

## PAPER

# Leveraging Mobile Interaction Technologies for Real-Time Decision Making in Enterprise Management Systems

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[2018000872@sjzpt.edu.cn](mailto:2018000872@sjzpt.edu.cn)**ABSTRACT**

With the widespread adoption of mobile internet and smart devices, enterprises face rapidly changing market environments and complex decision-making requirements. How to utilize mobile interaction technologies to enhance real-time decision-making capabilities in enterprise management systems has become a critical issue in modern business management. Through real-time data transmission and interaction via mobile devices, businesses can more flexibly acquire information, monitor statuses, and optimize decision-making processes, thereby improving the timeliness and accuracy of decisions. Existing research primarily focuses on traditional decision support systems (DSS) and data mining technologies, but these methods fall short when addressing the dynamic and real-time decision-making needs, especially in complex enterprise management scenarios. One major challenge remains the effective integration of multiple data sources. Therefore, leveraging real-time interactive data from mobile technologies to improve decision support in enterprise management systems becomes a pressing research topic. This paper proposes a real-time decision-making framework for enterprise management systems based on mobile interaction technologies, focusing on the problem description of real-time decision-making in enterprise management and a decision-making mining framework based on mobile interaction relationships and mixed user discourse (including decision belief propagation based on mobile interaction relationships and the UCBert model based on user content analysis). Through this framework, the paper aims to enhance decision-making accuracy and timeliness, enabling enterprises to make more informed and efficient decisions in a dynamically changing market.

**KEYWORDS**

enterprise management systems, real-time decision-making, mobile interaction technologies, data mining, decision support system (DSS), UCBert model, discourse content analysis

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## 1 INTRODUCTION

With the rapid development of information technology, the widespread adoption of mobile Internet, and the extensive use of smart devices, the decision-making methods in enterprise management are undergoing unprecedented changes [1–5]. Traditional enterprise management decisions typically rely on analysis tools based on static data, but these tools often lack sensitivity and the ability to respond to real-time changes [6, 7]. Especially in a dynamic business environment, enterprises face more complex and rapidly changing market competition, requiring quick responses to external environmental changes and more accurate and effective decision-making [8–11]. Therefore, how to leverage emerging mobile interaction technologies to enhance real-time decision-making capabilities in enterprise management systems has become an important issue that needs to be addressed in the current field of enterprise management.

The significance of this study lies in exploring how to combine mobile interaction technologies with enterprise management systems to achieve efficient and accurate real-time decision-making. In the era of mobile internet, decisions in enterprises are not only influenced by internal data but are also affected by external environments, market feedback, and the interactions and participation of stakeholders such as employees and customers. Through real-time data transmission and interaction via mobile devices, enterprise management systems can more flexibly acquire information, monitor statuses, and optimize decision-making processes, thus improving the timeliness and accuracy of decisions. Therefore, this study aims to propose a new framework and method to help enterprises better respond to rapidly changing market environments and enhance their competitiveness.

Most existing related research focuses on traditional decision support systems (DSS) and decision models based on data mining. Although these methods have made progress in the analysis of static and historical data, they are still insufficient in addressing real-time decision-making needs and dynamic changes [12–16]. Traditional methods often rely on the analysis of quantitative data while neglecting the impact of real-time interactive information and subjective judgment [17, 18]. Furthermore, when handling complex enterprise management scenarios, existing research often struggles to simultaneously consider the interactions of multiple variables. Particularly in the mobile interaction process, how to effectively integrate multiple data sources for real-time decision support remains an unsolved challenge [19–23].

This paper focuses on the research of “leveraging mobile interaction technologies to achieve real-time decision-making in enterprise management systems,” covering three main aspects. First, it explores the inference problem in real-time decision-making in enterprise management systems, analyzing how to model and predict uncertainty in the decision-making process in a rapidly changing business environment. Second, it proposes a real-time decision mining framework based on mobile interaction relationships and mixed user discourse, combining user interaction information and discourse content to construct a more intelligent and dynamic DSS. Finally, this paper will investigate the UCBert model based on enterprise management system user discourse content to improve the accuracy and timeliness of real-time decision-making. Through these studies, this paper not only provides enterprises with an innovative decision support tool but also offers new ideas and methods for research in related fields, with important academic and practical value.

