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Risk Prediction of Digital Human Resource Management Based on Artificial Intelligence

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The latest information technologies have greatly accelerated the digitalization progress of Human Resource Management (HRM) and many useful techniques and tools have been developed for that purpose. However, in terms of risk management, effective enough tools and methods are still insufficient. Existing studies generally fail to give a turnkey solution to the operational risks in digital HRM system, and the macro measurement models are not suitable for dealing with the risks in the digital HRM system of each single enterprise. In view of these defects, this paper studied the prediction of risks in digital HRM systems based on Artificial Intelligence (AI). Firstly, the paper outlined the functions of a digital HRM system, defined the risk management mechanism of a HRM system, and built a conceptual model for it. Then, this paper proposed a novel method for predicting the risks in the digital HRM system, which innovatively integrates the digital HRM risk event chains with the risk event graph. After that, the paper elaborated on the structures and building principles of the risk event representation layer, risk event chain module, risk event graph module, and attention fusion module. Finally, experimental results verified that the proposed model has obvious advantages in digital HRM risk prediction in terms of both stability and accuracy.

ACM CCS (2012) Classification: Applied computing → Operations research → Forecasting

Keywords: digital human resource management (HRM), risk prediction, risk event

1. Introduction

The 21st century is a globalized era of market and information, and it is dominated by knowledge. In an environment under new economic conditions, the HRM in enterprises must make proper changes accordingly [1–5]. The latest information technologies have greatly accelerated the digitalization progress of HRM and many useful techniques and tools have been developed for that purpose. However, in terms of risk management, effective enough tools and methods are still insufficient [6–11]. In most cases, the risk avoidance of digital HRM is judged based on the experience of managers, which greatly prevents digital HRM from fully exerting its role in the organizations.

To ensure the fulfillment of strategic goals, enterprises would apply more and more complex HRM policies and conducts [12, 13]. For HRM departments, relying solely on the conventional HRM experiences and methods is no longer enough to cope with the various risk issues in HRM. In the meantime, if we rely too much on the digital management technologies and ignore the operation risks with these technologies, then it would be impossible for the enterprises to realize their strategic goals and management tasks due to the inability to promote the corporate performance [14–16]. The digital HRM needs to summarize experiences in practice, thereby attaining theories and targeted methods that are applicable for the risk management of digital HRM.

Regarding the research topics of digital HRM and risk management, various studies were conducted. For instance, Butov *et al.* [17] discussed a few practical problems with the current digital HRM in Russia and its digital transformation distinguishing the differences in these concepts in the field of HRM. Then they studied the digitalization of HRM in the country, identified main tools for digitalization, and proposed corresponding suggestions. Makarova *et al.* [18] introduced the development concept of HRM evaluation system and the architecture of the labor risk module for project tasks. Considering the many environmental factors of the company Project Server and the external sources of company data such as the electronic pass systems and email system of Microsoft Outlook, they built a mathematical model for calculating labor risks. Ni [19] applied a deep neural network to model digital HRM knowledge with the aim to systematically study the human-job matching problem. Then, through 5G communication, cloud computing, big data, neural networks, user portraits, and other smart digital means, the author designed a few strategies for the digital transformation of HRM and proposed targeted measures for raising awareness of HRM and creating a culture of HRM. Liu and Yong [20] analyzed the actual requirements, business procedures, and existing problems of the performance management in modern enterprises and used a multi-objective decision-making model to calculate the optimal solution for the performance management of HRM. The paper also proposed a design for a digital management system for corporate performance assessment.

Current studies on digital HRM generally inform that the operational risks in digital HRM are caused by technological factors. Quantitative methods adopted in these studies include fuzzy hierarchical analysis, VAR model, Bayesian network model, revenue model, and others. However, existing studies generally fail to give a turnkey solution to the operational risks in digital HRM systems, while the macro measurement models are not suitable for dealing with the risks in the digital HRM system of each single enterprise. Therefore, in view of these defects, this paper studied the prediction of risks in a digital HRM system based on AI.

The rest of the paper is structured as follows: the second chapter overviewed the functions of a digital HRM system, presented the risk management mechanism of a HRM system and outlined a conceptual model for the risk management of HRM. Then, the third chapter proposed a novel method for predicting risks in a digital HRM system, which innovatively integrates the digital HRM risk event chains with the risk event graph. Finally, the structures and building principles of the risk event representation layer, risk event chain module, risk event graph module, and attention fusion module were elaborated, and the experimental results verified the effectiveness of the constructed model.

