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A fuzzy logic-based computational recognition-primed decision model

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Abstract

The recognition-primed decision (RPD) model is a primary naturalistic decision-making approach which seeks to explicitly recognize how human decision makers handle complex tasks and environment based on their experience. Motivated by the need for quantitative computer modeling and simulation of human decision processes in various application domains, including medicine, we have developed a general-purpose computational fuzzy RPD model that utilizes fuzzy sets, fuzzy rules, and fuzzy reasoning to represent, interpret, and compute imprecise and subjective information in every aspect of the model. Experiences acquired by solicitation with experts are stored in experience knowledge bases. New local and global similarity measures have been developed to identify the experience that is most applicable to the current situation in a specific decision-making context. Furthermore, an action evaluation strategy has been developed to select the workable course of action. The proposed fuzzy RPD model has been preliminarily validated by using it to calculate the extent of causality between a drug (Cisapride, withdrawn by the FDA from the market in 2000) and some of its adverse effects for 100 hypothetical patients. The simulated patients were created based on the profiles of over 1000 actual patients treated with the drug at our medical center before its withdrawal. The model validity was demonstrated by comparing the decisions made by the proposed model and those by two independent internists. The levels of agreement were established by the weighted *Kappa* statistic and the results suggested good to excellent agreement.

Keywords: Medical decision-making; Naturalistic decision-making; Recognition-primed decision model; Computational recognition-primed decision model; Experience-based reasoning; Adverse drug reactions; Fuzzy logic; Similarity measure

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1. Introduction

Classical decision-making strategies largely use various axiomatic models where the optimal choice is based on a specific criterion or evaluative standard, usually the maximization of expected utility [3,27,38]. Studies have shown that sometimes this class of models cannot adequately describe real-world decision-making [28]. The naturalistic decision-making (NDM) paradigm is an alternative, which investigates the cognition process of human decision makers in a more realistic setting. NDM researchers argue that experts extensively rely on situation assessment rather than generating a set of alternatives first and then weighing their probabilities and selecting the best one among them. Novices, on the other hand, are inclined to utilize a more deliberative decision-making approach. Image Theory [2] is one of the well-developed NDM approaches, where three different images are used to organize experts' thinking about decisions. It was recently used, among other applications, to assist clinicians in understanding medical decisions and developing ways to overcome the disparity between principle and clinical practice [9]. Another method is called Task Analysis where human decision processes are explored by analyzing a specific task in the natural environment of interest [35]. Some (healthcare) applications have been attempted [13,33].

Klein and his colleagues studied how fire commanders made decisions and found that the decision-making of the expert commanders was largely based on careful observation, situation recognition and past experience. After studying hundreds of experienced decision makers, Klein found that about 50–80% of all the decisions were made in this way [15]. They proposed a qualitative recognition-primed decision (RPD) model to characterize the decisions in naturalistic settings [19]. Instead of trying to find the best (i.e., optimal) solution, the RPD identifies the first workable option based on previous decision experiences (a decision strategy called satisfying) [16]. The reason is that real-world decision tasks are often characterized by ill-structured problems, dynamic environments, ill-defined or competing goals, etc., which make it difficult to find the optimum solution. The RPD model is more efficient and suitable for modeling experts. For a variety of applications, it can represent human decision behavior more reasonably than the optimizing approach, and thus is widely accepted by decision makers. For instance, a study showed that the RPD was followed for 95% of all the decisions made by the naval officers on a cruiser [14] The classical RPD model provides important implications for decision support system design, decision skill training, and personnel selection for critical incident managers [18].

Motivated by the need for quantitative computer modeling and simulation of human decision process as well as computerized assistance to enhance this process, researchers recently attempted to make the classical RPD model quantifiable. By quantifiable, we mean a quantitative and computable RPD model that is readily implementable by computer. A long-term memory structure was proposed to represent experience [40], resulting in a "decision-specific" architecture (other aspects of cognition such as cue abstraction, action evaluation, etc. were ignored). Liang et al. studied the simple match of RPD and employed a neural network to formalize an experience [22]. Robichaud further extended the neural network model by using fuzzy techniques to interpret the external environment [31]. There are also several studies in which the computational RPD model was developed and integrated with agent technologies. Norling et al. employed the computational RPD in the Belief-Desire-Intention agent framework as a more realistic way for simulating human societies [25]. More recently, Yen et al. developed an agent architecture (R-CAST) that includes a computational RPD model that extends the RPD model in order to support human agent collaboration and the sharing of relevant information within a team [10,42]. In R-CAST, experiences are organized in a hierarchical structure. Both the cue matching and the expectancy monitoring components of RPD are implemented as collaborative activities that involve agents reasoning about information that may be indirectly linked to cues and expectancy through inference rules. Fuzzy logic was used in [34] to incorporate a subjective and imprecise interpretation of the cue values, but the use of fuzzy logic was rather limited since environmental variables were still represented as crisp values, not as fuzzy numbers/sets. The fuzziness in the process of cue abstraction and feature matching were not dealt with, either.

Fuzzy set theory is an effective paradigm to quantitatively represent and process *deterministic* imprecision, uncertainty, or subjectivity, which are frequently encountered in real-world applications [4,24,37]. The basis of the theory is a fuzzy set [12,23,45]. As an example, a person's age is numerically precise. However, relating a particular age to "young" can be difficult, confusing, and uncertain. What age is young and what age is not?

The nature of this question to any particular person is deterministic, not random. Fuzzy set generalizes 0 and 1 membership values of a classical set to a membership function of a fuzzy set ranging from 0 to 1; 0 means no association, 1 indicates complete association, and any number in between means partial association. Fuzzy set theory lays a foundation for computing with words. To illustrate this, suppose that 30 years is "young" with a membership value of 0.8 and is "old" (a fuzzy set) with a membership value of 0.3. Then, the membership value for the age of 30 being "young and old" (a fuzzy set) is 0.24 if the algebraic product fuzzy AND operator is used. The membership value for the age being "young or old" (a fuzzy set) is 0.8 if Zadeh fuzzy OR operator is utilized. They are partial memberships because the memberships being ANDed and ORed are partial, not full. The membership values of "not young" and "not old" can be computed as 0.2 and 0.7, respectively.

Another important feature of the theory is fuzzy if–then rules (e.g., *if x is Small and y is Fast then z is High*, where Small, Fast, and High are fuzzy sets). Such rules have been widely used in fuzzy modeling and control as a powerful tool for quantitatively representing knowledge and experience [29,30,36]. Conclusions can be inferred from fuzzy rules for given partially matching inputs [44,46].

