decision-making and may sacrifice long-term privacy for short-term gain. Guo et al. (2021) proposed graph embedding-based intelligent industrial decision for complex sewage treatment processes (GE-STP), the neural computing structure was utilized to simulate uncertain biochemical transformation inside STP.

The above literatures provide many valuable insights into decision-making, but it is difficult to directly apply them to individual decision-making process of the general public in Digital Era. The Diffusion of Innovation Theory (Rogers 2010) points out that individuals' perception of technological innovation attributes, including relative advantages, compatibility, complexity, trialability and observability, determines whether to use technology. Among these innovation attributes, relative advantages, compatibility, and ease of use (complexity) are the most common factors in deciding whether to adopt a technology, their impact is relatively large before the adoption of technology (Liao et al. 1999). Among them, relative advantages refer to individual's perception of performance or usefulness brought by innovation, compatibility refers to the degree of consistency with individual's values, habits and past experience, and complexity refers to the difficulty of understanding and using.

Inspired by the above literatures, this article combines the three factors before technology adoption in DIT and the unique characteristics of HCS technology, establishes an individual decision model based on contract theory, and deduces the influence of digital transformation on individual use of technology behavior.

PROBLEM FORMULATION

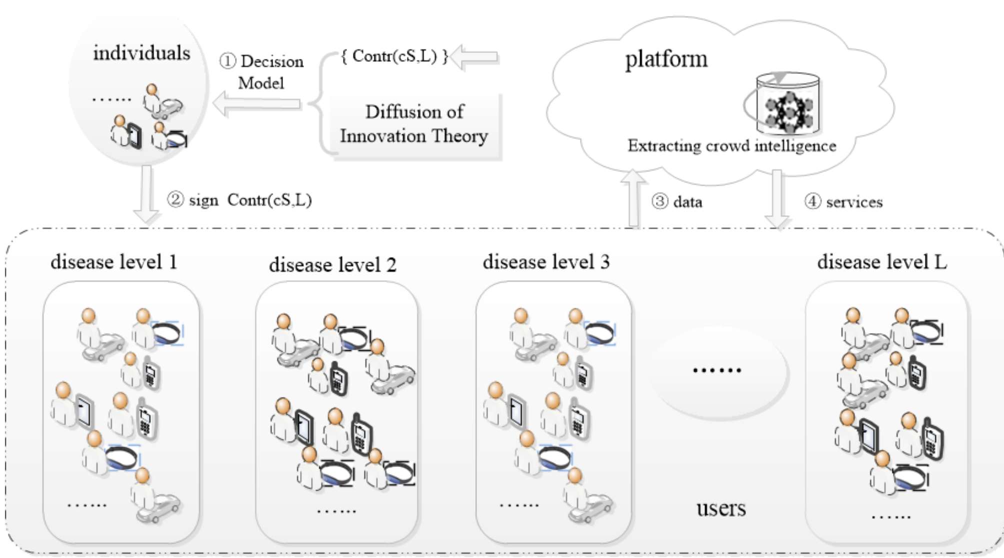
Since individuals use any technology is based on their need of services provided by technology, and HCS technology provides personalized diagnosis and treatment guidance services. Individuals could decide whether to use the technology based on their situation. This section introduces the HCS system and decision model construction background. Firstly, the cost utility of each party is analyzed based on the system architecture, and then the key factors affecting individual decision are extracted based on the cost utility.

System for HCS

A typical research scenario for individual decision model of using HCS technology, shown in Figure 1, has three roles, individuals, platform, and users. Individuals mean they have not yet used HCS technology. The platform is a technology provider that provides personalized medical guidance services to users. Users are individuals who have already adopted HCS technology. The difference between individuals and users is whether they have adopted HCS technology. The process of using this technology by individuals is:

1. Individuals decide whether to use the technology according to the decision model. If the result of decision model is adoption the technology, then Individuals will sign the contract (go to the next step), otherwise individuals will not adopt the technology. The {Contr(cS,L)} denotes the service contracts designed by the platform.
2. Individuals sign the service contract issued by the platform based on their disease grade, become users of the platform, and begin to use HCS technology. The Contr(cS,L) in Figure 1 denotes the service contract signed by an individual.

Figure 1. The individual decision model of using HCS technology



3. Users collect in-depth data related to individual health through intelligent terminals (such as mobile phones, wearable devices and embedded medical devices) and upload the collected data to the platform.
4. The platform extracts crowd intelligence and provides personalized diagnosis and treatment guidance services according to the contract signed by users and the data uploaded.

In the system, the platform not only provides users with personalized diagnosis and treatment guidance services, but also extracts crowd intelligence through in-depth data provided by users. The extracted intelligence is used for common disease diagnosis and treatment research and better provide personalized services for users. Therefore, what can create value for the platform is the data uploaded by users. Users upload data according to the signed contract and obtain personalized diagnosis and treatment guidance services, their aims to obtain the services provided by the platform.

In order to ensure the sustainability of HCS services, it is assumed that the platform and users are rational. In other words, the system works only if the revenue of the platform and users exceeds costs. Therefore, rational constraint should be met.

Hypothesis One: Rational constraint. The platform will provide users with personalized diagnosis and treatment services only when its utility is greater than zero. Users will upload individual deep health data only if their utility is greater than zero.