## 2 PROBLEM DESCRIPTION OF REAL-TIME DECISION INFERENCE IN ENTERPRISE MANAGEMENT SYSTEMS

In enterprise management systems, real-time decision inference requires handling large amounts of dynamic information and complex interaction relationships. To effectively support the decision-making process, this paper first defines a mobile interaction network graph for real-time decision inference in enterprise management systems. The graph is defined as an undirected graph  $H = (N, R)$ , where the set of nodes  $N$  represents all users in the enterprise management system, with each node  $n_{uk}$  representing a user in the system. The set of edges  $R$  represents the interaction relationships between users. Mobile interaction relationships can take many forms, such as social relationships between users, information exchange, task collaboration, etc. Each edge  $r_{uk}$  represents an interaction between user  $n_u$  and user  $n_k$ , which may include social connections, information flow, collaboration, and so on. Figure 1 shows the mobile interaction network graph for enterprise management.

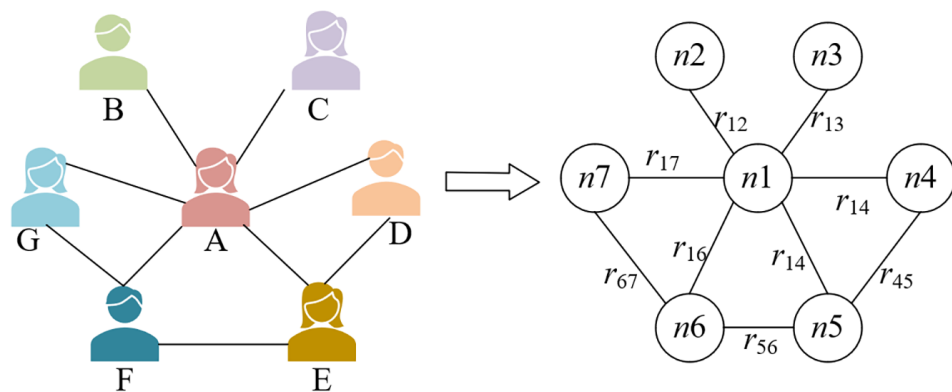


Fig. 1. Mobile interaction network graph for enterprise management

In the real-time decision inference process for enterprise management systems, real-time decisions are defined as decisions made by the enterprise management system based on real-time information for a specific task or goal under certain conditions. Specifically, an enterprise management real-time decision  $X$  is a decision result derived from the dynamic interactions and feedback of multiple participants in the system, such as managers, employees, and customers, at a certain point in time, based on real-time data analysis, inference, and judgment. The set  $X = \{X^0, X^1, \dots, X^j, \dots, X^v\}$  represents all possible real-time decisions in the mobile interaction network, where  $X^j$  denotes a specific type of decision or decision action, and  $v$  refers to the total number of different decision types in the network. Each enterprise management real-time decision  $X^j$  is inferred based on the interaction data and decision requirements of the relevant users in the network under a specific business scenario and management needs, which may involve strategic decisions, market adjustments, resource allocation, and other areas. Each enterprise management real-time decision  $X^j$  has a series of possible decision values. These decision values  $x_j = \{x_{j,0}, x_{j,1}, \dots, x_{j,l}\}$  represent all the available options given by the system to address specific situations or task goals under that decision type. Here,  $x_{j,k}$  refers to the  $k$ -th possible decision value corresponding to decision  $X^j$ , which can be a specific execution plan, resource allocation, action directive, etc. In practice, the choice of decision values is influenced by multiple factors such as real-time data flow, mobile interaction information, user behavior, and feedback in the enterprise management system. The set  $x_j = \{x_{j,0}, x_{j,1}, \dots, x_{j,l}\}$  represents the distribution of all possible decision

values for each decision scheme  $X_l$ , where  $l$  is the number of available decision values for enterprise management real-time decision  $X$ . By evaluating the weight, impact, and effects of different decision values, enterprises can select the optimal solution to implement, thus enabling them to make more timely and accurate decisions in a rapidly changing market environment.

### 3 REAL-TIME DECISION MINING FOR ENTERPRISE MANAGEMENT SYSTEMS USING MOBILE INTERACTIONS AND USER DISCOURSE

To achieve real-time decision inference in enterprise management systems, this paper proposes an innovative semi-supervised inference framework—the UAI framework. This framework combines the analysis of user interaction relationships in the mobile interaction network with the content of user discourse to comprehensively infer the potential outcomes of enterprise management real-time decisions. The core idea of the framework is that decisions in an enterprise management system are not only influenced by individual users but also by the behaviors, opinions, and information dissemination within the social network of other members.