In this paper, we develop, in a systematic manner, a fuzzy logic-based general-purpose computational fuzzy RPD model. Compared with the literature, our novelties include the following. First of all, fuzzy sets are employed to formalize the representation of imprecise cues, and fuzzy reasoning is used to abstract higher level cues from lower level elementary data. Second, to search for the experience that is most applicable to the situation of interest, similarity measures are developed to evaluate the degree of matching between the situation and a prior experience because dealing with partial matching is critical for many real-world problems. These similarity measures can handle different types of cues involving nominal values, quantitative data and fuzzy numbers/sets. Finally, a quantitative action evaluation strategy empowered by fuzzy logic is developed to examine whether a course of action is workable.

To better establish the validity of the proposed model and demonstrate its practical utility, we applied it to a pilot study of assessing the causality between a drug (we chose Cisapride) and its adverse effects in the context of post-marketing surveillance. One hundred hypothetical patients were involved in the study whose characteristics were created based upon the profiles of more than 1000 patients treated with the drug at our Veterans Affairs Medical Center before it was withdrawn from the market in late 1990s due to the severe adverse events. Decisions made by the model were compared to those made by two independent physicians. The extent of the agreement was evaluated by the weighted Kappa statistic and results suggested good to excellent agreement between the model and the physicians.

To the best of our knowledge, there is no report in the literature on medical application of the RPD modeling approach, conventional/classical or computational. Therefore, the evaluation itself is novel with respect to application.

The remainder of this paper is organized as follows. Section 2 briefly introduces the classical RPD model. Section 3 describes in detail the proposed computational fuzzy RPD model. To better present the theoretical development and also show the practice relevance of the model, we use detection of (unknown) drug adverse events as an illustrative example throughout this section. In Section 4, the model is preliminarily validated using 100 hypothetical patients. The statistic results of comparing the decisions made by the proposed model and two physicians are shown. We wrap up with conclusions in Section 5.

2. Brief background on classical recognition-primed decision model

Fig. 1 shows the classical RPD model that includes two processes: (1) assessing the current situation to recognize which course of action makes sense, and (2) evaluating the course of action by mental simulation [17,42]. It assumes that experts employ "situation-experience matching" decision rules in which they match the current situation with prior experiences. Once they are matched, the decisions (or actions) in that experience will be utilized to solve the current problem. Being more than simple matching, the RPD model provides a well-structured process in which decisions are part of a decision-action cycle rather than a single judgment. This process enables decision makers to adapt and refine a decision according to feedback and changing situation.

Four by-products are generated in the first process (Fig. 1): relevant cues, expectancies, plausible goals, and actions. Cues represent the higher-level information (synthesized from elementary or environmental data) that

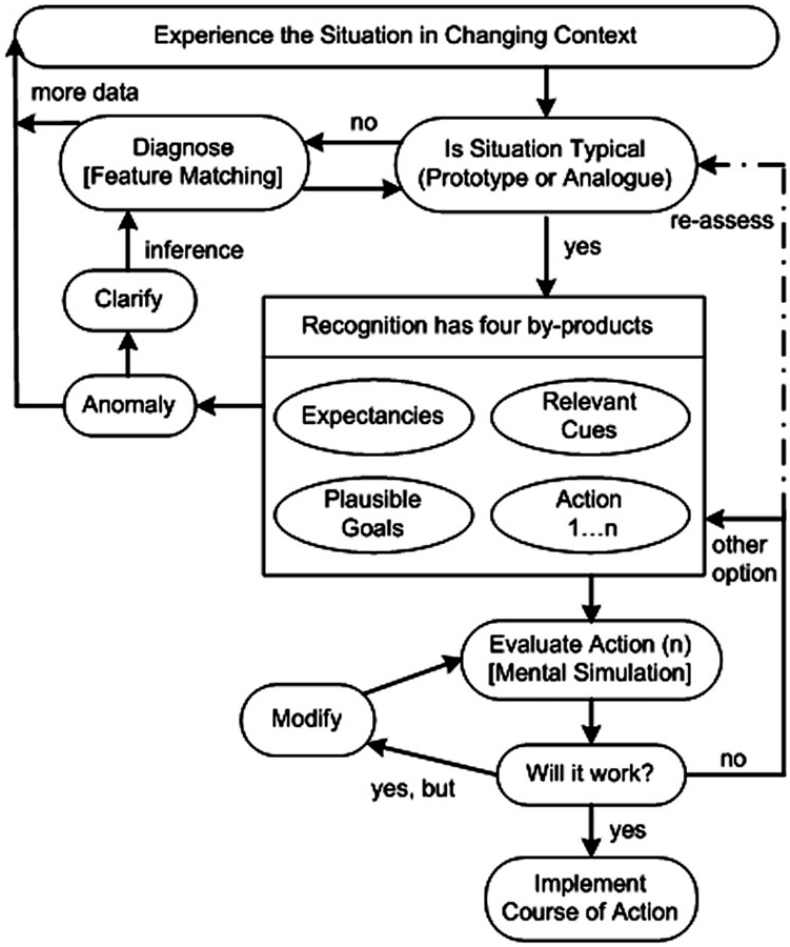

Fig. 1. The classical RPD model [17].

a decision maker must pay attention to. Expectancies describe what will happen next as the current situation continues to evolve in a changing context. If one of them is found to be "anomaly" (i.e. what the decision maker expects conflicts with the new observed facts), it indicates that the current situation is misinterpreted and adjustments may be required. Goals represent an end state that the decision maker is trying to achieve. Actions represent a set of potential decisions that the decision maker can take in the current situation.

In the second process illustrated in Fig. 1, the course of action will be singly evaluated by imaging how a particular action will evolve. The decision maker may either modify the course of action, or reject it and look for another option.

3. Proposed computational recognition-primed decision model

Our development of a computational decision-making model was motivated by a real medical application of computer assisted post-marketing surveillance of unknown severe adverse drug reactions (ADRs), which represents a significant public health problem. In the context of the present paper, an ADR refers to the unanticipated drug-associated adverse incident(s) that follows the administration of a drug when it is used properly and at an appropriate dosage [8]. ADRs can be severe with serious long-term effects and even cause death [20].

