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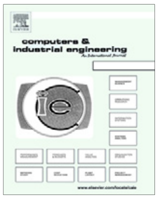

Social influence on the use of Clinical Decision Support Systems: Revisiting the Unified Theory of Acceptance and Use of Technology by the fuzzy DEMATEL technique

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ABSTRACT

The aim of study is to examine whether social influence affects medical professionals' behavioral intention to use while introducing a new Clinical Decision Support System (CDSS). The series of Technology Acceptance Models (TAMs) have been widely applied to examine new technology acceptance by scholars; nevertheless, these models omit system diversity and the user's profession. On the other hand, causal analysis greatly affects the efficiency of decision-making, and it is usually analyzed by Structural Equation Modeling (SEM); however, the method is often misapplied. This research applies the Decision-Making Trial and Evaluation Laboratory (DEMATEL) technique to explore the causal relationship between the significant Unified Theory of Acceptance and Use of Technology (UTAUT) variables. Fuzzy concept is applied to illustrate human vague judgment. It is significant that, in contrary with UTAUT, this study found that social influence does not matter in the behavioral intention to use the CDSS for medical professionals.

1. Introduction

Artificial intelligence has been focused on problem solving and processing capabilities that support problem solving (Clocksin, 2003). Expert system is a computer program that performs decision-making or problem solving functions in a very specialized and narrowed problem area (Subramanian, Yaverbaum, & Brandt, 1997). In the medical field, Clinical Decision Support System (CDSS) is utilized for patient care that mimics the decision-making behavior of a human expert and allows computer power to be applied to tasks that require the processing of human knowledge. According to Newman-Toker and Pronovost (2009), the CDSS can help prevent diagnostic errors. However, research on CDSS has been limited to the area of computer science in system development and rarely seen in causal modeling analysis from a social science perspective. Technology acceptance by users in the area of medicine has received less attention in the past, and therefore, studies on the models and factors that impact CDSS adoption by medical professionals are lacking.

In social science studies, causal relationship analysis significantly affects the efficiency of decision-making. Previous studies that examine the causal model of Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) mainly adopt Structural Equation Modeling (SEM). Collected statistical data, however, allows analysts to modify the model frequently to arrive at good model fitness, and SEM is often misapplied when the data are merely fitted to an SEM. The conceptual model or theory is then extended from the analytical results based on presumed hypotheses (Wei, Huang, Tzeng, & Wu, 2010).

Based on UTAUT (Venkatesh, Morris, Davis, & Davis, 2003), an amended TAM (Davis, 1989), this study aims to identify the relationship and influence among several research constructs towards the behavioral intention to adopt the CDSS for medical professionals. Previous studies on TAM and UTAUT focus only on public technology systems, and an empirical study can hardly obtain a large number of samples. Some technology systems, for example CDSS, are highly professional and complicated, and not all the subjects will be able to completely understand the technology system. When some variables do not meet the prerequisite assumptions and are coupled with the difficulty of obtaining a large number of samples, TAM will not be able to correctly analyze the causal relationship by SEM, which results in the insufficient conclusion (Lee, Li, Yen, & Huang, 2010).

In recent years, a number of scholars have proposed Multiple Criteria Decision-Making (MCDM) methods to strengthen the comprehensiveness and reasonableness of the decision-making process (Ali Khatami Firouzabad, Henson, & Barnes, 2008; Liao, 2011; Liou & Tzeng, 2010; Tseng, Lee, & Wu, 2010; Tzeng, Ou Yang, Lin, &

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Chen, 2005; Yang, Chiu, Tzeng, & Yeh, 2008), and the Decision-Making Trial and Evaluation Laboratory (DEMATEL) technique is one of the methods that supports MCDM in analyzing the impact relations within a framework. In many cases, however, the judgments of decision-making are often given as crisp values, which these values are an inadequate reflection of the vagueness of the real world (Bellman & Zadeh, 1970; Zadeh, 1975). Human judgment about preferences are often unclear and hard to estimate by exact numerical values, thus fuzzy concept is necessary for handling problems characterized by vagueness and imprecision (Zadeh, 1975). Hence, there is a need to extend the DEMATEL technique with fuzzy concept for making better decisions in fuzzy environments. To improve the above-mentioned drawbacks, the partial UTAUT variables are treated as MCDM criteria to address dependent relationships, and the fuzzy DEMATEL technique is applied to find the core variables that affect the intention of medical professionals to use the CDSS.

The rest of this paper is organized as follows. In Section 2, previous literature is reviewed to form the framework of this study. In Section 3, the conventional and fuzzy DEMATEL techniques are described. In Section 4, an empirical study is presented. In Section 5, the research findings are discussed, and their practical implications are drawn. Finally, concluding remarks are presented in Section 6.

2. Theoretical foundation and literature review

TAM is an adaptation of the Theory of Reasoned Action (TRA) proposed by Fishbein and Ajzen (1975) chiefly designed for modeling user acceptance of information technology (Davis, Bagozzi, & Warshaw, 1989). TRA explains behavior based on an individual's expectations of outcomes (Fishbein & Ajzen, 1975). In TRA, attitude and subjective norm jointly determine behavioral intention, which leads to the performance of actual behavior. TRA is valuable in predicting behavior, where the behavior in question is completely under the individual's volitional control. The inclusion of the subjective norm in TRA represents an important addition when compared to TAM. With this addition, TRA takes account of the elements of the social influence that are found in the social explanation of the use of technology. Mathieson (1991) and Ajzen (1991) later expanded TRA, which includes the control belief and perceived behavioral constructs that made the Theory of Planned Behavior (TPB).

The TAM excludes the subjective norm included in the TRA and TPB and adds two constructs, perceived usefulness and perceived ease of use, that refer to specific beliefs influencing attitude towards the intention of use. The TAM initiative was to examine psychological factors that impact new technology acceptance. Moreover, TAM offers a link between technology acceptance and utilization behavior. Davis (1989) further adopted the belief–attitude–intention behavior causal chain to predict users' acceptance of technology. Various scholars, for instance, Bajaj and Nidumolu (1998), Chau (1996), and Lee (2006) have demonstrated the validity of TAM across a wide range of information technology adoptions.

TAM2 (Venkatesh & Davis, 2000) is an extension of TAM with the purpose of measuring several social influence dimensions (*i.e.*, subjective norm and image). Venkatesh and Davis (2000) showed that subjective norm exerts a great impact on usage intentions and perceived usefulness. They concluded that subjective norm directly influences through internalization. People incorporate social influence into their usefulness perceptions and identification in that an individual uses the system to gain social status and improve job performance. TAM and TAM2 have become solid models for predicting the intentions of information technology usage.

Venkatesh et al. (2003) further proposed a unified model after TAM and TAM2 named UTAUT, which aims to explain user intentions to use an information system and subsequent usage behavior. The theory holds four key constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions, which are direct determinants of usage intention and behavior. In addition, gender, age, experience, and voluntariness of use, are four moderating constructs that are posited to moderate the impact of the four key constructs on usage intention and behavior. The theory was developed through a review and consolidation of the constructs of eight theories that earlier research had employed to explain information systems usage behavior. The eight theories include TRA, TPB, TAM, motivational model, a combined TPB/TAM, the model of personal computer utilization, innovation diffusion theory, and social cognitive theory. The key constructs adopted in this research are detailed in the following sub-sections.

2.1. Performance expectancy

According to Agarwal and Prasad (1997), Compeau and Higgins (1995), Davis, Bagozzi, and Warshaw (1992), Thompson, Higgins, and Howell (1991), and Venkatesh and Davis (2000), performance expectancy is defined as the degree to which an individual believes that using the system will benefit him or her in terms of improving job performance. Three factors that pertain to performance expectancy are the following: perceived usefulness, extrinsic motivation, and job fit. Perceived usefulness is defined by Davis (1989), Renaud and Biljon (2008), and Venkatesh et al. (2003) as the degree to which an individual believes that using the system would improve his or her job performance. Davis et al. (1992) and Teo, Lim, and Lai (1999) stated that extrinsic motivation is the perception that users will want to perform an activity because it is perceived to be instrumental in achieving valued outcomes that are distinct from the activity itself, such as improved job performance, pay, or promotions. Thompson et al. (1991) articulated that job fit is how the capabilities of a system can enhance an individual's job performance.

In general, performance expectancy is the strongest predictor of attitude toward use, and behavioral intentions. In addition, it remains significant at all points of measurement in both voluntary and mandatory settings and is consistent with previous tests (Agarwal & Prasad, 1999; Compeau & Higgins, 1995; Thompson et al., 1991; Venkatesh & Davis, 2000). As previously mentioned, the system performance needs to be evaluated in order to check and measure the attitude toward the usage of the CDSS. Information systems normally used by individuals need maintenance in order to avoid suffering technical problems. Snead and Harrell (1994) stated that this is the evidence which may explain why users often fail to accept and use the new systems that potentially offer significant performance gains. Bates et al. (2001) and Bates et al. (2003) reported that for the past decades, CDSSs have been used more frequently and as an aid in clinical diagnosis, which is delivered by using information systems ideally for storing electronic medical records and providing specialists a tool that enables improvements in professional performance and patient safety.

