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Optimized algorithm-driven enterprise human resource digital management and integrated training and assessment collaboration

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Abstract The traditional human resource management model is difficult to meet the development needs of the digital economy era, and enterprises urgently need to build a digital and intelligent human resource management system. Meanwhile, the integrated integration of assessment and training is of great significance for improving talent management efficiency and optimizing resource allocation. Based on Bayesian network theory, this study constructs a collaborative optimization analysis model for the integration of digitalization of enterprise human resource management and assessment and training. First, an evaluation index system covering five dimensions of human resource planning, recruitment and allocation, training and development, performance management, and labor relations management is established, the causal relationship between the influencing factors is determined by using the explanatory structure model, and the parameters of the Bayesian network are determined by using the maximum a posteriori estimation method. Then, through empirical analysis of 260 human resource management cases, it was found that the probability of safety problems in human resource planning was as high as 82%, and the probability of contract management and employee health and safety was 76% and 77%, respectively. The results show that the system's integrated co-optimization effect peaks at around 100 hours during the co-optimization process, followed by a second peak at 177 hours. The study verifies the effectiveness of Bayesian network in identifying key influencing factors and evaluating synergistic effects, and provides a scientific decision support tool for enterprises to promote the digital transformation of human resource management.

Index Terms Bayesian network, human resource management, digital transformation, measurement and training integration, collaborative optimization, explanatory structural model

I. Introduction

In today's science and technology continues to update and develop, digital transformation is also an important path for enterprises that want to achieve long-term development, human resource management occupies a core position in the enterprise management system, and actively promoting its digital transformation can make the core competitiveness of the enterprise steadily improve, and realize the scientific distribution of human resources [1]-[3]. However, in fact, the construction of digital transformation cannot be completed overnight, and enterprises have to go through thoughtful and scientific layout [4], [5]. Due to the rapid promotion and application of information technology, artificial intelligence technology, enterprises to create a set of desktop Internet technology, mobile Internet technology integration of cloud computing system, with the rapid updating of scientific and technological means, but also for the enterprise human resource management digital transformation to provide the necessary technical support [6].

Advanced digital technology continues to develop, interact, influence and promote each other, laying a good start for the comprehensive development of digital technology [7]. The organic combination of digitization technologies constitutes a functionally rich and data-intensive cloud computing system [8]. This system not only involves desktop Internet technology, but also interconnects with current mobile Internet technology and Internet of Things technology to promote the internal sharing of data [9], [10]. Based on this, the efficiency of diversified information services has steadily increased, and also fully demonstrates the advantageous role of the Internet in promoting the digital transformation process of enterprises [11]. In the context of the digital era, the digitization of human resource management is not only limited to emerging industries, but can also become an innovative driving force for traditional enterprises, promoting the quality management of human resources while promoting the sound operation of enterprises [12], [13]. Digital human resource management can promote the change of management style, realize the transformation from feeling to experience to quantification and refinement, and through the application of management platform, it can simplify the workflow and innovate the work style, so as to improve the efficiency of human resources and enhance the competitiveness of enterprises [14].

Enterprise human resource management is undergoing a major change from traditional mode to digital and intelligent transformation. In the context of digital economy, enterprises are facing challenges such as inefficient talent management, irrational resource allocation, and disconnection between training and assessment. The rapid development of digital technology provides new possibilities for human resource management innovation, but how to realize the effective synergy between management digitization and the integration of measurement and training is still a core issue for enterprises. Existing research mostly focuses on the optimization of a single dimension of human resource management, and lacks a systematic analysis of the synergistic effect of digital transformation and measurement and training system. As an effective tool for dealing with uncertainty, Bayesian network can reveal the causal relationship and mutual influence mechanism among the elements in a complex system. Applying Bayesian network to the field of human resource management can quantitatively analyze the synergistic effect of each management link and identify the key factors affecting organizational performance. Therefore, constructing a synergistic optimization model of HRM digitalization and measurement and training integration based on Bayesian network has important theoretical value and practical significance for improving the level of enterprise talent management. By integrating Bayesian network theory and explanatory structure model, this study establishes a comprehensive evaluation system, aiming to reveal the intrinsic connection of each link of human resource management and provide scientific basis for enterprise digital transformation. Firstly, starting from the theory of strategic human resource management, we construct an evaluation index system containing five dimensions: planning, recruitment, training, performance, and labor relations; secondly, we use the explanatory structure model to analyze the hierarchical relationship among the indexes and establish a Bayesian network topology; then we use the maximum a posteriori estimation based on the experts' priori knowledge to determine the parameters of the network; and finally, we validate the model by empirical analysis to assess the synergistic optimization effect. Through the above research design, it is expected to provide a systematic analysis framework and decision support tools for the digital transformation of enterprise human resource management.

II. Bayesian network model for enterprise human resources management-based assessment

II. A.Evaluation index system of enterprise human resources digital management level

In order to evaluate the level of enterprise human resources digital management, according to the six activities of human resources management, based on the theory of strategic human resources management and the theory of digital transformation, this paper establishes a system of evaluation indexes for the level of digital management of human resources from six aspects: human resources management, recruitment and allocation, training and development, performance management, compensation management, and labor relations management. The evaluation index system of enterprise HR digital management level is shown in Table 1.

