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A methodology to generate a belief rule base for customer perception risk analysis in new product development

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ABSTRACT

New product development (NPD) is crucial for a company's success in a competitive market. Meanwhile, NPD is a process associated with great complexity and high risk. To ensure its smooth operation, risks involved in an NPD process need to be analyzed in a proper way. In this paper, a novel method is proposed to generate a belief rule base (BRB), which is the basis of the Belief Rule-Base Inference Methodology using the Evidential Reasoning (RIMER). Due to its capability in dealing with complex reasoning problems under uncertainty, RIMER is then applied to assess customer perception risk (CPR) in an NPD process. To test and validate the method proposed in this paper, a case study of an "Interactive Doll" is conducted at the end of the paper.

1. Introduction

New product development (NPD) projects, especially for those involving radical innovation, are usually risky but bring considerable returns (Keizer & Halman, 2007). During the NPD period, although primary customer information is captured, target customer's attitudes and perceptions would not keep unchanged due to various reasons, e.g., variation of market situations in fashion and trends and rapid changes in technologies (McDermott & O'Connor, 2002). The risk incurred by changes in target customers' perceptions towards the new product in NPD process is to be explained by the customer perception risk (CPR) in this paper.

In current literature, many risk analysis methods have been introduced. However, most of them are based on qualitative analysis or oversimplified realities, thus, there is a need to find a method that can provide an analytical and realistic way to analyze risks with different kinds of uncertainties taken into consideration. The Belief Rule-Base Inference Methodology using the Evidential Reasoning (RIMER) (Yang, Liu, Wang, Sii, & Wang, 2006a) is such a method, which can provide a realistic and informative way for risk analysis. However, how to generate a belief rule base (BRB), which is the basis of RIMER, is seldom discussed.

Facing this situation, this paper is intended to propose a novel method to generate a BRB. The method establishes the relationship between Bayesian Network (BN) and BRB and provides a way to measure the influence of different antecedent attributes on the consequence in a belief rule in a quantitative way. More importantly, it can reduce biases and inconsistencies involved in the BRB generation process. Based on the generated BRB, RIMER (Yang et al., 2006a) can then be applied for CPR analysis.

The paper is organized as follows. In Section 2, relevant literature is reviewed. Section 3 is dedicated to introducing BRB and its advantages comparing with traditional rule base. In Section 4, CPR analysis model is proposed. The method to generate BRB is proposed in Section 5, followed by a case study to demonstrate the proposed method and the application of RIMER in CPR analysis in Section 6. The paper is concluded in Section 7.

2. Related research

2.1. Risk, risk management and risk in NPD

Risk is an inherent part of business, and it is usually modeled by probability of occurrence of undesirable events and impact of the corresponding consequences (Kallman, 2005; Webb, 2003).

As taking a certain level of risk in an appropriate manner could lead to a certain level of return (Kallman, 2005), companies usually make tradeoffs between benefits and risks (Ogawa & Pillar, 2006; Tchankova, 2002). Therefore, understanding and managing risks are utmost important (Gidel, Gautier, & Duchamp, 2005). One of common risks encountered is the gap between the assumed product strategies and the actual customer perceived image of new products (Cheng & Liao, 2007). In other words, customer perceptions towards new products may deviate from company

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expectation. Such a risk may lead to loss of customers or even threaten overall business performance (Langerak, 2001).

2.2. Research on risk analysis techniques in NPD

Different decision tools have been applied to conduct risk analysis in NPD, including behavioral models (Leithhead, 2000; Mobey & Parker, 2002; Mullins & Sutherland, 1998), Failure Mode and Effects Analysis (FMEA) (Carbone & Tippett, 2004), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Kahraman, Buyukozkan, & Ates, 2007), Analytical Hierarchy Process (AHP) (Chen, Lee, & Tong, 2006; Lam & Chin, 2005; Roger, Calantone, Anthony, & Jeffrey, 1999) and its generalization (Chen, Lee, & Tong, 2007), Analytical Network Process (ANP) (Ayag & Ozdemir, 2007; Cheng & Li, 2005; Meade & Presley, 2002; Meade & Sarkis, 1999), BN (Cooper, 2000; Nadkarni & Shenoy, 2001), etc.

However, there are limitations in applying the above-mentioned methods to NPD risk analysis. For example, a behavior model can neither deal with complex analysis tasks, nor can it offer quantitative analysis results. FMEA is often criticized for its over-simplification since it is based on a scoring method, which expresses human's judgments in just a single score. When applied in NPD risk analysis (Kahraman et al., 2007), TOPSIS can only deal with problems which can be constructed into a strict hierarchical structure. AHP also requires that a problem must be constructed in a strict hierarchical structure and that the elements in the same level of a hierarchy be independent of each other, which severely limit the scope of its application since NPD risk analysis is normally conducted in a complex environment with many inter-related elements. The above requirements of AHP are somehow relieved by the introduction of ANP. However, ANP cannot quantify and explicitly demonstrate influences among elements and it is incapable of updating judgments when new evidence becomes available, which is usually the case in an NPD process.

Most limitations mentioned above can be overcome by using BN, but BN requires input probabilities be precise and complete, which means the sum of the probabilities of all states at a node should be exactly 1. However, since risk analysis in NPD requires the consideration of multiple factors with various features under different kinds of uncertainties, it is therefore difficult, if not impossible, for experts to provide complete knowledge on estimating precise probabilities. Therefore, a new method is needed which can accommodate various forms of inputs with different kinds of uncertainties.

RIMER, which was proposed by Yang et al. (2006a), can be regarded as a potential alternative to handle the above problems. It is the combination of BRB and the Evidential Reasoning (ER) method (Yang & Singh, 1994; Yang & Xu, 2002), which is based on the Dempster–Shafer theory (Shafer, 1976) and uses belief degrees in the reasoning process. Similar to BN, RIMER can deal with complex problems which can be modeled in network structures, it can provide a reasoning process in a quantitative way, and it can also update knowledge in light of new evidence. Furthermore, RIMER has some unique features which BN does not have, among which the most important one is that RIMER can accommodate different forms of inputs with different kinds of uncertainties, including incomplete judgments. As such, it is expected that RIMER can provide a promising framework for risk analysis in NPD processes.

As the basis of RIMER is a BRB, how to build such a BRB from experts' knowledge in a rational and consistent way is very crucial to the performance of RIMER. However, the analyses and discussions in Yang et al. (2006a) are based on well-established BRBs and little attention has been paid on how to rationally and consistently generate such BRBs, which remains an open and domain dependent research question without a generic solution currently. Facing the above situation, this paper intends to propose a method to generate BRBs from experts' knowledge regarding CPR in NPD process in a rational and consistent way and then apply RIMER in CPR analysis based on the generated BRBs.