2.2. Effort expectancy

According to Venkatesh et al. (2003), effort expectancy is defined as the degree of ease associated with the system use. Its conceptualization can be traced back to the concept of "ease of use," which indicates the extent to which an individual believes that using the system is effortless (Davis et al., 1989). Effort expectancy is critical in the introduction of a new technology. The adoption process of a new technology can be constrained and can even fail when factors related to ease of use are not taken into account by technology designers (Orlikowski, 1992). Three factors from the existing models capture the concept of effort expectancy as follows: perceived ease of use, complexity, and ease of use. Davis (1989), Davis et al. (1989), Teo et al. (1999), and Venkatesh et al. (2003) asserted that perceived ease of use is the degree to which an individual believes that using the system would be free of effort. Goodhue and Thompson (1995) and Thompson et al. (1991) defined complexity as the degree to which a technology innovation is perceived as relatively difficult to understand and use. According to the definition of Prümper (1993), usability is the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use. Moore and Benbasat (1991) also indicated that ease of use is the degree to which using a technology innovation is identified as being easy or difficult to use. The effort expectancy construct within each factor is significant to the attitude towards use in both mandatory and voluntary usage context according to previous studies from Agarwal and Prasad (1997), Agarwal and Prasad (1998), Davis et al. (1989), Thompson et al. (1991), and Thompson, Higgins, and Howell (1994).

2.3. Social influence

Social influence is defined as the degree to which an individual values the importance of others persistence that he or she should use the new system. Social influence as a direct determinant of attitude towards use of the system and behavioral intentions is represented as a subjective norm and image. Subjective norm is defined as the person's perception from people he or she considers as important, that think he or she should or should not perform the behavior in question, in the case of this study, to use the CDSS. Moore and Benbasat (1991) defined image as the degree to which using a technology innovation is perceived to enhance individual's image or status in his or her social group. While subjective norm and image have different labels, each of these factors contains the explicit or implicit notion that the individual's behavior is influenced by the way in which they believe others will view them as a result of having used the technology.

2.4. Behavioral intention of use

In relation to modern technology within an information technology context, behavioral intentions represent the degree to which respondents will use the system at present and in the near future. Behavioral intention refers to the instructions that people give to themselves to behave in certain ways (Chau, 1996). Intention of use is the likelihood that an individual will use the technology in the future and is a precursor of actual usage of technology (Stoel & Lee, 2003).

Based on the above reviews, the dimensions and criteria of this study are summarized in Table 1 as the foundation for fuzzy DEMATEL causal analysis.

Table 1
Dimension and criteria of this study.

Dimensions	Criteria
Performance expectancy (D_1)	Perceived usefulness (C_{11}) Extrinsic motivation (C_{12}) Job fit (C_{13})
Effort expectancy (D_2)	Perceived ease of use (C_{21}) Complexity (C_{22}) Ease of Use (C_{23})
Social influence (D_3)	Subjective norm (C_{31}) Image (C_{32})
Behavior intension (D_4)	Behavior intension (C_{41})

3. DEMATEL technique for building structural model

DEMATEL is a comprehensive method for building and analyzing a structural model involving causal relationships between complex factors. To lay the foundation for extending the DEMATEL technique for making decisions in fuzzy environments, the essentials of the conventional DEMATEL and fuzzy DEMATEL methods are discussed below.

3.1. Conventional DEMATEL technique

The conventional DEMATEL technique (Fontela & Gabus, 1976; Gabus & Fontela, 1973) was used to study complicated phenomena regarding issues such as race, hunger, environmental protection, and energy (Fontela & Gabus, 1976). It was developed in the belief that the proper use of scientific research methods could facilitate comprehension of a specific *problematique*, a cluster of intertwined problems, and contribute to recognition of practical solutions by a hierarchical structure. The methodology, according to the characteristics of objective affairs, can verify the interdependence among the variables/attributes/criteria and confirm the relation that reflects the characteristics with an essential system and evolution trend (Chiu, Chen, Tzeng, & Shyu, 2006; Huang & Tzeng, 2007). The method is a practical and useful tool, especially for visualizing the structure of complex causal relationships with matrices or diagrams. The matrices or diagrams show a contextual relation between the elements of the system, in which a numeral represents the strength of influence of each element. Thus, the DEMATEL technique is able to convert the relationship between the causes and effects of criteria into an intelligible structural model of systems (Wei et al., 2010).

Recently, DEMATEL technique has been widely applied in various areas, including airline safety (Liou, Yen, & Tzeng, 2008), e-learning (Tzeng et al., 2005), decision-making (Hajime & Kenichi, 2007; Lin & Wu, 2008; Tseng, 2009), knowledge management (Shi, Peng, Kou, & Chen, 2005; Wu, 2008), operations research (Ou Yang, Shieh, Leu, & Tzeng, 2008; Zhang, Tian, Zhang, Shi, & Li, 2008), business policy (Wu & Lee, 2007), selecting systems (Tsai & Chou, 2009), agriculture (Kim, 2006), technology innovation (Huang & Tzeng, 2007; Lee et al., 2010; Yamashina, Ishida, & Mizuyama, 2005), marketing and consumer behavior (Hsu, Lee, Chen, & Tzeng, 2007; Wei et al., 2010), and others. The structure of DEMATEL and the steps of calculation are described as follows:

Step 1: Calculate the direct-influence matrix by scores (depending on the views of the experts) and evaluate the relationship among elements (also known as variables/attributes/criteria) of mutual influence, using a scale ranging from 0 to 4 (indicating "no influence (0)", to "very high influence (4)"); Subjects are asked to indicate the direct effect they believe each element i exerts on every other element j, as indicated by d_{ij}. The matrix $\boldsymbol{D}$ of direct relations is thus obtained, which shows the pairwise comparison of a causal relationship. Assume there are n variables that impact the system; the direct-influence matrix $\boldsymbol{D}$ is illustrated in the following matrix

$$\boldsymbol{D} = \begin{bmatrix} 0 & d_{12} & \cdots & d_{1n} \\ d_{21} & 0 & \cdots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{n1} & d_{n2} & \cdots & 0 \end{bmatrix}$$

Step 2: Normalize the direct-influence matrix: On the basis of the direct-influence matrix $\boldsymbol{D}$, the normalized direct-relation matrix $\boldsymbol{N}$ is acquired by using Eqs. (1) and (2)

$$\boldsymbol{N} = \boldsymbol{D}/u. \tag{1}$$

$$u = \max_{i,j}\left\{\max_{i} \sum_{j=1}^{n} d_{ij},\ \max_{j} \sum_{i=1}^{n} d_{ij}\right\},\quad i,\, j \in \{1,\, 2, \ldots,\, n\} \tag{2}$$

Step 3: Attain the total-influence matrix: Once the normalized direct-influence matrix $\boldsymbol{N}$ by summation of i or j is obtained, the total-influence matrix $\boldsymbol{T}$ is arrived at through Eq. (3), in which the $\boldsymbol{I}$ is denoted as the identity matrix

$$\begin{aligned} \boldsymbol{T} &= \boldsymbol{N} + \boldsymbol{N}^2 + \boldsymbol{N}^3 + \ldots + \boldsymbol{N}^q \\ &= \boldsymbol{N}(\boldsymbol{I} + \boldsymbol{N} + \boldsymbol{N}^2 + \ldots + \boldsymbol{N}^{q-1})[(\boldsymbol{I} - \boldsymbol{N})(\boldsymbol{I} - \boldsymbol{N})^{-1}] \\ &= \boldsymbol{N}(\boldsymbol{I} - \boldsymbol{N}^q)(\boldsymbol{I} - \boldsymbol{N})^{-1} \end{aligned} \tag{3}$$

Then $\boldsymbol{T} = \boldsymbol{N}(\boldsymbol{I} - \boldsymbol{N})^{-1}$, when $q \to \infty$, $\boldsymbol{N}^q = [0]_{n\times n}$, where $\boldsymbol{N} = [e_{ij}]_{n\times n}$, $0 \leqslant e_{ij} < 1,\ 0 < \left(\sum_{j=1}^{n} e_{ij}, \sum_{i=1}^{n} e_{ij}\right) \leqslant 1$. If the summation of either row $(\sum_{j=1}^{n} e_{ij})$ or column $(\sum_{i=1}^{n} e_{ij})$ equals 1 can we guarantee $\lim_{q\to\infty}\boldsymbol{N}^q = [0]_{n\times n}$.

Step 4: Determine the threshold value: It is necessary to set a threshold value α for explaining the structural relation among factors while simultaneously keeping the complexity of the whole system to a manageable level. Threshold value α is determined by experts to set up the minimum value of influence level. An influence relationship between two elements will be excluded from the map if their correlative value in the matrix $\boldsymbol{T}$ is smaller than α.