Table 1: The index of the digital management of human resources of enterprises

Index dimension	Index
A: Human resource planning	A1: Overall strategic planning support
	A2: Departmental planning support
	A3: Human resource expenditure is supported by budget
B: Personnel recruitment and configuration	B1: Recruitment requirements management
	B2: Personnel configuration quality management
	B3: Managerial competence management
C: Training development	C1: Training system application
	C2: Training requirements analysis
	C3: Training effect management
D: Performance management	D1: Test system application level
	D2: Employee performance analysis
	D3: Target tracking management level
E: Labor relations management	E1: Employee surveys and feedback
	E2: Employee complaints and dispute management
	E3: Contract management

II. B.Bayesian network theory

Bayesian networks [15], also called confidence networks, are models for solving uncertainty problems and reasoning. It is applied to judgmental decisions that rely on multiple synergistic network influences and can be analyzed from incomplete or uncertain data. Bayesian networks are presented in the form of a network topology, with objective data combined with structured graphs in an easy-to-understand manner.

II. B. 1) Bayesian network selection basis

Bayesian network's own intuition and relevance, can use simple and clear structural diagram to visualize the coupling relationship between the variables, so it can be applied to the enterprise human resource management synergistic network of influencing factors coupling role modeling method and its applicability to be discussed. In addition, the Bayesian network itself has the following advantages:

(1) Bayesian network itself can show the process of events. Bayesian network topology is essentially a directed acyclic graph, each node is connected by a directed line, which can form a Bayesian network topology. In the analysis of human resource management collaborative network influencing factors, judging the interrelationship between each node, the human resource management collaborative network analysis model based on Bayesian network can be established.

(2) Bayesian network each node through the directed acyclic graph to realize the mutual influence, and adjust the state probability of any node, or delete or add any effective node, will act on other nodes.

(3) Bayesian networks are capable of parameter learning. Based on the objective data set can establish a Bayesian network model for effective analysis, so as to analyze the various types of factors affecting the problem, to determine the positive and negative relationships between the various types of factors and events.

II. B. 2) Bayesian network grounded theory

A Bayesian network consists of network nodes, a distribution of state probability values for the nodes, and directed edges. The nodes of a Bayesian network can be the influences of an event or the probability of the integration of human resource management and measurement and training of the event itself, and the relationships between the nodes are connected and interact with each other by directed edges.

Bayesian network probability theory mainly consists of the following basic concepts:

(1) Prior probability

Prior probability refers to the probability obtained based on previous experience and analysis, also known as statistical probability, if $X_1, X_2, \cdots, X_n$ is the basic event in the sample space E, through the experience and knowledge of relevant experts or based on previous statistical data to obtain the probability of the event X_i $P(X_i)$, then $P(X_i)$ is called a priori probability.

(2) A posteriori probability

If $X_1, X_2, \cdots, X_n$ is a basic event in the sample space E, and if the event Y occurs, the probability of the event X occurring is $P(X_i | Y)$, and when the sample data changes, $P(X_i | Y)$ will change accordingly, then $P(X_i | Y)$ is called the posterior probability.

(3) Conditional probability

Let X, Y be two basic events in the set of events Ω, where $P(X) > 0$, then the conditional probability $P(X | Y)$ of the two is:

where $P(X | Y)$ is the conditional probability of occurrence of event X under the condition of occurrence of event Y; $P(Y)$ is the probability of occurrence of event Y; and $P(XY)$ is the probability of simultaneous occurrence of event X and event Y.

(4) Joint probability

If X, Y are two events in the set of events Ω, where $P(Y) > 0$, then the joint probability of the two is:

$$P(XY) = P(Y)P(X | Y) \tag{1}$$

The joint probability can be extended to multiple events, from which the formula for the joint probability distribution of event X can be deduced:

$$P(x_1, x_2, \cdots, x_n) = \prod_{i=1}^{n} P(X, Y) \tag{2}$$

where $P(X_1, X_2, \cdots, X_n)$ is the set of probability of occurrence of event X, $P(X \mid Y)$ is the probability of occurrence of event X under the condition that event Y occurs

(5) Full probability formula

If the set of space of the full set Ω is E, $X_1, X_2, \cdots, X_n$ and $Y_1, Y_2, \cdots, Y_n$ are the basic events in the sample space E and X_i are mutually exclusive, $X_1 \cup X_2 \cup \cdots \cup X_n = E$, $P(X_i) > 0$, satisfies $i = 1, 2, \cdots, n$, and the full probability formula is shown below:

$$P(Y) = \sum_{i=1}^{n} P(Y \mid X_i) P(X_i) \tag{3}$$

where $P(Y \mid X_i)$ is the probability that event Y occurs under the condition that event X occurs; $P(X_i)$ is the probability that event X occurs. In the process of research, sometimes $P(Y)$ is difficult to find or obtain directly, but $P(X)$ and $P(Y \mid X_i)$ can be obtained based on the learning of a priori and sample data, and therefore the value of $P(Y)$ can be obtained according to the full probability formula.