To illustrate our model more clearly, we will utilize some of the cognitive processes that a physician would employ when making decisions regarding causality assessment between drug and adverse effect. The description and formalization of this application do not, and cannot, cover all aspects of the decision making related to the ADR detection problem. We focus on how a physician assesses the evidence for the causality in an individual patient case. Our intention here is to demonstrate the applicability of the proposed model in the medical

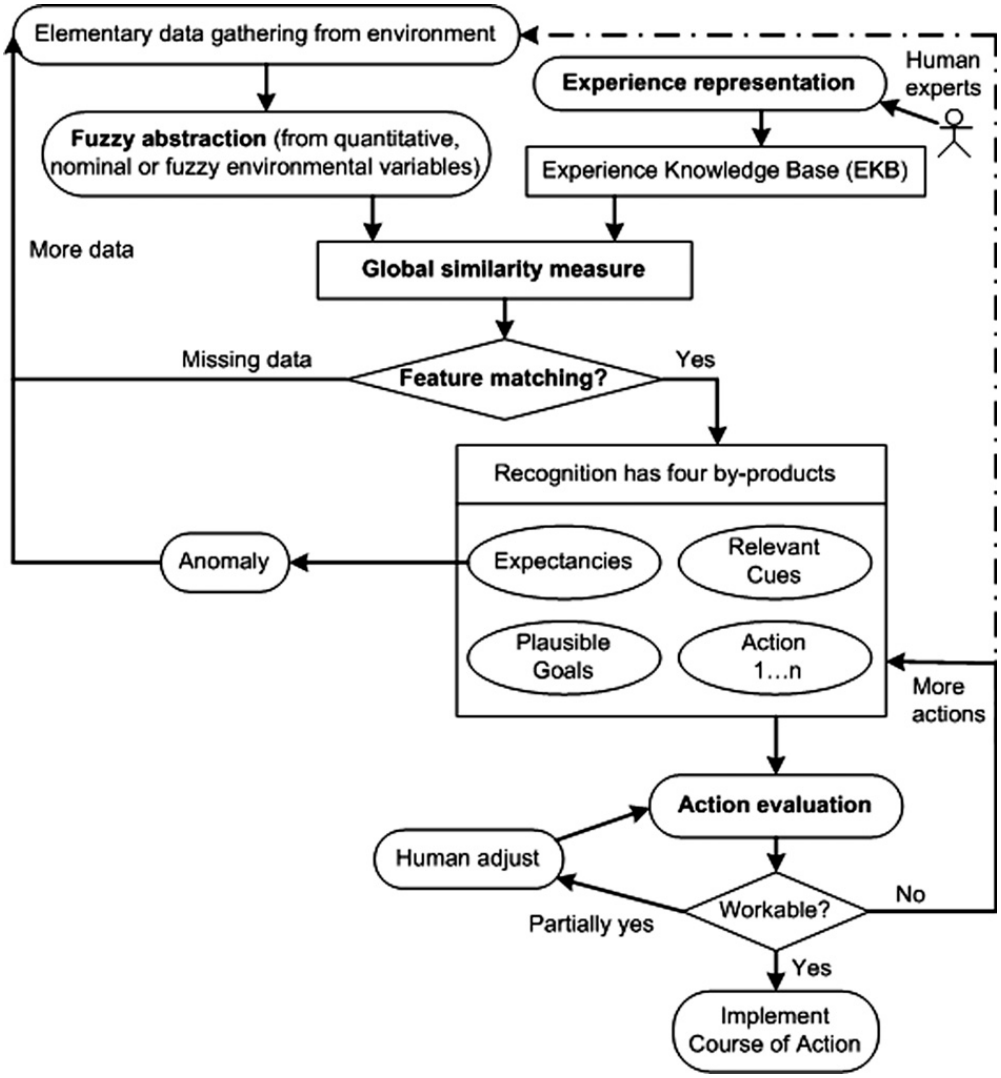

Fig. 2. The proposed fuzzy logic-based computational fuzzy RPD model. The differences between Figs. 1 and 2 outline the proposed fuzzy RPD framework with respect to the classical qualitative RPD model.

domain. We stress that the proposed model is general and useful for many application domains besides medicine.

To develop such a model, the primary difficulties are: (1) how to quantitatively represent an experience, (2) how to quantitatively perceive, comprehend, and assess current situation, (3) how to quantitatively decide which past experience is most similar to the current situation, and (4) how to quantitatively evaluate whether the course of action is workable or not.

Our fuzzy RPD model deals with these issues (Fig. 2). The box ''Elementary data gathering from environment'' is the input of the model and the ''implementation'' of the chosen action is the output. Compared with the classical RPD model shown in Fig. 1, two boxes, ''Fuzzy abstraction'' and ''Experience representation'', are added in order to help the reader better understand the computational model. In the classical model, these two processes are assumed to be internal activities of human mind and are not explicitly represented in Fig. 1. We now explain the proposed fuzzy RPD model component by component.

3.1. Situation awareness

A decision task is often characterized by a pattern of higher level cues. In the phase of situation awareness, each cue is abstracted or synthesized from some external environmental variables whose values are observable.

Feature-matching is then used to diagnose the current situation. That is, these synthesized cues are compared with the pre-specified domain-dependent features. If they match, the current situation is recognized as typical and four by-products are achieved (i.e., the types of goals, important cues, next expectancies, and a course of action that likely will succeed). If this fails due to lack of information on experience, more information will be collected and a new feature-matching process will be performed.

3.1.1. Cue types

Cue is a key concept in the RPD methodology since both the situation awareness and action evaluation processes are centered on cues. Cues are usually abstracted or fused from elementary data and their types could be quantitative, nominal or fuzzy in the proposed computational fuzzy RPD model. A quantitative cue refers to a variable whose values are described by a certain order. It can be either continuous or discrete. While a quantitative continuous cue uses real values (e.g., blood pressure), a quantitative discrete cue uses integer values (e.g., number of children). A nominal or symbolic cue is a discrete cue whose values are not necessarily in any order (e.g., patient gender). The addition of fuzzy cues to our model is novel relative to the literature and is inspired by the need for representing information encountered in the real world that is imprecise in nature. Fuzzy information may be due to the imprecision of real data or arise from subjective judgments. For instance, the representation of causal relationship between an adverse event and a specific drug may be qualitative using such words as probable, possible, unlikely, rather than precise values. Sometimes even though a variable has precise values one may only care about categories (e.g., young, old). Such imprecise classes play an important role in human thinking. Therefore, the cues in an experience are more likely to be vague due to the imprecise nature of abstract thoughts and concepts.