Step 5: Analyzing the results: At this stage, the sum of rows (given influence) and the sum of columns (received influence) are separately expressed as influential vector $\boldsymbol{d} = (d_1, \ldots, d_i, \ldots, d_n)'$ by factor j $(j = 1,2,\ldots,n)$ and influential vector $\boldsymbol{r} = (r_1, \ldots, r_j, \ldots, r_n)'$ by factor i $(i = 1,2,\ldots,n)$ using Eqs. (4)–(6). Then, when $i, j \in \{1, 2, \ldots, n\}$ and $i = j$ the horizontal axis vector $(\boldsymbol{d} + \boldsymbol{r})$ is made by adding vector $\boldsymbol{d}$ to vector $\boldsymbol{r}$, which exhibits total important influence of each criterion. Similarly, the vertical axis vector $(\boldsymbol{d} - \boldsymbol{r})$ is made by deducting vector $\boldsymbol{d}$ from vector $\boldsymbol{r}$, which may separate criteria into a cause group and an affected group. In general, when the value of $d_i - r_i$ is higher, the criterion is to belong to the cause group. On the contrary, if the value of $d_i - r_i$ is lower, the criterion is to belong to the affected group. Therefore, the cause-and-effect graph can be achieved by plotting the data set of $\{(d_i + r_i, d_i - r_i) | i = 1,2,\ldots,n\}$, providing a valuable approach for making decisions

$$\boldsymbol{T} = [t_{ij}]_{n\times n},\quad i,j \in \{1,2,\ldots,n\}, \tag{4}$$

$$\boldsymbol{d} = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} = [t_i]_{n\times 1} = [d_i]_{n\times 1}, \tag{5}$$

$$\boldsymbol{r} = \left[\sum_{i=1}^{n} t_{ij}\right]'_{1\times n} = [t_j]_{n\times 1} = [r_j]_{n\times 1}, \tag{6}$$

where vector $\boldsymbol{d} = (d_1, \ldots, d_i, \ldots, d_n)'$ and vector $\boldsymbol{r} = (r_1, \ldots, r_j, \ldots, r_n)'$ express the sum of rows and the sum of columns based on the total-influence matrix $\boldsymbol{T} = [t_{ij}]_{n\times n}$, respectively.

3.2. Fuzzy DEMATEL method

Fuzzy set theory can efficiently deal with the vagueness of human thought and expression in making decisions. To tackle the ambiguities involved in the process of decision-making, the linguistic terms can be more effective in estimation. A linguistic variable is a variable whose values have the form of phrases or sentences in a natural language (Von Altrock, 1996). The linguistic variables are used as variables whose values are not numbers but linguistic terms (Zadeh, 1975) and can effectively describe the quantitative expressions (Asan, Erhan Bozdag, & Polat, 2004). The linguistic term approach is a natural and effective way for decision makers to express their assessments. In practice, linguistic values can be represented by fuzzy numbers, and the triangular fuzzy number is commonly used.

A fuzzy set $\tilde{A}$ is a subset of a universe of discourse X, which is a set of ordered pairs and is characterized by a membership function $\mu_{\tilde{A}}(x)$ representing a mapping $\mu_{\tilde{A}}(x) : X \to [0, 1]$. The function value of $\mu_{\tilde{A}}(x)$ for the fuzzy set $\tilde{A}$ is called the membership value of x in $\tilde{A}$, which represents the degree of truth that x is an element of the fuzzy set $\tilde{A}$. It is assumed that $\mu_{\tilde{A}}(x) : X \in [0, 1]$, where $\mu_{\tilde{A}}(x) = 1$ reveals that x completely belongs to $\tilde{A}$, while $\mu_{\tilde{A}}(x) = 0$ indicates that x does not belong to the fuzzy set $\tilde{A}$

$$\tilde{A} = \{x, \mu_{\tilde{A}}(x)\},\quad x \in X \tag{7}$$

where $\mu_{\tilde{A}}(x)$ is the membership function and $X = \{x\}$ represents a collection of elements x.

A triangular fuzzy number $\tilde{N}$ can be defined as a triplet (l, m, r), and the membership function $\mu_{\tilde{N}}(x)$ is defined as:

$$\mu_{\tilde{N}}(x) = \begin{cases} 0, & x < l \\ (x - l)/(m - l), & l \leqslant x < m \\ (r - x)/(r - m), & m \leqslant x < r \\ 0, & x \geqslant r \end{cases} \tag{8}$$

where l, m, and r are real numbers and $l < m < r$.

According to the characteristics of triangular fuzzy numbers and the extension principle put forward by Zadeh (1965), the operational laws of two triangular fuzzy numbers, $\tilde{A} = (a_1, a_2, a_3)$ and $\tilde{B} = (b_1, b_2, b_3)$, are as follows:

(1) Addition of two fuzzy numbers $\oplus$:

$$(a_1, a_2, a_3) \oplus (b_1, b_2, b_3) = (a_1 + b_1, a_2 + b_2, a_3 + b_3) \tag{9}$$

(2) Subtraction of two fuzzy numbers $\ominus$:

$$(a_1, a_2, a_3) \ominus (b_1, b_2, b_3) = (a_1 - b_3, a_2 - b_2, a_3 - b_1) \tag{10}$$

(3) Multiplication of two fuzzy numbers $\otimes$:

$$(a_1, a_2, a_3) \otimes (b_1, b_2, b_3) \cong (a_1 b_1, a_2 b_2, a_3 b_3) \tag{11}$$

(4) Multiplication of any real number k and a fuzzy number:

$$k \otimes (a_1, a_2, a_3) = (ka_1, ka_2, ka_3) \tag{12}$$

(5) Division of two fuzzy numbers $\oslash$:

$$(a_1, a_2, a_3) \oslash (b_1, b_2, b_3) \cong (a_1/b_3, a_2/b_2, a_3/b_1) \tag{13}$$

To deal with the problems of group decision-making in a fuzzy environment, an effective fuzzy aggregation method is required.

Table 2
Linguistic scales for the importance weight of criteria (as example).

Linguistic variables	Corresponding triangular fuzzy numbers
No influence	(0,0.1,0.3)
Very low influence	(0.1,0.3,0.5)
Low influence	(0.3,0.5,0.7)
High influence	(0.5,0.7,0.9)
Very high influence	(0.7,0.9,1.0)

Table 3
The fuzzy direct-influence matrix $\widetilde{\boldsymbol{D}}$.

	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{41}
C_{11}	(0.0000,0.0000,0.0000)	(0.0429,0.1714,0.3704)	(0.0510,0.1837,0.3827)	(0.0296,0.1531,0.3531)	(0.0439,0.1776,0.3776)	(0.0316,0.1551,0.3551)	(0.0061,0.1122,0.3122)	(0.0071,0.1143,0.3143)	(0.6173,0.8163,0.9429)
C_{12}	(0.4398,0.6367,0.8000)	(0.0000,0.0000,0.0000)	(0.3816,0.5796,0.7684)	(0.0510,0.1837,0.3837)	(0.0429,0.1714,0.3714)	(0.0398,0.1714,0.3714)	(0.0071,0.1133,0.3112)	(0.0061,0.1122,0.3122)	(0.5357,0.7347,0.8980)
C_{13}	(0.4163,0.6102,0.7949)	(0.0337,0.1673,0.3673)	(0.0000,0.0000,0.0000)	(0.0500,0.1857,0.3857)	(0.0327,0.1653,0.3653)	(0.0327,0.1633,0.3633)	(0.0051,0.1102,0.3102)	(0.0092,0.1163,0.3163)	(0.5622,0.7612,0.9153)
C_{21}	(0.3429,0.5439,0.7449)	(0.2541,0.4449,0.6449)	(0.2214,0.4122,0.6122)	(0.0000,0.0000,0.0000)	(0.0306,0.1612,0.3612)	(0.1163,0.2959,0.4959)	(0.0051,0.1082,0.3082)	(0.0041,0.1082,0.3082)	(0.5357,0.7347,0.8939)
C_{22}	(0.3000,0.4918,0.6714)	(0.0316,0.1592,0.3592)	(0.0347,0.1653,0.3653)	(0.3510,0.5449,0.7327)	(0.0000,0.0000,0.0000)	(0.4061,0.5980,0.7684)	(0.0041,0.1082,0.3082)	(0.0061,0.1122,0.3122)	(0.5571,0.7571,0.9041)
C_{23}	(0.2337,0.4204,0.6204)	(0.2102,0.3939,0.5939)	(0.1980,0.3714,0.5714)	(0.4745,0.6643,0.8316)	(0.0398,0.1673,0.3663)	(0.0000,0.0000,0.0000)	(0.0061,0.1122,0.3122)	(0.0061,0.1102,0.3102)	(0.5592,0.7592,0.9041)
C_{31}	(0.0041,0.1082,0.3082)	(0.0061,0.1122,0.3122)	(0.0061,0.1102,0.3102)	(0.0041,0.1082,0.3082)	(0.0051,0.1102,0.3102)	(0.0051,0.1082,0.3082)	(0.0000,0.0000,0.0000)	(0.0061,0.1143,0.3184)	(0.0051,0.1102,0.3102)
C_{32}	(0.0051,0.1102,0.3102)	(0.0061,0.1102,0.3102)	(0.0051,0.1102,0.3102)	(0.0010,0.1020,0.3020)	(0.0041,0.1082,0.3082)	(0.0071,0.1122,0.3122)	(0.0051,0.1102,0.3102)	(0.0000,0.0000,0.0000)	(0.0061,0.1122,0.3122)
C_{41}	(0.0296,0.1592,0.3592)	(0.0316,0.1612,0.3612)	(0.0306,0.1592,0.3592)	(0.0337,0.1633,0.3633)	(0.0296,0.1551,0.3551)	(0.0327,0.1633,0.3633)	(0.0061,0.1102,0.3102)	(0.0031,0.1061,0.3061)	(0.0000,0.0000,0.0000)

Table 4
The fuzzy normalized direct-influence matrix $\widetilde{\boldsymbol{N}}$.

