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Team Situation Awareness Measure Using Semantic Utility Functions for Supporting Dynamic Decision-Making

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Abstract Team decision-making is a remarkable feature in a complex dynamic decision environment, which can be supported by team situation awareness. In this paper, a team situation awareness measure (TSAM) method using a semantic utility function is proposed. The semantic utility function is used to clarify the semantics of qualitative information expressed in linguistic terms. The individual and team situation awareness are treated as linguistic possibility distributions on the potential decisions in a dynamic decision environment. In the TSAM method, team situation awareness is generated through reasoning and aggregating individual situation awareness based on a multi-level hierarchy mental model of the team. Individual and team mental models are composed of key drivers and significant variables. An illustrative example in telecoms customer churn prediction is given to explain the effectiveness and the main steps of the TSAM method.

Keywords dynamic decision-making, situation awareness measurement, utility function, qualitative information

1 Introduction

Team decision-making is an effective strategy for complex and dynamic decision problems in which an individual decision maker focuses on limited aspects of the decision problem and team members make the final decision cooperatively. Team decision-making can efficiently reduce bias and incompleteness within the observation, inference, and other information processes in the personal decision-making procedure, and can improve the reliability of a decision [22]. In an implementation of dynamic team decision-making, team members are required to collaborate with others by sharing their individual situation awareness so that team situation awareness of the decision context is developed [7].

Customer churn management is a typical dynamic team decision-making problem in many businesses [18]. Service providers such as insurance companies, telecoms and commercial banks face an increasingly changeable market which has been saturated with cheaper services and powerful competitors. Thus, retaining potential churning customers becomes a challenging issue in their business strategies. To achieve a retention goal, team members, who are responsible for different duties and are distributed in various geographical locations, should efficiently share their individual awareness. Based on team awareness of market divisions, the company's service performance, customer potential behaviors, technique progress in relevant support systems, and other related aspects, the team can take corresponding timely reactions. Hence, improving the situation awareness of a management team can help to support appropriate business decisions and business strategies.

Customer churn prediction is a key component in customer churn management [9]. Traditional predictive models for customer churn are mainly established on statistics and machine learning techniques, such as logistics regression, decision tree, time-serial analysis, artificial neural networks, genetic algorithms, and data mining techniques [11]. Practices indicate that those

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models are successful in handling data of a quantitative nature: for instance, data stored in a company's internal databases. However, these methods have limitations in applications due to the absence of consideration of managers' qualitative awareness. A manager's individual awareness of customer churn is generated based on their domain knowledge and experience with collected observations from various sources, including public media, and public data sources, as well as internal databases. Qualitative nature is a remarkable feature in managers' individual awareness. Improving team situation awareness in a quickly changing market requires a method to handle qualitative awareness with various forms such as probability estimations and linguistic judgments. This paper takes qualitative awareness expressed by linguistic terms as the main subject and discusses how to measure team situation awareness from those linguistic terms.

Existing studies indicate that linguistic method is a powerful technique to handle qualitative information [13,19,22,33]. Applying linguistic method to handle individual awareness of a qualitative nature in the customer churn prediction problem is an alternative means to improve managers' team awareness in a dynamic situation. Based on this consideration, this paper presents a team situation awareness measure (TSAM) method. In the TSAM method, the semantics of a set of linguistic terms are clarified by a semantic utility function; an individual awareness is expressed by a linguistic possibility distribution on the potential states of a given decision object; the team's domain knowledge and experience about the decision problem is expressed by a multi-level variable-driver hierarchy and a set of reasoning rules; and the team's awareness in a situation is obtained through approximate reasoning and aggregation on individual awareness.

The remaining parts of the paper are organized as follows. In Section 2, related work on situation awareness, linguistic method, and customer churning prediction is reviewed. Section 3 describes the TSAM method. A case study of customer churn management illustrates the effectiveness of the TSAM method in Section 4. Finally, conclusions and our future work are discussed in Section 5.

2 Related works

Situation awareness (SA)[5,6] has received considerable attention from the human factors and ergonomics community during the past two decades and is widely used in complex dynamic systems where human factors are involved, such as nuclear power plant operations [3], air traffic control [15,31], and emergency response [2,28].

Improving team situation awareness (team SA) requires team members to share perceptions (i.e., individual SA) and comprehension of a situation among team members. Effective communication and cooperation are two primary aspects for developing team SA. Moreover, three other demands are required to improve team SA [16,27,29]. First, the increasing complexity of dynamic contexts provides a great challenge to decision makers for the timely recognition of the external environment and to conduct ongoing analysis. Second, correct awareness is the basis for appropriate decision-making; in particular, when team members are working at different geographical locations. Finally, team SA should be appropriately measured.

Currently, existing team SA measure models are mainly based on statistics and inference established for operator training in industrial and military control procedures [17,24,30,29], which cannot be directly applied to team decision-making due to the difference between control procedure and decision-making. The difference lies with two issues. On the one hand, the subject in a control procedure often has several normal states which play the roles of potential standards for measuring team SA, i.e., team SA can be measured through the deviation between the subject's running state and normal state. However, it is hard to define such a standard for measuring team SA in decision making problems. Decision problems seldom regulate a subject's behavior and states to a fixed standard; rather, they change their decision targets to fit the change of subject accordingly. Hence, team SA measure in a decision problem is a dynamic procedure. On the other hand, the information in control procedure is often quantitative nature and is processed at the technical level. However, information used in the decision-making process is often of a qualitative nature which is processed not only at the technical level but also at psychological, conceptual, and behavior levels. Therefore, team SA measurement in decision-making problems is required to deal with more qualitative information.