2.3. Summary

Risks are prevalent in NPD process, and the gap between the assumed product strategies and the actual customer perceived image of a product is one of the most important risks which need careful investigation and analysis. To analyze risks in NPD process, several methods are proposed, among which RIMER provides a promising framework. However, how to generate BRB, which is the basis for application of RIMER, remains a problem. In this paper a novel method will be developed to generate BRB for RIMER regarding CPR in NPD process, and RIMER will be applied to analyze CPR subsequently.

3. A summary of belief rule base

3.1. Belief rule base and its components

A conventional rule base is composed of simple IF-THEN rules, and the kth rule can be written in the following form:

$$R_k : if\ A_1^k \wedge A_2^k \wedge \cdots \wedge A_{T_k}^k,\ then\ D_k \tag{1}$$

where $A_i^k (i = 1, 2, \ldots, T_k)$ is a referential value of the$i$th antecedent attribute in the kth rule, and it can take different types of value. T_k is the number of the antecedent attributes used in the kth rule. D_k is the consequence in the kth rule. The symbol $\wedge$ refers to the 'AND' relationship among the antecedent attributes.

The rule expressed in (1) is relatively simple. It does not consider the distribution of consequences, the relative importance of each antecedent, or the relative importance of rules in the rule base.

To take the above aspects into consideration, three concepts are introduced:

- Belief degrees of consequence: in a complex situation, it is likely that the consequence of a rule may take a few values with different degrees of belief to express experts' opinions on the extent to which a consequence value may be true. Suppose the consequence D has N different values, $D_1, D_2, \ldots, D_N$, and the belief degree of D_i is represented by $\beta_i (i = 1, 2, \ldots, N)$, then the consequence with a belief structure can be represented by:

  $$(D_1, \beta_1), (D_2, \beta_2), \ldots, (D_N, \beta_N)$$
- Attribute weight: as indicated in Yang et al. (2006a), the relative importance of an attribute to the consequence of a rule plays an important role in rule base inference. Thus, there is a need to assign a weight to each attribute to describe such importance.
- Rule weight: in order to represent the relative importance of a rule in the whole rule base, we also need to assign a weight to the rule itself, referred to as rule weight (Yang et al., 2006a).

Based on the above three concepts, the simple rule as expressed in (1) can be extended to the following form (Yang et al., 2006a):

$$\begin{aligned} &R_k : if\ A_1^k \wedge A_2^k \wedge \cdots \wedge A_{T_k}^k,\ then\ \{(D_1, \beta_{1k}), (D_2, \beta_{2k}), \ldots, (D_N, \beta_{Nk})\},\\ &\sum_{i=1}^{N} \beta_{ik} \leqslant 1, \quad with\ a\ rule\ weight\ \theta_k\ and\ attribute\ weight\\ &\times \delta_{k1}, \delta_{k2}, \ldots, \delta_{kT_k},\ k \in \{1, 2, \ldots, L\} \end{aligned} \tag{2}$$

where $A_i^k (i = 1, 2, \ldots, T_k)$ is the referential value of the ith antecedent attribute in the kth rule, T_k the number of antecedent attributes used in the kth rule, $\beta_{ik} (i \in \{1, 2, \ldots, N\})$ the belief degree to which D_i

is believed to be the consequence if in the kth rule the input satisfies the packet antecedents $A^k = \left\{A_1^k, A_2^k, \ldots, A_{T_k}^k\right\}$, L the number of all rules in the rule base, θ_k the relative weight of the kth rule, and $\delta_{k1}, \delta_{k2}, \ldots, \delta_{kT_k}$ the relative weights of different antecedent attributes used in the kth rule. If $\sum_{i=1}^{N}\beta_{ik} = 1$, the kth rule is said to be complete; otherwise, it is incomplete. $\sum_{i=1}^{N}\beta_{ik} = 0$ denotes total ignorance about the output, given the input in the kth rule.

If a rule is given in the form of expression (2), it is called a belief rule, and if a rule base is composed of belief rules, the rule base is called a BRB.

According to its definition, in general, a BRB is composed of three components: belief rules in BRB, the weight of each antecedent attribute, and the rule weight of each rule. All the components need be determined to construct a BRB.

3.2. The advantage of BRB over traditional methods

Compared with traditional rule base, BRB has some advantages, summarized below:

- In BRB, the consequence of a rule is in a distribution form. In this way, any difference in antecedent attributes can be clearly reflected in the consequence. While in a traditional rule base, different antecedents may lead to the same consequence.
- With the introduction of attribute weights and rule weights, expert knowledge can be more precisely modeled and the BRB model will be more close to reality (Yang et al., 2006a).
- With the input transformation techniques introduced in Yang (2001), various inputs can be accommodated in BRB. The permissible inputs include but not restrict to precise numbers, random variables, fuzzy numbers, linguistic variables and so on. All such inputs can be either complete or incomplete. In this way, knowledge collected from various sources with different features and different kinds of uncertainties can be handled under a unified framework.

In summary, compared with traditional rule bases, BRB is more informative, more flexible and more close to reality, thus, RIMER, which is based on BRB, can provide a more rational way for modeling and reasoning under a complex environment with different kinds of uncertainties, and the above features may offer great advantages in risk analysis in NPD processes.

4. NPD risk analysis model

As risk is usually modeled by probability of occurrence of undesirable events and impact of the corresponding consequences, all risks mentioned in this paper are the comprehensive consideration of the above two dimensions, i.e., probability and impact. The NPD risk analysis model adopted in this paper is extracted from Wong, Chin, Tang, and Yang (submitted for publication), which discusses the risk model development when new product launches. Since the objective of this paper is to propose a method to generate BRBs, the risk analysis model is only introduced briefly.

4.1. Customer perception risk factors

CPR is defined as the extent of inability of a product to satisfy customers' desire. CPR originates from the failure in delivering expected product value to customers. It happens when customers believe that the specific product is not worthwhile to purchase at the priced amount or customers refuse to possess the products due to a loss of confidence on the product.

In the following part, the factors associated with CPR will be described briefly. Then, RIMER will be applied to evaluate CPR in an interactive doll case after BRBs for the case are generated using the method proposed in this paper.

A CPR model consists of two levels. The lower level includes

PLPR Risk in Planned Product Requirement and Excitement,
COM Risk incurred by Actions of Competition,
OMF Risk in Original Market and Fashion Situation, and
BIEC Risk in Brand Image and External Communication.

PLPR is defined as the risk incurred due to customers' failure to perceive the values of the planned product requirements and excitements. Although delight features can provide positive impact on customer, it may be perceived to be negative if unexpected shortcomings of the features are mistakenly interpreted. For instance, the customer may refuse to use the delight features as they are unfamiliar with the newly introduced technology and control mechanisms (Heath & Tversky, 1991; Ogawa & Pillar, 2006). COM is the risk associated with competitors' actions. This occurs because opponents' actions may bring new insights to customers who may in turn no longer perceive the excitement features to be valuable. The idea can be exemplified by the recently introduced iPhone to the mobile phone industry which revolutionarily rises up the customers' expectation towards mobile phone (McDonald, 2007). OMF is the risk in capturing original market and fashion situations during the product development stages. Current market and fashion situations inevitably influence how customers perceive the product. Uncertainties may be found in terms of biases and errors in market survey at the early stages of product development and hence customers' desire may not be translated into finalized products. BIEC is risk associated in failure in maintaining good Brand Image and External Communication. This risk may be found because customer no longer perceive the product to be worthy with the priced amount if the established brand image is lost. An authentic communication with customer is one of the essential elements to maintain the brand image, over promise and inaccurate information provided may lead to a serious loss in the customer perception on product.