Obviously, the utility of a platform is equal to the revenue generated by user data minus its operation and service costs. i.e.:

$$Vp_{data} = \theta \cdot p - cOpe - cSer \qquad s.t.\ \ \theta = \begin{cases} \tilde{\theta} & if\ p \geq \sigma \\ 0 & otherwise \end{cases} \tag{1}$$

where p denotes data performance, that is, the ability of all the data uploaded by users to generate income (Data of a certain quantity can be used to train the model of disease diagnosis and treatment). θ denotes the conversion parameter of data performance into revenue. σ denotes the data performance threshold set by the platform based on actual conditions. When the data performance obtained by the platform is greater than or equal to this threshold, the data is valuable and can be converted into revenue, otherwise, data could not generate revenue. $cOpe$ denotes the total operating costs of the platform, that is, the costs of receiving, storing and processing data of users. $cSer$ denotes the total service costs of providing services to users.

$$p = \left(2/\pi\right)\arctan\left(\eta\sum_{i=1}^{N}\left(\left(data_i\right)\cdot\left(l_i\right)^{\gamma}\right)\right) \quad i \in N, l \in L \tag{2}$$

where p depends on the sum of data, $data_i$ denotes the data submitted by user i, l_i denotes the disease grade of user i . η , γ denote the weight factors, which can be adjusted according to platform need. N denotes the total number of users, $N = \{1, 2, \cdots, N\}$. Users are classified into L disease grades according to the contract they signed, $L = \{1, 2, \cdots, L\}$, $l \in L$:

$$cOpe = c \cdot N \tag{3}$$

For the sake of simplicity, the system assumes that the platform spends the same operating costs per user c, so operation cost $cOpe$ has a linear growth relationship with the number of users.

The platform may require data provided from users with different disease grades when it is in different stages, so the platform can obtain data it required by adjusting the services for users with different disease grades to attract them. Specifically, when the platform wants more data of users with higher disease grades, it can increase the services available to users with higher disease grades. When the platform wants more data of users with low disease grades, it can increase the services available to users with low disease grades. In this study, the research result of Pryss et al. (2017) was followed, the platform expects more data of users with lower disease grades. Therefore, the services provided by the platform for users with different disease grades are negatively correlated with their disease grades, that is, the lower the disease level, the more services are available. The total service costs of the platform $cSer$ consists of the service costs per user:

$$\begin{aligned} &cSer = \sum_{i=1}^{N} cSer_i \\ &cSer_i = \alpha \cdot {}^{1}\!/_{l_i} \qquad i \in N, l \in L \end{aligned} \tag{4}$$

where, α denotes the value conversion coefficient of disease grade and service cost. Since the platform provides the same service content for users with the same disease grade, the cost is the same.

According to equation (2), $\lim_{N\to\infty} p = 1$ indicates that there is a limit to data performance when N tends to infinity. That is, when the number of users reaches a certain threshold, the data uploaded by additional users cannot increase revenue for the platform (there is a limit of data performance). This is consistent with the situation that the precision of the model cannot be further improved by the newly added data, when the accurate of model arrives a threshold in reality. However, the platform operation costs $cOpe$ and the service costs $cSer$ for providing services to users will still increase with the number of users. Therefore, from the perspective of profit maximization, the platform will not accept new users to join, or will reduce the operation and service costs. This study assumes that in the context of digital transformation, the platform needs a large number of users to join in order to acquire enough data to extract crowd intelligence (training model), which is far from reaching the limit of data performance. Sometimes data performance p may be less than σ, namely, the platform doesn't have enough data to train a model to make a profit. It is supported by charging advertising fees ξ, which makes it is possible for platform to serve any number of users. Therefore, the platform utility function is rewritten as:

$$\begin{aligned} &Vp_{total} = Vp_{data} + \xi = \theta \cdot p - c \cdot N - \sum_{i=1}^{N} \alpha \left({}^{1}\!/_{l_i} \right) + \xi \\ &s.t.\ V_{total} > 0, \qquad i \in [1, N], l \in [1, L] \end{aligned} \tag{5}$$

For user i, its utility function is the value of service provided by the platform minus the value of privacy disclosure risk r_i and use-cost m_i. Privacy disclosure risk refers to the risk of disclosure of personal identity, location, data and other privacy information when users collect and submit data. The use-cost refers to the cost of time, energy consumption, computing power, and traffic required by users to collect and upload data. Then its utility Vu_i is:

$$Vu_i = cS_i - r_i - m_i \qquad i \in N \tag{6}$$

cS_i denotes the value of services provided by the platform. Obviously, the service costs of platform $cSer_i$ is equivalent to cS_i.

Note: Due to the privacy nature of health data, the platform does not know the disease grade of individuals until they sign a contract to use the HCS technology, and individuals only know their own information.

Problem Formulation

This research focuses on the decision-making process of individuals whether to adopt the technology. HCS, as a new technology has the technological innovation attributes pointed out by the Diffusion of Innovation Theory, also has its cost and risk of use, so individuals are uncertain about whether to use it. In this part, the key factors will be extracted and discussed, they are used to generate individual utility function, which is the basis of decision model.

From individuals, there are five key factors that influence their decision making. Among them, those derived from HCS technology are services provided by platform cS, the cost of using technology (use-cost m), and the risk of privacy leakage (risk-taking r). Those come from DIT theory are the technological relative advantages, the compatibility and complexity of technology com. The services provided by platform and the technological relative advantages refer to the same term in this decision model, so they are considered together. Finally, the intrinsic motivation of individual w also plays an important role.

Intrinsic motivation has a profound impact on individual behavior. People, especially in developed countries, are increasingly aware that monitoring body behavior plays an important role in maintaining health (Jaimes & Steele 2017). Such intrinsic motivation will encourage individuals to use HCS technology. The relative advantages of technology are represented by personalized medical guidance services provided by the platform, such as abnormal detection and health intervention (Hovsepian et al. 2015). This attribute will also promote individuals to use HCS technology. Compatibility attributes refer to the similarity of services or value obtained through the new technology compared with traditional method. Complexity refers to the difficulty individuals faced in understanding and using the new technology. Obviously, compatibility attribute and complexity attribute have negative impact on individuals' use of new technology, which is uniformly expressed as com.