Customer churn management is one of the primary business strategies of service providers that is widely used in the wireless telecoms service industry [1]. In a typical five-stage customer churn management framework, customer churn prediction is a vital stage which works with the other four stages, i.e., identification of the best data, data semantics, feature selection, and validation of results [4,11]. The most-used techniques in the development of predictive models include genetic algorithm , regression, neural networks, decision tree, Markov model, clustering analysis, etc [11]. Although these techniques are successful in some applications, practices indicate that they are weak in handling qualitative information. Business surveys have identified various reasons for customer churn which cannot be quantitatively expressed in accurate data but are qualitative expressions. Effective qualitative information process is, then, required to meet the demand of measuring team SA in dynamic decision-making.

Linguistic methods (or linguistic approaches) in an uncertain information process community refer to a kind of technique that is mainly developed to process information expressed in natural or artificial languages [20, 21, 32]. Linguistic methods have been successfully used in management [25], industry [26], and decision-making [12, 23], as well as the social sciences [10]. Most linguistic methods follow a three-step solution scheme [12]: 1) choose linguistic terms; 2) choose aggregation operators for linguistic information; and 3) choose the best alternative by aggregation and exploitation. In the solution schema, qualitative information is represented by linguistic terms, which are elements in a designed processing framework, and is processed by the computation model in that framework. For example, fuzzy sets and fuzzy logic are the most used processing frameworks, in which fuzzy sets are used to interpret the semantics of linguistic terms, and computation and inference algorithms for fuzzy sets are used to implement the syntactic process of linguistic terms. Automatic process of qualitative information can partly be implemented in linguistic methods.

3 A team situation awareness measure method using utility functions

This section overviews the proposed TSAM method, explains individual and team mental models, discusses semantic utility functions, and develops an algorithm to measure team SA.

3.1 Overview

To meet the demands of customer churn prediction in competitive and changeable markets, this paper develops a TSAM method using utility functions to support team managers to develop better awareness of a segment of customers' potential behaviors. In this method, a utility function is used for the semantic perception of qualitative information, i.e., linguistic terms. A general procedure and information flow of the TSAM method is shown in Figure 1.

The processing procedure mainly includes three processing modules with related components:

(1) Managers collect observations from various information sources. These observations are the input of an individual mental model (IMM).
(2) The manager's mental model processes those observations to general individual SA. Manager's individual SA is then collected as the input of the team mental model (TMM).
(3) The TMM processes team members individual SA and generates the team SA, which is treated as the production of members' communication and cooperation.

The following sub-sections will present these modules in detail.

3.2 Individual and team mental models

A human being's mental model in a complex dynamic decision context is the core of their perception of the external environment, the generation of appropriate awareness, and timely decision making. A real mental model is very complicated. To reduce its complicity, a mental model can be simplified by a variety of core elements. For instance, in a customer churn prediction problem in telecoms, a real mental model can be simplified by drivers and variables, and the relationships among them, as well as relevant responses.

In the TSAM method, individual or team mental models adopt a similar structure, i.e., they are composed of a set of significant variables and a multi-level hierarchy of key drivers. These drivers are certain important factors related to a decision problem, and significant variables are indicators whose values can reflect the current state of a situation. In the customer churn prediction example, significant variables may be customer-related attributes, such as the monthly payments, bill and payments, call details, and customer care and services as shown in Figure 2[14]. The terms "driver" and "variables" are both taken from the telecoms community.

Moreover, a mental model in the TSAM method also includes three other components, i.e., a given decision problem or given decision object; possible solutions of a given decision problem or possible states of a given decision object; and domain knowledge and experience for relationships among solutions of the given decision problem, its drivers and significant variables.

Formally, a mental model is expressed by a five-tuple

$$\langle O, D, V, H, R \rangle, \tag{1}$$

where O is the decision problem (or decision object), D is the hierarchy of drivers, V is the set of significant