In the case of ADR assessment, the cues employed to evaluate the causality are abstracted from the description in Edwards' paper [8] and summarized in Table 1. The degree of causality is categorized as ''very likely'', ''probable'', ''possible'', ''unlikely'', and the evidence to determine each term is defined by a pattern of cue values. Among these cues, *temporal association* is the most important one. It refers to the temporal relationship between taking the drug and occurrence of the adverse event. *Other explanations* denote alternative explanations by concurrent disease or other drugs. *Dechallenge* is defined as the relationship between withdrawal of the drug and abatement of the adverse effect. Contrary to *dechallenge*, *rechallenge* describes the relationship between re-introduction of the drug and recurrence of the adverse event. The weights for these cues are design parameters and are assigned by domain experts.

The cues *temporal association*, *dechallenge* and *rechallenge* are all fuzzy variables which can be represented by fuzzy sets or derived through fuzzy reasoning. Interestingly, the linguistic terms like ''possible'' or ''unlikely'' employed to represent these cues are frequently used in the literature [8], which indicates the vagueness of both these cues and the problem. This also suggests fuzzy set theory is a natural way to formalize this problem.

3.1.2. Fuzzy abstraction

In this subsection, we demonstrate how to use fuzzy reasoning to abstract high level cues from elementary data in the proposed computational fuzzy RPD model. Fuzzy sets and fuzzy if–then rules are widely used to represent imprecise information and model human expertise in a variety of domains [1,39,43]. Fuzzy reasoning provides an inference procedure that derives conclusions from known facts and a set of fuzzy if–then rules. These theories suggest a systematic strategy to comprehend observable environmental variables and abstract or synthesize higher level cues.

Table 1
Cues for drug causality assessment

Cues	Cue type	Examples of cue values	Abstraction method	Significance weight
Temporal association	Fuzzy	Likely, possible, unlikely	Fuzzy reasoning	1
Other explanations	Nominal	Yes, no	Crisp reasoning	0.6
Dechallenge	Fuzzy	Likely, probable, unlikely	Fuzzy reasoning	0.7
Rechallenge	Fuzzy	Likely, possible, unlikely	Fuzzy reasoning	0.8

For the cues listed in Table 1, we chose *temporal association* as an example to show how fuzzy reasoning is employed to achieve this process. The cue value of *temporal association* can be inferred from the time duration between taking the drug and appearance of an adverse effect (t_d). It should be noted that in the case of a suspected ADR, exposure to the causal agent (drug) should always precede the effect (ADR) of interest. This distinction is important because the clinical manifestations of an ADR might result from entirely different causes (e.g., underlying diseases). Therefore we define the following fuzzy reasoning rules to link cause (drug) to effect (ADR):

If t_d is short, then *temporal association* is likely.
If t_d is medium, then *temporal association* is possible.
If t_d is long, then *temporal association* is unlikely.

Both t_d and *temporal association* are fuzzy variables which are characterized by the triangular fuzzy sets (Fig. 3). Other fuzzy rules that we used cover the adverse effect of interest (e.g., ventricular tachycardia, syncope) as shown below:

If t_d is *short* and ventricular tachycardia is found, then temporal association is *likely*.
If (t_d is *medium* and ventricular tachycardia is found) or (t_d is *short* and only syncope is found), then temporal association is *possible*.
If t_d is *long*, then temporal association is *unlikely*.

The triangular, trapezoidal, and Gaussian fuzzy sets are arguably the most widely used fuzzy set types in the literature. Note that the triangular type is a special case of the trapezoidal type. The trapezoidal type is considered, to some extent, similar to the Gaussian type. There does not exist a general theory to guide the user to select the best type for a given application. Section is case by case and in most application is based on the trial and error approach. The fuzzy values for the variables as well as the fuzzy sets were determined after intensive consultation with an experienced internal medicine physician on the research team.

For a particular ADR, $t_d = 1$ day, then only the first two rules are activated. If the algebraic product fuzzy AND operator and Zadeh fuzzy OR operator are used, we can compute the fuzzy set for the corresponding temporal association:

$$\mu_{c_{\text{temporal\_association}}}(x) = \begin{cases} \frac{2}{15}x, & 0 \leqslant x < 0.5 \\ \frac{2}{225}(28x^2 + 153x - 76), & 0.5 \leqslant x \leqslant 1 \end{cases} \quad (1)$$

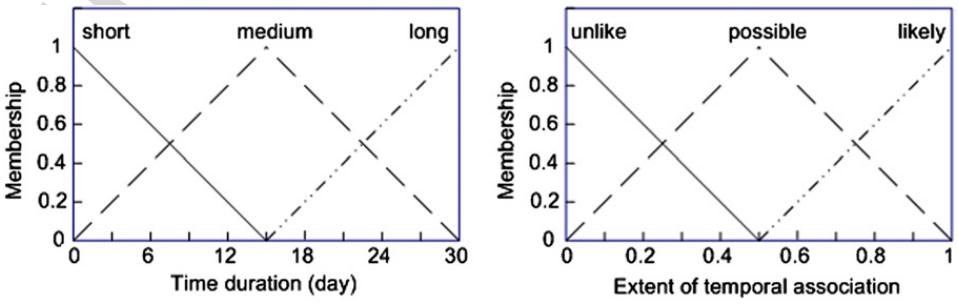

Fig. 3. Fuzzy sets for time duration and temporal association.

This membership function represents the fuzzy cue value abstracted from time duration through fuzzy reasoning. Its value will be compared with the corresponding cue values stored in the experience knowledge base.

The following shows relevant rules that are utilized to extract the fuzzy values of *dechallenge*.

If stop date is available during the time of admission and the patient is discharged alive, then dechallenge is *likely*.
If stop date is not available during the time of admission and the patient is discharged alive, then dechallenge is *possible*.
If temporal association is unlikely, then dechallenge is *unlikely*.

To extract the fuzzy values of *rechallenge*, we use p_1 to represent the first drug-ADR pair and p_2 the second drug-ADR pair on the same patient. The following rules are defined:

If p_1 has *likely* temporal association and p_2 has *likely* temporal association, then rechallenge is *likely*.
If p_1 has *likely* temporal association and p_2 has *possible* temporal association, then rechallenge is *likely*.
If p_1 has *likely* temporal association and p_2 has *unlikely* temporal association, then rechallenge is *possible*.
If p_1 has *possible* temporal association and p_2 has *likely* temporal association, then rechallenge is *likely*.
If p_1 has *possible* temporal association and p_2 has *possible* temporal association, then rechallenge is *possible*.
If p_1 has *possible* temporal association and p_2 has *unlikely* temporal association, then rechallenge is *possible*.
If p_1 has *unlikely* temporal association and p_2 has *likely* temporal association, then rechallenge is *possible*.
If p_1 has *unlikely* temporal association and p_2 has *possible* temporal association, then rechallenge is *possible*.
If p_1 has *unlikely* temporal association and p_2 has *unlikely*temporal association, then rechallenge is *unlikely*.

