J. Management and Humanity Research
Vol. 9, 2023, 43-57
ISSN: 2582-7766 *(online)*
Published on 30 June 2023
www.researchmathsci.org
DOI: http://dx.doi.org/10.22457/jmhr.v09a042358

Journal of
Management and Humanity Research

A Data-driven Method for Dynamic Emergency Decision-making in Public Emergencies

Liu Liu*

School of Economics and Management
Beijing University of Posts and Telecommunications
Beijing 100876, China
*Corresponding author. Email: liuliutem@163.com

Received 10 May 2023; Accepted 30 June 2023

Abstract. The evolution of a public emergency situation is often dynamic, random and multi-stage, requiring multiple decisions and dynamic updates to the emergency response plan according to the event situation until the best outcome is achieved. This research proposes a data-driven approach to dynamic emergency decision-making for public emergencies based on lens model and prospect theory, which in details are: 1)using lens model foe reference, the state in the next stage is predicted through the proximal information in current stage; 2) considering the uncertainty of the public emergencies decision-making environment, using the fuzzy number to describe the information cues obtained by the decision-maker; 3) to simulate the real decision-maker better, the method is proposed in the framework of prospect theory. Based on the above ideas, two key parameters are invented for the dynamic emergencies decision-making method: predict prospect value and predict performance. At last, a case in public emergencies is applied to illustrate the performance of the proposed method.

Keywords: emergency decision-making; data-driven; lens model; prospect theory

1. Introduction

The complex and volatile nature of public emergencies and the dramatic increase in the amount of information and data related to them place a heavy burden on emergency decision makers, who can more easily formulate the ideal emergency response plan if they have timely and accurate access to scenario information and other relevant decision information. Data can provide a clear picture of the evolution of a public emergency from a dynamic, multi-dimensional perspective, and decision makers can take full advantage of the continuous stream of real-time data coming into the emergency decision-making system to develop an accurate perception of what is happening and how it is developing, and to gain a warm, tangible sense of what is happening [1]. The data generated and dynamically changed in real time provides a powerful basis for predicting the state of an event, and decision makers can use the constantly updated data to make judgements about the state of the event and form reliable preference information [2]. Generally speaking, the closer the preference information is to the actual situation, the more accurate the decision outcome will be. Some scholars have explored the issue of emergency decision-making based on event status updates, but there are still some shortcomings in the existing research: (1) Traditional emergency decision-making is usually based on a static historical database, and as the dynamics of public emergencies evolve, the available event data information increases, making the decision information available for reference clearer, more accumulated and more complete. However, in the actual emergency decision-making process, the deeper value of data updating in the emergency decision-making process is overlooked due to the constraints of the level of data mining technology, data thinking and awareness of decision-makers, etc. (2) Existing emergency decision-making methods usually focus only on the impact of each emergency plan on the current emergency response, ignoring the impact of the implementation of the emergency plan on the state of the event in the next period. (3) Past research has shown that decision makers need to predict the next state of a public emergency at each decision point, and adjust the emergency response plan based on the prediction results, and activate the emergency response plan that matches the current state of the public emergency to obtain the final emergency response decision result. However, the effectiveness of this decision-making method is affected by the level of decision-makers' predicting ability, which has not been explored in depth in previous studies.

Given the complexity and uncertainty of public emergencies, higher requirements are placed on the flexibility and timeliness of emergency decision-making. In the big data environment, the data-driven emergency decision-making model presents dynamic and predictive characteristics, which has significant application advantages and becomes an effective path to improve the quality of emergency decision-making [3]. This study proposes a data-driven dynamic emergency decision-making approach, the essence of which is to continuously collect real-time updated event status data, and comprehensively consider the dynamic changes of contextual elements related to the evolutionary trend of public emergencies, and then make adjustments and updates to the current decision. At the same time, considering the limited rationality of decision makers in actual decision-making situations, this study embeds prospect theory into a data-driven dynamic emergency decision-making approach to characterise the risk preferences of decision makers in the face of gains and losses. In addition, the lens model depicts the process of exploring the state of distant variables through proximal observable cues, which fits the decision making context of dynamic contingency decision making in which decision makers predict the next state of an event by observing current data cues, and therefore this study uses the lens model to portray the decision makers' prediction process of the next state of an event in dynamic contingency decision making.

In summary, this study introduces foreground theory and the lens model, and proposes a data-driven dynamic emergency decision-making method for public emergencies. The decision-making basis of this method mainly includes: (1) predicting "prospect" values: first, decision-makers assign current clues based on real-time data and generate predicted values for the next state of the event by drawing on the idea of the lens model; then, the predicted values are converted into predicted "prospect" values by applying prospect theory. (2) Predict performance: The predict value may have subjective bias due to the level of predicting ability of the decision maker, so the historical predict value of the decision maker and the historical true value of the event state are collected, and the correlation coefficient between them is the predict performance.