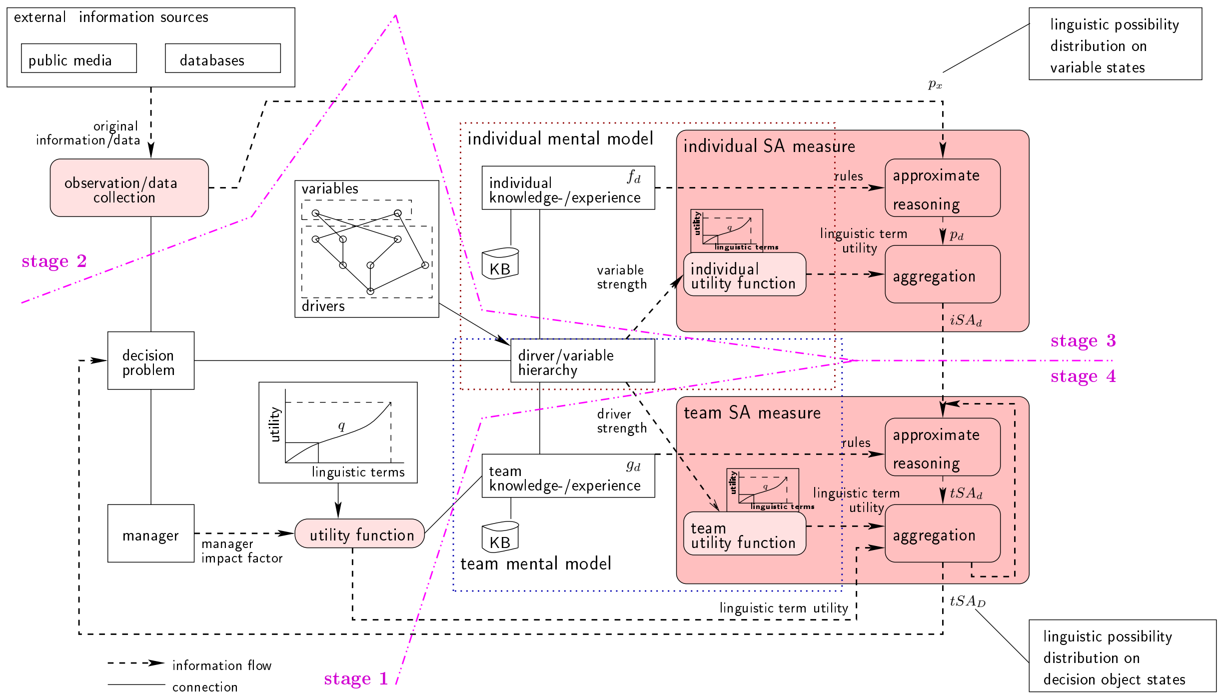

Fig. 1 A general procedure and information flow of the TSAM method

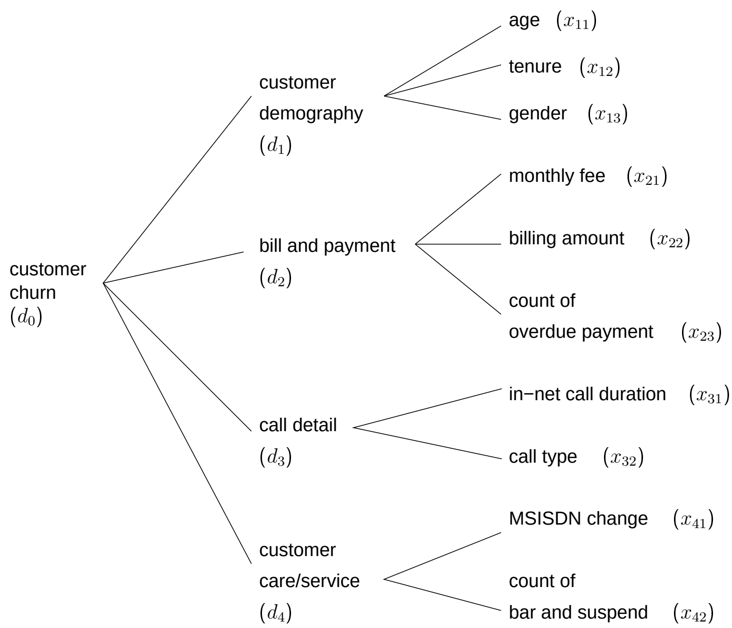

Fig. 2 An example of customer churn drivers

variables, H is the set of possible solutions (or states) of the decision problem O, and R is the relations among D, V, and H.

3.2.1 Driver hierarchy

Let

$$D = \bigcup_{i=0}^{n} D^{(i)} = D^{(0)} \cup \bigcup_{i=1}^{n} \{d_1^{(i)}, \cdots, d_{j_i}^{(i)}\} \tag{2}$$

be the hierarchy of identified drivers, where $D^{(i)}$ is the set of drivers at the level i and $d_j^{(i)}$ is the j-th driver at level i. In particular, let $D^{(0)} = O$ indicate the decision problem or decision object. In order to clearly indicate the parent-children relationship between two drivers, we also use $d_{j/i}$ to represent the j-th sub-driver of the driver d_i. Symbol $d_j(d_{j_1/j}, \cdots, d_{j_m/j})$ is used to indicate that a driver d_j is supported by a set of sub-drivers $d_{j_1/j}, \cdots, d_{j_m/j}$, and $d_{j_i} \prec d_j$ is used to indicate that $d_{j_i/j}$ is a sub-driver of d_j.

3.2.2 Significant variable set

Let $V = \{x_1, \cdots, x_m\}$ be the set of identified significant variables. Each variable $x \in V$ has a universe of discourse U_x from which its real date is taken from. On $\mathscr{F}(U_x)$, the TSAM method selects a set of status, denoted by S_x $(\subseteq \mathscr{F}(U_x))$, which is treated as the observed values about the variable x, where $\mathscr{F}(U_x)$ is the family of fuzzy sets on U_x. The TSAM method uses status as observed values of a variable for the purpose of capturing qualitative information in a natural way and reducing the computation complexity on fuzzy sets.

Take the "monthly fee" for example. Suppose the possible spends interval for "monthly fee" is [\$39-\$200], then we can define states "normal," "slightly high," "high," and "very high" as shown in Figure 3 to describe the observation of a customer's monthly spending.

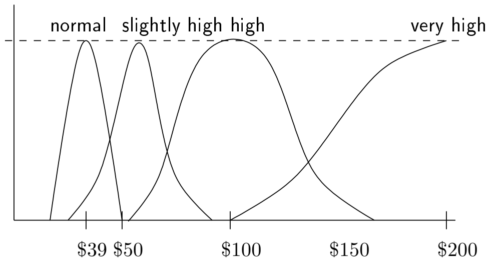

Fig. 3 Example of observations of significant variable "monthly fee."