2. Risk Factor Analysis of Digital HRM

Table 1 lists the functions of a digital HRM system. Users of this system include the candidates, employees, HR managers, and enterprise managers. Prediction, suggestion, instruction, and decision analysis are the core functions of an HRM system, and they provide targeted services for HR planning and policy development and integration, recruitment and employment, compensation and incentives, employment development and training, employment dispatch and retirement, information management, and other aspects.

Figure 1 presents the mechanism of risk management in a digital HRM, and the core in this mechanism is the building of a dataset, during each management activity, the dataset will be updated. By attaining relevant data from a digital HRM dataset and combining with the input of a series of history risk events, countermeasures could be formulated and implemented for risk management in digital HRM.

The important risk factors of digital HRM are related, which makes it possible to identify the system risks. In this paper, these factors were divided into three dimensions: the enterprise dimension, the HRM process dimension, and the management risk domain dimension. From these three dimensions, a risk management system of digital HRM was constructed to provide assistance for HR managers and staff to carry out the risk management works. Figure 2 gives the conceptual model of the risk management system of a digital HRM.

Table 1. Statistics of the functions of digital HRM system.

	Candidates		**Employees**
Recruitment	Online questionnaires	Department matching	–
Talent requirement analysis	–	–	–
Employee management	–	–	–
Compensation, benefits, and incentives	–	–	–
Employee development and training	–	–	Personalized learning suggestions
HR planning and policy	–	–	Career development guidance
Employee dispatch and retirement	–	–	Self-service
	HR managers	**Enterprise managers**	
Recruitment	Screen resumes	–	–
Talent requirement analysis	Forecast requirements	–	–
Employee management	Satisfaction survey	Reminds about talents	Personalized suggestions
Compensation, benefits, and incentives	Give framework of salary and benefits	Reminds about retaining the talents	Formulate organizational goals
Employee development and training	Mark learning content	–	–
HR planning and policy	Develop and integrate HR plans and policies	–	Formulate corporate performance goals
Employee dispatch and retirement	Ensure reasonable management cost	–	–

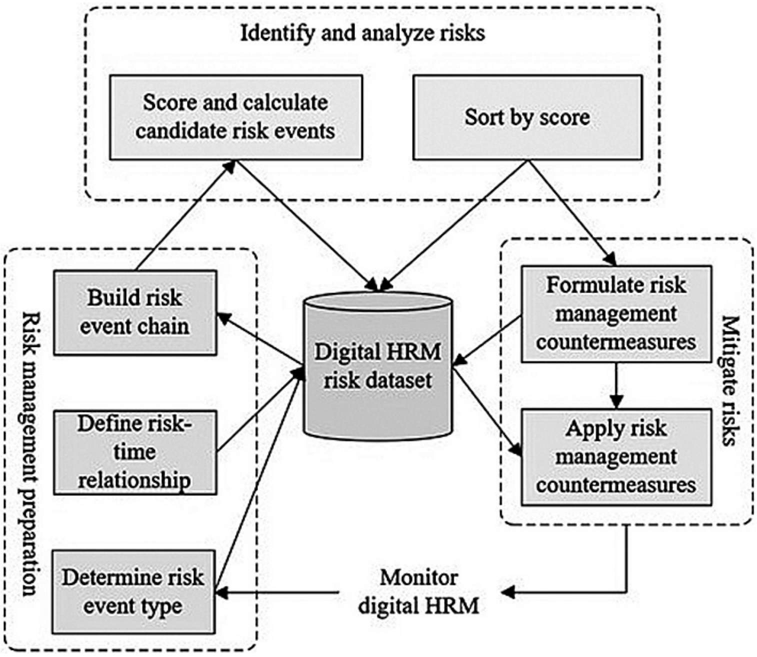

Figure 1. The mechanism of risk management in a digital HRM.