Comparing relevant cue values with the cue values stored in prior experiences requires similarity measures. We will introduce new measures for the proposed model. But first, let us discuss how to quantitatively represent an experience and define an experience knowledge base.

3.1.3. Experience representation

The proposed model is grounded on domain experts' experiences. As such, prior experiences need to be acquired from human experts and stored in an experience knowledge base for future use. Below, we first give a sample ADR experience and then abstract its formal representation.

Our knowledge base for the task of assessing suspected ADR is achieved by intensive discussion with an experienced internist as well as by careful analysis of relevant papers in the literature. According to the classification scheme in [8], a particular pattern of cue values characterizes a specific type of causality which may require certain courses of action to handle the ADR. Therefore, we can define various experiences, each of which is associated with a type of causality (e.g. very likely, probable, and possible). These experiences form an experience knowledge base. The following is a sample experience which is illustrated in natural language for the easier understanding:

Experience_N: The causality between the drug and a particular ADR is *very likely*.
Cues: (1) The occurrence of ADR has a *likely* temporal association with the drug.
(2) There is *no* other explanation.
(3) The ADR has *likely* dechallenge relationship with the drug.
(4) The ADR has *likely* rechallenge relationship with the drug.
Goal: Find the strength of the causality between a drug and a particular ADR.
Actions: (1) Suggest for further analytical studies.
(2) Suggest filing an ADR report online.
Expectancy: (1) More similar cases are available.
(2) Relevant information for filing an ADR report is available.

Note that the definition of an experience knowledge base is always goal-oriented. From physician's perspective, another critical goal in the ADR problem would be how to manage the patient who most likely has the ADR. In this case, more relevant cues may be required, and the action would be to reduce the dosage of the drug or discontinue the drug and initiate alternative therapy.

To make our work systematic, we now provide a general representation. An experience can be represented by a quintuple:

$$e_i = (x_i, C_i, E_i, G_i, A_i)$$

in which x_i is the name of the ith experience in an experience knowledge base. C_i is a collection of high-level cues that are abstracted from environment variables. For a medical problem, environment variables could be any lower level information that may affect a decision-making, such as physician's observation (e.g., symptoms), patient's medical history, and laboratory tests. E_i and G_i denote the set of expectancies and goals of the experience, respectively. A_i is a set of courses of action associated with the experience, each of which is a sequence of lower level actions. In Sections 3.1.5 and 3.2, we will describe how a fuzzy logic-based representation of cues and courses of action is used in the proposed fuzzy RPD model for realizing cue matching and evaluating courses of action.

3.1.4. Similarity measures

In the proposed computational fuzzy RPD model, similarity measures are employed to assess the degree of likeness between the current situation and past experience so as to find out whether the past experience could be used to solve the current problem. Other computational RPD models use different ways (e.g. crisp matching [25], neural network [22,31]) to achieve the matching between the current situation and past experience, but they either cannot capture partial matching or assume that all cues are crisp values. Our approach can overcome these limitations.

We assume that (1) the cues in current situation and the ones in the past experience have the same set of features or attributes, and (2) the values assigned to them characterize the current situation and past experiences. Suppose that V and V', two vectors, denote the set of cue values in the current situation and a prior experience, respectively:

$$V = (c_1, c_2, \ldots, c_j, \ldots, c_n),$$
$$V' = (c'_1, c'_2, \ldots, c'_j, \ldots, c'_n),$$

where cues c_j and c'_j can be nominal, quantitative or fuzzy values. The similarity measure between V and V', called *global similarity*, is needed and such measure should be computed using the *local similarities* calculated for the cue value pairs c_j and c'_j. There are many similarity measures in the literature [7,41]. However, they are not capable of handling the different types of cues in our model. Furthermore, they do not provide a means to aggregate local similarities for pattern matching when the required information is not satisfied. Therefore, we had to develop new ones ourselves.

We propose a local similarity measure that can handle heterogeneous types of cues. After a set of local similarities for known cue value pairs are obtained, they are amalgamated into a *global similarity* measure. We define the following heterogeneous similarity measure to calculate the local similarity between c_j and c'_j:

$$S_L(c_j, c'_j) = \begin{cases} 0, & \text{if } c_j \text{ or } c'_j \text{ is unknown} \\ overlap(c_j, c'_j), & \text{if cue } j \text{ is nominal} \\ 1 - normalized\_diff(c_j, c'_j), & \text{if cue } j \text{ is quantitative} \\ fuzzy\_sim(c_j, c'_j), & \text{if cue } j \text{ is fuzzy value} \end{cases} \tag{2}$$

Decision makers often have to make decisions under the condition of incomplete information. In the above definition, the cue similarity is set 0 if either of the cue values is unknown. The function *overlap( )* is defined as:

$$overlap(c_j, c'_j) = \begin{cases} 1, & \text{if } c_j = c'_j \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

That is, for nominal cue values, the similarity is 1 if the cue values are equal; otherwise it is 0. Computing the similarity for quantitative cue values involves distance measure *normalized_diff*:

$$normalized\_diff(c_j, c'_j) = \frac{|c_j - c'_j|}{\Delta_j} \tag{4}$$

where $\Delta_j = a_j - b_j$ is employed to normalize the cue difference, and a_j and b_j are the maximum and minimum values for cue j, respectively.

The last expression in the above formula, $fuzzy\_sim(c_j, c'_j)$, deals with cues represented by fuzzy sets. Let cue j be defined on the universe of discourse X and x be an element of X. In this case, fuzzy cue values c_j and c'_j are two fuzzy sets whose membership functions are defined in terms of x. Their similarity could be defined on the basis of possibility measures on the $[0, 1]$ interval [5]:

$$fuzzy\_sim(c_j, c'_j) = \begin{cases} poss(c_j, c'_j) & \text{if } poss(\bar{c}_j, c'_j) < 0.5 \\ (1.5 - poss(\bar{c}_j, c'_j)) * poss(c_j, c'_j) & \text{otherwise} \end{cases} \tag{5}$$

where

$$poss(c_j, c'_j) = \max_x(\min(\mu_{c_j}(x), \mu_{c'_j}(x))) \quad \forall x \in X \tag{6}$$

Here, $\mu_{c_j}(x)$ and $\mu_{c'_j}(x)$ are the membership functions of fuzzy set c_j and c'_j, respectively. The min( ) and max( ) are standard fuzzy operators, and hence $\max_x(\min(\mu_{c_j}(x), \mu_{c'_j}(x)))$ computes the maximum of all the minimums between pairs $\mu_{c_j}(x)$ and $\mu_{c'_j}(x)$ for all the elements x. $\bar{c}_j$ is the complement of c_j (i.e., $\mu_{\bar{c}_j}(x) = 1 - \mu_{c_j}(x)$).