The upper level composes of

PPP Projected Risk in Product Performance and Excitement, and
PMF Projected Risk in Market and Fashion.

The upper level risk factors are the projected risks associated with the risk factors in lower level. PPP happens when the actions of competitors change the customer expectations and eventually diminish the planned excitements before the product arrives to market (Bukszar, 1997; Cressman & Nagle, 2002) as customers are already educated and no longer be satisfied. Furthermore, other than the existing market and trend, new trends from competed products may also affect the overall market tendency, and thus have an effect on PMF. The fierce competition of Sony Betamax and VHS player' in TV recording market was a good example (Kajko, 2007). VHS player won the market because they successfully created a trend in TV recording format which leads to Betamax fading out rapidly (Bradbury, 2007).

4.2. Relationship among the customer perception risk factors

According to the above discussion, the relationship among the CPR factors can be represented by the BN in Fig. 1.

If all the information about the factors in the above BN can be represented by a set of precise probabilities with the sum of them being exactly 1, BN can be applied to analyze CPR. However,

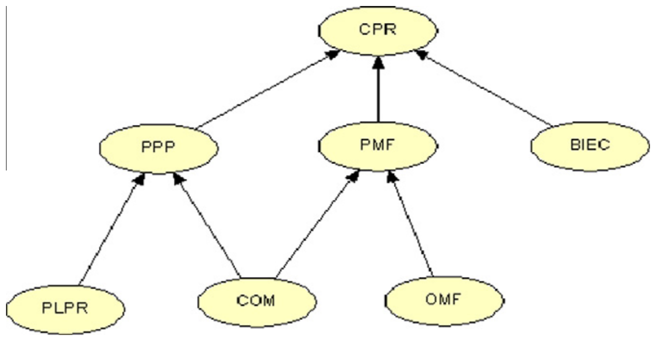

Fig. 1. Bayesian Network for CPR analysis.

because of the complex and innovative features of NPD, the form of information about the CPR factors is various, and the information may even be incomplete. In this case, the method of RIMER can be applied to perform the analysis.

5. Generation of BRB

To apply RIMER, the first step is to find out how to generate an initial BRB in a consistent and rational way. Since a BRB is composed of three components, namely, belief rules, weight of each rule in BRB and weight of each antecedent attribute in belief rules, the generation of a BRB will also be divided into three steps, i.e., the generation of belief rules, the generation of rule weights and the generation of attribute weights. As the generation of BRB will be based on BN, the relationship between BRB and BN will be clarified first.

5.1. Relationship between belief rule base and Bayesian Network

BN is a Directed Acyclic Graph (DAG) with nodes connected by directed arcs, which points from a parent node to a child node (Pearl, 1988). Generally, any complex BN can be decomposed into several fragments, each of which has one child node with its parent(s). In this paper, the fragment with one child node with its parents is called a 'basic BN fragment'. A typical basic BN fragment can be presented in Fig. 2:

In the above fragment, child node D has T parent nodes $A_i(i = 1, 2,\ldots,T)$. Suppose node D has N states, $D_1, D_2,\ldots,D_N$ while node $A_i(i = 1,2,\ldots,T)$ has m_i states, namely, $A_{i1}, A_{i2},\ldots, A_{im_i}$.

In BN, an arc between a parent node and a child node represents the casual relationship between them. Therefore, we can naturally translate the above basic BN fragment into a BRB, and the kth rule in such a BRB can be expressed as:

$$R_k : \textit{if } A_1 \textit{ is } A_{1p_1} \wedge A_2 \textit{ is } A_{2p_2} \wedge \cdots \wedge A_T^i s A_{Tp_T}, \textit{ then}$$
$$\{(D_1, \beta_{1k}), (D_2, \beta_{2k}), \ldots, (D_N, \beta_{Nk})\}, \ (p_i \in \{1, 2, \ldots, m_i\})$$

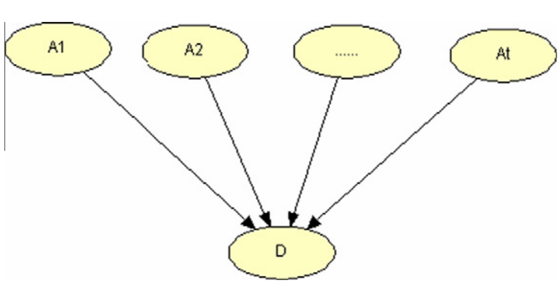

Fig. 2. A typical basic BN fragment.

In the above rule, the parameters can be explained from the perspective of BN as follows: A_{ip_i} is the p_ith state of node $A_i(i = 1,2,\ldots,T)$, $D_q(q = 1,2,\ldots,N)$ is the qth state of node D, and β_{qk} equals to the probability of D_q, under the condition that each $A_i(i = 1,2,\ldots,T)$ is in the state of A_{ip_i}, i.e., $\beta_{qk} = P(D = D_q | A_1 = A_{1p_1}, A_1 = A_{2p_2}, \ldots, A_T = A_{Tp_T})$.

Correspondently, from the perspective of BRB, the packet antecedent of the kth rule can be expressed as $A = \{A_1 = A_{1p_1}, A_2 = A_{2p_2}, \ldots, A_T = A_{Tp_T}\}$ $(p_i \in \{1, 2, \ldots, m_i\}, \ i = 1, 2, \ldots T)$, and the consequence of the rule is represented by D, with the degree of $\beta_{qk}(q = 1,2,\ldots,N)$ assigned to its possible value $D_q(q = 1,2,\ldots,N)$. Further, the rule can be explained as follows. When A_1 takes the referential value of A_{1p_1} and A_2 takes the referential value of A_{2p_2} and $\ldots$ and A_T takes the referential value of A_{Tp_T}, the consequent can take the value of D_q with the belief degree of β_{qk}.

Since each $A_i(i = 1,2,\ldots,T)$ has m_i states, there will be $\prod_{i=1}^{T} m_i$ different combinations for packet antecedent, and each combination will induce a belief rule. Therefore, the BRB corresponding to the basic BN fragment in Fig. 2 will have $\prod_{i=1}^{T} m_i$ belief rules.

From the above illustration, the following conclusions regarding the relationship between a BRB and a basic BN fragment can be drawn:

- The packet antecedent of a specific belief rule in BRB is corresponding to the parent nodes and a specific state combination of the parent nodes in a basic BN fragment, while the consequence of a belief rule in BRB is corresponding to the states of the corresponding child node and its conditional probability distribution in the basic BN fragment.
- The BRB containing the above belief rules is corresponding to the conditional probability table of the above basic BN fragment.