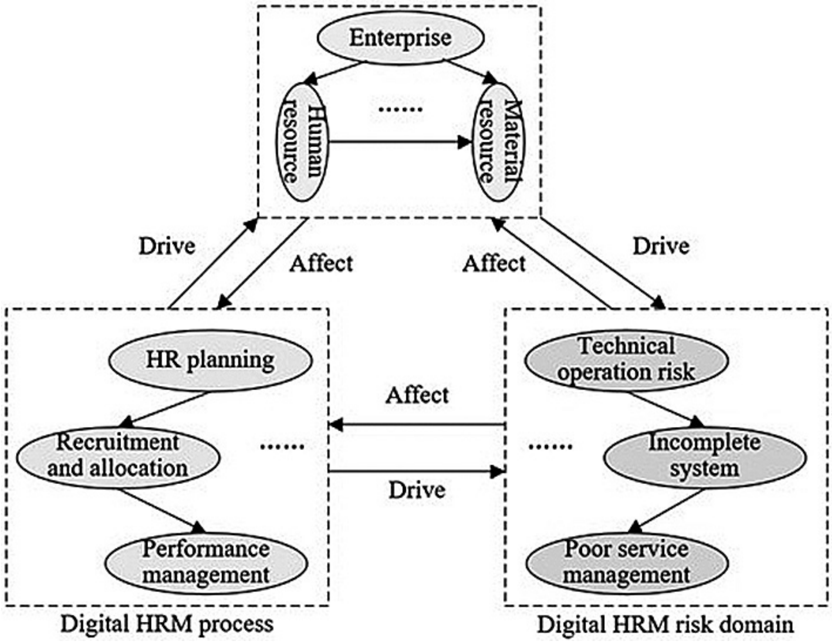

Figure 2. The conceptual model of risk management of digital HRM.

3. Risk Prediction Model for Digital HRM

The primary goal for the risk prediction of digital HRM is to forecast unknown risk events that may occur in the future based on history risk events that happened within a fixed research period. Previous studies on digital HRM risk prediction generally ignored the possibility to learn relationships among risk events from multiple angles. Therefore, this paper proposed a novel digital HRM risk prediction method that innovatively integrates the digital HRM risk event chains with the risk event graph.

The dataset of digital HRM risks used in this paper covered 186 types of risk events, and corresponding index values were set for each type of risk events, wherein the frequencies of three types of risk events were higher, namely the technical operational risk, the incomplete system risk, and the poor service management risk. This paper took each enterprise as a unit to build the dataset, that is, history risk event chains and actual candidate risk events were constructed first, then each history risk event chain was filled with the candidate risk events.

The construction of risk event chain set considers history risk event chains and actual candidate risk events. Main functions of this set were to carry out digital HRM risk event presentation training and build digital HRM risk event graph. To attain the initial vector representation of risk events, the representation training of digital HRM risk events was completed based on Gated Recurrent Unit (GRU), Gated Graph Neural Network (GGNN), and other deep neural network models. The digital HRM risk event graph was the model training corpus for Word2Vec and DeepWalk.

The prediction model of digital HRM risks built in this paper consists of four parts: risk event presentation layer, risk event chain module, risk event graph module, and attention fusion module. Figure 3 shows the framework of the prediction model.

This paper set a risk event presentation layer to give the embedded representation of each risk event, and the structure of the risk event presentation layer is shown in Figure 4. Due to the particularity of the dataset of the digital HRM risks, this paper collected 1,142,712 history risk event chains and used them to build the corpuses used in the experiment. Assuming: u_{o1}, u_{o2}, ..., u_{om} represent the embedded presentation sequences of history risk event chains and $u_{oi} \in R^c$. The Skip-gram model in Word2Vec was used to train the documents generated after all history risk event chains had been merged,

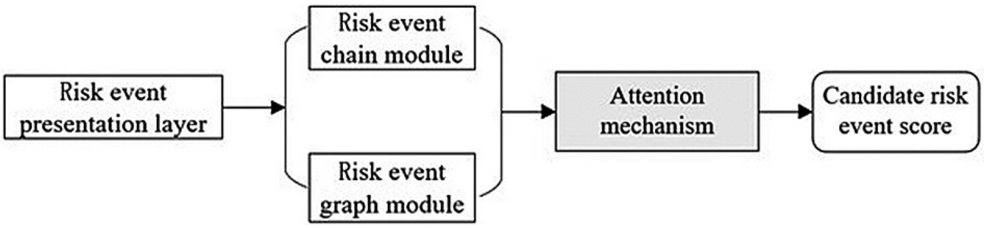

Figure 3. Framework of the prediction model.

then u_{o1}, u_{o2}, ..., u_{om} were attained. Since the predicted candidate risk events also originated from the 186 types of risk events in the data-set, the embedded representation sequences of candidate risk events can be expressed as u_{od1}, u_{od2}, ..., u_{odl}. If there are new risk events in the digital HRM process, then they are coded using a zero vector.