So, according to equation (6), the utility function Vi that individuals use to decide whether to use HCS technology is as follows:

$$\begin{aligned} & Vi = cS + w - r - m - com \\ & s.t. \quad Vi > 0 \end{aligned} \tag{7}$$

where cS is corresponding to the $cSer_i$ in equation (4), and the $cSer_i$ sums up to $cSer$ in equation (1).

DECISION MODEL AND OPTIMIZATION

The decision in this article refers to an individual's judgment or choice about whether to use HCS technology. According to continuous finite comparison decision theory, an individual chooses a satisfactory solution among alternatives according to the various factors that can be captured in the decision-making environment. Therefore, based on individual utility function, this section will extract the common point among key factors to build a decision model and optimize it.

Decision Model

According to the individual utility function equation (7), it can be seen that intrinsic motivation, use-cost, risk-taking, services provided by the platform are all closely related to individual's disease grade, which is consistent with that the key factor of the contract provided by platform is the disease grade. Therefore, the specific relationship between the key factors in equation (7) and the disease grade will be extracted to establish the following constraints. They are the foundation of building decision models. The commonly used symbols are shown in table 1.

Hypothesis Two: There is a linear increasing relationship between individuals' disease grade and their intrinsic motivation to use HCS technology (Schickler et al. 2016). That is, in order to improve their quality of life, health and life expectancy, individuals with higher disease grades have greater intrinsic motivation to improve their health through monitoring and management:

$$w = \lambda_w l \;\; if \;\; l_1 < l_2 < \ldots < l_L \;\; then \;\; w_1 < w_2 < \ldots < w_L \tag{8}$$

where, λ_w denotes the conversion coefficient between intrinsic motivation and disease grade (also be used as the value coefficient of intrinsic motivation).

Hypothesis Three: There is a linear decreasing relationship between the services provided by the platform and disease grades. That is, the services provided by the platform will decrease with the increase of disease grade (for example, individuals with low disease grade can enjoy other services besides the necessary diagnosis and treatment guidance):

$$\begin{aligned} & cS = {}^{\lambda_{cS}}\!/_{l} \;\; if \;\; l_1 < l_2 < \ldots < l_L \;\; then \;\; cS_1 > cS_2 > \ldots > cS_L \\ & s.t. \;\; cS_m > cS_n, cS_n \not\subset cS_m, m < n, m, n \in L \end{aligned} \tag{9}$$

where, λ_{cS} denotes the conversion coefficient between services and disease grade (also be used as the value coefficient of the services). There are $cS_m > cS_n$, $cS_n \not\subset cS_m$ $m < n, m, n \in L$ because

Table 1. The commonly used symbols

Notation	Description	Notation	Description
cS	services provided by platform	w	intrinsic motivation
l	individual disease grade	r	risk-taking
c	platform's operation costs for each user	m	use-costs
com	impact of compatibility and complexity attributes of technology	λ_w	the value coefficient of intrinsic motivation
η, γ	weight factors of data performance	λ_{cS}	the value coefficient of services
α	the conversion coefficient of the services value	λ_r	the value coefficient of risk-taking
θ	the conversion parameter of revenue	λ_m	the value coefficient of use-cost
σ	the data performance threshold	λ_1	$\lambda_{cS} - \lambda_r$
ξ	platform's advertising revenue	λ_2	$\lambda_w - \lambda_m$

individuals with lower disease grade receive more services than individuals with higher disease grade. Since the contents of personalized diagnosis and treatment guidance are different for individuals with different disease grades, the services for individuals with lower disease grade could not meet the needs of individuals with higher disease grade, so individuals will only choose to sign contract consistent with their disease grade.

Hypothesis Four: There is a linear decreasing relationship between risk-taking and disease grades. In other words, the higher an individuals' disease grade is, the higher they are willing to bear the privacy risk in order to obtain the necessary personalized diagnosis and treatment services, that is, the less they worry about privacy risk:

$$r = {\lambda_r}/{l} \quad if\ l_1 < l_2 < \ldots < l_L\ \ then\ r_1 > r_2 > \ldots > r_L \tag{10}$$

where, λ_r denotes the conversion coefficient between risk-taking and disease grade (also be used as the value coefficient of the risk-taking).

Hypothesis Five: There is a linear increasing relationship between use-cost and disease grade (Schickler et al. 2016). That is, the higher the disease grade is, the higher the cost of data collection and data uploading will be. This is because as disease levels increase, individuals need to submit more detailed data, resulting in more use costs:

$$m = \lambda_m l\ \ if\ l_1 < l_2 < \ldots < l_L\ \ then\ m_1 < m_2 < \ldots < m_L \tag{11}$$

where, λ_m denotes the conversion coefficient between use-cost borne by the individual and disease grade (also be used as the value coefficient for the cost of use).

Hypothesis Six: In the digital transition period, HCS as a new technology has the same degree of negative impact on all individuals in compatibility attributes and complexity attributes com.

Hypothesis Seven: As rational individuals, when their utility is greater than zero, they will choose to use the HCS technology.