5.2. Generation of rules

From the discussion in Section 5.1, we can see that in order to find out the relationship between the packet antecedent and the consequence from a BRB view, we need to figure out the relationship between each state combination of the parent nodes and the states' conditional probability distribution of the corresponding child node in a basic BN fragment from a BN view.

Specifically, the relationship between parent nodes and a child node in BN is represented by the child node's probability conditional on the different state combinations of its parent nodes. Such conditional probabilities can be specified by the pair-wise comparison method and the aggregation method proposed in Chin, Tang, Yang, and Wong (2009). The advantage of applying the methods in Chin et al. (2009) to specify conditional probabilities is that it can help reduce the biases of experts' judgments and maintain the consistency of the judgments during the process of such specifications. Further, in addition to estimating probabilities of child node's states conditional on state combinations of its parents, we can also get probabilities of such a child node's states conditional on each of its parents' state during the above process, which will be used in the process of attribute weight generation.

Note that, in real applications, a complex BN may contain many different basic BN fragments, and each basic BN fragment is corresponding to a BRB.

5.3. Generation of rule weight

In Yang et al. (2006a), it is mentioned that rule weight is used to represent the relative importance of a rule to the associated conclusions. In the context of the BRB, such 'importance' can be explained as the reliability of the rule. In other words, the rule weight should represent experts' confidence in the rule or the degree to which the rule is consistent with the actual fact.

The rule weight can be assigned directly by experts based on their domain knowledge and experience. Alternatively, when there are enough data, the rule weight can also be generated using the training algorithm proposed in Yang, Liu, Xu, Wang, and Wang (2007). If there is neither experts' knowledge nor enough training data sets, a possible way is to initially assign equal weights to all rules and update the weights using the training algorithm (Yang et al., 2007) when data become available.

5.4. Generation of attribute weight

In essence, the weight of an antecedent attribute in a packet antecedent expresses the relative importance of the antecedent attribute regarding its influence on the consequence of a rule. In other words, an antecedent attribute with a higher weight will be more influential on the consequence than that with a lower weight.

Therefore, to determine an antecedent attribute's weight is to find a way to measure the relative intensity of the influence which the antecedent attribute can impose on the consequence in comparison with other antecedents. In this section, such a measurement will be quantified by a so-called Influential Factor (IF).

As indicated in Section 5.1, the packet antecedent of a rule corresponding to the basic BN fragment in Fig. 2 is expressed by $A = \{A_1 = A_{1p_1}, A_2 = A_{2p_2}, \ldots, A_T = A_{Tp_T}\}$. Thus, T antecedent attribute weights need to be estimated, which can be represented by $\delta_1, \delta_2, \ldots, \delta_T$.

From the aspect of BN, to specify the influence of the antecedent attribute $A_j (j = 1,2,\ldots,T)$ on the consequent D in comparison with the influences caused by $A_k (k \neq j)$, the first step is to specify the probability of each state of D conditional on each state of A_j, i.e.,

$$P(D = D_i | A_j = A_{jp_j})(i = 1,2,\ldots,N; j = 1,2,\ldots T; p_j = 1,2,\ldots m_j)$$

Note that the above probabilities have already been specified when the belief rules are generated, as mentioned in Section 5.2.

Next, the influence of each $A_j (j = 1,2,\ldots,T)$ on D in comparison with the influences caused by $A_k (k \neq j)$ on D can be measured on the basis of $P(D = D_i | A_j = A_{jp_j})$ in the following way.

From the Bayes' theorem, the marginal probability of different states of D, i.e., $P(D_i)(i = 1,2,\ldots,N)$, will change as A_j takes different values among A_{jp_j}. In this section, we will use the relationship between the changes of different states that A_j takes and the changes of marginal probabilities of $D_i (i = 1,2,\ldots,N)$ to determine the influence that A_j imposes on D regardless of the influence imposed by $A_k (k \neq j)$.

To synthesis the distribution information of different states of D, the utility of $D_i (i = 1,2,\ldots,N)$ is introduced, and such utility can be represented by:

$$utility(D_i) = U_i (i = 1,2,\ldots,N)$$

Therefore, the information of D can be expressed by the utility of D:

$$utility(D) = \sum_{i=1}^{N} U_i P(D = D_i)$$

In this way, we can transform the changes of marginal probabilities of $D_i (i = 1,2,\ldots,N)$ into the changes of the utility of D.

On the other hand, considering D's parent A_j, when it is in state A_{jp_j}, it will lead to a specific set of marginal probabilities of $D_i (i = 1,2,\ldots,N)$, which can be represented by $P_{p_j}(D = D_i)(i = 1, 2,\ldots,N)$. Accordingly, the utility of D on the condition that A_j is in the state of A_{jp_j} can be represented by:

$$U_{p_j}(D) = \sum_{i=1}^{N} U_i P_{p_j}(D = D_i)$$

Thus, when A_j changes its state from A_{jp_j} to $A_{j(p_j+1)} (p_j = 1, 2,\ldots m_j - 1)$, the change of the utility of D is:

$$\Delta U_{p_j}(D) = \left| \sum_{i=1}^{N} U_i P_{(p_j+1)}(D = D_i) - \sum_{i=1}^{N} U_i P_{p_j}(D = D_i) \right|$$

Then, when p_j changes from 1 to $m_j - 1$, the average change of the utility of D is given by:

$$\Delta U_j(D) = \frac{\sum_{p_j=1}^{m_j-1} \left| \sum_{i=1}^{N} U_i P_{(p_j+1)}(D = D_i) - \sum_{i=1}^{N} U_i P_{p_j}(D = D_i) \right|}{m_j - 1}$$

In this paper, we define $\Delta U_j(D)$ as the Influential Factor (IF) of antecedent A_j on consequence D, i.e.,

$$IF_j = \Delta U_j(D)$$

Further, $\delta_j (j = 1,2,\ldots,T)$, the attribute weight of antecedent A_j, can be generated from the normalized IF_j as follows:

$$\delta_j = \frac{IF_j}{\sum_{j=1}^{T} IF_j}$$

An attribute with a higher attribute weight is regarded to be more influential to the consequence D than that with a lower attribute weight.

6. Case study

A case study of "Interactive Doll" is used to illustrate the proposed BRB generation method and the application of RIMER to evaluate CPR.

6.1. Case description

A toy manufacturer is developing an innovative new product of "Interactive Doll", called HKID. HKID is very life-like, interactive and entertaining; HKID is an interactive toddler doll with advanced voice recognition technology. This is a part of the new generation of dolls and is for people who are looking for something different in a doll. HKID is equipped with voice recognition software which enables the doll to understand and recognize her owner's voice. She can recognize her "mommy's" voice and some objects. The doll can also recognize objects like pizza, cookie, toothbrush, cup, potty and much more. HKID can smile when happy and pout when sad. HKID can play games with your child, sing, pretend to eat and even go to the potty. It is truly a unique doll – the next generation of dolls.