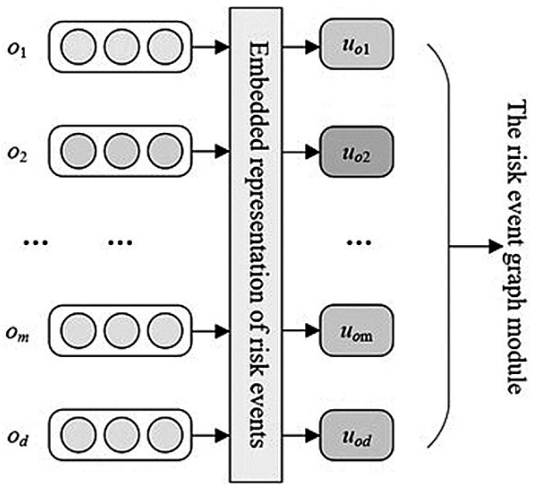

Figure 4. Structure of the risk event presentation layer.

The risk event chain module attains the time series relationships among risk events appeared during the digital HRM process based on GRU. The structure of this module has two parts: the history risk event hidden state sub-module and the candidate event hidden state sub-module. The modules were used to get the embedded representations of the hidden states of history risk events and candidate events. Figure 5 shows the structure of the risk event chain module. Assuming: u_{o1}, u_{o2}, ..., u_{om} represent the embedded representation sequence of history risk events; f_1, f_2, ..., f_m represent the hidden state sequence of history risk events; u_{o1}, u_{o2}, ..., u_{om} that were input into the GRU model one by one. Then f_1, f_2, ..., f_m were attained based on the following formula:

Assuming: $\otimes$ represents the product of elements; f_{p-1} represents the hidden state of history risk events at the time moment $p-1$; f_m represents the hidden state of the last risk event in the history risk event chain; u_{od1}, u_{od2}, ..., u_{odl} represent the embedded representation sequence of candidate risk events; $F = \{f_1, f_2, ..., f_m, f_{d1}, f_{d2}, ..., f_{dl}\}$ represents the hidden state sequence of risk event chain attained at last and $F \in R^{(m+l)\times c}$, then f_m and u_{od1}, u_{od2}, ..., u_{odl} were respectively combined and input into the GRU, where:

$$c_p = \varepsilon\left(Q_c u_{o_{p-1}} + V_c f_{p-1}\right) \tag{1}$$

$$s_o = \varepsilon\left(Q_s u_{o_{p-1}} + V_s f_{p-1}\right) \tag{2}$$

$$m_p = tanh\left(Q u_{o_{p-1}} + V\left(s_o \otimes f_{p-1}\right)\right) \tag{3}$$

$$f_p = \left(1 - c_p\right) \otimes m_p + c_p \otimes f_{p-1} \tag{4}$$

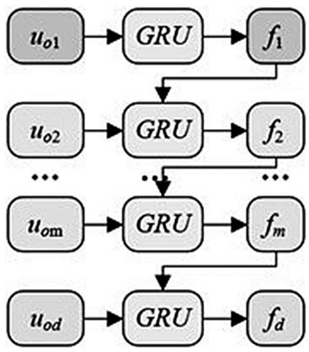

Figure 5. Structure of the risk event chain module.

The risk event graph module extracts the spatial features of risk events during the process of digital HRM based on the constructed risk event graph. The structure of this model has two parts: the risk event graph construction sub-module, and the GGNN, which were used to construct the risk event graph and encode the node information of the risk event graph based on history risk event chains.