2. Reviews of the Literature

2.1. Emergency decision-making

Emergency decision-making for public emergencies refers to a special management activity that makes full use of decision-making theories and methods to carry out dynamic planning of emergency disposal plans or emergency response measures in order to effectively respond to the casualties, property losses and social hazards caused by public emergencies after the emergence of signs or the occurrence of public emergencies [4]. On the one hand, scientific and reasonable emergency decision-making can effectively control the evolution of public emergencies in a timely manner and prevent the deterioration of the situation from bringing about greater losses; on the other hand, it can make efficient use of the available emergency rescue resources, maximise the effectiveness of resources and provide solid human and material security for carrying out emergency rescue work. Emergency decision-making in public emergencies is a complex multi-objective dynamic optimisation problem.

The problem of emergency decision-making in public emergencies is multi-stage in nature, as evidenced by the following:

(1) The initial phase is the scenario when the precursors of a public emergency are visible or just about to occur;

(2) The intermediate stage is the state in which a public emergency has occurred and has developed to a certain point in time, either through natural laws or human intervention. This stage is a collection of scenarios consisting of multiple sub-stages, depending on the development of the emergency and the emergency response that has been taken;

(3) The final stage is when a public emergency is effectively controlled as the event state evolves and updates, and eventually reaches a state of extinction or termination [5].

In addition, emergency decision-making in public emergencies is dynamic in nature, mainly because the effective handling of public emergencies is based on the continuous coupling and overlapping implementation of multiple single-stage emergency response plans [6]. At each stage, decision-makers need to assess the effectiveness of the emergency response plan in controlling the situation based on real-time information about the emergency, and to predict the evolution of the situation, so as to make a scientific and reasonable emergency response decision. This means that the decision-making process is not a one-off decision, but a process of dynamically adjusting the emergency plan based on scenario updates until the emergency is effectively managed.

From an analysis of the evolution of events, the development of public emergencies is a continuous process in time, and the corresponding emergency decision-making activities are also a continuous process in time, and the whole process is full of uncertainty [7]. However, decision-makers are often faced with uncertainties such as difficulties in obtaining information about deterministic events, internal differences in perceptions of events, and conflicting decision-making preferences, so the emergency decision-making process for public emergencies is also characterised by significant uncertainties [8].

From the above analysis, the characteristics of emergency decision-making in public emergencies are mainly reflected in three aspects: firstly, the multi-stage nature of the emergency decision-making process, and the importance of each stage is different; secondly, as the situation of public emergencies evolves, taking full advantage of information technology, the information available on the event scenario is constantly clear and complete; thirdly, as the decision information available for reference is constantly updated, the subjective emotions and Third, as the information available for decision making is constantly updated, the subjective emotions and preferences of decision makers are adjusted and updated by the influence of uncertain information, and gradually converge.

2.2. Prospect theory

Decision experts are usually finitely rational rather than fully rational in the emergency decision-making process [9]. Prospect theory was proposed in 1979 by Kahneman and Tversky, two scholars who designed various behavioural experiments in their study of decision-making behaviour based on expected utility theory and found that expected utility theory ignored the irrational factors of decision-making subjects. The basic idea of prospect theory is that under risky decision-making conditions, subjects exhibit heterogeneous psychological preferences and limited rational behavioural tendencies when faced with losses and gains, including certainty effects, reflexive effects, reference dependence and loss aversion [10]. The behavioral tendencies described by prospect theory are more in line with the objective reality and are widely used in the study of decision problems. For example, Bharsakade et al. considering the influence of limited rationality on the subject's decision making behavior, a multi-attribute decision making method is proposed in the intuitionistic fuzzy language environment by combining prospect theory and evidence-based reasoning methods [11]. Xu et al. considered the heterogeneous preference problem of group decision making and designed an emergency decision framework based on cumulative prospect theory, which can effectively improve the consistency level of group decision-making [12]. Liu and Li used prospect theory in a probabilistic linguistic setting to construct a prospect decision matrix, combined with decision indicator weights to calculate the combined prospect values of alternatives, and proposed a new emergency response decision method [13].

This study makes full use of the advantages of prospect theory in effectively portraying the heterogeneous psychological preference behaviour of decision-making subjects and introduces it into the process of contingency decision analysis to describe the limited rational behaviour of subjects in dynamic decision-making situations. According to the basic principle of prospect theory, decision subjects are more sensitive to "loss" than "gain", they are often risk-averse when faced with loss, and risk-averse when faced with gain. Applying prospect theory to the real world of decision-making, the prospect of an alternative a is calculated as

$$V(a)=\sum_{i=1}^{n} v(y_i)w(p_i)$$

The greater the prospect value $V(a)$ of the solution a, the better the decision subject's expected prospect for the solution. The value function v reflects the subjective feeling of the decision subject about the gain or loss and is expressed as

$$v(y)=\begin{cases}-\lambda(y_0-y)^{\beta} & y-y_0<0\\ (y-y_0)^{\alpha} & y-y_0\geq 0\end{cases}$$

where y represents the objective gain and y_0 the gain reference point $y-y_0$. This represents the deviation of the actual return of the scenario a from the reference point y_0, with a gain at $y-y_0 \geq 0$ and a loss at $y-y_0 < 0$. α and β are the risk sensitivity coefficients of the decision maker to gains and losses respectively , which take values in the range $0<\alpha<1$ and $0<\beta<1$. λ is the loss aversion coefficient and $\lambda>1$ indicates that the decision maker is more sensitive to losses.

$$w(p)=\begin{cases}\dfrac{p^{\delta}}{\left[p^{\delta}+(1-p)^{\delta}\right]^{1/\delta}} & y-y_0<0\\[2ex] \dfrac{p^{\gamma}}{\left[p^{\gamma}+(1-p)^{\gamma}\right]^{1/\gamma}} & y-y_0\geq 0\end{cases} \tag{2-1}$$

(2-1) is the subjective probability weight of the decision maker, the weight that the decision maker subjectively assigns to the probability of the expected outcome occurring. Where p is the probability of the expected outcome, γ and δ are the risk attitude coefficients of the decision maker when the psychological expected outcome is a gain and a loss, respectively.