HKID will be developed with two innovative unique features, namely, voice and object recognition, and capability in "expressing" to her mommy. These features are developed with advanced object and voice recognition technologies and an intelligent response algorithm so that HKID can recognize different objectives and can "express" emotion and engage in a sort of two-way communication with its owner. She shows facial expressions while talking. She is supposed to recognize her mommy's voice after hearing it several times, and will respond with expressions and words when mommy or others talk to her. The doll has an internal clock so that she knows time and can remind her owner of upcoming holidays, including Mother's Day and Father's Day.

However, there are also some uncertainties about the HKID project regarding the innovative toy market, e.g., design deficiencies, reliability, customer acceptance, competition, etc. Taking the risk of losing customer acceptance as an example, there exist several potential risk elements which may affect customers' perception on the market. Based on the historical information and market research in the innovative toy market, three major facts which are more or less equally important should be considered in order to secure customer acceptance. First, customers are aware of the recognized product performance, the overall user friendliness of the product and the perceived excitement features. It is also found that the customer perception on the projected product performance and excitement can be proportionately explained by the planned product design features and the latest introduction of opponents' products. Second, customers concern the market and fashion trend of the overall toy market industry. For instance, recently, there is market tendency towards interactive and responsive toy because parents perceive such two-way communication environment is good for child growth. For the projected risk in market and fashion, traditionally, it will be equally affected by the original market fashion situation and the action of competitors. Third, the reputation of the product brand and a suitable advertisement campaign are also important. Parents are interested in the safety issues on the product as well as the safety records of the producer as they would not jeopardize their child's life.

In order to analyze CPR, an in-depth discussion with industrial experts in toy market was conducted to generate BRBs, and the process is illustrated in the following section.

6.2. BRB generation

According to the discussion in Section 5, the generation of BRB can be divided into three parts, including belief rule generation, rule weight generation and attribute weight generation.

6.2.1. Rule generation

The generation of rule is based on the BN in Fig. 1. To simplify the analysis, each node in the BN has three states: high (H), medium (M) and low (L).

As the BN in Fig. 1 can be decomposed into three basic BN fragments, there are three rule bases accordingly. Among those rule bases, rule base 1 defines the relationship among 'COM', 'PLPR' and 'PPP'; rule base 2 specifies the relationship among 'COM', 'OMF' and 'PMF'; while rule base 3 determines the relationship among 'PLPR', 'PMF', 'BIEC' and 'CPR'. Such decomposition can be illustrated in Fig. 3 as follows:

Since the structure of the BN has already been decided in Fig. 1, we only need to specify the quantitative part, i.e., the conditional probabilities of the nodes in BN, before we can get the belief rules.

In Chin et al. (2009), the conditional probabilities of nodes in BN can be generated with the help of a method containing a pair-wise comparison technique and an aggregation technique. The method will be illustrated for the construction of rule base 1.

From Fig. 3, it can be seen that the probability of 'PPP' conditional on different state combinations of 'PLPR' and 'COM' should be specified to generate belief rules in rule base 1. Such specification will be based on experts' judgments, which are expressed using pair-wise comparison matrixes. For example, given that the influence of COM on PPP is fixed, when PLPR is in the state of 'H', the pair-wise comparison matrix concerning state distribution of PPP is shown in Table 1 as follows.

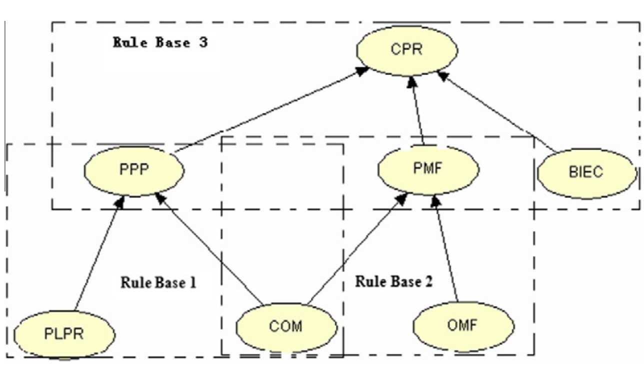

Fig. 3. Relationship between the rule bases and the Bayesian Network for CPR analysis.

Table 1
The evaluation of the probabilities of PPP conditional on PLPR (H).

P (PPP|PLPR = H)	PPP = H	PPP = M	PPP = L	Eigenvector
PPP = H	1	2[b]	3[b]	0.5396
PPP = M	1/2[a]	1	2[b]	0.2970
PPP = L	1/3[a]	1/2[a]	1	0.1634

[a] Experts' judgments.
[b] Reciprocal of experts' judgments.

In the case study, the experts gave their judgments by answering questions like 'Without considering the influence of other parents on 'PPP', when 'PLPR' is in the state of 'H', which state of 'PPP' is more likely to occur, and how much more likely?' From the matrix, one can see that given that 'PLPR' is at high (H) level, the probability of 'PPP' being at medium (M) level is 1/2 times as much as the probability of 'PPP' being at high (H) level, and the probability of 'PPP' being at low (L) level is 1/3 times as much as the probability of 'PPP' being at high (H) level. This is reasonable since higher PLPR naturally leads to higher PPP.

The eigenvector of the above comparison matrix is shown in the last column of the table, and from the discussion in Chin et al. (2009), we can get the following results:

$$\begin{aligned} &\mathrm{P(PPP = H|PLPR = H) = 0.5396} \\ &\mathrm{P(PPP = M|PLPR = H) = 0.2970} \\ &\mathrm{P(PPP = L|PLPR = H) = 0.1634} \end{aligned}$$

In the same way, we can get:

$$\begin{aligned} &\mathrm{P(PPP = H|COM = H) = 0.6442} \\ &\mathrm{P(PPP = M|COM = H) = 0.2706} \\ &\mathrm{P(PPP = L|COM = H) = 0.0852} \end{aligned}$$

According to the aggregation technique discussed in Chin et al. (2009), we can get the following equations:

$$\mathrm{P(PPP = H|PLPR = H, COM = H)} = \alpha \mathrm{P} \\ \mathrm{(PPP = H|PLPR = H)P(PPP = H|COM = H)}$$

$$\mathrm{P(PPP = M|PLPR = H, COM = H)} = \alpha \mathrm{P} \\ \mathrm{(PPP = M|PLPR = H)P(PPP = M|COM = H)}$$

$$\mathrm{P(PPP = L|PLPR = H, COM = H)} = \alpha \mathrm{P} \\ \mathrm{(PPP = L|PLPR = H)P(PPP = L|COM = H)}$$

with $\alpha = \frac{1}{K}$ where

$$\begin{aligned} K = {} & \mathrm{P(PPP = H|PLPR = H)P(PPP = H|COM = H)} \\ & + \mathrm{P(PPP = M|PLPR = H)P(PPP = M|COM = H)} \\ & + \mathrm{P(PPP = L|PLPR = H)P(PPP = L|COM = H)} \end{aligned}$$

Thus, we can get:

$$\begin{aligned} &\mathrm{P(PPP = H|PLPR = H, COM = H) = 0.7866} \\ &\mathrm{P(PPP = M|PLPR = H, COM = H) = 0.1819} \\ &\mathrm{P(PPP = L|PLPR = H, COM = H) = 0.0315} \end{aligned} \tag{3}$$

Similarly, we can get the probability of PPP conditional on the other state combinations of PLPR and COM. Also, the conditional probability tables for the other nodes in the BN can be generated in the same way.