Eq. (5) is one of the most commonly used similarity functions for fuzzy pattern matching [6,7], and furthermore, it has been incorporated into some fuzzy inference engines (e.g. software FuzzyJess [26]) for general use.

What we have discussed so far involves only the local similarity for a single cue value pair c_j and c'_j. For our proposed model, a global similarity measure is also needed to combine the local similarities. Let us continue to use the ADR problem as an example to illustrate the development. We now calculate all the local similarities first and then combine them.

Recall that the cue value for *temporal association* has been abstracted in Section 3.1.2. It is represented as a fuzzy set whose membership function is given by Eq. (1). Its cue value stored in *Experience_N* is "likely" with the membership function being:

$$\mu_{c'_{\text{temporal\_association}}}(x) = \begin{cases} 0, & 0 \leqslant x \leqslant 0.5 \\ 2x - 1, & 0.5 \leqslant x \leqslant 1 \end{cases} \tag{7}$$

To calculate the local similarity between these two cue values, we apply Eq. (5) and get

$$S_L(c_{\text{temporal\_association}}, c'_{\text{temporal\_association}}) = 0.92$$

where $c_{\text{temporal\_association}}$ and $c'_{\text{temporal\_association}}$ represent the cue values of *temporal association* in the current situation and the chosen experience in the past, respectively.

For cues *dechallenge* and *rechallenge*, we can employ the same procedure to abstract their actual cue values and find out their similarities with corresponding cue values store in *Experience_N*. Here, without loss of generality, we simply assume that $S_L(c_{\text{dechallenge}}, c'_{\text{dechallenge}}) = 0.86$ and $S_L(c_{\text{rechallenge}}, c'_{\text{rechallenge}}) = 0.79$. For the cue *other explanations*, we regard it as a nominal variable since its values "yes" and "no" are not fuzzy. We assume that the value of this cue is "no" for the current situation. Therefore, we can compute $S_L(c_{\text{other\_explanations}}, c'_{\text{other\_explanations}}) = 1$ by applying Eq. (3).

After obtaining the similarities for each of the cue value pairs, our next step is to integrate them into a global similarity $S_G(V, V')$ using the following formula, where V and V' represents two sets of cue values:

$$S_G(V, V') = \begin{cases} 0, & \text{if there exists } j \in (1, n), \text{ for which } w_j = 1 \text{ and } S_L(c_j, c'_j) < \delta \\ \dfrac{\sum_{j=1}^{n} w_j S_L(c_j, c'_j)}{\sum_{j=1}^{n} w_j}, & \text{otherwise} \end{cases} \tag{8}$$

where $\delta \in [0, 1]$ is a threshold design parameter determined by the user. $w_j \in [0, 1]$ is the weight for cue j, which represents the relative significance of the cue and is also assigned by the user. To reuse the actions in a past experience, some important cue or cues are often required to be satisfied. That is, if the value of a required cue in the current situation is not close to the value of the same cue in a past experience, this experience cannot be utilized to solve the current problem no matter how similar the other cues are. For example, *temporal association* is a required cue to assess the causal relationship between a drug and an adverse event. If there is no reasonable temporal relationship between the time of taking the drug and the time that development of an adverse event occurs, it is almost certain that this adverse event is not caused by the drug even if all the other factors (e.g., dechallenge) match well. In (8), we deal with this issue by assigning 0 to $S_G(V, V')$ when one of the important cues whose weight is 1 is not similar.

Outside of this exception, global similarity is computed by the second half of the formula, which is the normalized weighted local similarities, making the global similarity lie in [0, 1].

Continue our ADR example. Using Eq. (8), we can calculate the global similarity value between the current situation and *Experience_N* as:

$$S_G(V, V') = (0.92 \times 1 + 1 \times 0.6 + 0.86 \times 0.7 + 0.79 \times 0.8)/(1 + 0.6 + 0.7 + 0.8) = 0.89$$

Here, V refers to the set of observed cue values and V' represents the set of cue values stored in *Experience_N*.

3.1.5. Feature matching

The feature matching process is carried out through the global similarity measure. We assume that there are different types of experience knowledge bases, and each base can deal with a specific decision type which could be inferred from the information associated with the decision task [42]. Once the decision type is determined, the experience knowledge base (and thus the collection of cues) to be matched is fixed. After that, the current situation is compared with the past experiences in the selected experience knowledge base. Suppose that V is a set of observed cues in the current situation and V'_i $(i = 1, 2, \ldots, M$, where M is the number of experiences in the experience knowledge base) is a set of cues considered in a past experience. The matching is performed through computing the global similarity between V and V'_i coordinate-wise using Eq. (8) in the feature space. The current situation is said to be matched with the past experience to degree α, if $S_G(V, V'_i) \geqslant \alpha$ where $\alpha \in [0, 1]$ is a similarity threshold chosen by the user. If more than one experience is matched with the current situation, the one with the highest global similarity is chosen as the matching result.

3.2. Action evaluation

While situation awareness is to diagnose a problem, action evaluation is a process of selecting a workable course of action to solve the problem. When applying the RPD methodology to medical decision making, a course of action may refer to a medical procedure, a treatment plan, etc. For human decision makers, action evaluation can be achieved through mental simulation: people image how to assemble a course of action, how the actions may evolve and whether the relevant goal can be fulfilled. For the computational fuzzy RPD model, we assume that each course of action has an initial state, a terminal state and several actions between

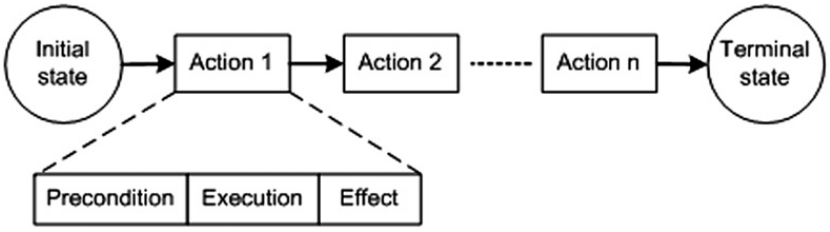

Fig. 4. A course of actions of the computational fuzzy RPD model.

them. Each action has three parts in sequence: *precondition*, *execution* and *effect* (Fig. 4). While an initial state is usually the trigger for a series of actions, the terminal state often stands for our final expectation to be reached after these actions. For instance, the diagnosis result (e.g., a disease) for a patient could be an initial state to prompt a therapy plan, and in this case the terminal state could be the cure of that disease. The *precondition* of an action is a set of cues that serve as the prerequisite of *execution*. For example, a patient's age, physical conditions, and medical history may be important factors that must be considered when his/her physician makes a plausible treatment action. The *effect* is our expectation for the execution of an action. Note that the *effect* is not the actual execution results which may be different from our expectation. Usually, two actions in sequence have causal relationship, that is, the effect of one action is one of the preconditions for the subsequent action. Intuitively, the initial state is one of the preconditions for the first action, and the terminal state is the effect of the last action.