#### 3.1 Belief propagation for real-time decision-making based on mobile interaction relationships

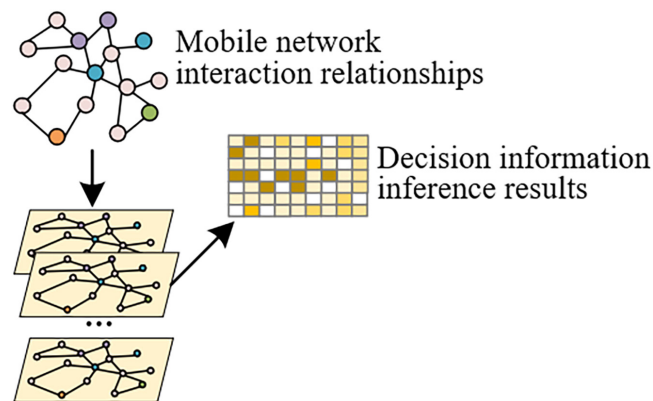


Fig. 2. Principle of belief propagation for real-time decision-making based on mobile interaction relationships

Figure 2 shows the principle of belief propagation for real-time decision-making in enterprise management systems based on mobile interaction relationships. In this algorithm, the construction of the prior belief matrix is fundamental to the algorithm’s execution, as it determines the initial state of each enterprise management system user in the decision inference process and influences the subsequent belief propagation process. The prior belief matrix  $Y$  is an  $N \times X$  matrix, where  $N$  is the number of users in the enterprise management system, and  $X$  is the set of all possible real-time management decisions. Each element  $Y_{uj}$  of the matrix represents the initial belief of the user node  $n_u$  about decision type  $X_p$ , indicating whether the user  $n_u$  has chosen that particular decision. If user  $n_u$  has clearly made decision  $X_p$ , then  $Y_{uj} = 1$ , meaning the decision has been chosen by the user; if user  $n_u$  has not made that decision, then  $Y_{uj} = 0$ , meaning the decision has not been chosen by the user. This binary representation clearly indicates whether a user has participated in a particular real-time decision.

In the algorithm, the construction of the belief propagation matrix is crucial for determining how information spreads across the network. This matrix describes the decision information propagation paths and propagation strengths between user nodes in the enterprise management system. In the mobile interaction network, user nodes in the enterprise management system are connected through social relationships, and the decision information of each node is influenced not only by its own decision but also by the decision information of its neighboring nodes. To capture this phenomenon, the belief propagation matrix  $Q$  is defined as a weighted adjacency matrix, where each element  $Q_{uk}$  represents the weight or probability of information propagation between nodes  $n_u$  and  $n_k$ . This weight is influenced not only by the strength of the interaction between the users but also by the historical behavior of the users. For example, if nodes  $n_u$  and  $n_k$  have had frequent interactions or similar decision patterns in the past, the value of  $Q_{uk}$  will be larger, indicating a higher probability that  $n_k$  will receive decision information from  $n_u$ . Let the decision information value of user node  $n$  be represented by  $o(n_u = x | V_u |)$ , the adjacency matrix of the network structure be represented by  $L_{uk}$ , and the normalization parameter be denoted by  $C_u$ . The influence strength between different decision information types is represented by  $E_{op}$ , and the probability of decision propagation between neighboring nodes can be calculated as follows:

$$o(n_u = x_0 | V) = \frac{1}{C_u} \sum_{k \in X/x_p} L_{uk} o(n_u = x_0 | V) E_{jx_p} \quad (1)$$

Next, this paper details the process of real-time decision belief propagation in enterprise management systems.

The first step is to complete the preliminary setup using the prior belief matrix  $Y$  and the belief propagation matrix  $O$ . Each element  $Y_{uj}$  of matrix  $Y$  represents the initial belief of the user node  $n_u$  about decision type  $x_j$ , indicating the user's initial potential choice among different real-time enterprise management decisions before the decision-making process begins. Meanwhile, matrix  $O$  describes the strength or probability of information propagation between nodes, i.e., the likelihood that node  $n_u$  will pass its decision information to neighboring node  $n_k$ . Typically, the construction of a propagation matrix  $O$  depends on the strength of social relationships between nodes in the network, such as friendship, interaction frequency, or consistency in historical decisions. Let the normalization parameter be represented by  $C$ , the  $uk$ -th item of the adjacency matrix  $L$  be represented by  $L_{uk}$ , and the influence strength parameter be represented by  $\phi$ . The computation of real-time decision belief propagation is as follows:

$$T_{uj}^e = \frac{1}{C_u} \left( Y_{uj} + \phi \sum_k L_{uk} \sum_x T_{kx}^e E_{xj} \right) \quad (2)$$