3.2.3 States of decision object

A decision object is the subject with which a team is concerned in a decision problem, which may have some possible states. For instance, a segment of customers is a possible decision object in the customer churn prediction example. The customers' potential behaviors, such as "churning immediately" or "leaving end of the contract", are possible states. In the TSAM method, a decision object's possible states are denoted by $H = \{h_1, h_2, \ldots, h_K\}$.

3.2.4 Domain knowledge and experience

Managers' domain knowledge and experience is abstracted to be relationships among drivers, variables, and decision object's states. The TSAM method mainly depicts three kinds of relationships.

(1) The TSAM method establishes connections between significant variables and drivers and assumes that significant variables only connect to leaf drivers. Let $LD \subset D$ be the set of leaf drivers. For any $d \in LD$, the symbol $d(x_{d(1)}, x_{d(2)}, \cdots, x_{d(k)})$ is used to indicate that driver d is linked to variable $x_{d(1)}, x_{d(2)}, \cdots, x_{d(k)}$. For convenience, let V_d be the set of significant variables connected to driver d and D_x the drivers set which the significant variable x connecting to.

(2) Considering the different impacts of drivers and significant variables on a given decision problem, the TSAM method will assign different strengths to drivers and significant variables respectively. For each driver $d_j^{(i)} \in D^{(i)}$, the assigned strength is denoted by $w_j^{(i)}$, $i = 1, \ldots, n$, which is expressed by a linguistic term as shown in Table 1. For each significant variable x, a set of strengths will be assigned to it because it may have different impacts on different leaf drivers. Let $\omega_x = \{w_{xj} : d_j \in D_x\}$ be the set of strengths, which is also expressed by a set of linguistic terms in Table 1.

Table 1 Linguistic weights.

Linguistic weight id	Impact factor
v_1	Absolutely unimportant
v_3	Unimportant
v_3	Slightly unimportant
v_4	Medium
v_5	Slightly important
v_6	Important
v_7	Absolutely important

(3) The TSAM method defines a set of rules which link the observations of variables as well as the awareness of drivers and the states of decision objects. Below is an example of those rules.

$$\text{IF } \frac{\text{absolutely possible}}{\text{“high” monthly fee}} \text{ AND } \frac{\text{very possible}}{\text{“low” amount of upload / download}} \text{ THEN } \frac{\text{very possible}}{\text{change plan}}.$$

Formally, a mapping

$$f_d : \prod_{x \in V_d} (S_x \times T) \rightarrow H \times T, \tag{3}$$

can be used to present a set of rules related to the leaf driver $d(\in LD)$, where S_x is the status set of significant variable x and T is a linguistic terms used to describe linguistic possibility (shown in Table 2). Moreover, similar rules between non-leaf drivers and states of decision object is used. A mapping

$$g_d : \prod_{d_j \prec d} (H \times T)_{d_j} \to H \times T, \tag{4}$$

is used to indicate the rule about a non-leaf driver d and the states of the decision object. Therefore, in the TSAM method, the relationship set R is denoted by:

$$R = \{f_d : d \in LD\} \cup \{g_d : d \in D - LD\}. \tag{5}$$

Table 2 Linguistic possibilities

Linguistic possibility ID	Linguistic term
u_1	Impossible
u_2	Almost impossible
u_3	Slightly possible
u_4	Quite possible
u_5	Possible
u_6	Highly possible
u_7	Absolutely possible

3.3 Utility of linguistic terms

Utility is a term used to measure relative satisfaction [8]. A utility function clarifies the meaning of different satisfactory degrees. Figure 4 describes three typical utility functions. Here the TSAM method uses "utility" to measure the relative semantic perception of a set of linguistic terms. In fact, most linguistic methods have adopted the utility function shown in Figure 4(a) in the process of linguistic information. Suppose Σ is a linguistic term set, a utility function q with respect to Σ is a mapping from Σ to [0, 1] and denoted by q_Σ. In the TSAM method, utility functions are defined for strengths of drivers and variables as well as the impact factors of managers. Using the utility function, there exist two obvious merits to deal with linguistic information: 1) a set of linguistic terms can be distributed in asymmetric linear order which is better than a symmetric linear order; and 2) any two linguistic term sets can be compared through terms' utilities so that it is possible to implement a linguistic information process crossing multiple term sets.

3.4 Managers and their impact factors

Team decision-making allows managers in different functional departments and geographical locations to share collected information and their individual awareness of changes in a situation. Inevitably, each manager's individual awareness of the situation is incomplete and unbalanced. To narrow down the gap between individual awareness and a real situation, individual awareness aggregation is conducted. In the course of this, managers' impacts on the decision problem are addressed.

Managers' impacts on the decision problem have two noticeable features. First, different managers may have different impacts on the same aspect of a decision problem. Second, a manager may exert different impacts on different aspects. Based on these two features, the TSAM method assigns a set of impact factors to each manager.

Suppose $M = \{e_1, \ldots, e_L\}$ is the team of managers. Let $D_e(\in LD)$ the drivers influenced by a manager e $(\in M)$. Then σ_{ij} is used for the impact factor of the j-th driver influenced by e_i, where $\sigma_{ij} \in \Sigma$ a linguistic impact factor set as shown in Table 1.