(6) Bayesian formula

If the space set of the full set Ω is E, $X_1, X_2, \cdots, X_n$ and $Y_1, Y_2, \cdots, Y_n$ are the basic events in the sample space E and X_i are mutually exclusive, $X_1 \cup X_2 \cup \cdots \cup X_n = E$, $P(X_i) > 0$, satisfies $i = 1, 2, \cdots, n$, and the Bayesian formula is shown below:

$$P(X_i \mid Y) = \frac{P(Y \mid X_i) P(X_i)}{\sum P(Y \mid X_i) P(X_i)} \tag{4}$$

where $P(X_i)$ is the probability that event X occurs, i.e., the prior probability; $P(Y \mid X_i)$ is the posterior probability that event Y occurs under the condition that event X occurs; and $P(X \mid Y_i)$ is the posterior probability that event X occurs under the condition that event Y occurs.

II. B. 3) Bayesian network modeling approach

As a directed acyclic network topology, the Bayesian network model can represent the probability distribution among the influencing factor variables and analyze the interrelationships among the variables. Bayesian network model construction is divided into the following three steps.

(1) Determination of Bayesian network nodes

Determination of Bayesian network nodes is the basis of Bayesian network model construction, Bayesian network nodes include a total of three types, the target node refers to the risk of the event corresponding to the problem of the study; the root node represents the determination of the most basic risk influencing factors in the event, and its a priori probability can be obtained through the collected data; the intermediate node is in the middle between the root node and the target node, which indicates that the root node and the target node have a causal and logical relationship, and can be analyzed. causal and logical relationships, which can simplify the structure of the Bayesian network and make the Bayesian network model more intuitive.

(2) Bayesian network structure construction

The structure construction of Bayesian network is the process of establishing the network topology on the basis of determining the Bayesian network nodes. There are three main ways to learn the structure of the Bayesian network, the first is the learning algorithm based on analysis, which is more efficient and simpler to use; the second is the learning algorithm based on scoring search; and the third is to construct the Bayesian network topology manually by using the a priori knowledge, which uses the expert experience and the a priori knowledge to continuously adjust the topology of the Bayesian network, so as to obtain the complete Bayesian network structure. complete Bayesian network structure.

(3) Bayesian network parameter learning

Bayesian network parameter learning is to determine the probability of each node according to the actual data, after determining the Bayesian network structure, parameter learning of the Bayesian network structure is carried out according to the causal relationship and logical relationship between the nodes, and parameter learning is carried out by utilizing the collected sample data to obtain the final Bayesian network model.

II. C.Bayesian Network Modeling for Collaborative Effectiveness Assessment

II. C. 1) Bayesian networks

The previous work combines graph theory and probabilistic BN model [16] and applies it to practical problems. The construction of BN includes structure construction and parameter determination. The structure of BN consists of nodes and directed edges. Each node represents a variable and the directed edges pointing to the child nodes from the parent node represent the causal relationship between the node variables. If no directed edges are connected between 2 nodes, it means that there is no causal relationship between them, i.e., they are independent of each other.

The synergistic effect of digitalization of enterprise human resource management and integration of measurement and training is used as an indicator of network performance under the influence of facing disturbances. Namely:

$$P(t)=\frac{\sum_{w\in Wr\in R_w}\frac{f_{wk}(t)}{c_{wk}(t)}}{\sum_{w\in W}d_w} \tag{5}$$

where, $P(t)$ is the performance of the road network when the moment after the occurrence of the disturbance is t; W is the set of OD pairs in the network; R_w is the set of paths between any OD pairs $w(w\in W)$; d_w is the demand for transportation between any OD pairs w, independent of the disturbance; and $f_{wk}(t)$ is the actual transportation on any path k between OD pairs w when the moment after the occurrence of the The actual transportation quantity on any path k between any OD pair w at moment t after the disturbance; $c_{wk}(t)$ is the occurrence of Eq. where, $Parents(A_i)$ is the set consisting of the parents of node A_i; $P(A_i\mid Parents(A_i))$ is the conditional probability of a node if the parent of A_i is known; when $Parents(A_i)$ is the empty set, the value of $P(A_i\mid Parents(A_i))$ is the prior probability $P(A_n)$.

II. C. 2) Evaluation of synergistic effect BN structure construction

The BN structure is constructed through data learning or relying on experience to respond to the causal relationship between variables at each node. There are many factors affecting the synergistic effect of enterprise HRM digitalization and measurement and training integration, and the basic data used to construct the BN structure is difficult and expensive to obtain. The Interpretive Structural Model (ISM) [17] can not only empirically determine the logical relationship between the complexity and variety of influencing factors, but also hierarchical visualization of the interactions between the factors, suitable for post-interference moments of t when the OD on the w between the path of k on the resistance.

Co-optimization effects are described in terms of performance changes due to unexpected events. To wit:

$$R=\int_{t_a}^{t_b}(P_0-P(t))dt \tag{6}$$

where, R is the network toughness value of the network at time $[t_a,t_b]$; P_0 is the performance of the network in the normal state; and $P(t)$ is the performance of the network at moment t.