To evaluate a course of action, we first compare the initial state (often along with a few other cues) against the *precondition* of *action 1* using the similarity measures introduced earlier. If they well match (i.e., their global similarity measure is greater than a predetermined threshold), the *effect* of *action 1* and other cues will be employed to compare with the *precondition* of *action 2*. We continue this process until we reach the terminal state which is one of the effects of the last *action*. If we use $S_G(V_1, V'_1), S_G(V_2, V'_2), \ldots, S_G(V_n, V'_n)$ to represent the similarities between the current state and the preconditions of *action 1* until *action n*. Consequently the degree of our confidence, represented as confidence factor (CF), with this course of action is defined as:

$$\mathrm{CF} = S_G(V, V'_i) \otimes [S_G(V_1, V'_1) \otimes S_G(V_2, V'_2) \cdots S_G(V_n, V'_n)] \tag{9}$$

where $\otimes$ denotes a fuzzy conjunction operator (e.g. algebraic product, Zadeh min operator). V and V'_i represent the sets of cue values in the current situation and in the prior experience that is selected through the feature matching process, respectively. $S_G(V, V'_i)$ is added to the formula because it reflects the degree of appropriateness to use the chosen experience. As such, its value should affect our total confidence with the selected course of action. CF provides a quantitative way to measure the extent to which the initial state can be transferred to the terminal state through a course of action. The larger the CF value is, the more confident we are.

To show the action evaluation process, we take the action "Suggest for further analytical studies" in *Experience_N* as an example. This action is the simplest in that it cannot be further divided into lower level actions. The *precondition* and *effect* of this action would be "the strength of signal pair (i.e. a drug and a particular ADR associated with this drug) in the current patient is evaluated as 'very likely'" and "this patient is selected for further analytical studies", respectively. Calculating the similarity between the current situation and the *precondition* for the action using Eqs. (2) and (8) yields $S_G(V_1, V'_1) = 1$, if we assume that the strength of signal pair is "very likely" after evaluating the relevant cues, Now we can calculate the confidence factor: $\mathrm{CF} = 0.89 \times 1 = 0.89$ using the algebraic product operator for the conjunction. If this CF is satisfactory according to a predefined user criterion, the course of action will be implemented or adjusted by human intervention in order to handle the current situation. Otherwise, a different course of action will be evaluated using the same procedure. If a satisfactory course of action is not achieved after all the actions have been evaluated, more relevant information needs to be collected. A new evaluation procedure starts or a novel course of action is added through human intervention.

The process of selecting a workable course of action is straightforward in the above example. In general, this is usually the case because it is an important feature of the RPD methodology, which is based on the idea

that experts spend most of their time and energy on understanding the situation in naturalistic environments. Once the situation is recognized, properly selecting a course of action almost always automatically follows. The course of action is usually the one that was successful in the previous, similar situation [18,25].

4. Preliminary evaluation of the model

To establish the proposed model more firmly and also to demonstrate its practical utility, we carried out a preliminary evaluation experiment. The experiment was related to the ADR detection for post-marketing surveillance described above. More specifically, we sought to assess the model's ability to quantitatively identify the strength of the causal relationship between a drug and an adverse effect. We compared the model's decisions with physicians' and used the weighted Kappa statistics to establish the extent of their agreements.

4.1. Evaluation design

We targeted the drug Cisapride in this study. The drug was introduced into the marketplace in 1993 upon approval by the Federal Drug Administration (FDA) for the treatment of gastro-esophageal reflux. It provided symptomatic relief for this painful, but non-fatal condition. Spontaneous reports linking Cisapride with a sometimes fatal cardiac ventricular arrhythmia began to appear in the FDA and the medical literature. Approximately seven years later the drug was removed from the marketplace because of idiosyncratic, high-risk, adverse reactions.

With approval from the Human Investigations Committee, we undertook a descriptive study of all patients treated with Cisapride at our Veterans Affairs Medical Center between 1993 and 1999. The sources for data included the standard hospital discharge abstract database and the pharmacy database. Patient specific data were linked by patient identifiers, e.g. name, birth date. A statistically de-identified data set was provided to us for analysis by a hospital data analyst. 1,015 patients were identified that had received Cisapride on one or more encounters in the institution. Among this cohort, 21 patients were diagnosed with the cardiac arrhythmia of interest and 303 patients died during the period covered by this study. A group of 10,326 control patients that never received Cisapride were also identified by randomly selecting controls for every case that were matched by hospital admission date (+/−30 days). These patients were used to identify the data fields that would provide useful information for weighting potential causal linkages among signal pairs. After identifying relevant fields in the data set of the patients who were exposed to Cisapride, we then created a set of 100 hypothetical patients. Each case contained information regarding signal pairs including the administration of the drug and the adverse event under review as a potential toxic side-effect of the drug administration. Cases varied in the strength of the possible causal association between the drug and an event based on (1) the chronological association between the drug start date and onset of the adverse event; (2) evidence for dechallenge; (3) evidence for rechallenge; and (4) presence or absence of an alternative explanation for the adverse event. Hence, the signal pairs for the hypothetical patients represented a spectrum of causal weights from a "very likely" to "unlikely" causal link. The data set of the 100 hypothetical patients was comparable to real data sets of patients who received Cisapride. We created a Microsoft Access database for storing the hypothetical data that would be readily accessible for continuous scrutiny by a computer program.