Define: $H = <O, K>$ represents the risk event graph, where $O = \{o_1, o_2, ..., o_M\}$ represents the nodes of risk events, M represents the number of nodes, $K = \{k_1, k_2, ..., k_n\}$ represents the connection edges of the risk event nodes, and n represents the number of edges. Then, details of the construction method of the risk event graph are given below:

At first, for a given history risk event chain o_1, o_2, o_3, o_4, ..., o_8, the risk events in this chain were combined into risk event pairs and represented as $\{(o_1, o_2), (o_1, o_3), ..., (o_2, o_3), (o_2, o_4), ..., (o_7, o_8)\}$. The 1,142,712 history risk event chains were combined into risk event pairs, and the set of the risk event pairs was denoted as V. Then, directed connection edges with weights were set for all risk event pairs. Assuming k_i represents the directed connection edge of $o_i \rightarrow o_j$, θ represents the weight of the connection edge, $FC(o_i, o_j)$ represents the number of occurrences of risk event pair (o_i, o_j) in V, and $\Sigma_m FC(o_i, o_j)$ represents the total number of occurrences of o_i in pairs with other risk events, then the following holds:

$$\theta\left(o_j \mid o_i\right) = \frac{FC\left(o_i, o_j\right)}{\sum_v FC\left(o_i, o_v\right)} \tag{5}$$

The screening of the nodes in the risk event graph was realized by setting a threshold for the connection edge weights, that is, the risk event pairs whose connection edge weight was lower than the threshold had been screened out.

Then, GGNN was used to learn the hidden state of risk event nodes in the constructed risk event graph. Considering that the input of the GGNN should be the entire risk event graph and the model could not effectively process the large-scale digital HRM risk dataset containing multi-type risk events, this paper chose to divide the risk event graph. Specifically, the entire risk event graph was divided into sub-graphs according to each single history risk event chain and the corresponding candidate risk events, and then the sub-graphs were input into the GGNN model.

Assuming: $SE^{(0)}$ represents the embedded representation sequence $\{u_{o1}, u_{o2}, ..., u_{en}, u_{od1}, \ldots, u_{odl}\}$ of the history risk event chain and the candidate risk events; $X \in R^{(m+l)\times(m+l)}$ represents the adjacency matrix of a single risk event chain, wherein m represents the length of the historical risk event chain, and l represent the number of candidate risk events; then it can be considered that the initial inputs of the GGNN model are $SE^{(0)}$ and X.

For the risk event graph, this paper only considered the connection edges through which a risk event node passes informant to its adjacent risk event nodes. Thus the constructed adjacency matrix is given by the following formula:

$$X\left[i,\ j\right] = \begin{cases} \theta\left(o_j \mid o_i\right), & \text{if } o_i \rightarrow o_j \in K \\ 0, & \text{others} \end{cases}. \tag{6}$$

Assuming: $SE^{(p-1)}$ represents the risk event hidden state sequence updated at time moment $p-1$; $\beta(p)$ represents that the information transmission of the hidden state of risk event at time moment $p-1$ is performed via the adjacency matrix; $SE^{(p)} = \{u^{(p)}{}_{o1}, u^{(p)}{}_{o2}, ..., u^{(p)}{}_{om}, u^{(p)}{}_{od1}, ..., v^{(p)}{}_{odl}\}$ represents the risk event hidden state sequence updated at time moment p, and it satisfies $SE^{(t)} \in R^{(m+l)\times z}$. Figure 6 gives a diagram of the risk event hidden state sequence updated at time moment p. The computation of the GGNN model is given by the following formulae:

$$\beta^{(p)} = X^P\, SE^{(p-1)} + y \tag{7}$$

$$c^{(o)} = \varepsilon\left(Q^c\beta^{(o)} + V^c SE^{(o-1)}\right) \tag{8}$$

$$s^{(o)} = \varepsilon\left(Q^s\beta^{(o)} + V^s SE^{(p-1)}\right) \tag{9}$$

$$d^{(p)} = tanh\left(Q\beta^{(p)} + V\left(s^{(p)} \otimes SE^{(p-1)}\right)\right) \tag{10}$$

$$SE^{(p)} = \left(1 - c^{(p)}\right) \otimes SE^{(p-1)} + c^{(p)} \otimes d^{(p)} \tag{11}$$

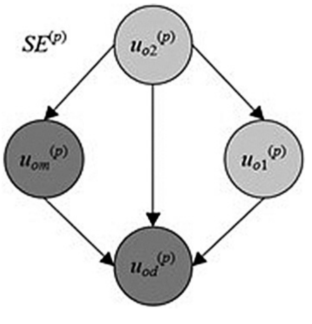

Figure 6. A diagram of the risk event hidden state sequence updated at time moment p.