Next, the belief propagation process enters the crucial iterative update stage. During this process, the decision information of each node will be influenced by the decision information of its neighboring nodes and adjusted according to the probabilities in the propagation matrix. For a target node  $n_u$ , the update of its decision belief is dependent not only on its previous decision state but also on the weighted influence of the decision belief passed from its neighboring node  $n_k$ . The propagation weight between nodes is determined by the element  $O_{uj}$  in the matrix, reflecting the strength of the information that node  $n_u$  receives from node  $n_k$ . In practice, nodes with higher degrees (i.e., more neighboring nodes) have greater influence in the propagation process. If a node has a higher degree, it can influence the decision

information of more neighboring nodes, accelerating the propagation of decision beliefs. However, for nodes with lower degrees, the lack of enough neighboring nodes may mean they cannot gather sufficient information from the network, leading to inaccurate decision inference. To address this issue, the paper introduces the parameter  $\varphi$  to adjust the influence of neighboring nodes on decision propagation. By appropriately setting  $\varphi$ , the influence of node degree on the propagation process can be controlled to avoid under-influenced or over-propagated information.

Finally, to obtain the final result of belief propagation for real-time decision-making, the algorithm needs to iteratively update the decision beliefs of the nodes. In each iteration, the decision information of each node is weighted and updated based on the information from its neighboring nodes until the decision beliefs of all nodes stabilize at a certain value or the predetermined number of iterations is reached. During this process, the variable  $D$  plays a key role as it represents the adjustment coefficient for the decision belief in the update process, which may involve prior information, the propagation weight of neighboring nodes, and external factors in the system. Assuming the value of  $D_{ij}$  in the  $e$ -th iteration is denoted as  $D_{ij}^e$ , the normalization factor is  $C_u = 1 + \varphi f_u$ , where  $f_u$  is the degree of node  $u$ , and the normalization matrix is given by:

$$T_{ij}^e \leftarrow \frac{1}{C_u} \left( Y_{ij} + \varphi \sum_k L_{uk} \sum_x T_{kx}^e E_{xj} \right) \tag{3}$$

Let  $C = U + \varphi F$  represent the normalization matrix,  $F = [f_u]$  represent the diagonal matrix of node degrees; then the matrix form of the above equation is:

$$T^e \leftarrow C^{-1} (Y + \varphi L T^{e-1} E) \tag{4}$$

### 3.2 UCBert model based on enterprise management system user discourse content

In this section, the BERT model is applied to this problem, designing a UCBert model based on the discourse of users in the mobile interaction network of an enterprise management system. This model is used to infer potential real-time decision-making information for users of the enterprise management system from their discourse content. The principle of the model is illustrated in Figure 3.

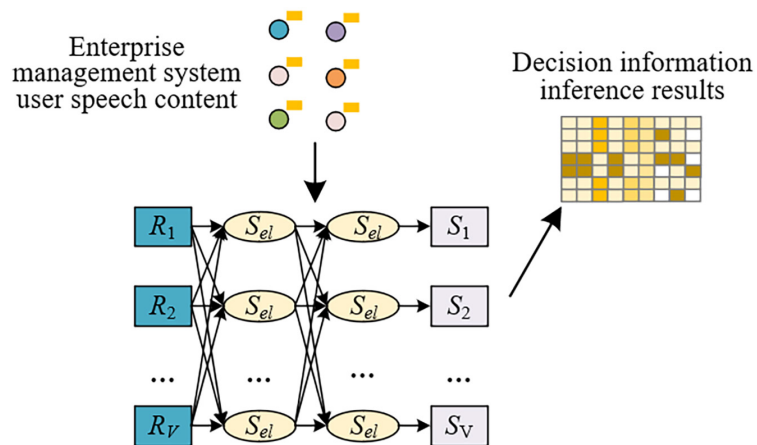


Fig. 3. Principle of UCBert model based on enterprise management system user discourse content

To improve the understanding of the discourse content of users in the mobile interaction network of the enterprise management system, the UCBert model first requires pre-training on a large-scale corpus to capture the structural patterns and semantic relationships between words and sentences in natural language. To learn language patterns, the UCBert model primarily uses two unsupervised learning tasks during pre-training: cloze tasks and next sentence prediction. First, in the Cloze task, the model learns how to infer missing parts of a sentence by masking certain words in a complete sentence and inferring the missing parts based on the context. During pre-training, 15% of words are randomly masked, where 80% of the masked words are replaced with a special mask identifier, 10% are replaced with random words, and the remaining 10% stay unchanged. Let the output layer of the Cloze task be represented by  $\varphi_1$ , and the masked word be represented by  $q_u$ , with  $N$  denoting the size of the corpus. The objective function is as follows:

$$M_L(\varphi, \varphi_1) = -\sum_{u=1}^N q_u \log o(q = q_u | \varphi, \varphi_1, q_0, q_1, \dots, q_{u-1}, q_{u+1}, \dots, q_v) \quad (5)$$