According to the utility function of individual (equation (7)) and Hypothesis one-seven, the decision model is constructed as follows:

$$VDec(l) = {\lambda_{cS}}/{l} + \lambda_w l - {\lambda_r}/{l} - \lambda_m l - com \quad (l \geq 1) \tag{12}$$

Model Optimization

Obviously, an individual with disease grade l, whose utility $VDec(l)$ is greater than zero, decides to use HCS technology. It can be seen from equation (12) that the services provided by the platform and the intrinsic motivation of individuals to use the technology play a positive role in the individual's technology adoption. That is, when other decision-making factors remain unchanged, the higher the service value provided by the platform, the more likely the individual is to adopt the technology. Similarly, the stronger an individual's intrinsic motivation (the need to use HCS technology to maintain their physical well-being (Jaimes & Steele 2017)), the more likely the individual is to adopt technology. On the contrary, use-cost, risk-taking, and technology compatibility and complexity have negative effects on individual technology adoption, that is, when other decision-making factors remain unchanged, the higher the use-cost, the less likely individuals are to adopt technology. The higher the risk-taking, the less likely the individual is to adopt it. The higher the compatibility and complexity of technologies, the less likely individuals are to adopt technology. Therefore, when these decision factors are determined, individuals can make the decision whether to adopt the technology or not.

Although there is a close relationship between individual disease grade and these decision factors, individuals with different disease grade may make different decisions even after the decision factors are determined. In order to analyze the decision-making differences of individuals with different disease grades under the same decision-making factors, and the influence of the changes of decision-making factors on individual decision-making results, the following optimization of the decision-making model will be carried out in this part, and the decision-making factors under different conditions will be analyzed:

$$\begin{aligned} &VDec(l) = {\lambda_1}/{l} + \lambda_2 l - com \\ &s.t.\ \ \lambda_1 = \lambda_{cS} - \lambda_R, \lambda_2 = \lambda_w - \lambda_m, l \geq 1 \end{aligned} \tag{13}$$

where the services provided by platform and individual's risk-taking in the decision model are inversely proportional to the individual disease grade, they are combined into one term λ_1. The intrinsic motivation and use-cost are directly proportional to the individual disease grade, they are combined into one term λ_2.

Next, the relationship between the disease grade and the utility function could be obtained by deducing the first and second derivatives of $VDec(l)$ respect to l. That is, how do individuals with different disease grades make decisions based on their utility function.

The first order derivative of $VDec(l)$ is:

$$\begin{aligned} &{\partial VDec(l)}/{\partial l} = -{\lambda_1}/{l^2} + \lambda_2 \\ &s.t.\ \ \lambda_1 = \lambda_{cS} - \lambda_R, \lambda_2 = \lambda_w - \lambda_m, l \geq 1 \end{aligned} \tag{14}$$

the second order derivative of $VDec(l)$ is:

$$\begin{aligned} &{\partial^2 VDec(l)}/{\partial l^2} = 2{\lambda_1}/{l^3} \\ &s.t.\ \ \lambda_1 = \lambda_{cS} - \lambda_R, \lambda_2 = \lambda_w - \lambda_m, l \geq 1 \end{aligned} \tag{15}$$

Finally, the values of λ_1, λ_2 are discussed. The specific analysis is divided into the following five parts:

1. When $\lambda_1 > 0, \lambda_2 > 0$, let the first derivative equal to zero, the value of l is got in equation (16) and the value of second derivative is got in equation (17). It is obvious that equation (17) is greater than zero, so the extreme point obtained is a minimum. The minimum of utility (equation (18)) is got when put equation (16) into the utility function (equation (13)). Next $\lambda_1 > \lambda_2$, $\lambda_1 \leq \lambda_2$ will be discussed in 1.1 and 1.2 respectively:

$$l_{\min} = \sqrt{\lambda_1 / \lambda_2} \tag{16}$$

$$\partial^2 VDec(l) / \partial l^2 = 2\left(\lambda_1 / \sqrt{\lambda_1/\lambda_2}^{\,3} \right) \tag{17}$$

$$VDec_{\min} = \lambda_1 / \sqrt{\lambda_1/\lambda_2} + \lambda_2 \sqrt{\lambda_1 / \lambda_2} - com = 2\lambda_2 \sqrt{\lambda_1 / \lambda_2} - com \tag{18}$$

a. As the first derivative (equation (14)) shows, its value goes from negative to positive when $\lambda_1 > \lambda_2$, the corresponding value of utility function should decrease first and then increase, so the minimum value of the utility function determines the range of disease grade. The minimum of utility function is detailed as follows.

When $VDec_{\min} > 0$, the utility of individual is greater than zero regardless of the its disease grade, so individuals will use HCS technology.

When $VDec_{\min} < 0$, the utility value is greater than zero when the range of disease grade belongs to (19) or (20), so the individuals will use HCS technology when their disease grade belongs to (19) or (20):

$$\begin{gathered} l \in \left[1, \left(com - \sqrt{com^2 - 4\lambda_1\lambda_2} \right) / 2\lambda_2 \right] \cup \left(\left(com + \sqrt{com^2 - 4\lambda_1\lambda_2} \right) / 2\lambda_2, \infty \right) \\ s.t.\ \ \lambda_1 = \lambda_{cS} - \lambda_R, \lambda_2 = \lambda_w - \lambda_m, \lambda_1 + \lambda_2 - com > 0, com^2 - 4\lambda_1\lambda_2 \geq 0 \end{gathered} \tag{19}$$

$$\begin{gathered} l \in \left(\left(com + \sqrt{com^2 - 4\lambda_1\lambda_2} \right) / 2\lambda_2, \infty \right) \\ s.t.\ \ \lambda_1 = \lambda_{cS} - \lambda_R, \lambda_2 = \lambda_w - \lambda_m, \lambda_1 + \lambda_2 - com < 0, com^2 - 4\lambda_1\lambda_2 \geq 0 \end{gathered} \tag{20}$$