According to the above equation, the network toughness value R is directly proportional to its performance loss, indicating that the larger the network toughness value R is, the worse the network's ability to cope with contingencies, i.e., the worse the network's toughness is under contingencies.

The parameters of BN consist of random variables and their conditional probabilities. Assuming a BN containing any n random variables $A_1,A_2,\cdots,A_n$, where each node in the BN is independent of its non-subnodes, the full joint probability distribution of the variables can be expressed in the form of the product of the prior probability and its conditional probability distribution. Then there are:

$$\begin{aligned}&P(A_1,A_2,\cdots,A_n)=P(A_1\mid A_2,A_3,\cdots,A_n)\\&P(A_2\mid A_3,A_4,\cdots,A_n)\cdots P(A_{n-1}\mid A_n)P(A_n)=\prod_{i=1}^{n}P(A_i\mid Parents(A_i))\end{aligned} \tag{7}$$

It is used for systems with many elements and complex relationships. Therefore, the BN structure is established based on ISM to realize the integration of digitization and measurement and training for enterprise human resource management.

Step 1: Determine the toughness influencing factors $S_1, S_2, \cdots, S_{n-1}$, and the target factor S_n, i.e. toughness.

Step 2: Establish the relationship between the influencing factors and build the adjacency matrix $X=[x_{ij}]_{n\times n}$, where x_{ij} is a 0-1 variable. When x_{ij} takes 1, it means that S_i and S_j are related; when x_{ij} takes 0, it means that S_i and S_j are not related.

Step 3: Boolean operation on the adjacency matrix X:

$$D=(X+I)^{r+1}=(X+I)^{r}\neq(X+I)^{r-1}\neq\cdots\neq(X+I) \tag{8}$$

where, $D=[d_{ij}]_{n\times n}$ is the reachability matrix, where d_{ij} is a 0-1 variable. When d_{ij} takes 1, it means that S_i and S_j are related; when d_{ij} takes 0, it means that S_i and S_j are not related; $r=1,2,3,\cdots$; and I is the unitary matrix of the same order as X.

Step 4: Decompose the reachable matrix $D=[d_{ij}]_{n\times n}$ into the set of antecedents, the set of consequences and the set of overlaps. Among them, the antecedent set $Q(S_i)$ of the factor S_i consists of the antecedent factors that can lead to the factor S_i, i.e., the set of factors corresponding to all rows of the matrix with a matrix element of 1 in the S_i column of the reachable matrix, and the consequent set $R(S_i)$ of the factor S_i consists of the consequence factors that can be caused by the factor S_i, i.e., the set of factors corresponding to all the columns in row S_i of the reachable matrix that have a matrix element of 1; and the overlap set of the factor S_i, $T(S_i)$, is the intersection of the set of antecedents and the set of consequences.

Step 5: Extract the factors and build the hierarchical structure. Take the decomposed reachable matrix as a criterion, if the set of consequences is consistent with the overlap set, extract the set of factors for hierarchical division. Cycle the above operations, and finally determine the hierarchical structure of the model based on the set at the end of extraction.

Step 6: Convert the structural model to BN structure: (1) BN node conversion, convert the corresponding influencing factors in the structural model to BN node set; (2) BN directed edge conversion, convert the causal relationship between factors in the structural model to BN directed edge E.

II. C. 3) Determination of BN parameters for toughness evaluation

BN parameters can be obtained through data learning or expert experience. The former requires a high amount of data, while the latter is subjective and difficult to give specific parameters. Based on the two, the Maximum A Posteriori Estimation (MAP) [18] method based on expert prior knowledge is proposed to determine the parameters. The MAP method based on experts' a priori knowledge is as follows.

Based on a known series of expert empirical data $(X=\{x_0,x_1,...,x_n\})$, solve for the maximum possible values of the BN parameter θ. To wit:

$$\arg\max_{\theta} P(\theta \mid x_0,x_1,\cdots,x_n) \tag{9}$$

According to the Bayesian formula, the above equation can be transformed into:

$$P(\theta \mid x_0,x_1,\cdots,x_n)=\frac{P(x_0,x_1,\cdots,x_n \mid \theta)\times P(\theta)}{P(x_0,x_1,\cdots,x_n)} \tag{10}$$

where, $P(\theta)$ is the prior probability distribution of the BN parameter θ based on expert experience; $P(x_0,x_1,\cdots,x_n \mid \theta)$ is the joint distribution function of the sample data; $P(x_0,x_1,\cdots,x_n)$ is the probability of occurrence of this data.

Since the data $x_0,x_1,\cdots,x_n$ are known, which is equivalent to this event having occurred, $P(x_0,x_1,\cdots,x_n)=1$.