3.5 Observations and situation awareness

As previously mentioned, the TSAM method uses the status of an significant variable as an observation value on that variable. Due to the potential overlap between two statuses of a significant variable, multiple statuses may be presented. On the consideration of that phenomenon, an observation about variable x in the TSAM method is defined as a linguistic possibility distribution by

$$p_x = \frac{t_1}{s_1} + \frac{t_2}{s_2} + \cdots + \frac{t_l}{s_l}, \tag{6}$$

where t_i is the linguistic possibility (shown in Table 2) of status s_i, and $s_i \in S_x$. Notice that significant variables are connected to leaf drivers, the TSAM method uses $d(x_{d(1)}, x_{d(2)}, \cdots, x_{d(k)})$ to emphasize this connection. Accordingly, the TSAM method uses $d(p_{x_{d(1)}}, p_{x_{d(2)}}, \cdots, p_{x_{d(k)}})$ to describe an observation of variables connected to driver d.

An individual SA is generated from observations, including various data collection, on variables and individual mental models. In the TSAM method, an individual SA is expressed in a similar way to the observation of variables except that it is a linguistic possibility distribution on states of the decision object, i.e.,

$$iSA_d = \frac{t_1}{h_1} + \frac{t_2}{h_2} + \cdots + \frac{t_K}{h_K}, \tag{7}$$

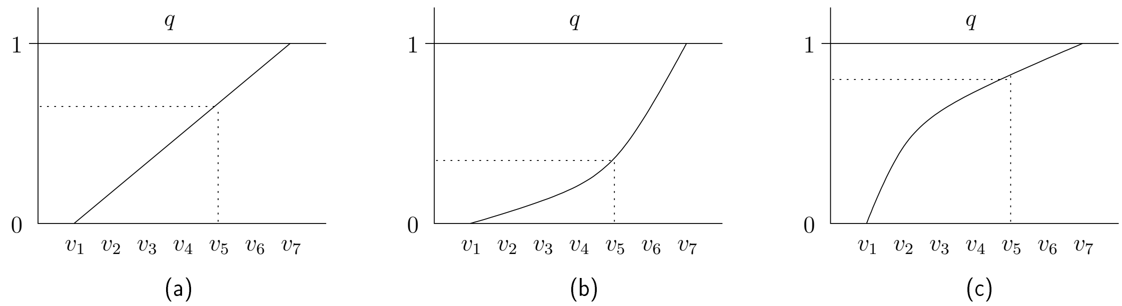

Fig. 4 Three typical utility functions.

where $t_i \in T$, $d \in LD$ is a leaf driver, and $H = \{h_1, \cdots, h_K\}$ is the set of decision object's possibility states. In the customer churn prediction example, the set H can be potential customer behaviors.

Team SA is generated from the SA of a set of individuals. Similarly, team SA takes the same expression as the individual SA, i.e., a team SA is a linguistic possibility distribution on H. Moreover, team SA has a difference with individual SA, that is, team SA is measured on non-leaf drivers but individual SA is measured on leaf drivers. In the following, the symbol tSA_d will be used for team SA on driver $d(\in D - LD)$. For the purpose of simplifying symbols in the TSAM method, we also use p_d to represent individual or team SA which can be identified according to d.

3.6 Team SA measure

To obtain individual and team SA, approximate reasoning and aggregation are used. Approximate reasoning is applied because observation of the variables and awareness of the drivers may not completely match the antecedents in f_d and g_d. Aggregation is used for integrating observations from different managers and on different variables.

Based on the structure of the mental model, team SA is measured by a four-stage information process through observing significant variables, inferring decision object states, and aggregating individual awareness.

The first stage is a preparation stage. At this stage, the decision problem, key drivers, significant variables, individual and team mental model, as well as utilities of linguistic terms, are identified and determined.

The second stage is an observation stage. Observations on variables are collected and expressed by linguistic possibility distribution on possible states of those variables at this stage.

The third stage is an individual SA generation stage.

The fourth stage is a team SA generation stage.

In the last two stages, approximate reasoning and aggregation are used. Approximate reasoning implements two kinds of information transformations: 1) from observations on variables to awareness of leaf drivers; and 2) from awareness of leaf drivers to awareness of non-leaf drivers. Aggregation conducts two kinds of information integration: 1) integrating multiple observations from managers; 2) integrating awareness of drivers.

To implement the four-stage information processing for measuring team SA, a ten-step algorithm is designed, as shown in Table 3.

The details of each step are briefly illustrated below by taking a customer churn prediction problem as an example.

Step 1: identify a decision problem and its decision object's states.

This step will determine 1) what the decision problem is; 2) in the problem, what the decision object is; and accordingly 3) the possible states that the decision object may have. Take the customer churn prediction problem as an example. The decision problem is to predict "whether customers will churn". Because customers may be divided into different segments, the problem may only focus on a particular segment of customers to answer that question. Thus the concerned customer segment is the decision object. Accordingly, the potential behaviors such as "leave quickly" and "under contract" can be chosen as the possible states.

Step 2: identify key drivers and their strengths with respect to the decision problem.

Key drivers and their strengths can be determined once the decision problem and decision object are defined. For example, "customer demography," "bill and payment," "call detail" can be selected as key drivers for the decision problem about customer churn prediction in a telecom. Those key drivers' strengths can also be determined according to profiles of that segment of customers. When the customer segmentation is changed, the strengths of those key drivers is also changed.

Table 3 Main steps of the TSAM method.