	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{41}
C_{11}	(0.0000,0.0000,0.0000)	(0.0070,0.0282,0.0609)	(0.0084,0.0302,0.0629)	(0.0049,0.0252,0.0581)	(0.0072,0.0292,0.0621)	(0.0052,0.0255,0.0584)	(0.0010,0.0185,0.0514)	(0.0012,0.0188,0.0517)	(0.1015,0.1343,0.1551)
C_{12}	(0.0723,0.1047,0.1316)	(0.0000,0.0000,0.0000)	(0.0628,0.0953,0.1264)	(0.0084,0.0302,0.0631)	(0.0070,0.0282,0.0611)	(0.0065,0.0282,0.0611)	(0.0012,0.0186,0.0512)	(0.0010,0.0185,0.0514)	(0.0881,0.1208,0.1477)
C_{13}	(0.0685,0.1004,0.1307)	(0.0055,0.0275,0.0604)	(0.0000,0.0000,0.0000)	(0.0082,0.0305,0.0634)	(0.0054,0.0272,0.0601)	(0.0054,0.0269,0.0597)	(0.0008,0.0181,0.0510)	(0.0015,0.0191,0.0520)	(0.0925,0.1252,0.1505)
C_{21}	(0.0564,0.0894,0.1225)	(0.0418,0.0732,0.1061)	(0.0364,0.0678,0.1007)	(0.0000,0.0000,0.0000)	(0.0050,0.0265,0.0594)	(0.0191,0.0487,0.0816)	(0.0008,0.0178,0.0507)	(0.0007,0.0178,0.0507)	(0.0881,0.1208,0.1470)
C_{22}	(0.0493,0.0809,0.1104)	(0.0052,0.0262,0.0591)	(0.0057,0.0272,0.0601)	(0.0577,0.0896,0.1205)	(0.0000,0.0000,0.0000)	(0.0668,0.0983,0.1264)	(0.0007,0.0178,0.0507)	(0.0010,0.0185,0.0514)	(0.0916,0.1245,0.1487)
C_{23}	(0.0384,0.0691,0.1020)	(0.0346,0.0648,0.0977)	(0.0326,0.0611,0.0940)	(0.0780,0.1092,0.1368)	(0.0065,0.0275,0.0602)	(0.0000,0.0000,0.0000)	(0.0010,0.0185,0.0514)	(0.0010,0.0181,0.0510)	(0.0920,0.1249,0.1487)
C_{31}	(0.0007,0.0178,0.0507)	(0.0010,0.0185,0.0514)	(0.0010,0.0181,0.0510)	(0.0007,0.0178,0.0507)	(0.0008,0.0181,0.0510)	(0.0008,0.0178,0.0507)	(0.0000,0.0000,0.0000)	(0.0010,0.0188,0.0524)	(0.0008,0.0181,0.0510)
C_{32}	(0.0008,0.0181,0.0510)	(0.0010,0.0181,0.0510)	(0.0008,0.0181,0.0510)	(0.0002,0.0168,0.0497)	(0.0007,0.0178,0.0507)	(0.0012,0.0185,0.0514)	(0.0008,0.0181,0.0510)	(0.0000,0.0000,0.0000)	(0.0010,0.0185,0.0514)
C_{41}	(0.0049,0.0262,0.0591)	(0.0052,0.0265,0.0594)	(0.0050,0.0262,0.0591)	(0.0055,0.0269,0.0597)	(0.0049,0.0255,0.0584)	(0.0054,0.0269,0.0597)	(0.0010,0.0181,0.0510)	(0.0005,0.0175,0.0503)	(0.0000,0.0000,0.0000)

Table 5
The fuzzy total-influence matrix $\widetilde{\boldsymbol{T}}$.

	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{41}
C_{11}	(0.0028,0.0240,0.1151)	(0.0082,0.0421,0.1436)	(0.0100,0.0465,0.1534)	(0.0066,0.0417,0.1478)	(0.0079,0.0397,0.1332)	(0.0065,0.0399,0.1411)	(0.0012,0.0262,0.1147)	(0.0013,0.0265,0.1152)	(0.1054,0.1643,0.2915)
C_{12}	(0.0788,0.1357,0.2619)	(0.0023,0.0208,0.1053)	(0.0648,0.1148,0.2300)	(0.0111,0.0527,0.1721)	(0.0086,0.0441,0.1497)	(0.0087,0.0480,0.1621)	(0.0014,0.0299,0.1295)	(0.0013,0.0298,0.1300)	(0.1049,0.1749,0.3234)
C_{13}	(0.0708,0.1232,0.2458)	(0.0073,0.0445,0.1527)	(0.0022,0.0205,0.1043)	(0.0101,0.0495,0.1621)	(0.0065,0.0404,0.1400)	(0.0070,0.0437,0.1514)	(0.0010,0.0275,0.1218)	(0.0017,0.0285,0.1229)	(0.1026,0.1671,0.3066)
C_{21}	(0.0642,0.1248,0.2612)	(0.0439,0.0925,0.2079)	(0.0411,0.0933,0.2150)	(0.0036,0.0260,0.1187)	(0.0067,0.0435,0.1523)	(0.0211,0.0684,0.1846)	(0.0011,0.0298,0.1326)	(0.0009,0.0298,0.1329)	(0.1052,0.1786,0.3317)
C_{22}	(0.0579,0.1184,0.2535)	(0.0114,0.0538,0.1724)	(0.0121,0.0575,0.1825)	(0.0643,0.1166,0.2344)	(0.0019,0.0187,0.0983)	(0.0692,0.1181,0.2281)	(0.0010,0.0305,0.1345)	(0.0013,0.0312,0.1354)	(0.1118,0.1864,0.3377)
C_{23}	(0.0496,0.1106,0.2505)	(0.0392,0.0888,0.2067)	(0.0391,0.0905,0.2149)	(0.0803,0.1304,0.2465)	(0.0084,0.0458,0.1566)	(0.0034,0.0248,0.1143)	(0.0013,0.0313,0.1364)	(0.0013,0.0310,0.1364)	(0.1122,0.1875,0.3409)
C_{31}	(0.0010,0.0307,0.1364)	(0.0011,0.0257,0.1142)	(0.0012,0.0270,0.1203)	(0.0008,0.0265,0.1188)	(0.0009,0.0233,0.1048)	(0.0009,0.0251,0.1132)	(0.0000,0.0040,0.0496)	(0.0010,0.0225,0.0996)	(0.0014,0.0385,0.1647)
C_{32}	(0.0011,0.0309,0.1364)	(0.0011,0.0254,0.1137)	(0.0010,0.0269,0.1200)	(0.0003,0.0255,0.1177)	(0.0007,0.0230,0.1043)	(0.0013,0.0257,0.1136)	(0.0008,0.0218,0.0980)	(0.0000,0.0040,0.0497)	(0.0015,0.0386,0.1646)
C_{41}	(0.0066,0.0441,0.1551)	(0.0058,0.0365,0.1295)	(0.0059,0.0383,0.1365)	(0.0064,0.0387,0.1358)	(0.0051,0.0325,0.1182)	(0.0060,0.0367,0.1293)	(0.0010,0.0232,0.1041)	(0.0005,0.0226,0.1037)	(0.0033,0.0293,0.1311)

The human judgments with fuzzy linguistic variables are fuzzy numbers, for which a defuzzification method is required to transform the crisp elements into scores. Proposed by Opricovic and Tzeng (2003), the CFCS (Converting Fuzzy data into Crisp Scores) defuzzification method is based on the procedure of determining the left and right scores by fuzzy min and fuzzy max, and the total score is determined as a weighted average according to the membership functions. This would provide a more appropriate crisp value when compared with other methods.