When $VDec_{\min} = 0$, the individuals will use HCS technology when their disease grade belongs to (21):

$$\begin{gathered} l \in \left(com + \sqrt{com^2 - 4\lambda_1\lambda_2} / 2\lambda_2, \infty \right) \\ s.t.\ \ \lambda_1 = \lambda_{cS} - \lambda_R, \lambda_2 = \lambda_w - \lambda_m, \lambda_1 + \lambda_2 - com = 0, com^2 - 4\lambda_1\lambda_2 \geq 0 \end{gathered} \tag{21}$$

b. As the first derivative (equation (14)) shows, its value is greater than zero when $\lambda_1 \leq \lambda_2$, so the utility function is monotonically increasing, and get the minimum $vDec_{\min} = \lambda_1 + \lambda_2 - com$ when $l = 1$, so the individuals will use HCS technology when their disease grade belongs to (22):

$$l \in \begin{cases} [1, \infty) & if\ \lambda_1 + \lambda_2 - com > 0 \\ \left[\left(com + \sqrt{com^2 - 4\lambda_1\lambda_2} \right) \Big/ 2\lambda_2, \infty \right) & otherwise \end{cases} \tag{22}$$
$$s.t.\ \ \lambda_1 = \lambda_{cS} - \lambda_R, \lambda_2 = \lambda_w - \lambda_m, com^2 - 4\lambda_1\lambda_2 \geq 0$$

According to the above derivation, when $\lambda_1 > 0, \lambda_2 > 0$, there will always be individuals who use HCS technology. Analyze the relationship between $\lambda_1\ and\ \lambda_{cS}, \lambda_R$, $\lambda_2\ and\ \lambda_w, \lambda_m$ in depth, it could be seen that there will always be individuals who adopt HCS technology, when the value of the services is greater than the value of risk-taken, and the value of intrinsic motivation is greater than the value of use-cost.

2. When $\lambda_1 < 0, \lambda_2 < 0$, the value of utility function (equation(13)) is less than zero, so individuals will not adopt HCS technology. According to the relationship $\lambda_1\ and\ \lambda_{cS}, \lambda_R$, $\lambda_2\ and\ \lambda_w, \lambda_m$, there will not be any individual who adopts HCS technology when the value of services is less than the value of risk-taken, and the value of intrinsic motivation is less than the value of use-cost.
3. When $\lambda_1 > 0, \lambda_2 < 0$, the value of first derivative (14) is less than zero, so the utility function is monotonically decreasing. The individuals will use HCS technology when their disease grade belongs to (23). According to the relationship $\lambda_1\ and\ \lambda_{cS}, \lambda_R$, $\lambda_2\ and\ \lambda_w, \lambda_m$, there will be part of individuals who adopt HCS technology when the value of services is greater than the value of risk-taken, and the value of intrinsic motivation is less than the value of use-cost:

$$l \in \left[1, \left. com - \sqrt{com^2 - 4\lambda_1\lambda_2} \right/ 2\lambda_2 \right) \tag{23}$$
$$s.t.\ \ \lambda_1 = \lambda_{cS} - \lambda_R, \lambda_2 = \lambda_w - \lambda_m, \lambda_1 + \lambda_2 - com > 0, com^2 - 4\lambda_1\lambda_2 \geq 0$$

4. When $\lambda_1 < 0, \lambda_2 > 0$, the value of first derivative (14) is greater than zero, so the utility function is monotonically increasing. The individuals will use HCS technology when their disease grade belongs to (24). According to the relationship $\lambda_1\ and\ \lambda_{cS}, \lambda_R$, $\lambda_2\ and\ \lambda_w, \lambda_m$, there will be part of individuals who adopt HCS technology when the value of services is less than the value of risk-taken, and the value of intrinsic motivation is greater than the value of use-cost:

$$l \in \begin{cases} [1, \infty) & if\ \lambda_1 + \lambda_2 - com > 0 \\ \left[\left(com + \sqrt{com^2 - 4\lambda_1\lambda_2} \right) \Big/ 2\lambda_2, \infty \right) & otherwise \end{cases} \tag{24}$$
$$s.t.\ \ \lambda_1 = \lambda_{cS} - \lambda_R, \lambda_2 = \lambda_w - \lambda_m, com^2 - 4\lambda_1\lambda_2 \geq 0$$

5. Obviously, when $\lambda_1 = 0, \lambda_2 = 0$, the value of utility is less than zero, individuals are only negatively affected by compatibility and complexity, so they will not adopt HCS technology. Next, the situation of $\lambda_1 = 0$ and $\lambda_2 = 0$ will be discussed respectively:
   a. When $\lambda_1 = 0, \lambda_2 > 0$, the value of first derivative (equation (14)) is greater than zero, so the utility function is monotonically increasing. The individuals will use HCS technology when their disease grade belongs to (25):

$$l \in \begin{cases} \left[1, \infty\right) & if\ \lambda_2 - com > 0 \\ \left({com}/{\lambda_2}, \infty \right] & otherwise \end{cases}$$
$$s.t.\ \ \lambda_1 = \lambda_{cS} - \lambda_R, \lambda_2 = \lambda_w - \lambda_m \tag{25}$$

   b. When $\lambda_1 = 0, \lambda_2 < 0$, the value of first derivative (equation (14)) is less than zero, so the utility function is monotonically decreasing and $VDec_{\max} = \lambda_2 - com < 0$. There will not be any individual who uses HCS technology.
   c. When $\lambda_1 > 0, \lambda_2 = 0$, the value of first derivative (equation (14)) is less than zero, so the utility function is monotonically decreasing. The individuals will use HCS technology when their disease grade belongs to (26):

$$l \in \left[1, {\lambda_1}/{com}\right)$$
$$s.t.\ \ \lambda_1 = \lambda_{cS} - \lambda_R, \lambda_2 = \lambda_w - \lambda_m, \lambda_1 - com > 0 \tag{26}$$

   d. When $\lambda_1 < 0, \lambda_2 = 0$, the utility function is $VDec(l) = {\lambda_1}/{l} - com < 0$, so there will not be any individual who uses HCS technology.