This transforms Eq. (10) into:

$$\arg\max_{\theta} P(\theta \mid x_0,x_1,\cdots,x_n)=\arg\max_{\theta} P(x_0,x_1,\cdots,x_n \mid \theta)\times P(\theta) \tag{11}$$

Since $P(x_0,x_1,\cdots,x_n \mid \theta)$ follows a binomial distribution with parameters n and p, i.e., $X\sim B(n,p)$, the expectation and variance are, respectively, given:

$$\begin{cases} E_x = np \\ D_x = np(1-p) \end{cases} \tag{12}$$

In order to facilitate the calculation and intuitively obtain the form of the posterior distribution of the BN parameter θ with respect to the sample data $x_0, x_1, \cdots, x_n$, the prior probability distribution of the parameter θ is determined in terms of the principle of conjugate prior distribution. Thus, $P(\theta)$ follows a Beta distribution, i.e., $\theta \sim B(\alpha, \beta)$, which can be expressed as:

$$P(\theta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \theta^{\alpha-1}(1-\theta)^{\beta-1} \tag{13}$$

$$\Gamma(\alpha) = \int_0^{+\infty} t^{\alpha-1} e^{-t} dt \tag{14}$$

where, α and β are non-negative hyper-parameters that are not determined by the data and can be subjectively set to well represent the probability distribution curve of the prior knowledge. Considering that the probability distribution curve should be a convex function, both α and β should be real numbers greater than one.

The expectation and variance of $\theta \sim B(\alpha, \beta)$ are respectively:

$$\begin{cases} E_\theta = \dfrac{\alpha}{\alpha+\beta} \\ D_\theta = \dfrac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)} \end{cases} \tag{15}$$

According to the principle of great likelihood estimation, minimizing the distance between the variances of the binomial distribution $X \sim B(n, p)$ and the Beta distribution $\theta \sim B(\alpha, \beta)$ is taken as the objective function, and equality of expectation is taken as the constraint. To wit:

$$\begin{aligned} &\min(D_\theta - D_x)^2 \\ &s.t. \begin{cases} E_\theta = E_x \\ \alpha > 1 \beta > 1 \end{cases} \end{aligned} \tag{16}$$

Substituting Eq. (12) and Eq. (15) into Eq. (16), the following objective optimization problem can be obtained. Namely:

$$\begin{aligned} &\min\left[\frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)} - np(1-p)\right]^2 \\ &s.t. \begin{cases} \dfrac{\alpha}{\alpha+\beta} = np \\ \alpha > 1, \beta > 1 \end{cases} \end{aligned} \tag{17}$$

Solving Eq. (17) yields the parameters α and β of the Beta distribution, which are substituted into Eq. (11) to compute the posterior probability distribution of the parameter θ under this condition.

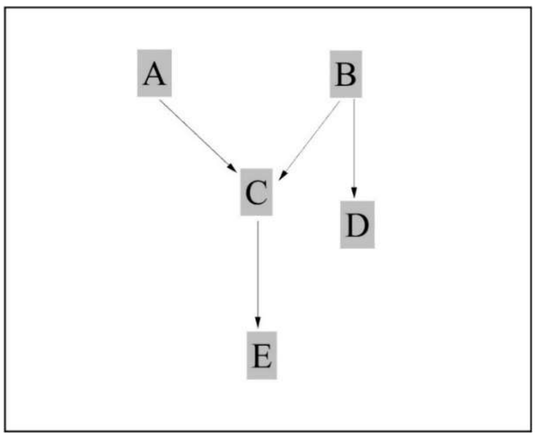
III. Digitalization of human resources management and synergistic optimization of the integration of testing and training

III. A. Assessment of the effectiveness of optimization of human resources management and training and measurement

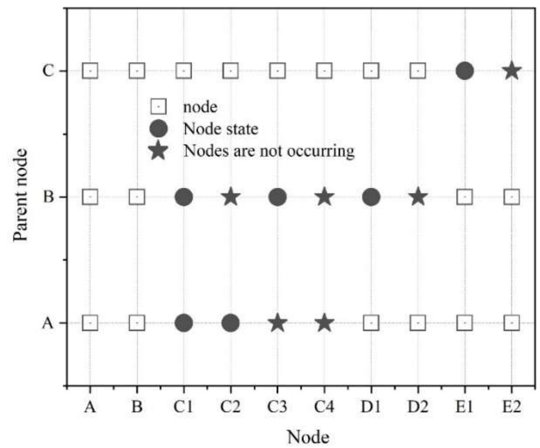
III. A. 1) Assessment of the likelihood of occurrence of human resources management nodes

According to the constructed Bayesian network-based node occurrence probability model, the process of calculating the conditional probability of Bayesian network nodes is illustrated with the example of the evolutionary sub-network of human resource management and the integrated planning chain of measurement and training. Nodes A, B, C, D and E represent human resource management, recruitment and staffing, training and development, performance management and labor relations management, respectively. The nodes in the Bayesian network are discretized, where the nodes are modeled as binary variables, i.e., in the state of node occurrence (yes) or non-occurrence (no), and the dependence between each node in the Bayesian network and its parent node reflects the distribution of conditional probability corresponding to each node in the different states of the parent node.