Let $\tilde{z}_{ij}^k = (l_{ij}^k, m_{ij}^k, r_{ij}^k)$ indicate the fuzzy assessment of evaluator k ($k = 1, 2, \ldots, p$) about the degree to which the criterion i affects the criterion j, the CFCS algorithm can be described in the following five steps:

(1) Normalization:

$$xl_{ij}^k = (l_{ij}^k - \min l_{ij}^k)/\Delta_{\min}^{\max} \tag{14}$$

$$xm_{ij}^k = (m_{ij}^k - \min l_{ij}^k)/\Delta_{\min}^{\max} \tag{15}$$

$$xr_{ij}^k = (r_{ij}^k - \min l_{ij}^k)/\Delta_{\min}^{\max} \tag{16}$$

where $\Delta_{\min}^{\max} = \max r_{ij}^k - \min l_{ij}^k$.

(2) Compute left (ls) and right (rs) normalized value:

$$xls_{ij}^k = xm_{ij}^k/(1 + xm_{ij}^k - xl_{ij}^k) \tag{17}$$

$$xrs_{ij}^k = xr_{ij}^k/(1 + xr_{ij}^k - xm_{ij}^k) \tag{18}$$

(3) Compute total normalized crisp value:

$$x_{ij}^k = [xls_{ij}^k(1 - xls_{ij}^k) + xrs_{ij}^k xrs_{ij}^k]/[1 - xls_{ij}^k + xrs_{ij}^k] \tag{19}$$

(4) Compute crisp values:

$$z_{ij}^k = \min l_{ij}^k + x_{ij}^k \Delta_{\min}^{\max} \tag{20}$$

To further the practicality of the conventional DEMATEL technique for group decision-making in a fuzzy environment, the process is illustrated as follows:

Step 1: Design the fuzzy linguistic scale: To deal with the ambiguities of human assessments, the linguistic variable "influence" is used with five linguistic terms as {No, Very low, Low, High, Very high} that are expressed in positive triangular fuzzy numbers (l_{ij}, m_{ij}, r_{ij}) as shown in Table 2.

Step 2: Calculate the fuzzy direct-influence matrix: Based on the views of the experts by linguistic scales of natural language and the relationship among elements based on Table 2, the fuzzy direct-influence matrix $\widetilde{\boldsymbol{D}}$ can be obtained by

$$\widetilde{\boldsymbol{D}} = [\tilde{d}_{ij}]_{n\times n}, \quad \text{where} \quad \tilde{d}_{ij} = (d_{ij}^l, d_{ij}^m, d_{ij}^r) \tag{21}$$

Step 3: Normalize the fuzzy direct-influence matrix: Based on the fuzzy direct-influence matrix $\widetilde{\boldsymbol{D}}$, the normalized fuzzy direct-relation matrix $\widetilde{\boldsymbol{N}}$ is acquired by using

$$\widetilde{\boldsymbol{N}} = \widetilde{\boldsymbol{D}}/u, \quad \text{where} \quad u = \max_{i,j}\left\{\max_i \sum_{j=1}^n d_{ij},\ \max_j \sum_{i=1}^n d_{ij}\right\}, \quad i,j \in \{1, 2, \ldots, n\} \tag{22}$$

$$\widetilde{\boldsymbol{N}} = [\tilde{e}_{ij}]_{n\times n}, \tilde{e}_{ij} = (e_{ij}^l, e_{ij}^m, e_{ij}^r)$$

Step 4: Attain the fuzzy total-influence matrix: Once the normalized fuzzy direct-influence matrix $\widetilde{\boldsymbol{N}} = (N^l, N^m, N^r)$ is obtained, where $\mathbf{N}^l = [e_{ij}^l]_{n\times n}$, $\mathbf{N}^m = [e_{ij}^m]_{n\times n}$ and $\boldsymbol{N}^r = [e_{ij}^r]_{n\times n}$, the fuzzy total-influence matrix $\widetilde{\boldsymbol{T}}$ is arrived at through Eq. (23), in which the $\boldsymbol{I}$ is denoted as the identity matrix

$$\widetilde{\boldsymbol{T}} = [\tilde{t}_{ij}]_{n\times n}, \quad \text{where} \quad \tilde{t}_{ij} = (t_{ij}^l, t_{ij}^m, t_{ij}^r) \tag{23}$$

where $\boldsymbol{T}^l = [t_{ij}^l]_{n\times n} = \boldsymbol{N}^l(\boldsymbol{I} - \boldsymbol{N}^l)^{-1}$, $\boldsymbol{T}^m = [t_{ij}^m]_{n\times n} = \boldsymbol{N}^m(\boldsymbol{I} - \boldsymbol{N}^m)^{-1}$ and $\boldsymbol{T}^r = [t_{ij}^r]_{n\times n} = \boldsymbol{N}^r(\boldsymbol{I} - \boldsymbol{N}^r)^{-1}$, respectively; the elements of triangular fuzzy numbers in fuzzy total-influence matrix $\widetilde{\boldsymbol{T}}$ are divided into $\boldsymbol{T}^l$, $\boldsymbol{T}^m$ and $\boldsymbol{T}^r$, and $\boldsymbol{T}^l = [t_{ij}^l]_{n\times n} \prec \boldsymbol{T}^m = [t_{ij}^m]_{n\times n} \prec \boldsymbol{T}^r = [t_{ij}^r]_{n\times n}$, when $e_{ij}^l < e_{ij}^m < e_{ij}^r$ for any $i, j \in \{1, 2, \ldots, n\}$.

Step 5: Defuzzify into the crisp values: Using the CFCS method shown in Eqs. (14)–(20), the total fuzzy influence matrix $\widetilde{\boldsymbol{T}} = [\tilde{t}_{ij}]_{n\times n}$ is defuzzified as crisp values into the total influence matrix $\boldsymbol{T} = [t_{ij}]_{n\times n}$.

Step 6: Determine threshold value α, then establish and analyze the structural model. A causal diagram can be drawn as same as conventional DEMETAL method.

The fundamental concept for acquiring the initial fuzzy direct-influence matrix $\widetilde{\boldsymbol{D}}$, the normalized fuzzy direct-influence matrix $\widetilde{\boldsymbol{N}}$, the fuzzy total-relation matrix $\widetilde{\boldsymbol{T}}$, then defuzzying $\widetilde{\boldsymbol{T}}$ into $\boldsymbol{T}$, and drawing a causal diagram are the same as the conventional DEMETAL technique. However, with the fuzzy concept, the decision maker can observe more insightful information that benefits the decision-making.

4. Empirical study: case of CDSS

This research conducted a paper-based survey by convenience sampling over a 3-month period between February and April of 2010. The candidates were selected from major medical centers in Taiwan. The respondents who were considered as experts were required to be medical doctors who practice in clinical diagnosis. The pair-wise comparison questionnaire was developed based on the criteria shown in Table 1. A total of 98 valid questionnaires were collected for this study.

The initial fuzzy direct-influence matrix $\widetilde{\boldsymbol{D}}$ was produced as shown in Table 3. Based on the Eq. (21), $u = 6.0806$. The normalized fuzzy direct-influence matrix $\widetilde{\boldsymbol{N}}$, as shown in Table 4, is then retrieved based on Eq. (22). Subsequently, the fuzzy total-influence matrix $\widetilde{\boldsymbol{T}}$ was calculated as displayed in Table 5. Next, the CFCS method listed in Eqs. (14)–(20) was used to aggregate the fuzzy data. Table 6 shows the defuzzied total-influence matrix $\boldsymbol{T}$. The fuzzy and defuzzied influence of concern factors in criteria level are presented in Tables 7 and 8, respectively.

Confirmed with a group of experts, the medium value of linguistic variable 'no influence' was set as the threshold value α. The impact value below 0.1 is ignored as it were considered to have no influence. Based on the above analysis, a comprehensive impact relation map can be generated as illustrated in Fig. 1. The causal relation map can be drawn as illustrated in Fig. 2. The cause-and-effect relations among the factors/criteria were generated in Table 9.

5. Discussion and implications

According to the fuzzy DEMATEL analysis, the following statements can be generated:

(1) The key cause factors with values of $(d_i - r_i)$ were positive, including Performance Expectancy (D_1) and Effort Expectancy (D_2), intensely affect others. These factors acted as independent variables.

(2) The main effect factor with values of $(d_i - r_i)$ were negative, *i.e.* Behavior Intension (D_4) was intensely affected by the others. These factors played the part of dependent variables.

(3) The key causal factors with values of $(d_i + r_i)$ and $(d_i - r_i)$ were very small, *i.e.* Social Influence (D_3) showed low prominence and low relation. This factor was filtered out because it was below the threshold value α, and showed an insignificant relationship with others.

Table 6
The defuzzied total-influence matrix ***T***.