Algorithm:
Step 1. Set O and $H = \{h_1, \cdots, h_k\}$.
Step 2. Set $D = D^{(0)} \cup D^{(1)} \cup \cdots \cup D^{(n)}$ and $w_j^{(i)}$ for any $d_j^{(i)} \in D^{(i)}$, $i = 1, \ldots, n$.
Step 3. Set $V = \{x_1, \cdots, x_m\}$ and S_x for any $x \in V$.
Step 4. Set V_d for any $d \in LD$, ω_x for any $x \in V_d$, and $R = \{f_d : d \in LD\} \cup \{g_d : d \in D - LD\}$.
Step 5. Set $M = \{e_1, \cdots, e_L\}$ and σ_{ij} for any $d \in D_{e_i}$.
Step 6. Set q_Σ for used linguistic terms Σ.
Step 7. Collect p_x^e for any $e \in M$ and $x \in V$.
Step 8. Measure iSA_d for any $d \in LD$.
Step 9. Measure tSA_d for any $d \in LD$.
Step 10. Measure tSA_d for any $d \in D - LD$. If d is the decision problem, then stop; otherwise go to 9).

Step 3: identify significant variables and their possible status.

Based on the decision problem, decision object, and key drivers, significant variables can be identified. These variables provide support information to solve the decision problem. In order to determine the possible states of each variable, the decision object's characteristics should be considered. For example, the "normal" state of "monthly fee" for customers who signed a \$49 cap plan is completely different from customers who signed a \$99 cap plan. In general, the possible states of a variable can be obtained through divisions on its universe of discourse.

Step 4: identify knowledge and experiences, and express them by rules between key drivers and significant variables as well as determine the strengths of those variables with respect to key drivers.

Using the mental model, the solution of the decision problem is evaluated by means of the information process step by step along the links between key drivers and significant variables. For instance, to predict customer churn, Figure 2 describes the relationships among key drivers and significant variables. Observations on variables and awareness of key drivers can then be integrated in terms of the hierarchy.

Step 5: identify team members and their impact factors on the leaf drivers.

Team decision-making cannot be conducted without communication and cooperation among team members. In this step, team members' individual impact on leaf drivers, which is the primary aspect in their duties, is determined. The impact is expressed by linguistic terms such as "very important," or "unimportant,"(shown in Table 1) which indicate to what extent a manager's observation or individual SA should be adopted when measuring a team's SA.

Step 6: identify utilities of used linguistic terms in the information process procedure.

This step distinguishes the managers' preference on used linguistic terms, which include the strengths of key drivers, the strengths of significant variables, and impact factors of managers, as well as linguistic possibilities. The utility functions clarify the semantics of those linguistic terms, which can be determined by experiments on statistic data and discussion among team members.

Step 7: collect observations of significant variables from managers.

In this step, managers present observations of significant variables, which are the evaluation of those managers on a situation. In the customer churn prediction example, observations of customers' "age,", "monthly fee," "call type" and other variables generate a first-hand perception of the decision problem. Thereafter, the first-hand perception is processed by the personal individual mental model and the individual SA is obtained. The collected observations are the input of processing in next step.

Step 8: measure individual SA with respect to the leaf drivers by approximate reasoning.

Further to step 7, the observations of variables reflect the perception on the decision problem and decision object. The first-hand perception must be analyzed and processed before it is used to obtain awareness of a decision problem and the related decision object. This step implements the process. In this step, each manager's observations are transferred into individual awareness of a special aspect of the decision problem and decision object by approximate reasoning on the basis of a personal mental model. This procedure is illustrated below.

Suppose d is a key driver which is the concern of a manager, and $V_d = \{x_1, \cdots, x_k\}$ is the significant variables connected to d. Let domain knowledge and experience about leaf drivers of the manager be f_d. Then notice that f_d is a set of rules defined as

$$f_d : \prod_{x \in V_d} (S_x \times T) \Rightarrow H \times T, \tag{8}$$

therefore, for any combination of $\frac{t_1}{s_{x_1}} \wedge \cdots \wedge \frac{t_k}{s_{x_k}}$, where $s_{x_i} \in S_{x_i}$, t_i $(\in T)$ a linguistic possibility shown in

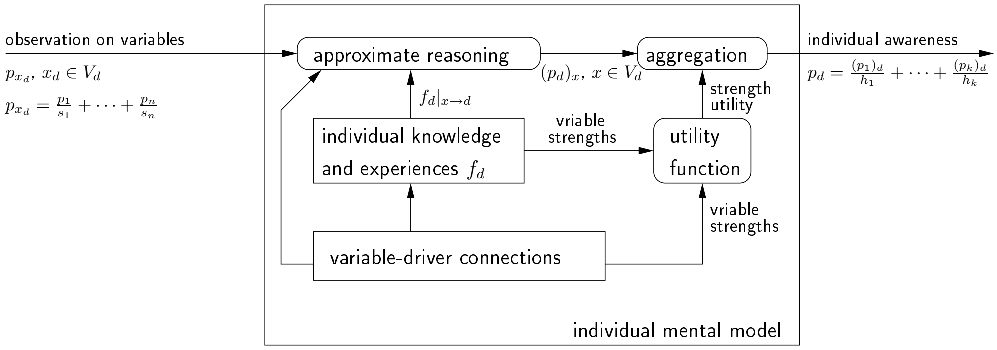

Fig. 5 A procedure of individual SA generation

Table 2, $i = 1, \cdots, k$, if

$$\frac{t_1}{s_{x_1}} \wedge \cdots \wedge \frac{t_k}{s_{x_k}} \in \prod_{i=1}^{k} (S_{x_i} \times T)\Bigg|_{f_d}, \tag{9}$$