After the BN has been constructed, the rules can be determined based on the relationship between belief rules and BN as discussed in Section 5.1.

Again, take rule base 1 for example. Firstly, we assign 'H' as the state of both PLPR and COM. The results shown in (3) indicate that when both PLPR and COM are in the state of 'H', we will have:

$$\mathrm{P(PPP = H) = 0.7866,\ P(PPP = M) = 0.1819,\ P(PPP = L) = 0.0315}$$

Therefore, we can get the first rule of rule base 1 as:

If PLPR is H and COM is H, then PPP is {(H, 0.7866), (M, 0.1819), (L, 0.0315)}

The other rules in rule base 1 and the rules in rule base 2 and rule base 3 can be generated in the same way, which are shown in the appendix.

6.2.2. Rule weight generation

In this case study, there are no training data sets, and because of the innovative nature of NPD, there is little experts' knowledge on the reliability of the rules in the BRB. Therefore, all the weights of the rules in the BRB are initially assumed to be equal.

Note that with the accumulation of real data, the rule weights can be updated using the training technique (Yang et al., 2007).

6.2.3. Attribute weight generation

According to the analysis in Section 5, to get the attribute weights, we should calculate the Influence Factor (IF) for each attribute first. To clarify the methodology introduced in Section 5.4, we still choose rule base 1 as our example.

Before determining the IF of PLPR and COM on PPP, we first assign utilities to different states of PPP as follows:

$$U_H = 0,\ U_M = 0.5,\ U_L = 1$$

When considering the influence of PLPR on PPP, the following results can be directly generated from the results in Section 6.2.1:

- When 'PLPR' is in state 'H', the marginal probability of the states of 'PPP' is:

  $$\mathrm{P(PPP = H) = 0.5396,\ P(PPP = M) = 0.2970,}$$
  $$\mathrm{P(PPP = L) = 0.1634}$$

- When 'PLPR' is in state 'M', the marginal probability of the states of 'PPP' is:

  $$\mathrm{P(PPP = H) = 0.2809,\ P(PPP = M) = 0.4638,}$$
  $$\mathrm{P(PPP = L) = 0.2553}$$

- When 'PLPR' is in state 'L', the marginal probability of the states of 'PPP' is:

  $$\mathrm{P(PPP = H) = 0.1591,\ P(PPP = M) = 0.2627,}$$
  $$\mathrm{P(PPP = L) = 0.5782}$$

Based on the above results, we can get the utilities of the consequence corresponding to different states of PLPR:

$$U_{\mathrm{PLPR=H}} = 0.3119,\ U_{\mathrm{PLPR=M}} = 0.4872,\ U_{\mathrm{PLPR=L}} = 0.7096$$

Therefore, the IF of PLPR with respect to PPP can be generated by

$$\mathrm{IF}_{\mathrm{PLPR/PPP}} = \frac{|0.4872 - 0.3119| + |0.7096 - 0.4872|}{2} = 0.1989$$

The IF of COM with respect to PPP can be generated in a similar way, and the result is:

$$\mathrm{IF}_{\mathrm{COM/PPP}} = 0.1995$$

As discussed in Section 5, the attribute weights of PLPR and COM regarding PPP are given by

$$\delta_{\mathrm{PLPR/PPP}} = \frac{\mathrm{IF}_{\mathrm{PLPR/PPP}}}{\mathrm{IF}_{\mathrm{PLPR/PPP}} + \mathrm{IF}_{\mathrm{COM/PPP}}} = 0.4992$$

$$\delta_{\mathrm{COM/PPP}} = \frac{\mathrm{IF}_{\mathrm{COM/PPP}}}{\mathrm{IF}_{\mathrm{PLPR/PPP}} + \mathrm{IF}_{\mathrm{COM/PPP}}} = 0.5008$$

In the same way, we can get the attribute weight for the other rule bases, which are shown as follows:

$$\delta_{\mathrm{OMF/PMF}} = 0.5013;\ \delta_{\mathrm{COM/PMF}} = 0.4987$$
$$\delta_{\mathrm{PPP/CPR}} = 0.3387;\ \delta_{\mathrm{PMF/CPR}} = 0.3375;\ \delta_{\mathrm{BIEC/CPR}} = 0.3238$$

Based on the above results, the following conclusions can be made. PPP, PMF and BIEC have similar impact on CPR. Considering the effect on PPP, the importance of PLPR and COM are approximately equal. The effect of OMF and COM are equally imposed on PMF. The conclusions are consistent with the background information in innovative toy market which has already been discussed in Section 6.1.

6.3. Inference and result analysis

One of the most important features of the reasoning process of RIMER is that it can accommodate inputs in various formats, and the inference is conducted after all kinds of inputs are transformed to a unified scale.

6.3.1. Input transformation

In order to examine CPR on HKID, its overall product features, potential actions of competitors, existing Market & Fashion situation and brand reputation and effectiveness of external communications are evaluated.

Similar to most of breakthrough products in NPD cycle, HKID is not designed in a fully user-friendly way. It requires a certain period of time in programming to start its functions. She is a bit heavy due to 4 "C" batteries used to power the doll and the batteries run out rather quickly. Although two innovative unique features were embedded, namely, voice and object recognition capabilities, the reliability problem of HKID has not been fully fixed. It is found that HKID will not recognize her "mommy's" voice in some occasions as the stability of the new IC circuit is not yet fully secured. The situation is also found in the object recognition function. In addition, reports show that not all children like talking to an interactive doll at their first glance because some children may be frightened by the doll. Concerning the strengths and weaknesses of the product design, the ability to fulfill original product specifications is still satisfactory although some level of uncertainty is inevitable.

Furthermore, the competition of the toy market is tough, particularly from the newly introduced "Talking Dora" by Fisher Price and "Talking Chou Chou Baby" by Mattel. Before HKID is officially launched to the toy market, those new products have been introduced with similar but not comparable interactive and responsive features at a comparable price.

Concerning the market situation, positive feedbacks from the market research on this innovative HKID are received mainly because of her "newness" to the market. From the historical data, it is confident that the market is relatively stable without substantial change in customer requirements in a short period of time. However, since HKID is a totally new product in the market, the actual market response is hard to be fully assured by the historical data and market survey only.

In the meantime, the producer of HKID receives good brand recognition. No major safety failure was found regarding the manufacturer in the past. It is confident that in most cases, the

Table 2
Original inputs for case study and the corresponding explanation.