	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{41}
C_{11}	0.0378	0.0577	0.0630	0.0581	0.0537	0.0554	0.0393	0.0396	0.1772
C_{12}	0.1507	0.0332	0.1300	0.0713	0.0604	0.0657	0.0452	0.0452	0.1880
C_{13}	0.1390	0.0612	0.0327	0.0669	0.0555	0.0603	0.0418	0.0428	0.1807
C_{21}	0.1417	0.1088	0.1102	0.0401	0.0603	0.0856	0.0457	0.0458	0.1913
C_{22}	0.1354	0.0722	0.0768	0.1319	0.0301	0.1323	0.0467	0.0474	0.1978
C_{23}	0.1289	0.1056	0.1082	0.1451	0.0630	0.0382	0.0477	0.0475	0.1989
C_{31}	0.0472	0.0388	0.0410	0.0403	0.0350	0.0381	0.0085	0.0333	0.0588
C_{32}	0.0473	0.0384	0.0409	0.0393	0.0346	0.0387	0.0324	0.0085	0.0589
C_{41}	0.0613	0.0505	0.0533	0.0535	0.0451	0.0506	0.0348	0.0342	0.0452

Table 7
The fuzzy influence of concern factors in criteria level.

Dimensions/criteria	$\tilde{d}_i$	$\tilde{r}_i$	$\tilde{d}_i - \tilde{r}_i$	$\tilde{d}_i + \tilde{r}_i$
D_1 Performance expectancy				
C_{11} Perceived usefulness	(0.1499, 0.4509, 1.3556)	(0.3328, 0.7423, 1.8159)	(0.4826, 1.1932, 3.1715)	(−1.6661, −0.2913, 1.0228)
C_{12} Extrinsic motivation	(0.2819, 0.6507, 1.6639)	(0.1203, 0.4303, 1.3458)	(0.4022, 1.0810, 3.0098)	(−1.0640, 0.2203, 1.5436)
C_{13} Job fit	(0.2093, 0.5449, 1.5075)	(0.1773, 0.5153, 1.4768)	(0.3866, 1.0601, 2.9844)	(−1.2675, 0.0296, 1.3302)
D_2 Effort expectancy				
C_{21} Perceived ease of use	(0.2879, 0.6867, 1.7370)	(0.1837, 0.5076, 1.4540)	(0.4716, 1.1943, 3.1910)	(−1.1661, 0.1791, 1.5533)
C_{22} Complexity	(0.3308, 0.7313, 1.7769)	(0.0467, 0.3110, 1.1574)	(0.3775, 1.0423, 2.9343)	(−0.8266, 0.4204, 1.7302)
C_{23} Ease of use	(0.3348, 0.7408, 1.8032)	(0.1240, 0.4303, 1.3376)	(0.4588, 1.1711, 3.1408)	(−1.0028, 0.3105, 1.6792)
D_3 Social influence				
C_{31} Subjective norm	(0.0083, 0.2232, 1.0215)	(0.0090, 0.2243, 1.0212)	(0.0172, 0.4474, 2.0427)	(−1.0129, −0.0011, 1.0125)
C_{32} Image	(0.0078, 0.2216, 1.0178)	(0.0093, 0.2259, 1.0259)	(0.0171, 0.4475, 2.0437)	(−1.0180, −0.0042, 1.0085)
D_4 Behavior intension				
C_{41} Behavior intension	(0.0407, 0.3019, 1.1434)	(0.6483, 1.1652, 2.3921)	(0.6889, 1.4671, 3.5355)	(−2.3515, −0.8633, 0.4951)

It is notable that this study found insignificant relationships on Social Influence towards the intension of using the CDSS, which contradicts previous findings. This implies medical doctors are trained and skillful professionals who are less likely to be influenced by social norms in their professional field. That is, doctors tend to experience the value of CDSS from their own medical practice instead of being influenced socially. Roberts and Henderson (2000) observed in their study that Social Influence did not have an impact on attitude towards using an information system in government employees, which addressed a similar exception of a subjective norm instrument in UTAUT and TAM2. To address the comment of Davis et al. (1989) that, "more sophisticated methods for assessing the specific types of social influence processes at work in a computer acceptance context are clearly needed," (p. 998) this study adopted the fuzzy DEMATEL technique and found the social influence has no impact on medical professionals to CDSS adoption.

In contrary with UTAUT, this study shows a direct relation from Effort Expectancy to Performance Expectancy. According to TAM, the intention to accept or use new technologies is determined by their perceived ease of use (C_{21}) and perceived usefulness (C_{11}). The aforementioned relationship was supported by Davis (1989) in which perceived ease of use was significantly linked to attitude towards use and both directly or indirectly had an impact on perceived usefulness. In this study, it can be concluded that effort expectancy has a positive impact on performance expectancy due to the influence in criteria level: the perceived ease of use impacts on perceived usefulness.

Consistent with Davis (1989), this study found Performance Expectancy to have a significant impact on Behavior Intention. Wei (2006) affirmed this correlation and stated that individuals who have certain positive attitudes toward the system would show a better satisfaction. Garg et al. (2005) concluded that the performance of the CDSS has a relationship with the higher intention to use it. If the practitioners realized the well performance of CDSS, the attitude towards using it would be more positive. Confirmed by Stacey, Pomey, O'Connor, and Graham (2006), if users felt comfortable using the decision support system, this would enhance the reuse intention. A few studies verified that the use of CDSS improves the medical professional's job performance. Kawamoto, Houlihan, Balas, and Lobach (2005) concluded that the CDSS significantly improved clinical practice, which was confirmed by Dreiseitl et al. (2007), and that the CDSS significantly improves the medical experts' performance in terms of accuracy and efficiency in diagnosis, which makes doctors have higher intention towards the use of the CDSS. Bergman and Fors (2005) have also shown that physicians had a positive attitude towards the use of the CDSS when they realized the performance of CDSS was acceptable.

Table 8
The defuzzied influence of concern factors in criteria level.

Dimensions/Criteria	$\tilde{d}_i$	$\tilde{r}_i$	$\tilde{d}_i - \tilde{r}_i$	$\tilde{d}_i + \tilde{r}_i$
D_1 Performance expectancy				
C_{11} Perceived usefulness	0.5818	0.8892	1.4710	−0.3074
C_{12} Extrinsic motivation	0.7898	0.5664	1.3561	0.2234
C_{13} Job fit	0.6809	0.6563	1.3372	0.0247
D_2 Effort expectancy				
C_{21} Perceived ease of use	0.8296	0.6465	1.4761	0.1831
C_{22} Complexity	0.8707	0.4379	1.3085	0.4328
C_{23} Ease of use	0.8831	0.5650	1.4481	0.3181
D_3 Social influence				
C_{31} Subjective norm	0.3411	0.3421	0.6832	−0.0010
C_{32} Image	0.3391	0.3443	0.6835	−0.0052
D_4 Behavior intension				
C_{41} Behavior intension	0.4283	1.2967	1.7251	−0.8684

The relationship between Effort Expectancy and Behavior Intention found in this study is supported by Davis (1989), Davis et al.