Figure 7 shows the structure of the risk event graph module. Based on the previous section and the risk event chain module, the output hidden state sequence F can be attained, and the output hidden state sequence SE can be attained based on the risk event graph module. The purpose of setting the attention fusion module is to fuse F and SE. This paper used three methods to fuse the two. The first method is to sum and take average, that is, F and SE are aligned and summed, and their average is computed. The second method is a non-linear combination computed by the formula $fh_i = tanh(Q_f f_i + Q_h u^{(p)}_{oi} + y)$. Finally, the third method is the vector splicing method, and its formula is $fh_i = f_i \otimes u^{(p)}_{oi}$, where $fh_i \in R^{2z}$.

Figure 7. Structure of the risk event graph module.

After F and SE were fused, the hidden state sequences of history risk event chains and candidate risk events were attained and denoted as $fh_1, fh_2, ..., fh_m$ and $fh_{d1}, fh_{d2}, ..., fh_{dl}$. In order to find out the risk event with the highest probability in the next digital HRM process from the candidate risk events, this paper used the function $r(fh_i, fh_{dj})$ to calculate the score of the correlation between the history risk event fhi and the candidate risk event fh_{dj}. The lower the score, the smaller the probability of this candidate risk event; and the higher the score, the greater the probability of this candidate risk event. There are four methods for calculating the score of correlation:

Method 1: By calculating the distance between the hidden state of two risk events, the cosine similarity between them could be attained, and the formula is $\cos(fh_i, fh_{dj}) = fh_i \times fh_{dj} / \|fh_i\| \times \|fh_{dj}\|$.

Method 2: By normalizing the hidden state of two risk events and calculating the Euclidean distance between the processed results, the Euclidean distance similarity between them could be attained, and the formula is $EDS(fh_i, fh_{dj}) = \| fh_i / \|fh_i\| - fh_{dj} / \|fh_{dj}\| \|$.

Method 3: By calculating the inner product of the hidden state of two risk events, the dot product similarity of the two could be attained, and the formula is $PMS(fh_i, fh_{dj}) = fh_i \times fh_{dj}$.

Method 4: By linearly combining fh_i with fh_{dj} and using the *sigmoid* function to activate the combination results, the *linear* + *sigmoid* similarity of the two could be attained, and the formula is $LS(fh_i, fh_{dj}) = sigmoid(Q_f f_i + Q_h u^{(p)}_{oi} + y)$.

Considering that the history risk events during digital HRM may have different degrees of influence on correctly predicting the subsequent risk events, this paper assigned weights to the risk events in the history risk event chains based on the attention mechanism, and the predicted result output by the model could be determined as the candidate risk event with the highest score. The score of candidate risk event RES is computed as follows:

$$v_{ij} = tanh\left(Q_f fh_i + Q_d fh_{dj} + y_m\right) \tag{12}$$

$$\beta_{ij} = \frac{\exp(v_{ij})}{\sum_m \exp(v_{ij})} \tag{13}$$

$$r_{ij} = \beta_{ij}\, r\left(fh_i, fh_{dj}\right) \tag{14}$$

$$RES_j = \max_j \sum_i r_{ij} \tag{15}$$

4. Experimental Results and Analysis

In this study, the regression prediction model (reference model 1), Kalman filter prediction model (reference model 2), BP neural network model (reference model 3), combined prediction model (reference model 4), and the model proposed in this paper (reference model 5) were tested on the digital HRM risk dataset in order to compare their performance. The *ROC* curves of these models are given in Figure 8, and their *P-R* curves are given in Figure 9. According to the comparison results of the performance tests of the five prediction models, the proposed model exhibited obvious advantages in terms of the stability and accuracy of digital HRM risk prediction. Thus, the results verified that the idea of assisting prediction by deeply mining the more complex relationships between events presented in this paper is feasible and scientific.