The strength of the causal relationship between the drug and an adverse effect is categorized as "very likely", "probable", "possible" and "unlikely". Based on the assignment of the likelihood of association between signal pairs as determined by our proposed fuzzy RPD model, patients would be selected for further studies (i.e., actions of the proposed model) if the likelihood is high or for no further action if the likelihood is low. More specifically,

- Signal pairs assigned to "very likely" association or "probable" association will be included in a cohort of exposed subjects for further analytical studies.
- Signal pairs assigned to "unlikely" association will be excluded from further analytical studies.
- Signal pairs assigned to "possible" association will be excluded from further analytical studies. It is conceivable, however, that if the analytical study design adjusts for the weight of the association this group might be included in further studies.

The further actions would include the following steps: (1) more information regarding the drug exposure and adverse outcomes will be sought from the medical records of the selected signal pairs; (2) an appropriate group of control subjects will be identified; and, (3) an analytical study will be completed. These tasks, however, are beyond the scope of the present paper and will be addressed in our future work.

These 100 hypothetical patients were used to validate the assignment of causal link strengths by the proposed computational fuzzy RPD model and physicians. The model was used to identify and assign likelihoods of causal associations between the drug (cause) and adverse event (effect) for the 100 hypothetical patients. To provide preliminary validation for the capacity of the proposed model, two physicians, both trained in internal medicine, participated in the experiment. They were provided a general overview of the objectives of the study and were asked to independently review each of the 100 scenarios and make a judgment regarding the likelihood of a significant causal association between the drug and adverse events. Physicians assigned a numerical score between 1 and 4 based on the strength of the perceived causality, where 4 means ''very likely causal relationship'', 3 is ''probable casual relationship'', 2 indicates ''possible causal relationship'', and 1 stands for ''unlikely causal relationship''.

We examined agreement between the scores generated by the proposed fuzzy RPD model and those by each of the two physicians. Because scoring of the causal association was based on ordinal data, we utilized the weighted Kappa statistic to estimate the levels of agreement [11,32]. The Kappa coefficient is an estimate of the agreement between two raters after chance agreement is controlled. Kappa scores range between 1 (complete agreement) and 0. Because there are no ''absolute'' interpretations of the Kappa coefficients, experts have offered opinions regarding interpretations of agreement. Landis and Koch [21] suggest that for values of Kappa greater than 0.75, there is excellent agreement. For values less than 0.4, there is poor agreement, and for values between 0.40 and 0.75, there is fair to good agreement.

Table 2
Drug causality assessment results generated by the proposed computational fuzzy RPD model and two independent physicians (P1 and P2 mean physician #1 and physician #2, respectively)

Patient ID	Fuzzy RPD model	P1	P2	Patient ID	Fuzzy RPD model	P1	P2	Patient ID	Fuzzy RPD model	P1	P2	Patient ID	Fuzzy RPD model	P1	P2
1	1	1	1	26	2	2	3	51	2	2	2	76	3	3	3
2	3	3	3	27	3	3	4	52	2	2	2	77	2	2	2
3	2	2	3	28	4	4	4	53	3	3	3	78	1	1	1
4	4	4	4	29	3	3	4	54	2	2	2	79	4	4	4
5	4	4	3	30	3	3	3	55	3	3	4	80	4	4	4
6	4	4	4	31	2	2	3	56	3	3	4	81	2	2	2
7	1	1	2	32	2	2	2	57	2	2	2	82	3	3	4
8	4	3	4	33	4	3	4	58	4	4	4	83	3	3	4
9	2	2	3	34	3	3	4	59	2	2	2	84	2	2	2
10	4	4	4	35	2	2	2	60	3	3	3	85	2	2	2
11	3	3	3	36	3	3	3	61	4	4	4	86	2	2	2
12	1	1	1	37	1	1	1	62	3	3	3	87	2	2	2
13	2	2	2	38	3	3	3	63	2	2	2	88	4	4	4
14	2	2	2	39	3	4	4	64	4	4	4	89	2	2	2
15	1	1	1	40	2	2	3	65	2	2	2	90	3	3	4
16	2	2	2	41	2	2	3	66	1	1	1	91	4	4	3
17	4	3	4	42	3	3	4	67	3	3	4	92	1	1	1
18	3	3	3	43	3	3	3	68	2	2	2	93	2	2	2
19	2	2	2	44	4	4	4	69	3	3	4	94	2	2	2
20	1	1	1	45	4	3	4	70	3	3	3	95	4	4	3
21	3	3	3	46	4	3	4	71	3	3	4	96	3	3	4
22	2	2	3	47	2	2	2	72	4	4	3	97	2	2	2
23	3	3	3	48	3	3	4	73	4	4	4	98	2	2	2
24	2	2	3	49	2	2	2	74	2	2	2	99	4	4	3
25	3	3	4	50	3	3	4	75	2	2	2	100	3	3	4

Table 3
95% confidence intervals for weighted Kappa coefficients from Asymptotic formula and Jackknife method

	Kappa coefficient	Asymptotic 95% confidence interval	Jackknife 95% confidence interval
Physician 1 vs. fuzzy RPD model	0.939	(0.891, 0.986)	(0.891, 0.988)
Physician 2 vs. fuzzy RPD model	0.700	(0.605, 0.792)	(0.606, 0.798)
Physician 1 vs. Physician 2	0.657	(0.560, 0.754)	(0.561, 0.760)

4.2. Evaluation results

Table 2 summarizes the assignment of scores for the strength of the causal association provided by the proposed computational fuzzy RPD model and the two physician reviewers. The estimate of agreements is as follows: Kappa = 0.939 for physician 1 and the model; Kappa = 0.700 for physician 2 and the model; Kappa = 0.657 for physician 1 and physician 2. These coefficients suggest good to excellent agreement between the proposed model and the physicians. We computed the confidence intervals using both the asymptotic formula and the jackknife method (leave one out method). The results of these two methods agreed to the second decimal as shown in Table 3.

5. Conclusion

We have developed a novel general-purpose computational fuzzy RPD model using fuzzy logic technology. Our approach has several desirable features. First, fuzzy sets and fuzzy reasoning are employed to quantitatively represent and interpret imprecise information, and handle the uncertainty in the decision-making process. Second, local and global similarity measures are created to evaluate the degree of feature matching. These similarity measures are very flexible since they can not only handle different types of information (e.g. quantitative, nominal, and fuzzy) but also incorporate various conditions including the calculation of similarity at presence of missing information and the aggregation of similarity values even when the required information is not satisfied. Finally, we have developed a more realistic action evaluation strategy, an issue that has not been well addressed in the literature. Based on the hospital patient data, we have designed and implemented a preliminary validation experiment for the proposed model in the context of drug ADR detection. The resulting Kappa statistics indicate excellent agreement between the model and the two physicians.

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