Next, the next sentence prediction task helps the model learn the relationship between sentences. In the context of the enterprise management system, user discourse is often influenced by preceding and succeeding contexts, so understanding these relationships is crucial. The core of the next sentence prediction task is for the model to determine whether a given sentence is logically related to another, i.e., whether one sentence can likely follow the other. To achieve this, the model needs to understand the logical connections and semantic coherence between sentences. During training, 50% of sentence pairs are randomly selected for prediction, strengthening the model's ability to handle ambiguous or complex contexts. Let the output layer of the next sentence prediction task be represented by  $\varphi_2$ , and the masked word be represented by  $t_u$ , with  $N$  denoting the corpus size. The objective function is:

$$M_V(\varphi, \varphi_2) = -\sum_{u=1}^N t_u \log o(t = t_u | \varphi, \varphi_2, q_0, q_1, \dots, q_{u-1}, q_{u+1}, \dots, q_v) \quad (6)$$

In the mobile interaction network-based enterprise management system, user discourse tends to be brief and casual, presenting challenges for the accuracy and effectiveness of real-time decision-making. To address this challenge, the proposed UCBert model maps each user's discourse in the enterprise management system to the corresponding real-time decision category for classification inference. Specifically, the UCBert model adds a hidden layer  $G(q)$  to each user's discourse to infer the decision category associated with that text. Let user  $n$  have  $l$  pieces of discourse, and let the parameters for each word in the hidden layer be  $H(q)$ . The probability that the  $u$ -th discourse of user  $n$  belongs to decision type  $x_j$  is:

$$o(x_j | g, z_u) = \log \frac{r^{G(q), H(q)}}{\sum_q r^{G(q), H(q)}} \quad (7)$$

However, users in the enterprise management system typically do not make a single statement but participate in multiple discussions across different topics. Therefore, the inference from a single statement cannot fully represent the user's overall decision tendencies. To solve this issue, the UCBert model further integrates all the social discourse of each user, performing a comprehensive analysis of the inference results for each discourse to derive an overall probability for the user's

real-time decision tendencies across different enterprise management decisions. Let the normalization parameter be  $C_n$ . For user  $n$ , the score  $t_{x_j}^n$  for decision type  $X$  under decision value  $x_j$  is:

$$t_{x_j}^n = \frac{1}{C_n} \sum_{u=1}^{Z_n} o(x_j | g, z_u) \quad (8)$$

The model also enhances the accuracy of decision inference by analyzing multi-dimensional information such as the language, content themes, and sentiment tendencies of the user's discourse. For example, the language of the discourse can reflect the user's country or region, and the use of certain languages can provide additional contextual information to help infer the user's background and interests. By comprehensively analyzing all the social discourse of a user, the UCBert model can infer the user's inclination towards various types of real-time enterprise management decisions. If there are  $l$  possible decision values under decision type  $X$ , the probability vector for user  $n$  with respect to decision type  $X$  is:

$$t_n = (t_{x_0}^n, t_{x_1}^n, \dots, t_{x_l}^n) \quad (9)$$

### 3.3 Enterprise management real-time decision information mining

In order to more accurately infer as many enterprises management real-time decision categories as possible, this paper combines the two previous sections, considering both mobile interaction relationships and enterprise management system users' discourse. The impact of both factors on the real-time decision-making inference of different enterprise management system users is integrated. A framework for enterprise management system users' real-time decision-making inference is proposed, which is based on a mixture of mobile interaction relationships and users' discourse. By overlaying two different enterprise management system real-time decision distributions, the final real-time decision representation required by this study is obtained. Let  $t_n^D$  represent the decision information inference result obtained from the confidence propagation part of the enterprise management real-time decision, and  $t_n^S$  represent the decision information inference result obtained from the discourse-based UCBert model. The control parameters for the two different factors, mobile interaction relationships and discourse, are represented by  $\beta$  and  $\alpha$ , respectively. The final decision information distribution is given by:

$$t_n = \beta \cdot t_n^D + \alpha \cdot t_n^S \quad (10)$$

The probability of any real-time enterprise management decision value can be calculated as:

$$t_n = [o_{x_0}, o_{x_1}, \dots, o_{x_v}] \quad (11)$$

The enterprise management real-time decision value with the highest probability is considered the most likely real-time decision value for the enterprise management system, namely:

$$x_{n,POT} = \arg \max(t_n) \quad (12)$$

#### 4 EXPERIMENTAL RESULTS AND ANALYSIS

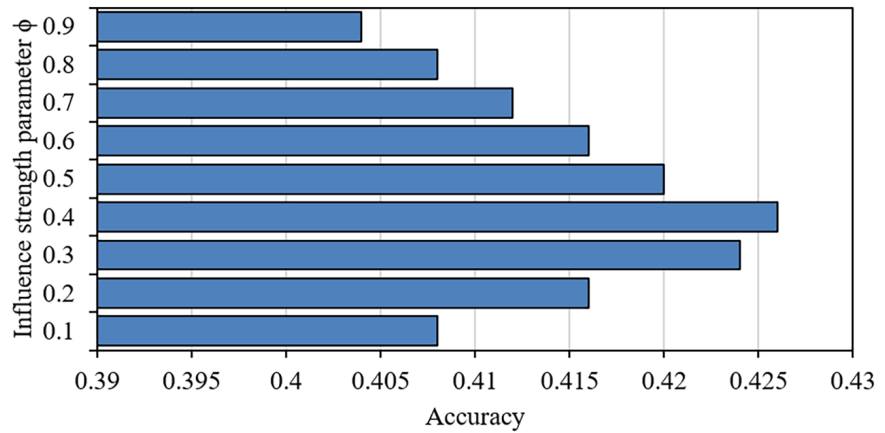


Fig. 4. Analysis of the impact of parameter  $\phi$  on real-time decision inference performance in enterprise management systems

Figure 4 shows the effect of varying the influence strength parameter  $\phi$  on the real-time decision inference task in enterprise management systems, where the accuracy fluctuates with changes in  $\phi$ . As  $\phi$  increases from 0.1 to 0.4, the accuracy gradually rises from 0.408 to 0.426, suggesting that a moderate impact strength improves the model's inference performance. However, as  $\phi$  continues to increase (from 0.5 to 0.9), the accuracy slightly declines from 0.42 to 0.404. This indicates that too large an impact strength may cause the system to overly rely on specific features, thereby reducing the accuracy of the decision-making process. Overall, the highest accuracy occurs when  $\phi = 0.4$ , demonstrating that this value provides the best performance for the model.

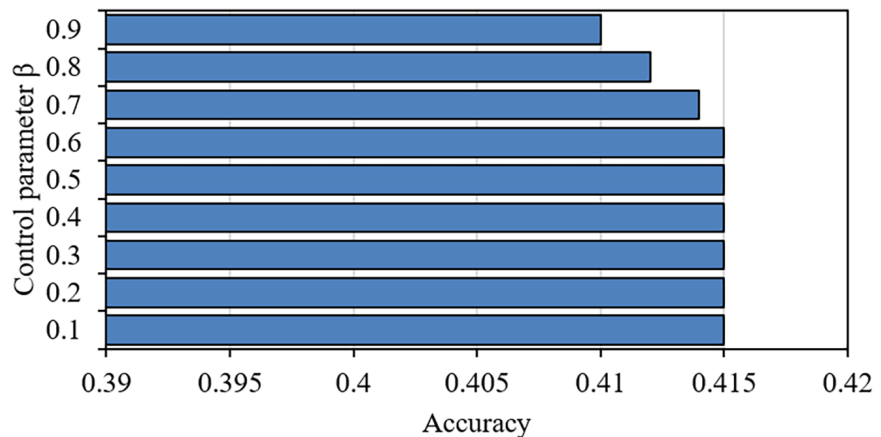


Fig. 5. Analysis of the impact of parameter  $\beta$  on real-time decision inference performance in enterprise management systems

Figure 5 presents the effect of varying the control parameter  $\beta$  on the real-time decision inference performance in enterprise management systems. The accuracy remains extremely stable as  $\beta$  changes. Over the entire range of  $\beta$  from 0.1 to 0.9, the accuracy stays around 0.415, with a slight decrease to 0.412 and 0.41 when  $\beta$  is 0.8 and 0.9, respectively. This suggests that the control parameter  $\beta$  has a limited effect on the model's performance, and the accuracy is almost unaffected by changes in  $\beta$ .

This stability may imply that the contribution of  $\beta$  to improving decision accuracy is minimal in the current model and task settings.