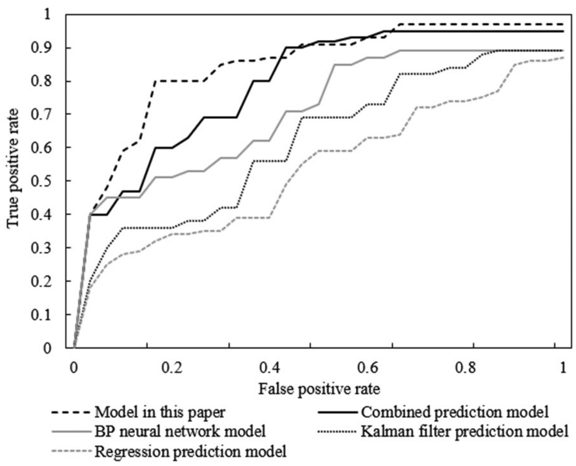

Figure 8. ROC curves of different risk prediction models.

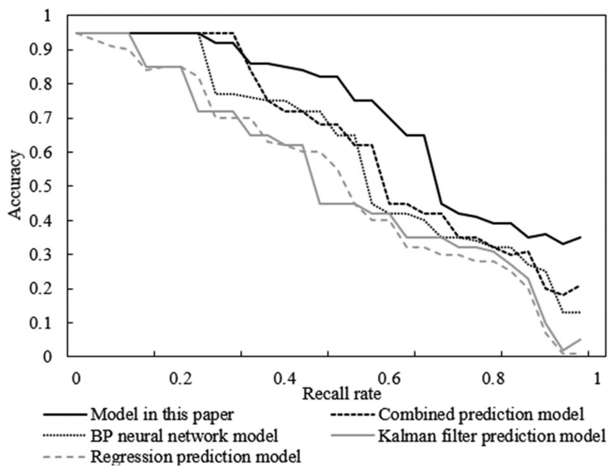

Figure 9. P-R curves of different risk prediction models.

By expanding the samples in the digital HRM risk dataset, mono-factor analysis was performed in this paper on four types of risk events, three types of risk event chain divisions, and five evaluation indexes. The number of the four types of risk events was, respectively, 1000, 1500, 2000, and 2500; the number of the three types of risk event chain divisions was, respectively, 10, 20, and 30; and the five evaluation indexes were *AUC*, *Accuracy*, *Precision*, *Recall*, and F1-value. Table 2 shows the statistical results of the model prediction performance for a different number of risk events. Table 3 shows the model prediction performance for a different number of divisions of risk event chains. According to the data in the tables, there are certain differences in the experimental results but the results were statistically significant ($P < 0.0001$). Under the conditions of different numbers of risk events and divided risk event chains, the prediction performance of the model was relatively stable. Specifically, when the number of risk events was 1500 and the number of risk event chains was 20, the prediction performance of the model reached the optimal value.

The digital HRM risk dataset was divided into a training set and a test set at a ratio of 5:1. 10%, 20%, ..., 100% of the samples were randomly selected from the training set to perform training for 100 times, and then the test set was used to test the validity of the model. Figure 10 shows the sample volume validation of the digital HRM risk dataset. In the figure, the horizontal axis is the proportion of training set sample volume, and the vertical axis is the AUC/ROC value. As can be seen from the figure, when the sample volume proportion reached 60%, the AUC/ROC curve tended to be stable, and the prediction performance of the model increased slowly.

Table 2. Model prediction performance under the condition of different number of risk events.

		1000	1500	2000	2500	***P*-value**
AUC	*Mean* ± *SD* 95%*CI*	0.748 ± 0.162 0.705-0.715	0.769 ± 0.037 0.715-0.784	0.719 ± 0.125 0.726-0.711	0.753 ± 0.168 0.795-0.126	$P < 0.0005$
Accuracy	*Mean* ± *SD* 95%*CI*	0.625 ± 0.137 0.628-0.635	0.728 ± 0.062 0.758-0.719	0.739 ± 0.037 0.795-0.711	0.681 ± 0.158 0.638-0.611	$P < 0.0005$
Precision	*Mean* ± *SD* 95%*CI*	0.617 ± 0.138 0.639-0.641	0.731 ± 0.195 0.785-0.706	0.683 ± 0.105 0.619-0.682	0.615 ± 0.127 0.691-0.648	$P < 0.0005$
Recall	*Mean* ± *SD* 95%*CI*	0.675 ± 0.142 0.692-0.637	0.529 ± 0.182 0.516-0.529	0.637 ± 0.137 0.617-0.651	0.611 ± 0.155 0.629-0.635	$P < 0.0005$
F1-value	*Mean* ± *SD* 95%*CI*	0.627 ± 0.118 0.628-0.615	0.635 ± 0.128 0.619-0.674	0.621 ± 0.184 0.629-0.616	0.674 ± 0.105 0.637-0.658	$P < 0.0005$

Table 3. Model prediction performance for different number of divisions of risk event chains.