2.3. The lens model

The lens model, proposed by cognitive psychologist Brunswick (1956), is based on an 'organism-environment' structural model that uses a series of directly proximal observable cues to explore and gain insight into the reality of distal variables [14]. The lens model has been widely used in decision making as it can resolve the internal processes and mechanisms by which decision makers generate decision information.

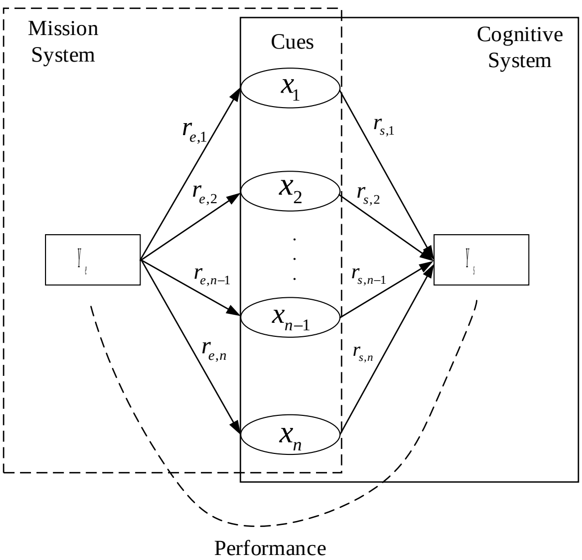

Figure 2.1: Lens model

As can be seen in Figure 2.1, the lens model is a symmetrical model consisting of a task system and a cognitive system, connected by a series of information cues, which are the reference elements that the subject relies on when making decisions. The task system reflects the association between the true outcome of the observed target Y_e and the information cues; the cognitive system reflects the association between the decision subject's predicted outcome of the observed target Y_s and the information cues.

In a task system, the correlation between the true outcome of the observed target Y_e and a set of information cues can be fitted with a linear model of

$$Y_e = r_{e,1}x_1 + r_{e,2}x_2 + \cdots + r_{e,n}x_n + \varepsilon_e$$

where $x_1, x_2, \cdots, x_n$ is the cue associated with the true result Y_e and the predicted result Y_s, $r_{e,1}, r_{e,2}, \cdots, r_{e,n}$ corresponds to the weight of each cue and reflects how closely each cue is associated with the true result Y_e, and ε_e is the residual, which represents the random error between the fitted result calculated from the cue values and weights and the true result Y_e.

In a cognitive system Y_s represents a decision subject's judgement and prediction of the developmental state of an observed target based on a series of information cues, and its association with the cues can be fitted by another linear model:

$$Y_s = r_{s,1}x_1 + r_{s,2}x_2 + \cdots + r_{s,n}x_n + \varepsilon_s$$

where $r_{s,1}, r_{s,2}, \cdots, r_{s,n}$ corresponds to the weight of each cue in the cognitive system and reflects the extent to which the decision maker refers to and uses each cue in making the predicted outcome Y_s, and ε_s is the residual, which represents the random error between the fitting result calculated from the cue values and weights and the decision maker's predicted outcome Y_s.

After a decision subject has made a prediction, its prediction performance is measured by r_a, $r_a = corr(Y_e, Y_s)$, which represents the correlation coefficient between the true outcome Y_e and the predicted outcome Y_s, generally calculated using the Pearson correlation coefficient. The correlation coefficient r_a reflects the correlation between the prediction made by the decision subject and the true state of the observed target and portrays the degree of accuracy of the prediction made by the decision maker.

3. Emergency decision-making methods

3.1. Problem description and analysis

Decision makers rely on a series of information clues to form their perceptions of the current real state of public emergencies and their predictions of the future state of development, and event data is the concrete expression of these information clues. In the big data environment, decision makers make decisions through the mining and analysis of event data, forming a data-driven emergency decision-making model. The main characteristic of dynamic emergency decision-making problems is that the state of a public emergency evolves dynamically over time, and decisions made by decision-makers at each decision point are based on predictions of the state of events at the next point in time. The lens model can be used to analyse and present the process by which decision makers combine cues to form predictions. This chapter will draw on the ideas of the lens model to design a data-driven approach to dynamic emergency decision-making.