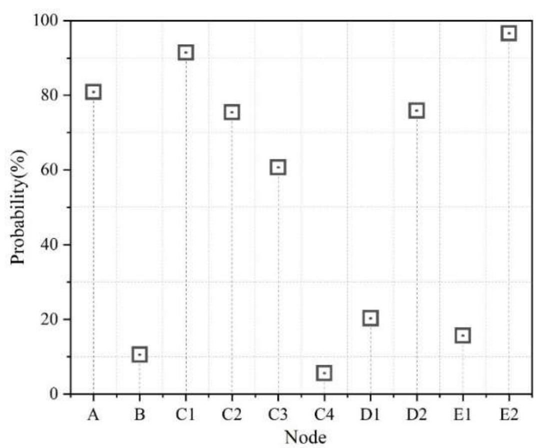
Figure 1 shows the results of conditional probability distribution of HRM evolutionary sub-network, where (a)~(c) represent the evolutionary sub-network, node state and node conditional probability distribution respectively. The results show that nodes A and B have no parent nodes, and the occurrence probability does not depend on the state of other nodes, while the probability of nodes C, D and E depends on other nodes. The parent nodes of node C are nodes A and B. When A and B are in different states respectively, the probability that node C is in the occurrence state can be categorized into four cases C1, C2, C3 and C4, and the probability cases of nodes D and E can be obtained in the same way.



(a) Evolutionary subnetwork



(b) Node state



(c) Node condition probability distribution

Figure 1: The probability distribution of the node evolutionary subnetwork condition

III. A. 2) Co-optimization assessment of human resources management nodes

Collecting economic data of enterprise human resources and measurement and training synergistic optimization, and establishing the loss assessment model of management digitalization and measurement and training integration. The results of the dynamic change of the loss of enterprise resource management and measurement and training are shown in Figure 2. According to the calculated total loss of enterprise human resource management in each time step, the post-cooptimization value of each moment is obtained and analyzed. Figure 3 shows the co-optimization change process after the enterprise human resource management. It can be seen that in the process of HRM digitalization and the integration of measurement and training co-optimization, the post- HRM co-optimization shows a tendency of first increasing, then decreasing, then increasing and then decreasing. Through the network propagation model of post-cooptimization, the quantitative value of post-cooptimization of each node is obtained. The integration of management digitization and measurement and training is set to find and confirm that HRM co-optimization has occurred, that is, the integration of management digitization and measurement and training nodes of the enterprise human resources co-optimization nodes do not exist between the intervention force, resource management intervention capacity r of the discriminant coefficient is 0.

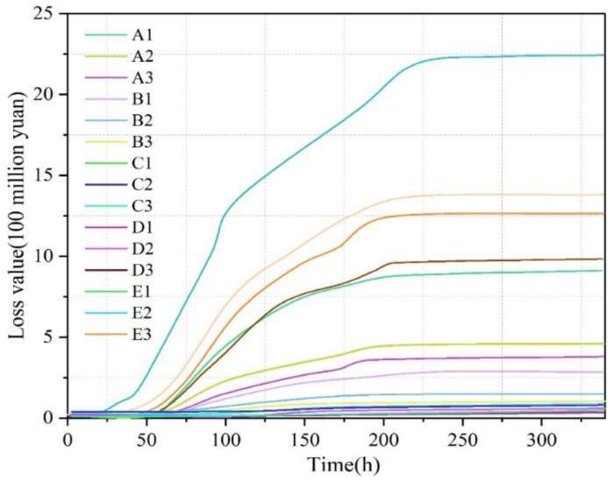


Figure 2: The loss of enterprise resource management and survey loss

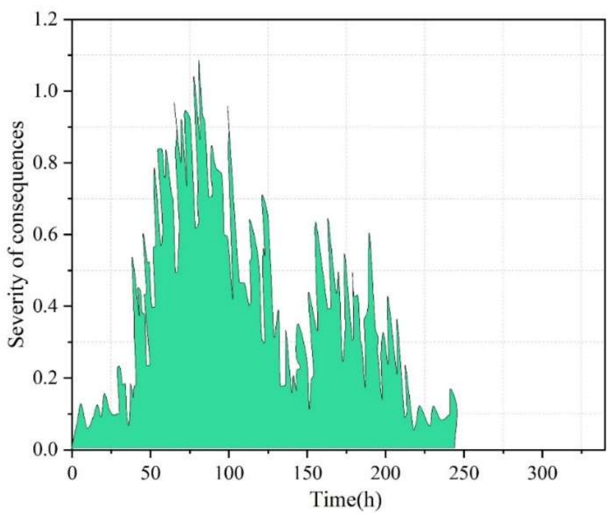


Figure 3: Collaborative optimization of enterprise human resources planning

III. A. 3) Analysis of the effectiveness of human resources management optimization

According to the possibility of node occurrence and the level of co-optimization after the classification, through the risk matrix to find the node risk corresponding to the value of the interval, quantify the level of risk, and then find the example of human resources management chain comprehensive risk level, human resources optimization effect shown in Figure 4. As can be seen from the figure, the enterprise human resources optimization simulation after the beginning of the integrated synergistic optimization effect level continues to increase until about 100h to reach the integrated synergistic optimization effect of the maximum value, followed by a downward trend, about 177h to reach the second peak, followed by a significant slowdown in the rate of decline. Comparing the effect of HRM digitization and measurement and training integration co-optimization over time, the peak value of the integrated system co-optimization effect of HRM is considered to be larger than that of traditional HRM, and the moment of reaching the peak value lags behind, while the duration of the time period with better co-optimization effect is longer, due to the fact that in the digitization of resource management, the system co-optimization effect is composed of multiple node factors This is due to the fact that in the process of resource management digitization, the synergistic optimization effect of the system is composed of the cumulative superposition of multiple node factors, and there is a synergistic optimization transfer relationship between nodes. At the same time, the level of the synergistic optimization effect of most nodes shows a tendency of increasing and then decreasing in the evolution of human resources management, and some nodes even have multiple peaks of the synergistic optimization effect.