then a conclusion about the decision object with respect to the driver d is obtained and denoted by $\frac{t_d}{h_d}$. However, if

$$\frac{t_1}{s_{x_1}} \wedge \cdots \wedge \frac{t_k}{s_{x_k}} \notin \prod_{i=1}^{k} (S_{x_i} \times T)\Bigg|_{f_d}, \tag{10}$$

an approximate reasoning is used to obtain a similar conclusion and is denoted by $\frac{t'_d}{h'_d}$. In general, conclusions obtained by approximate reasoning about the same $h \in H$ may be many. Without loss of generality, let T_h be the set of linguistic possibilities on h. From T_h, the most frequently occurring term t_h will be selected and assigned to h. Similar for other $h' \in H$, there is a t'_h which is assigned to h'. Then collecting all $\frac{t_h}{h}$ ($h \in H$), a linguistic possibility distribution on H is obtained which is the manager's individual SA, i.e., iSA_d.

Step 9: measure a team's SA with respect to leaf drivers by aggregation.

This step integrates managers' individual SA on the same leaf driver. Suppose $d \in LD$ is a leaf key driver and $M_d = \{e_{d1}, \cdots, e_{dl}\}$ the set of managers who have impact on d. Let $(iSA_d)_i$ and σ_{id}be the individual SA and impact factor on d of the manager e_{di}. Then the team SA in the integration of $\{((iSA_d)_i, \sigma_{id}) : i = 1, \ldots, l\}$. To do so, an aggregation operator Agg is used as below:

$$\begin{aligned} tSA_d &= tSA_d|_{M_d} \\ &= \left\{ \frac{\text{Agg}\left\{(p_{di}|_h, q(\sigma_{id})) : i = 1, \ldots, l\right\}}{h} : h \in H \right\} \\ &= \left\{ \frac{\text{Agg}\left\{\left(t_h|_{e_i}, q(\sigma_{id})\right) : i = 1, \ldots, l\right\}}{h} : h \in H \right\}. \end{aligned}$$

That means the aggregation is conducted for each $h \in H$ respectively on the basis of t_h and the utility of σ_{id}.

Step 10: measure a team's SA on non-leaf drivers (including the decision problem) by approximate reasoning and aggregation operations.

Based on the team SA on leaf key drivers, the team SA on non-leaf key drivers can be obtained. The primary process is similar to that in Step 9.

Through the 10-step algorithm, the team SA is thus measured. In the next section, a simple case is studied to illustrate the main steps and effectiveness of the algorithm.

4 A case study

In this section, we use an illustrative example in telecoms customer churn prediction to explain the main steps in the TSAM method. The main drivers and significant variables are taken from [14], and the data is a combination of marketing advertisements of telecoms in Australia.

Step 1: Let $D^{(0)}$ (the decision problem) be "whether a segment of customers will churn". The decision object is "the segment of customers" and its possible states are their "potential behavior". Here suppose the segment of customers has seven potential churning behaviors which are denoted by $H = \{h_1 < h_2 < h_3 < h_4 < h_5 < h_6 < h_7\}$ based on the churning risk of each behavior from lowest to highest.

Step 2: Let the key drivers be those shown in Figure 2. The strength of each driver is given in Table 4.

Table 4 Example of strength of identified drivers.

d_1	d_2	d_3	d_4
Important	Very important	Important	Important

Step 3: Let the variables be those shown in Figure 2 and suppose each variable's possible states are shown in Table 5.

Table 5 Example states for observations of variables.

Variable name	States of variables				
Age	Young	Middle-age	Old		
Tenure	Long contract	Short contract	Prepaid		
Gender	Male	Female			
Monthly fee	Normal	Higher	Very high	Low	Very low
Billing amount	Normal	High	Very high	Low	
Overdue payment	Little	No	Medium	Much	
In-net call	Seldom	Often	Most		
Call type	Video	Voice	Message	Download	
Count change	Often	Seldom	None		
Bar and suspend	Never	Often	Seldom		

Step 4: Let the connections between drivers and variables be shown in Figure 2 and the strengths of variables be listed in Table 6

Table 6 Example of strengths for drivers and variables.

Driver	Variable	Strength
d_1	x_{11}	Very important
	x_{12}	Very important
	x_{13}	Medium
d_2	x_{21}	Very important
	x_{22}	Very important
	x_{23}	Important
d_3	x_{31}	Important
	x_{32}	Important
d_4	x_{41}	Important
	x_{42}	Medium

Some rules for the driver "bill and payment" for this problem can be expressed such as

- High monthly fee $\Rightarrow$ churn;
- High billing amount $\Rightarrow$ churn;
- Often due payments $\Rightarrow$ churn;

Rules for other drivers can be obtained accordingly.

Step 5: Suppose a team of four managers from a marketing department (e_1), net service support department (e_2), financial department (e_3), and customer service department (e_4) respectively. The impact factors of these four managers are assigned as shown in Table 7.