The core of the approach lies in the decision maker's prediction of the next state of a public emergency through the following process: The emergency decision maker is faced with a set of options $A=\left(a_1,a_2,\cdots a_j\right)$. At any given decision point t, the decision maker collects and analyses a range of real-time data to form a judgement about the cues $x_1,x_2,\cdots x_n$ that are associated with the state of the event at the next point in time. Considering that the contingency plan $a_j\left(j=1,2,\cdots,m\right)$ implemented by decision makers in the current period also has an impact on the next state of a public emergency, this study uses the contingency plan $a_j\left(j=1,2,\cdots,m\right)$ implemented in the current period as one of the cues to predict the next state of the event. Thus, at any decision point t, decision makers form an analysis of the cues $x_1,x_2,\cdots x_n$ and scenario cues a_j based on a series of real-time data to obtain a prediction of the next state of the event $Y\left(a_j\right)_{s,t+1}$.

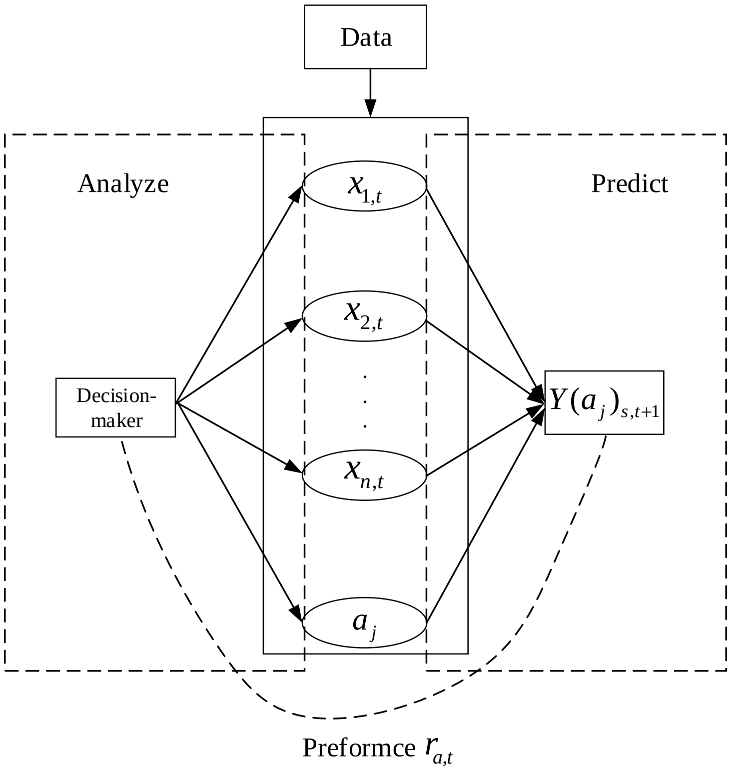

Figure 3.1: Prediction process

Traditional lensing models generally use a single term to describe cues, but emergency decision-making situations for public emergencies are often highly uncertain, and decision-makers have difficulty evaluating a cue with precision, preferring instead to give fuzzy evaluations. Pythagorean fuzzy sets are more expressive in dealing with uncertainty and fuzzy information [15]. When using the lensing model to predict the state of an event, the advantage of Pythagorean fuzzy numbers in portraying uncertain information can fully express the fuzzy nature of the decision maker's evaluation of a cue. Therefore, this study applies Pythagorean fuzzy numbers to assign cue evaluations, while assembling cue information based on the Pythagorean fuzzy numbers' algorithm to form the decision maker's prediction of event states.

In emergency decision-making situations where information is uncertain and time pressure is high, decision makers tend to be limitedly rational and have subjective distortions in their perception of benefits and risks, such as pursuing the "certainty effect", given the same expected benefits, decision makers tend to choose certain benefits over risky ones [16]. The decision maker's attitude towards risk in the face of gain and loss affects the outcome of his or her decision, and prospect theory better portrays the limited rationality of decision makers. Therefore, this study embeds prospect theory into a data-driven dynamic contingency decision-making approach as a way to simulate real decision-making situations and portray the limited rationality of decision makers.

3.2. Methodological analysis

In dynamic emergency decision-making problems, decision makers predict the next state of a public emergency based on real-time data and current cues. If the decision maker is fully rational, then the predicted value can be used directly as the basis for the decision maker's choice of scenario. In reality, however, due to the limited rationality of the decision maker, the predicted 'prospect' value can better reflect the decision maker's subjective perception of gains and losses, and better match the actual decision-making situation. Therefore, this study uses the predicted 'prospect' value as the basis for decision makers to choose the current contingency plan. As the calculation of the predicted 'prospect' value is based on the decision maker's prediction of the next state of the event, there is subjectivity in the decision maker's weighting and assignment of cues when solving for the predicted value, which means that the accuracy of the predicted outcome is affected by the decision maker's own factors. In this case, the predicted 'prospect' value should not be used as the only basis for decision making, so this study refers to the judgmental performance in the lens model and introduces the prediction performance indicator, which is obtained by calculating the correlation coefficient between the decision maker's predicted value and the true value of the event. Predict performance reflects the degree of accuracy of the decision maker's subjective predict and is one of the bases for decision making.

Based on the above analysis, this study improves the decision-making method proposed by Jing Gu et al. [17] and introduces it into the field of emergency decision-making for public emergencies:

1. Predict "prospect" values

Based on the task system in the lens model, the prediction process of the decision maker in Figure 3.1 is used as the basis for the analysis and the calculation method for predicting the "prospect value" is proposed.