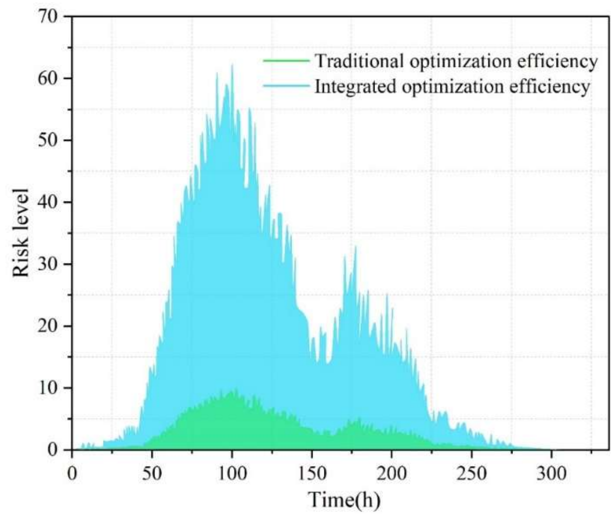


Figure 4: Resource management digital and measurement optimization effect

III. B. Bayesian Networks-based Human Resource Management and Measuring Training Effectiveness

III. B. 1) Human resources management and Bayesian network construction for testing and training

According to the strong association rules determined in the algorithm of this paper, the indicators appearing in the strong association rules are defined as the nodes of the Bayesian network, and combined with the interrelationship between the indicators determined by the strong association rules, the human resource management and measurement and training Bayesian network is established. Based on 260 up human resource management and measurement and training synergistic network, using the parameter learning function in the Bayesian network, to determine the probability of the occurrence of security problems in each node of the Bayesian network, human resource management and measurement and training Bayesian network is shown in Figure 5.

Among the secondary indicators, human resource planning is the most prominent, with a probability of occurrence of 82%, and a total of at least 168 synergistic networks involving human resource planning out of 205 synergistic networks of human resource management and measurement and training, and the results of the Bayesian network analysis are consistent with the actual situation. This is mainly due to the fact that some enterprises neglect safety education and training, and the implementation of safety production responsibility is not in place, and these reasons are very likely to lead to weak safety awareness of operators, and the phenomenon of random operation and unauthorized operation by operators is common.

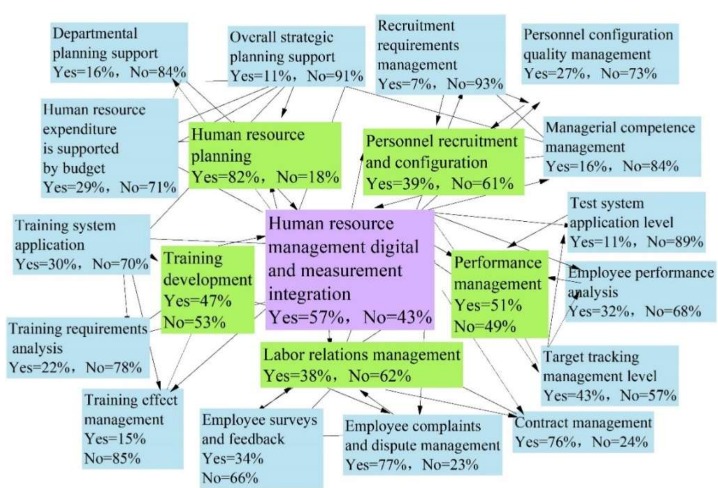


Figure 5: Human resource management and the pabespus network

In the analysis of tertiary indicators, the probability of contract management and employee health and safety is higher, 76% and 77% respectively. This is mainly due to the fact that some enterprises, in order to catch up with the schedule, temporarily hire personnel to carry out operations, the implementation of the contract is not in place as well as the health of the temporary employees do not pay attention to, resulting in weak safety awareness of the employees, which in turn led to the emergence of the phenomenon of disputes over the management of labor relations.

III. B. 2) Posterior probability analysis

Adjust the probability that the state of the nodes in the original HRM and training collaborative network of the enterprise is “yes” to 100%, and get the a posteriori probability of each node of the Bayesian network of human resource management and testing and training. The results of the comparison between the a priori and a posteriori probabilities are shown in Figure 6. The comparison reveals that the nodes with large change values before and after the occurrence of the explicit synergy network, i.e., the key nodes affecting the occurrence of the synergy network of human resource management and measurement and training. The probability of the occurrence of employee health and safety and contract management changes significantly, consistent with the results of the analysis above, which is mainly due to the fact that some enterprises do not pay attention to safety education and training, “focus on production, light on safety” and other serious phenomena, the identification of hidden dangers on the site is not clear, and the scope of human resources management and testing and training is not clearly divided into the scope of safety, weak safety awareness, violation of operating procedures random operation, etc., is very likely to lead to the occurrence of synergistic network.