		10	20	30	***P*-value**
AUC	*Mean* ± *SD* 95%*CI*	0.748 ± 0.129 0.736-0.719	0.781 ± 0.152 0.759-0.726	0.714 ± 0.184 0.762-0.736	$P < 0.0005$
Accuracy	*Mean* ± *SD* 95%*CI*	0.638 ± 0.058 0.629-0.647	0.736 ± 0.074 0.748-0.735	0.749 ± 0.069 0.795-0.711	$P < 0.0005$
Precision	*Mean* ± *SD* 95%*CI*	0.658 ± 0.169 0.612-0.637	0.651 ± 0.269 0.635-0.647	0.638 ± 0.127 0.612-0.639	$P < 0.0005$
Recall	*Mean* ± *SD* 95%*CI*	0.625 ± 0.145 0.617-0.695	0.659 ± 0.241 0.637-0.648	0.627 ± 0.137 0.619-0.635	$P < 0.0005$
F1-value	*Mean* ± *SD* 95%*CI*	0.658 ± 0.147 0.674-0.635	0.692 ± 0.159 0.619-0.684	0.636 ± 0.182 0.681-0.695	$P < 0.0005$

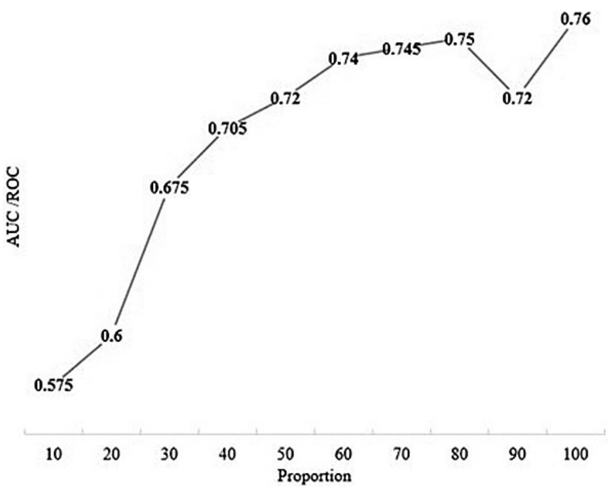

Figure 10. Sample volume validation of the digital HRM risk dataset.

5. Conclusion

This paper studied the risk prediction of digital HRM based on AI. At first, the paper introduced the functions of digital HRM system and its mechanism, and a conceptual model was built for the HRM system. Then, this paper proposed a novel method for predicting the risks in digital HRM which innovatively integrates the digital HRM risk event chains with the risk event graph. After that, this paper elaborated on the structures and building principles of the risk event representation layer, risk event chain module, risk event graph module, and attention fusion module. Experimental results showed the ROC and P-R curves of different risk prediction models, and verified that the proposed model exhibited obvious advantages in terms of stability and accuracy of digital HRM risk prediction. Moreover, mono-factor analysis was performed on four types of risk events, three types of risk event chain divisions, and five evaluation indexes. The results verified that the model prediction performance reached the optimum when the number of risk events reached 1500 and the number of risk event chain divisions reached 20. At last, a diagram was plotted for the sample volume validation of the digital HRM risk dataset.

The work presented in this paper enriched the research of digital HRM risk prediction and provided a reference for management decision-making. With its help, companies can better supervise their human resources, protect the rights and interests of their employees, thereby ensuring the healthy development of both the company and the employees.

For the research done in this paper, there's still room for further improvements, for example, this paper combined the risk event presentation layer, the risk event chain module, the risk event graph module, and the attention fusion module, and this can bring a lot of noise which might result in performance decline of the model, so in the next step, this problem will be fully considered to further improve the prediction performance of the model in the future.

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