(1) Cue selection and weighting. A number of variables with the highest relevance to the public emergency situation were selected as clues, and the weights of each clue were calculated using the DEMATEL method.

(2) Collect real-time data and calculate predictive values. Based on the cue weights solved in the previous step, the decision maker assigns a value to the cue based on the real-time data to predict the next state of the event.

$$Y\left(a_j\right)_{s,t+1}=\sum_{i=1}^{n} r_{s,i} x_{i,t}+r_{s,n+1} a_j \tag{3.1}$$

In the equation (3-1), $x_{i,t}\left(i=1,2,\cdots n\right)$ represents the i cues for decision makers at the point in time t ; $a_j\left(j=1,2,\cdots,m\right)$ is the j option from the set of options $A=\left\{a_1,a_2,\cdots,a_m\right\}$ as an additional lead for predicting the 'prospect' value, $r_{s,n+1}$ is the weight of the option 'cues' $a_j\left(j=1,2,\cdots,m\right)$, s.t. $\sum_{i=1}^{n+1} r_{s,i}=1$; $Y\left(a_j\right)_{s,t+1}$ represents the decision maker's prediction of the state of a public emergency at the $t+1$ point in time following the adoption of the contingency $a_j\left(j=1,2,\cdots,m\right)$.

(3) Inscription of uncertain decision information. Assigning value cues and solution cues in the form of Pythagorean fuzzy numbers, we get

$$Y\left(a_j\right)_{s,t+1}=r_{s,1} x_{1,t} \oplus r_{s,2} x_{2,t} \oplus \cdots \oplus r_{s,n} x_{n,t} \oplus r_{s,n+1} a_j$$

where $x_{i,t}=\left(\mu_{i,t},\nu_{i,t}\right)\left(i=1,2,\cdots,n\right)$ is the Pythagorean fuzzy number, $\mu_{i,t}$ indicates the extent to which the decision maker believes that the state of $x_{i,t}$ meets the "ideal" level, and $\nu_{i,t}$ indicates the extent to which the decision maker believes that the state of $x_{i,t}$ does not meet the "ideal" level. The above equation is based on the Pythagorean fuzzy number algorithm and the Pythagorean fuzzy weighted average operator.

(4) Calculating the predicted "prospect" value. Based on the predicted state of the next public emergency, decision makers have a sense of the value and weight of each cue and further calculate the predicted "prospect" value.

First, choose the reference point. Choose the reference point $x_0=\left(0.5,0.5\right)$ according to the definition of the Pythagorean fuzzy number and the score function;

Second, based on prospect theory, the value function of the clue $x_{i,t}\left(i=1,2,\cdots n\right)$ is obtained as

$$v\left(x_{i,t}\right)=\begin{cases}-\lambda D\left(x_{i,t},x_0\right)^{\beta} & x_{i,t}<x_0 \\ D\left(x_{i,t},x_0\right)^{\alpha} & x_{i,t}\geq x_0\end{cases}$$

Of which. $D\left(x_{i,t},x_0\right)=\left(1-\max\left(L_{i,t},H_{i,t}\right),\min\left(L_{i,t},H_{i,t}\right)\right)$

$$L=\frac{\min\left(0.5,\mu_{i,t}\right)}{\max\left(0.5,\mu_{i,t}\right)},\quad H=\frac{\min\left(0.5,1-\nu_{i,t}\right)}{\max\left(0.5,1-\nu_{i,t}\right)}$$

The value function $v\left(x_{i,t}\right)$ is a Pythagorean fuzzy number, that is the predicted "prospect" value of the lead is a fuzzy number, $v\left(x_{i,t}\right)=\left(\mu_{v\left(x_{i,t}\right)},\nu_{v\left(x_{i,t}\right)}\right)$.

The weights of the leads $x_{i,t}\left(i=1,2,\cdots,n\right)$ are then calculated as

$$w\left(r_{s,i}\right)=\begin{cases}\dfrac{r_{s,i}^{\delta}}{\left[r_{s,i}^{\delta}+\left(1-r_{s,i}\right)^{\delta}\right]^{\frac{1}{\delta}}} & x_{i,t}<x_0\\ \dfrac{r_{s,i}^{\gamma}}{\left[r_{s,i}^{\gamma}+\left(1-r_{s,i}\right)^{\gamma}\right]^{\frac{1}{\gamma}}} & x_{i,t}\geq x_0\end{cases}$$

Finally, the decision maker's predicted "prospect" of adopting a particular contingency option is obtained as follows:

$$\begin{aligned}V\left(a_j\right)_{t+1}&=v\left(x_{1,t}\right)w\left(r_{s,1}\right)\oplus v\left(x_{2,t}\right)w\left(r_{s,2}\right)\oplus\cdots v\left(x_{n,t}\right)w\left(r_{s,n}\right)\oplus v\left(a_j\right)w\left(r_{s,n+1}\right)\\&=\left(1-\prod_{i=1}^{n}\left(1-\mu_{v\left(x_{i,t}\right)}\right)^{w\left(r_{s,i}\right)}\cdot\left(1-\mu_{v\left(a_j\right)}\right)^{w\left(r_{s,n+1}\right)},\prod_{i=1}^{n}v_{v\left(x_{i,t}\right)}^{w\left(r_{s,i}\right)}\cdot v_{v\left(x_{i,t}\right)}^{w\left(r_{s,i}\right)}\right)\end{aligned}$$

2. Predict performance

(1) Historical data collation. At each time point $k\left(k=1,2,\cdots,t-1\right)$ before the time point t, the decision maker gives the predicted value of the next state of the event $Y\left(a_j\right)_{s,k+1}$. When the decision process advances to the time point $k+1$, the true value of the event state $Y\left(a_j\right)_{e,k+1}$ is displayed and is in the form of a Pythagorean fuzzy number.