The above derivation process analyzes in detail the role of key factors including technological relative advantages (services), intrinsic motivation, use-cost, risk-taking, compatibility and complexity of technology in the decision-making model. The dynamic relationship between these key factors and the outcome of individual decision-making is also demonstrated.

EVALUATION AND DISCUSSION

In order to verify the influence of the change of key factors in the decision model on individual decision results, numerical analysis is used for evaluation in this section. The different values of key factors in the experiments were set according to the derivation process of the optimized decision model, and the individual's disease grades were set as $L = \left\{1, 2, 3\right\}$. The software environment was Python 3.8, and the code was uploaded to https://github.com/kathleen2021bj/endUser.

Evaluation for Decision Model

Considering the visibility of the experimental results, the following figures only show the situations that there were individuals adopt HCS technology, the situations that individuals did not adopt HCS technology were also verified by numerical experiments. The abscissa of figures is individual disease grade L, and the ordinate is individual utility $VDec$. The specific experimental analysis is as follows.

As shown in Figure 2, when $\lambda_1 > 0, \lambda_2 > 0$, and $\lambda_1 > \lambda_2$, the utility function curves of individuals with different disease grades were in four situations. The values of key factors in the decision model were set respectively for the four cases, and the corresponding decision results of different individuals were given. where the VDecmin denotes the minimum of the utility function in Figure 2-4:

Figure 2. The utility curve of individuals

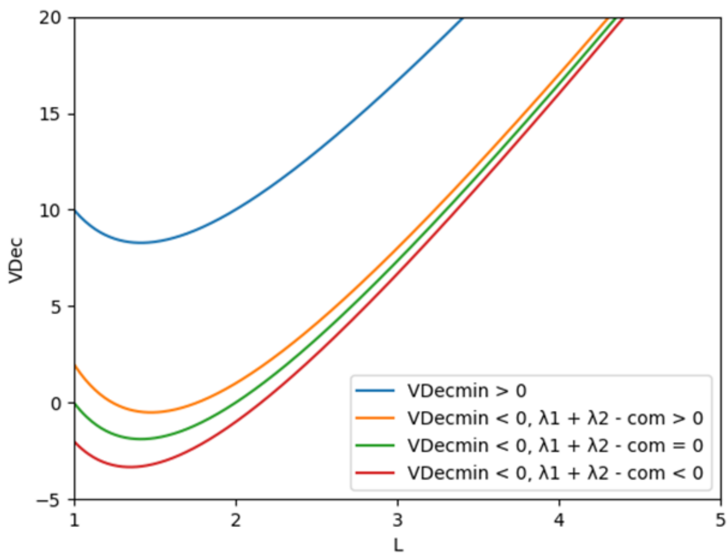


Figure 3. The utility curve of individuals

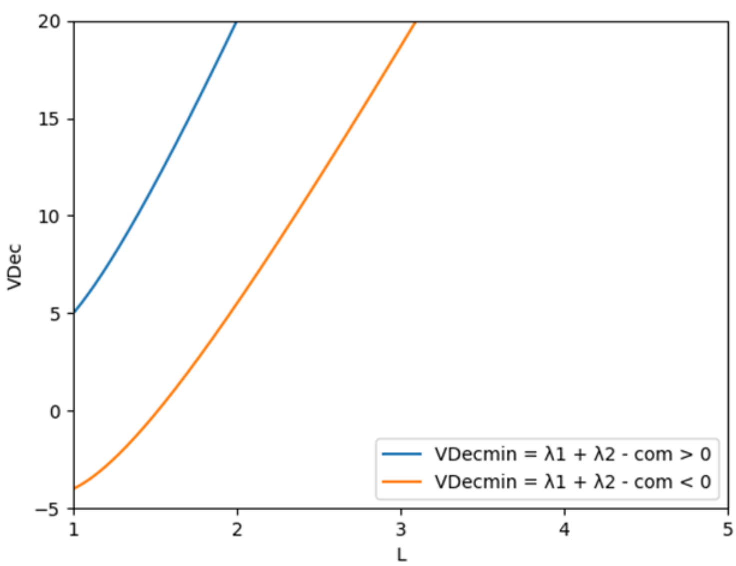
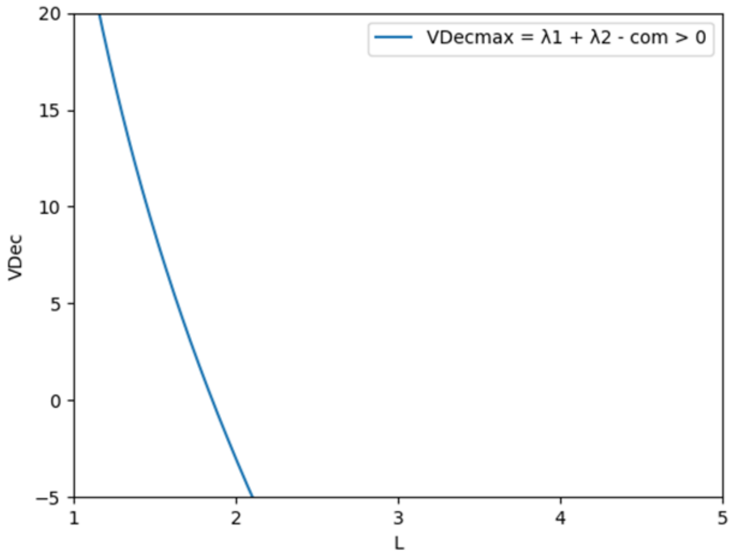