Step 6: In the illustrative example, there are two kinds of linguistic term sets, i.e., the linguistic weights W for the strengths of drivers, variables, and impact factor of managers; and the linguistic possibilities T. For the linguistic weight W, let the utility function q_W be defined as

$$q_W(v_i) = \left(\frac{i}{7}\right)^2. \tag{11}$$

For the linguistic possibility T, let the utility function q_T be

$$q_T(u_i) = \frac{i}{7}. \tag{12}$$

Step 7: Suppose manager e_1 has observations of the variables for driver d_2 and they are

$$p_{x_{21}}^{e_1} = \frac{u_2}{\text{normal}} + \frac{u_5}{\text{higher}} + \frac{u_4}{\text{very high}} + \frac{u_2}{\text{low}} + \frac{u_1}{\text{very low}}$$
$$p_{x_{22}}^{e_2} = \frac{u_5}{\text{normal}} + \frac{u_4}{\text{high}} + \frac{u_1}{\text{low}}$$
$$p_{x_{23}}^{e_1} = \frac{u_2}{\text{little}} + \frac{u_1}{\text{never}} + \frac{u_6}{\text{much}}$$

Based on these observations, manager e_1 can have an awareness about d_2.

Step 8: Assume that the individual SA of these four managers on the four drivers is obtained from observations of those variables as shown in Table 8.

Based on the individual SA and utilities of managers, the team SA on each leaf driver is obtained. Suppose the used aggregation operator is the weighted-sum, then the team SA on driver d_1 is

$$p_{d_1} = (u_4, u_5, u_5, u_3, u_4, u_2, u_1), \tag{13}$$

where the calculation of linguistic possibility on each state h_i is as below: take h_1 for example,

$$\begin{aligned} u_{h_1} &= \frac{q_T(u_2)\cdot q_W(v_6) + q_T(u_5)\cdot q_W(v_2) + q_T(u_6)\cdot q_W(v_6)}{q_W(v_6) + q_W(v_2) + q_W(v_6)} \\ &= \frac{0.29 \times 0.73 + 0.71 \times 0.08 + 0.86 \times 0.73}{0.73 + 0.08 + 0.73} \\ &\approx \frac{4.05}{7} \approx u_4. \end{aligned}$$

For the other three drivers, we obtained:

$$p_{d_2} = (u_3, u_4, u_3, u_4, u_3, u_4, u_3),$$
$$p_{d_3} = (u_1, u_7, u_7, u_4, u_7, u_2, u_1),$$
$$p_{d_4} = (u_6, u_5, u_5, u_5, u_4, u_5, u_3).$$

Step 9: Based on the team awareness of the four drivers, the team SA on d_0 is obtained. Suppose the strengths of all drivers is equal and the aggregation operator is the weighted-sum, then the team SA tSA_{d_0} is

$$tSA_{d_0} = (u_4, u_5, u_5, u_4, u_5, u_3, u_2). \tag{14}$$

Table 7 Linguistic weights and their utilities for managers.

Driver id	e_1	utility	e_2	utility	e_3	utility	e_4	utility
d_1	High	0.73	Low	0.08	NA	NA	High	0.73
d_2	High	0.73	Medium	0.33	High	0.73	Medium	0.33
d_3	NA	NA	High	0.73	NA	NA	NA	NA
d_4	Medium	0.33	NA	NA	High	0.73	High	0.73

Table 8 Observations on variables.

Driver id	e_1	e_2	e_3	e_4
d_1	$(u_2, u_2, u_7, u_5, u_3, u_2, u_1)$	$(u_5, u_5, u_1, u_3, u_4, u_2, u_6)$	NA	$(u_6, u_7, u_3, u_2, u_6, u_1, u_1)$
d_2	$(u_7, u_2, u_2, u_5, u_3, u_4, u_1)$	$(u_3, u_2, u_5, u_2, u_6, u_3, u_6)$	$(u_1, u_5, u_2, u_3, u_2, u_4, u_5)$	$(u_1, u_7, u_7, u_6, u_1, u_6, u_1)$
d_3	NA	$(u_1, u_7, u_7, u_4, u_7, u_2, u_1)$	NA	
d_4	$(u_7, u_2, u_4, u_5, u_2, u_3, u_3)$	NA	$(u_4, u_4, u_6, u_3, u_2, u_3, u_1)$	$(u_6, u_6, u_2, u_5, u_5, u_6, u_3)$

This result indicates that the given segment of customers' potential behaviors are h_2, h_3, and h_5. From the viewpoint of practice, an offer may be provided based on h_5 because it is the highest possible churning behavior.

5 Conclusions and future work

In this paper, a TSAM method is presented to measure team SA in a complex and dynamic context using identified drivers and significant variables which are used as components of individual and team mental models. The method uses utility functions to capture semantics of linguistic terms which are used to describe the strengths of drivers, variables, the impact of managers. Utility functions can be used to create unbalanced and asymmetric representation of linguistic terms. Individual and team SA is expressed by a linguistic possibility distribution on the decision object's possible states, which can be used to express awareness more naturally and easily. A simple example in telecoms customer churn prediction is presented to illustrate the main steps of the method.

To improve team decision-making efficiency and accuracy, effective cooperation is the most important issue. Team members often express their awareness in forms with various natures. Hence, how to effectively integrate multiple natures of awareness will be studied, which may include the perception of semantics in different expressions as well as reasoning based on those semantics. Moreover, a correct mental model is the basis of team decision-making which will affect the generation and measurement of individual and team SA. Therefore, how to construct an appropriate and flexible mental model will also be another task in our future study.

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