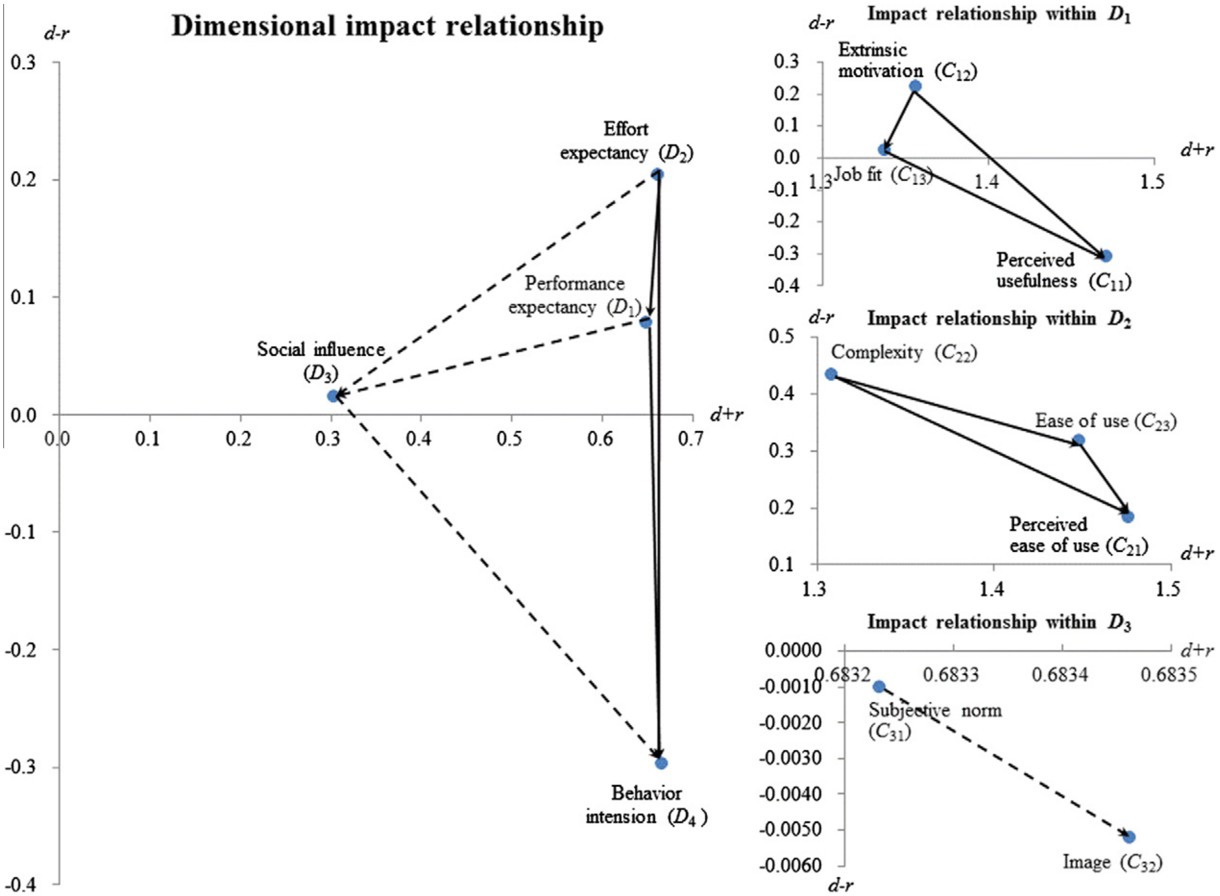

Fig. 1. The comprehensive impact relation map.

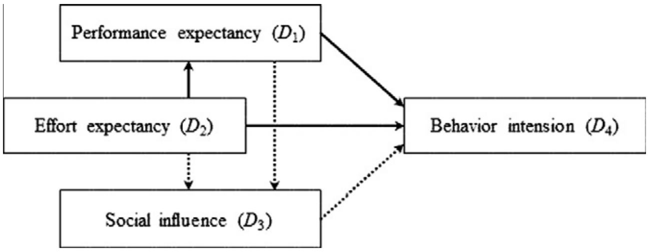

Fig. 2. The causal relation map.

Table 9
The causal relationship.

Cause factors	Effect factors
Performance expectancy (D_1)	Behavior intension (D_4)
Effort expectancy (D_2)	Performance expectancy (D_1) Behavior intension (D_4)
Social influence (D_3)	–

(1989), Moore and Benbasat (1991), Plouffe, Hulland, and Vandenbosch (2001), and Thompson et al. (1991) who have shown that the higher the level of perceived ease of use, the greater the willingness of the consumer to adopt the system. Based on the results of this research and the previously mentioned studies, it can be concluded that when the users have a higher ease of use expectation and engage with a system that is easy to employ, this will result in easy adoption of new technology into their daily operation. In addition, Stacey, Pomey, O'Connor, and Graham (2006) found nurses to have positive attitude towards the use of the CDSS when they were aware the system does not take too much effort from them and it was easy to learn. The study by Liu, Wyatt, and Altman (2006) stated that the success of clinicians in adopting the CDSS was due to the following conditions: They understood what it was for, the prevailing clinical culture patronized it, their patients or peer groups supported it, it was fast, and it was linked to the electronic patient record (EPR). Chismar and Wiley-Patton (2003) applied the TAM in their study and concluded that physicians' behavior intention towards the use of the CDSS related positively with their attitude toward the system. A recent article from Trivedi et al. (2009) reported on a survey of factors affecting clinicians' acceptance of CDSS and revealed that even though a majority of the clinicians were not explicitly following the clinical support suggestions provided, they did feel that such systems were of benefit and reported that they would be even more so if they had more time to make use of them (Sittig, Krall, Dykstra, Russell, & Chin, 2006).

6. Concluding remarks

Does social influence matter in the use of expert systems? This research found no significant influence on medical doctors in adopting the CDSS. This study applied the fuzzy DEMATEL technique, where the fuzzy concept is applied to address the vagueness of human judgments and approximate reason it. The research finding contradicts the UTAUT and further proves the UTAUT can vary depending on the sampled objective, profession, and systems. This research is among limited studies attempting to explore the use of expert systems from a social science perspective. In addition to its academic contributions, the findings of this study may also provide information for systems developers in designing a CDSS, as well as providing key marketing insights while introducing a new CDSS to medical professionals.

In this study, the fuzzy DEMATEL technique was adopted to explore cause-and-effect relationships from a top-down approach. Compared with the SEM, it reduces the model specifications errors, minimizes the occurrence of capitalization on chance error, and maintains the maturity of confirmatory. Causal analysis largely influences the effectiveness of decision-making and operation actions. This study demonstrated that the fuzzy DEMATEL technique may be an efficient, complementary, and effective approach for examining causal relationships. This work only study on those key factors in UTAUT. Future research may further examine the complete model and combine the fuzzy DEMATEL technique with MCDM methods for strategic improvement.

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References

Agarwal, R., & Prasad, J. (1997). The role of innovation characteristics and perceived voluntariness in the acceptance of information technologies. *Decision Sciences, 28*(3), 557–582.

Agarwal, R., & Prasad, J. (1998). A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research, 9*(2), 204–215.

Agarwal, R., & Prasad, J. (1999). Are individual differences germane to the acceptance of new information technologies? *Decision Sciences, 30*(2), 361–391.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211.

Ali Khatami Firouzabad, S. M., Henson, B., & Barnes, C. (2008). A multiple stakeholders' approach to strategic selection decisions. *Computers & Industrial Engineering, 54*(4), 851–865.

Asan, U., Erhan Bozdag, C., & Polat, S. (2004). A fuzzy approach to qualitative cross impact analysis. *Omega, International Journal of Management Science, 32*(6), 443–458.

Bajaj, A., & Nidumolu, S. R. (1998). A feedback model to understand information system usage. *Information & Management, 33*(4), 213–224.

Bates, D. W., Cohen, M., Leape, L. L., Overhage, J. M., Shabot, M. M., & Sheridan, T. (2001). Reducing the frequency of errors in medicine using information technology. *Journal of the American Medical Association, 8*(4), 299–308.

Bates, D. W., Kuperman, G. J., Wang, S., Gandhi, T., Kittler, A., & Volk, L. (2003). Ten commandments for effective clinical decision support: Making the practice of evidence-based medicine a reality. *Journal of the American Medical Informatics Association, 10*(6), 523–530.

Bellman, R. E., & Zadeh, L. A. (1970). Decision-making in a fuzzy environment. *Management Science, 17*(4), 141–164.

Bergman, L. G., & Fors, U. G. (2005). Computer-aided DSM-IV-diagnostics – acceptance, use and perceived usefulness in relation to users' learning styles. *BMC Medical Informatics and Decision Making, 5*(1). doi:10.1186/1472-6947-5-1.

Chau, P. Y. K. (1996). An empirical assessment of a modified technology acceptance model. *Journal of Management Information Systems, 13*(2), 185–204.

Chismar, W. G., & Wiley-Patton, S. (2003). Does the extended technology acceptance model apply to physicians. In *Proc. of 36th Hawaii international conference on system sciences* (Vol. 6, pp. 160a).

Chiu, Y. J., Chen, H. C., Tzeng, G. H., & Shyu, J. Z. (2006). Marketing strategy based on customer behaviour for the LCD-TV. *International Journal of Management and Decision Making, 7*(2/3), 143–165.

Clocksin, W. F. (2003). Artificial intelligence and the future. *Philosophical Transactions: Mathematical, Physical and Engineering Sciences, 361*(1809), 1721–1748.

Compeau, D., & Higgins, C. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS Quarterly, 19*(2), 189–211.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982–1003.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology, 22*(14), 1111–1132.

Dreiseitl, S., Binder, M., Vinterbo, S., & Kittler, H. (2007). Applying a decision support system in clinical practice: Results from melanoma diagnosis. In *AMIA annual symposium proceeding*, Austria (p. 191–195).

Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention and behavior: An introduction to theory and research. *Journal of Advertising Research, 47*(1), 25–32.

Fontela, E., & Gabus, A. (1976). *The DEMATEL observer, DEMATEL 1976 report*. Switzerland, Geneva: Battelle Geneva Research Center.

Gabus, A., & Fontela, E. (1973). *Perceptions of the world problematique: Communication procedure, communicating with those bearing collective responsibility*. DEMATEL report no. 1, Geneva, Switzerland: Battelle Geneva Research Center.

Garg, A. X., Adhikari, N. K. J., McDonald, H., Rosas-Arellano, M. P., Devereaux, P. J., & Beyene, J. (2005). Effects of computerized clinical decision support systems on practitioner performance and patient outcomes: A systematic review. *Journal of the American Medical Informatics Association, 293*(10), 1223–1238.