$Y_s=\left\{Y\left(a_j\right)_{s,k+1}\middle|k=1,2,\cdots,t-1\right\}$ Collate historical data of predicted and true values at each point in time with Y_s representing the set of predicted values before the decision maker's point in time t for each element of the set $Y\left(a_j\right)_{s,k+1}=\left(\mu\left(Y_{s,j}\right),v\left(Y_{s,j}\right)\right)\left(j=1,2,\cdots,t\right)$ and Y_e representing the set of true state values before the decision maker's point in time t for each element of the set $Y_e=\left\{Y\left(a_j\right)_{e,k+1}\middle|k=1,2,\cdots,t-1\right\}$ for each element of the set

$$Y\left(a_j\right)_{e,k}=\left(\mu\left(Y_{e,k}\right),v\left(Y_{e,k}\right)\right).$$

(2) Predictive performance calculation

According to the solution of the Pythagorean fuzzy set correlation coefficient, the decision maker's predicted performance at the point in time t is

$$r_{a,t}=\rho_t\left(Y_e,Y_s\right)=\frac{COV\left(Y_e,Y_s\right)}{\sqrt{D\left(Y_e\right)D\left(Y_s\right)}}$$

where for $COV\left(Y_e,Y_s\right)$ are the covariances of the Pythagorean fuzzy sets Y_e and Y_s, $D\left(Y_e\right)$ and $D\left(Y_s\right)$ are the variances of the Pythagorean fuzzy sets Y_e and respectively Y_s.

$$COV\left(Y_e,Y_s\right)=\frac{1}{t-1}\sum_{j=1}^{n}\left\{\left(\mu\left(Y_{e,j}\right)-\bar{\mu}_{Y_{e,j}}\right)\left(\mu\left(Y_{s,j}\right)-\bar{\mu}_{Y_{s,j}}\right)+\left(\nu\left(Y_{e,j}\right)-\bar{\nu}_{Y_{e,j}}\right)\left(\nu\left(Y_{s,j}\right)-\bar{\nu}_{Y_{s,j}}\right)\right\}$$

$$D\left(Y_e\right)=\frac{1}{t-1}\sum_{j=1}^{n}\left\{\left(\mu\left(Y_{e,j}\right)-\bar{\mu}_{Y_{e,j}}\right)^2+\left(\nu\left(Y_{e,j}\right)-\bar{\nu}_{Y_{e,j}}\right)^2\right\}$$

$$D\left(Y_s\right)=\frac{1}{t-1}\sum_{j=1}^{n}\left\{\left(\mu\left(Y_{s,j}\right)-\bar{\mu}_{Y_{s,j}}\right)^2+\left(\nu\left(Y_{s,j}\right)-\bar{\nu}_{Y_{s,j}}\right)^2\right\}$$

where $\left(\bar{\mu}_{Y_{e,j}},\bar{\nu}_{Y_{e,j}}\right),\left(\bar{\mu}_{Y_{s,j}},\bar{\nu}_{Y_{s,j}}\right)$ is the mean of the actual Y_e set and the predicted Y_s set, respectively.

Let $b_j=\mu\left(Y_{e,j}\right)-\bar{\mu}_{Y_{e,j}}$ $c_j=\mu\left(Y_{s,j}\right)-\bar{\mu}_{Y_{s,j}}$ $d_j=\nu\left(Y_{e,j}\right)-\bar{\nu}_{Y_{e,j}}$ $e_j=\nu\left(Y_{s,j}\right)-\bar{\nu}_{Y_{s,j}}$, then the calculation of predicted performance can be simplified as

$$r_{a,t}=\frac{\sum_{j=1}^{t}\left(b_jc_j+d_je_j\right)}{\sqrt{\sum_{j=1}^{t}\left(b_j^2+d_j^2\right)\sum_{j=1}^{t}\left(c_j^2+e_j^2\right)}}$$

4. Case studies

4.1. Case background

At the end of 2019, a sudden outbreak and rapid spread of novel coronavirus to several provinces and cities in China caused huge casualties and economic losses, and seriously disrupted the normal social order. A study by Ge Honglei and Liu Nan [18] pointed out that the evolutionary status of the new coronavirus pneumonia epidemic could be judged from four dimensions: spatial distribution, transmission dynamics, scale of infection, and epidemic information characteristics, as shown in the table. Based on this, this study conducted emergency decision-making research and analysis by collecting historical and real-time data of these 4 dimensions. Data sources include data released by the Chinese Centre for Disease Control and Prevention, the Epidemic Prevention and Control Office, and the New Coronary Pneumonia Epidemic Query Platform.