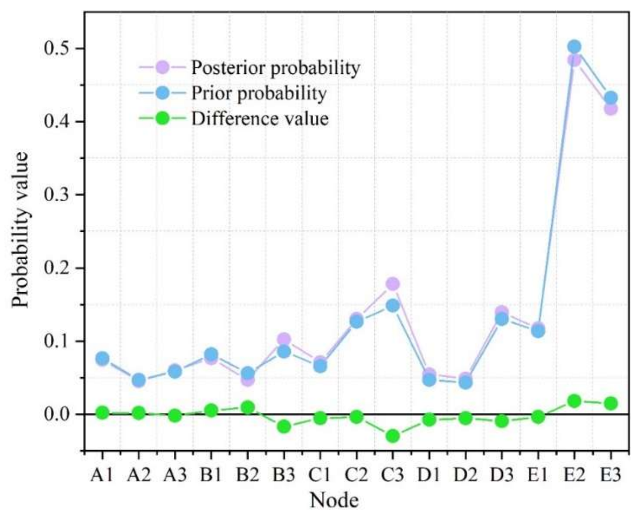


Figure 6: The prior probability and the posterior probability comparison result

III. C. Digitization of enterprise asset management and integration of measurement and training

III. C. 1) Overall design

In the preparatory stage of the construction of digital teaching resources for enterprise asset management, it is necessary to carry out the overall design of enterprise asset management construction and prepare an enterprise asset management construction plan in accordance with the functions of the online learning platform used for enterprise asset management. The enterprise asset management construction program mainly includes the overall description, the overall design program, the series of microcourse preparation program, the enterprise asset management assessment program and the progress arrangement of enterprise asset management construction. Preparing a good EAM construction program helps clarify the idea of EAM construction, arrange the construction of digital teaching resources for EAM in stages, and plan the construction tasks of each module based on the platform.

III. C. 2) Implementation pathways

In the implementation stage of EAM digital resource construction, the construction is carried out in three aspects, namely, video resources, text resources and test bank resources, according to the EAM construction program.

(1) Video resources

The video resources of enterprise asset management are mainly embodied in the form of 10~15min microclasses. Considering the learning characteristics of enterprise managers, the construction of video resources for enterprise asset management requires the production of microclasses in the form of knowledge explanation. The form of microclasses can be in the form of lectures in the form of recorded classes, presentations played and recorded screen form of microclasses, as well as the use of animation software for the production of microclasses and so on.

(2) Text resources

Text resources of enterprise asset management mainly include teaching documents and tutorial materials of enterprise asset management. The teaching documents are divided into five parts: description of enterprise asset management, syllabus, implementation rules, assessment instructions and teacher introduction. Before the formal study, the enterprise managers can understand the learning content and assessment mode of the whole enterprise asset management through the teaching documents, which is convenient for the enterprise managers to plan the learning progress according to the fragmented learning time.

(3) Test Question Bank Construction

The construction of the test bank of enterprise asset management is to meet the needs of enterprise asset management assessment, the construction of the test bank should reflect the scientific, rational and effective, not only to pay attention to the assessment of enterprise managers on the mastery of the basic theoretical knowledge of enterprise asset management, but also to pay attention to the assessment of the use of basic theoretical knowledge to analyze and solve problems, and to accurately evaluate the students' knowledge understanding, analysis, application, synthesis, etc. Learning effect in various aspects. There are various types of questions in the test bank, and the test bank for public sector human resource management enterprise asset management includes five types of questions: single-choice questions, multiple-choice questions, judgment questions, fill-in-the-blanks questions and questions and answers, and other types of questions can be constructed according to the design of the platform.

IV. Conclusion

This study has successfully constructed a collaborative optimization model based on Bayesian network for digitalization of enterprise human resource management and integration of measurement and training, and has achieved remarkable research results. The empirical analysis shows that among the secondary indicators, the probability of security problems in human resource planning is the highest, reaching 82%, which is highly consistent with the actual situation that 168 out of 205 cases involve planning problems. The analysis of tertiary indicators shows that the probability of occurrence of contract management and employee health and safety is 76% and 77% respectively, which become the key nodes affecting the synergy effect. The synergistic optimization effect shows dynamic evolution characteristics, and the integrated system effect reaches a great value at 100 hours, with a second peak at 177 hours, and the duration of the optimization effect is significantly prolonged compared with the traditional management mode. The study confirms the advantages of Bayesian network in identifying key risk factors of human resource management and quantifying the transmission relationship between nodes. The model effectively reveals the synergistic mechanism of each management link in the process of digital transformation, which provides a scientific basis for enterprises to formulate HRM strategies. Future research can further expand the sample size, refine the analysis of industry characteristics, and improve the generalizability and prediction accuracy of the model.

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