Items	Input value for HKID	Explanation on scale
Risk incurred by Failure in Meeting Planned Product Requirements (PLPR)	{(3.5,30%),(5,40%),(7.5,30%)}: The input information for PLPR is described by the scale values with belief degrees	1: All the original product specifications, in terms of functions, reliability as well as target cost are fulfilled 10: Final product fails to meet the planned product requirements, in terms of functions, reliability as well as target cost
Risk incurred by Competition (COM)	(3.5,6,7.5): The input information for COM is described by a fuzzy number, with a triangle membership function	1: No change to current situation (neither new product nor price cut of existing product during the NPD period) 10: Competitors launch new products with similar features or even with better features than the new model at comparable price during the NPD period
Risk incurred by Change in Market & Fashion (OMF)	{([3.8,4.7],70%),(6,30%)}: The input information for OMF is described by the scale values and intervals with belief degrees	1: The market is stable with little change of customer requirements in the future (in certain period of time) 10: The market is very dynamic with rapid change in customer requirement
Risk incurred by Brand Image and External Communication (BIEC)	{(2.8,80%)}: The input information for BIEC is described by the scale values with belief degrees, but such information is incomplete	1: The perceived brand image is maintain and no major communication problems with customer in the future 10: The reputation of the brand is hard to maintain and company message to customers is easily misinterpreted

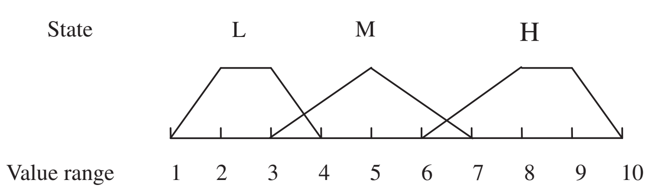

Fig. 4. The unified scale to accommodate different inputs.

perceived brand image can be well assured and no significant communication problems with customer can be foreseen in the future.

All the facts mentioned above will affect the customers' perception on HKID. Thus there is a need to evaluate CPR based on the facts.

According to the above analysis, the experts gave their opinions on the input information, which is summarized in Table 2:

From the above table, it can be seen that different inputs have different forms. As mentioned in Yang et al. (2006a), to transform those inputs into a unified form, a common scale is needed as the basis to accommodate those inputs.

In our case, the set of three states for each node in the BN (H,M,L), is selected as such a scale, and each state is represented by a fuzzy set with a trapezoidal or triangle distribution membership function, which is shown in Fig. 4.

With a triangle distribution membership function, the lower boundary, upper boundary, as well as the most likely value of each state can be specified, while with a trapezoidal distribution membership function, the lower boundary, upper boundary, as well as the most likely interval of each state can be specified.

Table 3
Transformed inputs of case study.

Items	Original value	Transformed value
COM	Fuzzy number: (3.5,6, 7.5)	(L,0.10), (M,0.58), (H,0.32)
PLPR	Belief structure with crisp number: {(3.5,30%),(5,40%),(7.5,30%)}	(L,0.18), (M,0.56), (H,0.26)
OMF	Belief structure with interval and crisp number: {([3.8,4.7],70%),(6,30%)}	(L,0.16), (M,0.84)
BIEC	Belief structure with crisp number (incomplete): {(2.8,80%)}	(L,0.8)

Based on the above scale, and according to the input transformation method in Yang et al. (2006a), the input information can be transformed as shown in Table 3.

6.3.2. Inference

As the states of H, M and L in the common scale as shown in Fig. 4 are described by fuzzy sets, the intersection of which are not empty, the ER method proposed in Yang, Wang, Xu, and Chin (2006 b) will be applied here for the inference.

After the inference, it can be concluded that under the input information, the states of CPR can be expressed by {(H,0.3594),(M,0.4874),(L,0.1016),(Unknown,0.0516)}. This result, which is expressed in the form of belief degrees, can provide the distribution information of different states of CPR. Further, the existence of the state 'unknown' in the evaluation result of 'CPR' is the reflection of the fact that the input for BIEC is incomplete.

6.3.3. Sensitivity analysis

Among the four input factors, in order to investigate which factor is the most influential to CPR, a sensitivity analysis is conducted as follows:

- If PLPR changes from {(L,1),(M,0),(H,0)} to {(L,0),(M,0),(H,1)}, while COM, OMF and BIEC are kept at the same levels as their original inputs, the status of CPR will change from {(H,0.2768),(M,0.4995),(L,0.1721),(Unknown, 0.0516)} to {(H,0.4414),(M,0.4354),(L,0.0708),(Unknown, 0.0524)}.
- If COM changes from {(L,1),(M,0),(H,0)} to {(L,0),(M,0),(H,1)}, while PLPR, OMF and BIEC are kept at the same levels as their original inputs, the status of CPR will change from {(H,0.1523),(M,0.5148),(L,0.2817),(Unknown, 0.0512)} to {(H,0.5202),(M,0.3661),(L,0.0613),(Unknown, 0.0524)}.
- If OMF changes from {(L,1),(M,0),(H,0)} to {(L,0), (M,0),(H,1)}, while PLPR, COM and BIEC are kept at the same levels as their original inputs, the status of CPR will change from {(H,0.2837),(M,0.5040),(L,0.1605),(Unknown, 0.0518)} to {(H,0.5086),(M,0.3639),(L,0.0749),(Unknown, 0.0526)}.
- If BIEC changes from {(L,1),(M,0),(H,0)} to {(L,0),(M,0),(H,1)}, while PLPR, COM and OMF are kept at the same levels as their original inputs, the status of CPR will change from {(H, 0.3788),(M,0.5154),(L,0.1058)} to {(H,0.7411),(M,0.2501),(L,0.0088)}.

Regarding CPR, if the utility of state 'L', 'M' and 'H' are 1, 0.5 and 0, respectively, according to the above result and the method to calculate utility in Yang et al. (2006a), the change of average utility of CPR due to the change of 'PLPR', 'COM', 'OMF' and 'BIEC' are 0.1329, 0.2942, 0.1552 and 0.2297, respectively. Therefore, it can be concluded that, among the four input factors, COM is the most influential to CPR, followed by BIEC, OMF and PLPR.

The above results can be summarized Table 4.

Note that, the above result only reveals the impact of a single input factor regarding CPR on the condition that the other factors remain fixed at their original inputs. As CPR is influenced by different inputs simultaneously, a more extensive sensitivity analysis is needed in the future to analytically show the impact of a combination of some certain factors on CPR, based on which a strategy can be developed to minimize CPR more effectively and efficiently.