Table 4.1: Evolutionary status of the new crown pneumonia outbreak

Status Features	S1:Uncontrolled and rapid spread	S2:Multi-city outbreak under traffic control	S3:National peak under community control	S4: Resumption of work and production and concurrent management

				of the epidemic period
Spatial distribution	Concentrated in a single city, distributed with neighbouring cities	Outbreak in multiple regions and cities	Serious outbreaks in multiple regions and cities	Outbreaks exist in a few cities
Propagation Dynamics	Population mobility transmission	Aggregate communication, community communication	Aggregate transmission	Aggregate transmission
Scale of infection	Smaller overall	The overall scale is large	Very large overall	Dwindling numbers
Outbreak information characteristics	Height uncertainty	High level of uncertainty	Decreasing uncertainty	Low uncertainty

This study addresses the sixth round of $(t=6)$ control options for decision making after the initial control phase of the outbreak, with three options $a=\{a_1,a_2,a_3\}$ as follows

a_1: normal inter-urban movement, quarantine gates and immediate isolation of those in abnormal health conditions;

a_2: Zone closure for key areas of the epidemic, normal access to the rest of the area, quarantine gates and immediate isolation of those in abnormal health conditions;

a_3: The city is closed to traffic.

4.2. Decision-making process

(1) Preparation

Step 1: Clue selection and assignment. Through reviewing literature and field research, and combining the results of Ge Honglei and Liu Nan (2020), a total of five clues indicators were selected for this study, including four clues $x_1=$ "spatial distribution", $x_2=$ "transmission dynamics", $x_3=$ " Infection size", $x_4=$ "Epidemic information characteristics", and one programme cue $a_j\ (j=1,2,3)$. The weight of each cue was obtained using the DEMATEL method at

$$r^T=(0.204,0.196,0.218,0.189,0.193)\ .$$

Step 2: Collation of historical data. Collect and collate the predicted values for the next period of the event state and the corresponding true values of the event made by decision makers at the point in time $t=1,2,3,4,5$, the results are shown in Table 4-2.

Step 3: Preset thresholds. Based on interviews with a number of emergency management experts, the threshold conditions for $r_{a,t}$ are: $r_{a,t}\geq 0.75$ and for $V(a_j)_{t+1}$

are: $\mu_{t+1} - \nu_{t+1} \geq 0$.

Step 4: Determining the parameters. In this study, the values taken for each parameter in Kahneman and Tversky's study were used to represent the decision maker's finite rational decision situation and the results were taken as $\alpha = \beta = 0.88$, $\lambda = 2.25$, $\delta = 0.69$, $\gamma = 0.61$.

(2) Actual decision-making process

The sixth round of decision-making for the Newcastle Pneumonia outbreak is currently underway, the fifth round of decision-making has been completed. Based on the definition of the decision point, the emergency decision-making process for the Newcastle pneumonia outbreak has reached point 6.

Step 1: Collect real-time data. Collect information on the spatial distribution, transmission dynamics, scale of infection, and epidemic information characteristics of the new crown pneumonia outbreak in immediate data.

Step 2: Lead assignment. The decision maker assesses the situation of each lead based on the real-time data and assigns a value to it. The results of the assignment are: $x_{1,5} = (0.76, 0.13)$, $x_{2,5} = (0.73, 0.11)$, $x_{3,5} = (0.82, 0.17)$, $x_{4,5} = (0.69, 0.08)$,

$a_1 = (0.23, 0.04)$, $a_2 = (0.38, 0.07)$, $a_3 = (0.19, 0.09)$.

Step 3: Calculate the predicted 'prospect' values. The predicted "prospect" values for each scenario $a_j\ (j = 1,2,3)$ are calculated as $V(a_1)_6 = (0.77, 0.14)$,

$V(a_2)_6 = (0.83, 0.08)$ and $V(a_3)_6 = (0.75, 0.11)$ respectively.

Step 4: Calculate the predicted performance. Calculate the predict performance of the decision-maker, $r_{a,5} = 0.8716$. Combined with Step2 in the preparatory work, the decision maker's predicted value $Y_{s,t}$, the corresponding true value $Y_{e,t}$ and predicted performance $r_{a,t}$ for each point in time up to time point 6 are collated and the results are shown in Table 4.2.

Table 4.2: Predicted, true and predicted performance for the state of the event next period before time point 6

t	$Y_{s,t}$	$Y_{e,t}$	$r_{a,t}$
1	(0.75,0.20)	(0.74,0.24)	-
2	(0.73,0.15)	(0.71,0.09)	0.8250
3	(0.70,0.10)	(0.69,0.10)	0.8423
4	(0.76,0.06)	(0.75,0.02)	0.9763
5	(0.70,0.14)	(0.72,0.06)	0.8716

Step 5: Tests whether the predicted 'outlook' value of $V(a_j)_{t+1}$ and the predicted performance of $r_{a,t}$ reach the 'satisfactory' level. The predicted "prospect" values of $V(a_1)_6 = (0.77, 0.14)$, $V(a_2)_6 = (0.83, 0.08)$ and $V(a_3)_6 = (0.75, 0.11)$ meet the threshold conditions of $\mu_6 - \nu_6 \geq 0$ and the predicted performance of $r_{a,5} = 0.8716 \geq 0.75$ meets the threshold conditions.