Figure 4. The utility curve of individuals



1. Set $\lambda_{cS} = 30, \lambda_w = 24, \lambda_r = 10, \lambda_m = 14, com = 20$, the blue line was drawn, the minimum of the utility function was greater than zero. Therefore, HCS technology would be used by individuals regardless of their disease grades (that is, individuals with disease grade 1, 2 and 3 would use HCS technology).
2. Set $\lambda_{cS} = 36, \lambda_w = 21, \lambda_r = 12, \lambda_m = 10, com = 33$, the orange line was drawn, the minimum utility function was less than zero and $\lambda_1 + \lambda_2 - com > 0$. When $VDec = 0$, the value of l was 1.24 and 1.76 respectively, namely $l \in [1, 1.24)$ and $l \in (1.76, \infty)$. Therefore, individuals with disease grades 1, 2 and 3 would use the HCS technology.
3. Set $\lambda_{cS} = 48, \lambda_w = 21, \lambda_r = 26, \lambda_m = 10, com = 33$, the green line was drawn, the minimum utility function was less than zero and $\lambda_1 + \lambda_2 - com = 0$. When $VDec = 0$, the value of l was 1 and 2 respectively, namely $l \in (2, \infty)$. Therefore, individuals with disease grades 3 would use the HCS technology.
4. Set $\lambda_{cS} = 36, \lambda_w = 21, \lambda_r = 16, \lambda_m = 10, com = 33$, the red line was drawn, the minimum utility function was less than zero and $\lambda_1 + \lambda_2 - com < 0$. When $VDec = 0$, the value of l was 0.84 and 2.16 respectively, namely $l \in (2.16, \infty)$. Therefore, individuals with disease grades 3 would use the HCS technology.

As shown in Figure 3, when $\lambda_1 > 0, \lambda_2 > 0$, and $\lambda_1 \leq \lambda_2$, the utility function curves of individuals with different disease grades were in two situations:

1. Set $\lambda_{cS} = 48, \lambda_w = 25, \lambda_r = 37, \lambda_m = 5, com = 25$, the blue line was drawn, the minimum utility function was greater than zero and $\lambda_1 + \lambda_2 - com > 0$, namely $l \in [1, \infty)$. Therefore, individuals with disease grades 1, 2 and 3 would use the HCS technology.

2. Set $\lambda_{cS} = 48, \lambda_w = 25, \lambda_r = 37, \lambda_m = 10, com = 30$, the orange line was drawn, the minimum utility function was less than zero and $\lambda_1 + \lambda_2 - com < 0$. When $VDec = 0$, the value of l was 0.48 and 1.52 respectively. discarding the values less than 1, got $l \in \left(1.52, \infty\right)$. Therefore, individuals with disease grades 2 and 3 would use the HCS technology.

As shown in Figure 4, there was the utility function curves of individuals with different disease grades when $\lambda_1 > 0, \lambda_2 < 0$ and $VDec_{\max} = \lambda_1 + \lambda_2 - com > 0$. Set $\lambda_{cS} = 48, \lambda_w = 15, \lambda_r = 8, \lambda_m = 25, com = 3$, the blue line was drawn, the maximum utility function was greater than zero. When $VDec = 0$, the value of l was -2.16 and 1.86 respectively. discarding the values less than 1, got $l \in \left[1,\ 1.86\right)$. Therefore, individuals with disease grade 1 would use the HCS technology.

As shown in Figure 5, when $\lambda_1 < 0, \lambda_2 > 0$, the utility function curves of individuals with different disease grades were in two situations:

1. Set $\lambda_{cS} = 15, \lambda_w = 35, \lambda_r = 25, \lambda_m = 20, com = 2$, the blue line was drawn, the minimum utility function was greater than zero $VDec_{\min} = \lambda_1 + \lambda_2 - com > 0$. Therefore, individuals with disease grades 1, 2 and 3 would use the HCS technology.
2. Set $\lambda_{cS} = 15, \lambda_w = 25, \lambda_r = 25, \lambda_m = 15, com = 6$, the orange line was drawn, the minimum utility function was less than zero $VDec_{\min} = \lambda_1 + \lambda_2 - com < 0$. When $VDec = 0$, the value of l was -0.74 and 1.34 respectively. discarding the values less than 1, got $l \in \left(1.34, \infty\right)$. Therefore, individuals with disease grades 2 and 3 would use the HCS technology.

As shown in Figure 6, when $\lambda_1 = 0\ or\ \lambda_2 = 0$, the utility function curves of individuals with different disease grades were in two situations:

Figure 5. The utility curve of individuals

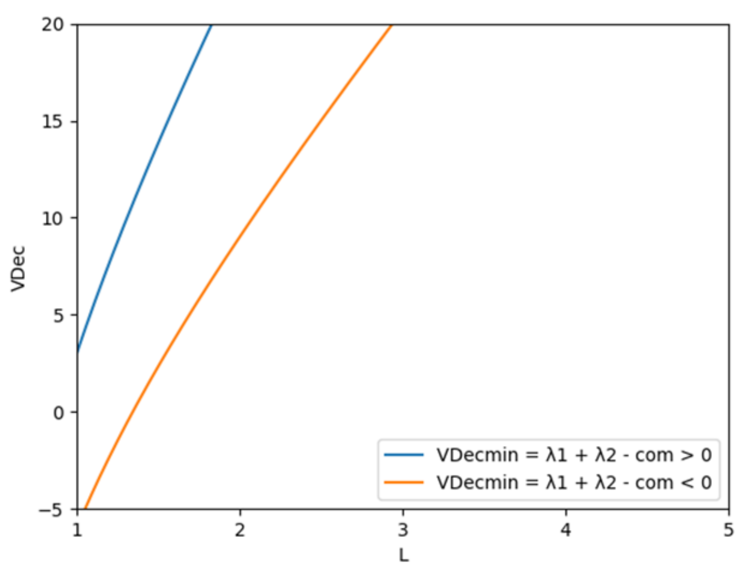
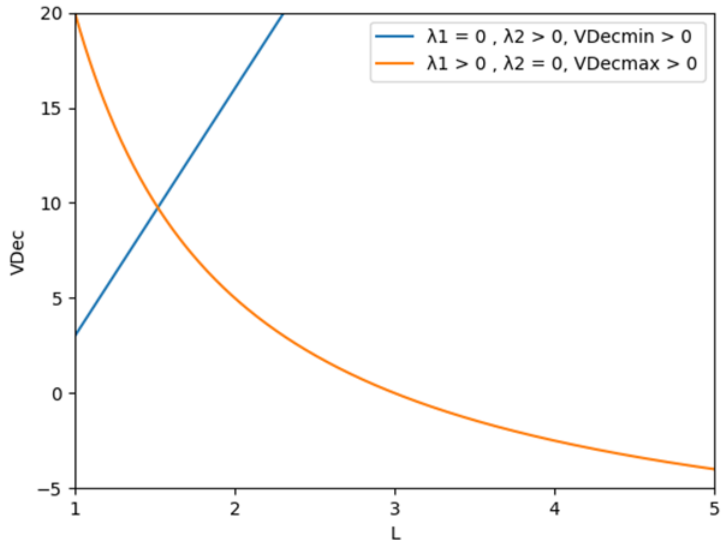


Figure 6. The utility curve of individuals



1. Set $\lambda_{cS} = 15, \lambda_w = 25, \lambda_r = 15, \lambda_m = 12, com = 10$, the blue line was drawn, the minimum utility function was greater than zero $VDec_{\min} = \lambda_2 - com > 0$. Therefore, individuals with disease grades 1, 2 and 3 would use the HCS technology.
2. Set $\lambda_{cS} = 48, \lambda_w = 15, \lambda_r = 18, \lambda_m = 15, com = 10$, the orange line was drawn, the maximum utility function was greater than zero $VDec_{\max} = \lambda_1 - com > 0$. When $VDec = 0$, the value of l was 3, namely $l \in [1,3)$. Therefore, individuals with disease grades 1 and 2 would use the HCS technology.

DISCUSSION

Numerical analysis further showed that individuals would have different decision results on whether to use technology when the key factors affecting decision-making change. With the further improvement of information technology in the digital era, the use-cost will be lower and lower, the technological complexity and compatibility will become smaller and smaller, and the demand for maintaining people's health will become more and more intense (Jaimes & Steele 2017). Meanwhile, as countries around the world continue to strengthen the regulation of privacy (Npc 2021, Goddard 2017), the risk-taking is also becoming less and less. According to equation (12), there must be more and more individuals who decide to use HCS technology because the λ_w gets bigger and the λ_r, λ_m, com gets smaller.

The goal of Santos et al. (2016; 2019) is to help commanders make effective decisions, as commanders are the individuals responsible for making critical decisions on the battlefield. The goal of Agwa-Ejon et al. (2017) is to use information technologies such as big data to help analysts and experts make decisions. Entani (2020) focused on individual decision-making in a group, his goal is to derive the individual decision of a decision maker considering the others' decisions. Qi and Liu (2017) studied the decision-making process of sudden events, which is not equated with general routine decisions because sudden events are influenced by the scarcity factor. Zhang et al. (2013) explored the relationships between self-construal and consumer decision-making styles. There are also studies on specific groups of people, such as developers of software projects, farmers' entrepreneurial (Pasek and Zbigniew 2006; Chen and Yang 2021). Lin (2020), Chen et al. (2017) and Peters (2011) studied the purchasing decisions of consumers who have already used e-commerce technology, rather than the process by which consumers decide whether to adopt the technology. Therefore, the decision-making model proposed by this article enriches the individual decision-making process of ordinary people in the existing individual decision-making theory system, and provides a theoretical basis for further research on the influence of digital transformation on whether individuals use technology or not.

CONCLUSION AND FUTURE RESEARCH

In this article, the Contract Theory and the Diffusion of Innovation Theory are combined to build a decision model to solve the challenges of individuals using new technologies in the digital age. The article extracts the common point among the key factors of individual decision-making based on the utility analysis of relevant parties using HCS technology, transforms the individual decision problem into the cost utility problem. By deducing individual utility, the dynamic relationship between decision key factors and decision results is obtained, and the validity of the model is verified by numerical analysis. Although the technology features in the decision model are derived from HCS, the decision model is constructed by the generality of contract theory and DIT theory, and emphasizes the intrinsic motivation of individuals, so it is suitable for the general decision process of individuals whether to use technology.

However, there are still limitations in this study. Firstly, although the decision model is deduced theoretically and verified by numerical analysis, it has not been applied in practice. Secondly, individuals always are affected by noises such as age, member of family and income. Therefore, the decision model will be deployed on the actual operation platform in the future. The sample data and noise of individual decision-making will be collected, and they will be used to modify decision model to better analyze the decision-making process of individuals.

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