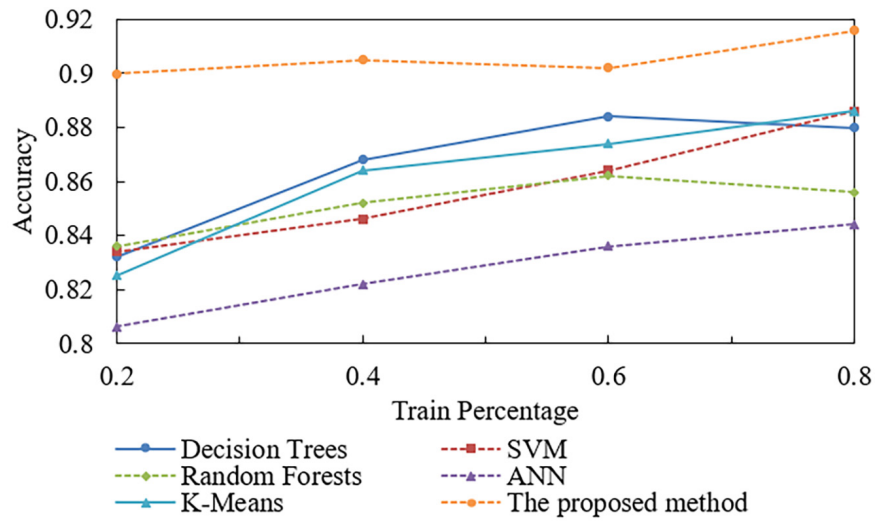


Fig. 6. Real-time decision inference results in enterprise management systems

Figure 6 compares the performance of different algorithms in terms of accuracy for the real-time decision inference task in enterprise management systems under different training set proportions. The results clearly show that the proposed method outperforms other commonly used algorithms across all training set proportions. For instance, when the training set ratio is 0.2, the proposed method achieves an accuracy of 0.9, significantly higher than other algorithms (SVM at 0.834, K-Means at 0.825). Even when the training set ratio is 0.8, the proposed method still maintains the highest accuracy, reaching 0.916, surpassing SVM at 0.886 and Decision Trees at 0.88. Regardless of whether the training set ratio is low (e.g., 0.2) or high (e.g., 0.8), the proposed method consistently demonstrates a notable advantage, showing its effectiveness in addressing uncertainty and complexity in real-time decision inference tasks.

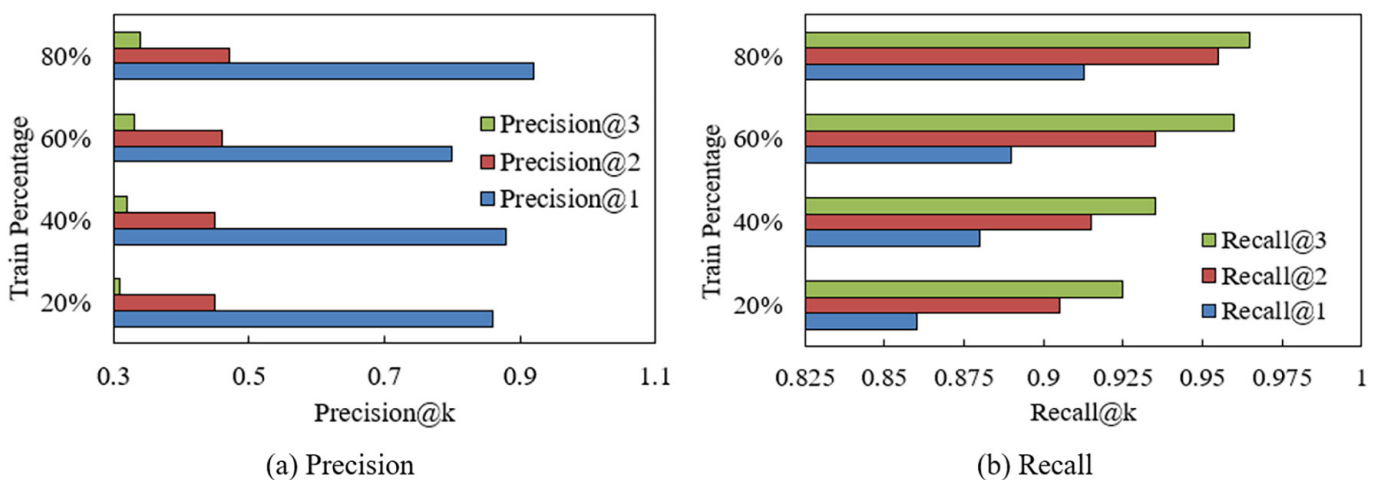
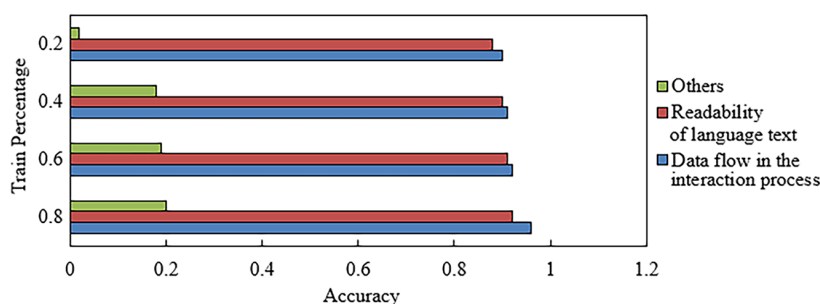