Step 6: Compare the ranking of $V(a_1)_6$, $V(a_2)_6$ and $V(a_3)_6$. According to the Pythagorean rule of comparison between fuzzy numbers, the score functions of the solutions $a_j\,(j=1,2,3)$ are $S(a_1)=0.65$, $S(a_2)=0.76$, $S(a_3)=0.62$, then there are $S(a_2)>S(a_1)>S(a_3)$, $V(a_2)_6>V(a_1)_6>V(a_3)_6$, so the optimal solution a_2 is chosen and the decision process is finished.

5 Conclusion

In the big data environment, the methodological process of emergency decision-making has been transformed, and decision-makers can acquire, research and judge dynamic data instantly and respond in real time, and adjust the emergency response plan through the latest interactive feedback back from the results of emergency decision-making and the state of public emergencies, improving the flexibility and accuracy of emergency decision-making. Based on this, this chapter proposes a data-driven dynamic emergency decision-making approach: firstly, based on the idea of the lens model, decision-makers assign current clues to predict the next state of public emergencies based on real-time data, while converting the predicted values into predicted 'prospect' values under the framework of prospect theory. Secondly, the historical predicted values of decision makers and the historical true values of event states are collected and the correlation coefficients between them are calculated to derive the prediction performance; then, the predicted "prospect" values and the prediction performance are analysed as the basis for emergency decision-making and specific decision-making steps are given. Finally, the validity and applicability of the data-driven dynamic emergency decision-making approach proposed in this chapter are further verified through the analysis and robustness testing of the cases.

REFERENCE

1. X.H.Xu and H.D.Wu, Approach for multi-attribute large group decision-making with linguistic preference information based on improved cloud model, *Journal of Industrial Engineering*, 32(1) (2018) 117-125.
2. H.Watson, R.I.Finn and K.Wadhwa, Organizational and societal impacts of big data in crisis management, *Journal of Contingencies and Crisis Management*, 25(1) (2017) 15-22.
3. Y.Tian, C.Peng, H.Ding, et al., A risk adaptive access control model based on Markov for big data in the cloud, *International Journal of High Performance Computing and Networking*, 13(4) (2019) 464-472.
4. A.Assaf, H.Charif and E.Demir, Information sharing among cryptocurrencies: Evidence from mutual information and approximate entropy during COVID-19, *Finance Research Letters*, 14 (2021) Article 102556.
5. X.H.Xu and Y.S.Yang, Method of dynamic emergency decision for risk type of large group based on cumulative prospect theory, *Control and Decision*, 32(11) (2017) 1957-1965.
6. S.Koshimura, Establishing the advanced disaster reduction management system by fusion of real-time disaster simulation and big data assimilation, *Journal of Disaster Research*, 11(2) (2016) 164-174.
7. K.Jun, M.Song and H.J.Park, The Dynamics of an interorganizational emergency management network: interdependent and independent risk hypotheses, *Public*

Administration Review, 79(2) (2019) 225-235.

8. C.Steven, Collaboration in disasters: A cultural challenge for the utilities sector, *Utilities Policy*, 54 (2018) 78-85.
9. Y.Qiu, X.Chen and W.Shi, Impacts of social and economic factors on the transmission of coronavirus disease 2019 (COVID-19) in China, *Journal of Population Economics*, (2020)1-46.
10. D.Kahneman and A.Tversky, Prospect theory: An analysis of decision under risk, *Econometrica*, 47(2) (1979) 263-291.
11. R.S.Bharsakade, O.S.Kulkarni, A.S.Afle and M.S.Kulkarni, Analysis of and modeling for emergency medical services facility location for road accidents on highway, *International Journal of Mechanical and Production Engineering Research and Development*, 8(1) (2018) 595-604.
12. X.H.Xu, X.Yang, X.Chen, et al., Large group two-stage risk emergency decision-making method based on big data analysis of social media, *Journal of Intelligent and Fuzzy Systems*, 36(3) (2019) 2645-2659.
13. W.Liu and L.Li, Emergency decision-making combining cumulative prospect theory and group decision-making, *Granular Computing*, 4(1) (2019) 39-52.
14. E.Brunswik, *Perception and the representative design of psychological experiments*, Berkeley, CA: University of California Press, 1956.
15. H.Wang, F.Zhang, Modified WASPAS method based on the pythagorean fuzzy frank interaction aggregation operators and its application in cloud computing product selection, *Journal of Intelligent & Fuzzy Systems*, 2022, 43(5): 5793-5816.
16. B.Sun, W.Ma and H.Zhao, An approach to emergency decision making based on decision-theoretic rough set over two universes, *Soft Computing*, 20(9) (2016) 1-12.
17. J.Gu, L.Zeng, W.Li, et al., A class of sequential decision-making methods: lens and intuitionistic fuzzy information perspective, *Chinese Journal of Management Science*, 29(01) (2021) 24-35.
18. H.Ge, and N.Liu, Modeling of emergency materials allocation decision-making problems based on the evolution scenarios of serious infectious disease: A case of COVID-19, *Journal of Management Engineering*, 34(03) (2020) 214-222.