6.3.4. Managerial implications

Based on the result of the above sensitivity analysis and the specific situation of the case in case study, it is found that both COM and BIEC have greater impact on CPR than other two factors in lower level. However, referring to the actual case situation, there is more area for improvement in COM than BIEC as BIEC is already optimized in a relatively low level by proper marketing advertisement policy, high assurance of product quality and a fairly stable and excellent brand reputation. Inversely, there is room for improvement in COM. It is found that COM has greatest impact on CPR and the belief degree of risk level in COM is relatively high. Based on the results, the toy manufacturer realized the most efficient way to reduce CPR is decreasing competition or increasing the clarity of competitive environment. To mitigate CPR, the company formulated co-petition strategy with some strategic alliances. By clearly distinguishing the competitive advantages in different target toy markets between the case company and the competitors, the case companies cooperated with their opponents under the competitive environment of toy market. Working under a judicious mixture of competition and cooperation, it was not easy but the case company found benefits to obtain clearer pictures of their competitor moves and shared common costs by working together for parts of their business. While company has better understanding about competitors' movement, the risk originated from competition is greatly decreased and ultimately the CPR of the interactive doll is reduced.

Table 4
Summary of sensitivity analysis in case study.

Factor in concern (X)	CPR		Change of average utility
	X is {(L,1),(M,0),(H,0)}	X is {(L,0),(M,0),(H,1)}	
PLPR	H: 0.2768 M: 0.4995 L: 0.1721 Unknown: 0.0516	H: 0.4414 M: 0.4354 L: 0.0708 Unknown: 0.0524	0.1329
COM	H: 0.1523 M: 0.5148 L: 0.2817 Unknown: 0.0512	H: 0.5202 M: 0.3661 L: 0.0613 Unknown: 0.0524	0.2942
OMF	H: 0.2837 M: 0.5040 L: 0.1605 Unknown: 0.0518	H: 0.5086 M: 0.3639 L: 0.0749 Unknown: 0.0526	0.1552
BIEC	H: 0.3788 M: 0.5154 L: 0.1058	H: 0.7411 M: 0.2501 L: 0.0088	0.2297

6.3.5. Summary

From the process of input transformation, inference, result generation and sensitivity analysis, several advantages of applying BRB and RIMER in CPR analysis in NPD can be summarized as follows:

- It provides great flexibility for experts to express their opinions in many different ways. This is very important since much uncertainty is involved in the process of NPD, which makes it unlikely for experts to provide their opinions in a unified way. Different ways to represent information can reflect different extents of experts' understanding on such information.
- The results, which represent risk by belief degrees to assessment grades like 'high', 'medium' and 'low', can provide a panoramic profile of the status of CPR. It is more informative than representing risk status by a 'risk score', which is usually applied in current risk analysis literature (Akomode, Lees, & Irgens, 1999; Baccarini & Archer, 2001; Royer, 2000).
- The belief degree of 'unknown' represents the incompleteness of the input information, which reveals the experts' ignorance in certain factors relevant to CPR during an NPD process. The existence of such ignorance is natural since there is little information available and much uncertainty is involved in NPD process. If further information is acquired, the degree of 'unknown' can be assigned to 'high', 'medium' or 'low'. Therefore, human's reasoning process under much uncertainty and little information can be naturally reflected in this way.

7. Conclusion

RIMER can be applied to perform reasoning under the environment with little information and much uncertainty due to its capability in accommodating different forms of information, which can be both complete and incomplete. However, its performance is highly dependant on the rationality and consistency of its basis, BRB. Traditionally, the parameters of BRB, including belief degrees in belief rules, attribute weights and rule weights, are specified by experts directly based on their knowledge. Due to the complexity of the reasoning task, such specifications will inevitably involve individual biases and inconsistencies.

Facing this situation, this paper proposes a novel method to generate BRBs. The method contains three steps: generating belief rules, generating rule weights and generating attribute weights. By applying the method, the biases and inconsistencies involved in the BRB generation process can be reduced as the method only need experts perform pair-wise comparison instead of specifying belief degrees, rules weights and attribute weights directly. In addition, the method provides a new way to quantify the influence of antecedent attributes on the consequence by means of the so-called 'Influence Factor'. Based on the generated BRBs, RIMER can be applied for reasoning.

A case study is performed to validate the method in NPD risk analysis. It is about the CPR analysis during the development of a new "Interactive Doll". From the case study, we can see that the method proposed in this paper can help to build a BRB rationally and consistently. Based on such a BRB, RIMER is applied to evaluate CPR with different forms of input information, which can be either complete or incomplete, and the input incompleteness is reflected in the analysis results. Under an environment with much innovation and little experience, such flexibility and rationality can provide an informative way for NPD risk analysis and decision making.

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Appendix A. Rule bases for evaluation of CPR

Tables A-1–A-3.

Table A-1
Belief rules in rule base 1.

IF		THEN		
PLPR	COM	PPP		
		H	M	L
H	H	0.7866	0.1819	0.0315
H	M	0.7402	0.2037	0.0561
H	L	0.4126	0.3275	0.2599
M	H	0.5513	0.3824	0.0663
M	M	0.4871	0.4021	0.1107
M	L	0.1897	0.4517	0.3586
L	H	0.4599	0.3190	0.2211
L	M	0.3657	0.3019	0.3324
L	L	0.0914	0.2176	0.6910

Table A-2
Belief rules in rule base 2.

IF		THEN		
OMF	COM	PMF		
		H	M	L
H	H	0.9183	0.0755	0.0062
H	M	0.6785	0.3097	0.0118
H	L	0.5071	0.3069	0.1860
M	H	0.7033	0.2851	0.0116
M	M	0.3035	0.6836	0.0129
M	L	0.2050	0.6122	0.1828
L	H	0.4635	0.3551	0.1814
L	M	0.1597	0.6795	0.1608
L	L	0.0359	0.2024	0.7617

Table A-3
Belief rules in rule base 3.

IF			THEN		
BIEC	PMF	PPP	CPR		
			H	M	L
H	H	H	0.9514	0.0478	0.0007
H	H	M	0.7981	0.1986	0.0033
H	H	L	0.7010	0.2710	0.0280
H	M	H	0.7955	0.2016	0.0029
H	M	M	0.4397	0.5516	0.0087
H	M	L	0.3186	0.6208	0.0606
H	L	H	0.7027	0.2669	0.0304
H	L	M	0.3208	0.6034	0.0758
H	L	L	0.1613	0.4711	0.3676
M	H	H	0.8093	0.1871	0.0036
M	H	M	0.4641	0.5312	0.0047
M	H	L	0.3321	0.5903	0.0776
M	M	H	0.4574	0.5329	0.0097
M	M	M	0.1453	0.8369	0.0168
M	M	L	0.0903	0.8090	0.1007
M	L	H	0.3333	0.5821	0.0846
M	L	M	0.0906	0.7838	0.1256
M	L	L	0.0360	0.4831	0.4809
L	H	H	0.7772	0.1987	0.0241
L	H	M	0.4106	0.5171	0.0723
L	H	L	0.2148	0.4201	0.3651
L	M	H	0.4106	0.5262	0.0632
L	M	M	0.1222	0.7753	0.1025
L	M	L	0.0527	0.5198	0.4275
L	L	H	0.2098	0.4031	0.3871
L	L	M	0.0486	0.4623	0.4891
L	L	L	0.0089	0.1308	0.8603

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