Fig. 7. Top-K evaluation for real-time decision mining in enterprise management systems

Figure 7 shows the precision and recall evaluation for real-time decision mining in enterprise management systems under different training set proportions, using

Top-1, Top-2, and Top-3 as metrics. Regarding precision, with the increase in the training set proportion, Precision@1 shows a steady rise, increasing from 0.86 at 20% training set proportion to 0.92 at 80%, indicating that with more training data, the model can provide higher quality decisions in the first recommendation. The model also improves in Precision@2 and Precision@3, reaching 0.47 and 0.34 at the 80% training set ratio, reflecting that the model can still maintain a high recommendation quality when providing multiple decision suggestions. In terms of recall, the model shows an upward trend as the training set proportion increases. Recall@1 rises from 0.86 at 20% to 0.9125 at 80%, suggesting significant improvement in the model's ability to return a higher coverage of correct recommendations with more training data. For Recall@2 and Recall@3, their values also increase with the training set ratio, reaching 0.955 and 0.965 at the 80% ratio. This shows that the model becomes increasingly effective at providing comprehensive recommendations, especially when returning multiple suggestions, with recall improving to enhance the overall adaptability and flexibility of the decision support system.

Figure 8 presents an analysis of key factors in implementing real-time decisions in enterprise management systems using mobile interaction technology under different training set proportions. Specifically, the data flow in the interaction process shows high stability at different training set proportions. As the training set proportion increases from 0.2 to 0.8, the data flow value increases from 0.9 to 0.96. This indicates that as the training data increases, the model's efficiency and accuracy in processing and flowing interactive data improve significantly. Additionally, the readability of language text is also a key factor. As the training set proportion increases, readability improves from 0.88 to 0.92, showing that as the training set grows, the model's ability to understand user discourse gradually strengthens. In contrast, other factors exhibit relatively low and stable values, especially when the training set ratio is 0.2, where the value is only 0.02. This suggests that the impact of other factors is limited in smaller datasets. From the experimental results, it can be concluded that the data flow in the interaction process and the readability of language text are critical factors for implementing real-time decision-making in enterprise management systems. As the training set proportion increases, the improvement in these two factors reflects the effectiveness of the real-time decision mining framework based on a mixture of mobile interaction relationships and discourse. The enhancement in data flow indicates that with more accumulated interaction data, the system can transmit information more efficiently, supporting decision-makers in making more timely and accurate decisions in complex business environments. Meanwhile, the improvement in language text readability highlights the advantages of the UCBert model in processing user discourse, allowing it to better understand and interpret user behavior patterns and needs, further improving the accuracy and timeliness of real-time decision-making.



**Fig. 8.** Key factor analysis for implementing real-time decisions in enterprise management systems using mobile interaction technology

## 5 CONCLUSION

This paper explores real-time decision-making in enterprise management systems through the use of mobile interaction technology and the UCBert model. First, the uncertainty in decision-making processes in dynamic business environments was analyzed, highlighting the importance of predicting decision uncertainties. Then, a decision framework combining mobile interactions and discourse content was proposed to enhance decision intelligence by incorporating user interaction data. Lastly, the UCBert model was applied to improve the accuracy and timeliness of real-time decisions. The experimental results indicate that the influence strength parameter  $\phi$  significantly influences decision accuracy, with a moderate value of  $\phi$  improving decision performance, while excessive  $\phi$  values lead to a decline. In contrast, the control parameter  $\beta$  has little effect on inference performance, maintaining stable accuracy. Additionally, the Top-K evaluation demonstrated the model's effectiveness, confirming that mobile interaction technology plays a critical role in decision performance, particularly in terms of data flow and text readability.

This study provides an intelligent framework for real-time decision-making in enterprise management systems, demonstrating the importance of mobile interaction data and user discourse content. The experimental results suggest that an optimal  $\phi$  value can improve decision performance, while the  $\beta$  or beta parameter has minimal impact, indicating that future research could focus on optimizing other parameters and reducing dependency on  $\beta$ . This paper offers innovative ideas for real-time decision systems, especially in decision support frameworks based on interaction data. However, the study has some limitations, particularly in the insufficient exploration of other influencing factors, and the model's application in large-scale data environments requires further validation. Future work could explore other potential influencing factors, further optimize the UCBert model, and investigate its adaptability in big data environments. Additionally, the integration of reinforcement learning and other techniques could enhance the intelligence of the model, broadening its application across industries and increasing its universal applicability and practical value.

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