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly, 19*(2), 213–236.

Hajime, M., & Kenichi, I. (2007). Systematic decision making process for identifying the contradictions to be tackled by TRIZ to accomplish product innovation. *Journal of Automation, Mobile Robotics & Intelligent Systems, 1*(4), 21–29.

Hsu, C. Y., Lee, W. H., Chen, K. T., & Tzeng, G. H. (2007). FMCDM with fuzzy DEMATEL approach for customers' choice behavior model. *International Journal of Fuzzy Systems, 9*(4), 236–246.

Huang, C. Y., & Tzeng, G. H. (2007). Reconfiguring the innovation policy portfolios for Taiwan's SIP mall industry. *Technovation, 27*(12), 744–765.

Kawamoto, K., Houlihan, C. A., Balas, E. A., & Lobach, D. F. (2005). Improving clinical practice using clinical decision support systems: A systematic review of trials to identify features critical to success. *British Medical Journal, 330*(7495). doi:10.1136/bmj.38398.500764.8.

Kim, Y. (2006). Study on impact mechanism for beef cattle farming and importance of evaluating agricultural information in Korea using DEMATEL, PCA and AHP. *Agricultural Information Research, 15*(3), 267–279.

Lee, Y. (2006). An empirical investigation into factors influencing the adoption of an e-learning system. *Online Information Review, 30*(5), 517–541.

Lee, Y. C., Li, M. L., Yen, T. M., & Huang, T. H. (2010). Analysis of adopting an integrated decision making trial and evaluation laboratory on a technology acceptance model. *Expert Systems with Applications, 37*(2), 1745–1754.

Liao, C. N. (2011). Fuzzy analytical hierarchy process and multi-segment goal programming applied to new product segmented under price strategy. *Computers & Industrial Engineering, 61*(3), 831–841.

Lin, C. J., & Wu, W. W. (2008). A causal analytical method for group decision-making under fuzzy environment. *Expert Systems with Applications, 34*(1), 205–213.

Liou, J. J. H., & Tzeng, G. H. (2010). A dominance-based rough set approach to customer behavior in the airline market. *Information Sciences, 180*(11), 2230–2238.

Liou, J. J. H., Yen, L., & Tzeng, G. H. (2008). Building an effective safety management system for airlines. *Journal of Air Transport Management, 14*(1), 20–26.

Liu, J., Wyatt, J. C., & Altman, D. G. (2006). Decision tools in health care: Focus on the problem, not the solution. *BMC Medical Informatics and Decision Making, 6*(4). doi:10.1186/1472-6947-6-4.

Mathieson, K. (1991). Predicting user intentions: Comparing the technology acceptance model with the theory of planned behavior. *Information Systems Research, 2*(3), 173–191.

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research, 2*(3), 192–222.

Newman-Toker, D. E., & Pronovost, P. J. (2009). Diagnostic errors – The next frontier for patient safety. *Journal of the American Medical Association, 301*(11), 1060–1062.

Opricovic, S., & Tzeng, G. H. (2003). Defuzzification within a multicriteria decision model. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 11*(5), 635–652.

Orlikowski, W. J. (1992). The duality of technology: Rethinking the concept of technology in organizations. *Organization Science, 3*(3), 398–427.

Ou Yang, Y. P., Shieh, H. M., Leu, J. D., & Tzeng, G. H. (2008). A novel hybrid MCDM model combined with DEMATEL and ANP with applications. *International Journal of Operational Research, 5*(3), 160–168.

Plouffe, C. R., Hulland, J. S., & Vandenbosch, M. (2001). Research report: Richness versus parsimony in modeling technology adoption decisions – Understanding merchant adoption of a smart card-based payment system. *Information Systems Research, 12*(2), 208–222.

Prümper, J. (1993). Software-evaluation based upon ISO 9241. In *Proceedings of the Vienna conference on human computer interaction*.

Renaud, K., & Biljon, J. V. (2008). Predicting technology acceptance and adoption by the elderly: A qualitative study. In *Proceedings of the 2008 annual research conference of the South African Institute of Computer Scientists and Information Technologists on IT research in developing countries: Riding the wave of technology*.

Roberts, P., & Henderson, R. (2000). Information technology acceptance in a sample of government employees: A test of the technology acceptance model. *Interacting with Computers, 12*(5), 427–443.

Shi, Y., Peng, Y., Kou, G., & Chen, Z. (2005). Classifying credit card accounts for business intelligence and decision making: A multiple-criteria quadratic programming approach. *International Journal of Information Technology and Decision Making, 4*(4), 581–599.

Sittig, D. F., Krall, M. A., Dykstra, R. H., Russell, A., & Chin, H. L. (2006). A survey of factors affecting clinician acceptance of clinical decision support. *BMC Medical Informatics and Decision Making, 6*(6). doi:10.1186/1472-6947-6-6.

Snead, K. C., & Harrell, A. M. (1994). An application of expectancy theory to explain a manager's intention to use a decision support system. *Decision Sciences, 25*(4), 499–510.

Stacey, D., Pomey, M.-P., O'Connor, A. M., & Graham, L. D. (2006). Adoption and sustainability of decision support for patients facing health decisions: An implementation case study in nursing. *Implementation Science, 1*(17). doi:10.1186/1748-5908-1-17.

Stoel, L., & Lee, K. H. (2003). Modeling the effect of experience on student acceptance of Web-based courseware. *Internet Research: Electronic Networking Applications and Policy, 13*(5), 364–374.

Subramanian, G. H., Yaverbaum, G. J., & Brandt, S. J. (1997). An empirical evaluation of factors influencing expert systems effectiveness. *Journal of System Software, 38*(3), 255–261.

Teo, T. S. H., Lim, V. K., & Lai, R. Y. C. (1999). Intrinsic and extrinsic motivation in Internet usage. *Omega, 27*(1), 25–37.

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. *MIS Quarterly, 15*(1), 125–143.

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1994). Influence of experience on personal computer utilization: Testing a conceptual model. *Journal of Management Information Systems, 11*(1), 167–187.

Trivedi, M. H., Daly, E. J., Kern, J. K., Grannemann, B. D., Sunderajan, P., & Claassen, C. A. (2009). Barriers to implementation of a computerized decision support system for depression: An observational report on lessons learned in "real world" clinical settings. *BMC Medical Informatics and Decision Making, 9*(6). doi:10.1186/1472-6947-9-6.

Tsai, W. H., & Chou, W. C. (2009). Selecting management systems for sustainable development in SMEs: A novel hybrid model based on DEMATEL, ANP, and ZOGP. *Expert Systems with Applications, 36*(2P1), 1444–1458.

Tseng, M. L. (2009). A causal and effect decision making model of service quality expectation using grey-fuzzy DEMATEL approach. *Expert Systems with Applications, 36*(4), 7738–7748.

Tseng, Y. F., Lee, T. Z., & Wu, C. H. (2010). Examining the impact of human resource practices on organizational performance by using the AHP/DEA Model. *International Journal of Innovative Computing, Information and Control, 6*(8), 3401–3412.

Tzeng, G. H., Ou Yang, Y. P., Lin, C. T., & Chen, C. B. (2005). Hierarchical MADM with fuzzy integral for evaluating enterprise intranet web sites. *Information Sciences, 169*(3–4), 409–426.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.

Von Altrock, C. (1996). *Fuzzy logic and neurofuzzy applications in business and finance*. New Jersey: Prentice-Hall.

Wei, T. (2006). The causal relationship between technologies attributes. *International Journal of Management Science, 23*(2), 782–793.

Wei, P. L., Huang, J. H., Tzeng, G. H., & Wu, S. I. (2010). Causal modeling of web-advertising effects by improving SEM based on DEMATEL technique. *International Journal of Information Technology & Decision Making, 9*(5), 799–829.

Wu, W. W. (2008). Choosing knowledge management strategies by using a combined ANP and DEMATEL approach. *Expert Systems with Applications, 35*(3), 828–835.

Wu, W. W., & Lee, Y. T. (2007). Developing global managers' competencies using the fuzzy DEMATEL method. *Expert Systems with Applications, 32*(2), 499–507.

Yamashina, H., Ishida, K., & Mizuyama, H. (2005). An innovative product development process for resolving fundamental conflicts. *Journal of the Japan Society for Precision Engineering, 71*(2), 216–222.

Yang, J. L., Chiu, H. N., Tzeng, G. H., & Yeh, R. H. (2008). Vendor selection by integrated fuzzy MCDM techniques with independent and interdependent relationships. *Information Sciences, 178*(21), 4166–4183.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*(3), 338–353.

Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning. *Information Science, 8*(2), 199–249. 301–357.

Zhang, P., Tian, Y., Zhang, Z., Shi, Y., & Li, X. (2008). Supportive instances for regularized multiple criteria linear programming classification. *International Journal of Operations and Quantitative Management, 14*(4), 249–263.