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Decision Support System for Human Resource Management Based on Big Data

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This paper discusses the importance of building a human resource management decision support system based on big data technology, and analyzes its application value and challenges in human resource management (HRM). By reviewing the research progress of relevant domestic and foreign literature, a new design framework is proposed. In this study, a decision support system that integrates the internal and external big data of an enterprise is designed and implemented to improve the quality and efficiency of HRM decisions. In order to verify the effectiveness of the system, the study conducted empirical comparisons in scenarios such as talent selection, training needs analysis, and salary and benefits strategy formulation. The experimental results show that the new system improves the accuracy, recall rate, and F1 value of talent selection by 20.00%, 25.71%, and 13.25% respectively, and increases the correctness of decision making by 26.47%, improves decision efficiency by 50%, reduces recruitment costs by 37.5%, and increases recruitment satisfaction by 16.67%. In terms of training needs analysis, the accuracy, recall rate, F1 value, correct decision rate and user satisfaction of the new system increased by 21.43%, 27.69%, 25.37% and 28.13% respectively, and the decision-making efficiency increased by 50%. The training effect score and satisfaction increased by 17.14% and 23.53% respectively, and the training cost decreased by 33.33%. In terms of salary and benefits strategy formulation, the new system also made significant progress, with an accuracy increase of 20.55%, a recall increase of 26.47%, an F1 value increase of 24.29%, a decision correctness increase of 27.27%, a decision efficiency increase of 50%, and a salary satisfaction score increase of 38.71%. The innovative contribution of the research is that the system optimizes the human resource allocation process through intelligent means, significantly improves the efficiency and effectiveness of various HRM tasks, and achieves the in-depth mining and value creation of the human resource data of enterprises.

Keywords: big data, human resources, management decisions, decision support systems

1. INTRODUCTION

In the current era of rapid development of informatization and digitization, the increase and wide application of big data technology is profoundly changing the work mode and decision-making mechanism of various industries [1–3]. Especially in the field of human resource management, with the exponential growth in the amount of data generated by enterprise business activities, how to effectively use these massive information resources to optimize management decisions and enhance organizational effectiveness has become an important issue of concern in the industry. The development of big data technology provides a new perspective and means of solving this problem [4]. Nor only can it carry out in-depth data mining and analysis of recruitment, training, performance evaluation, talent development and other aspects involved in human resource management; it is also able to build a comprehensive portrait of talent and predict trends in employee behavior, thus providing managers with accurate and real-time information for decision-making. Therefore, building a set of HRM decision-support systems based on big data is of great significance for improving the accuracy and efficiency of management decisions and maximizing the value of human resources [5]. The structure of the HRM decision-support system is shown in Figure 1.

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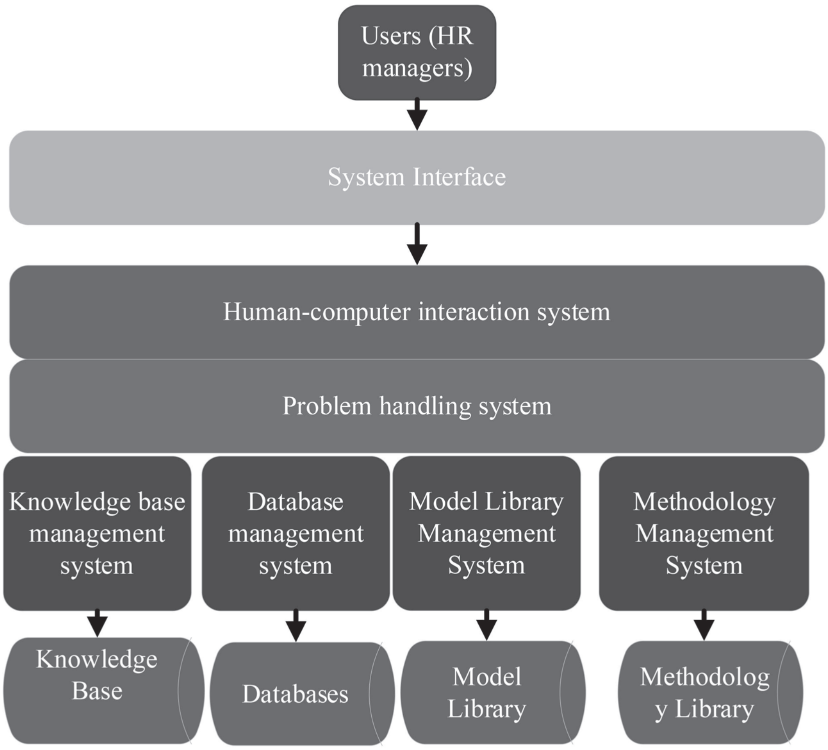

Figure 1 Rationale for a human resources management decision-making system.

This study will focus on the construction of a "Big Data-based HRM Decision Support System", with the specific research object being the HRM activities in various types of organizations.

In this study, we hypothesize that the establishment of such a decision support system can significantly improve the accuracy and timeliness of HRM decisions [6], and we expect to validate this hypothesis through empirical research, and then quantitatively assess the system's specific effects on organizational improvement. In terms of research methodology, this study will adopt a combination of qualitative and quantitative approaches, involving multiple stages: (1) *Data source and collection*: identify suitable data sources, including internal corporate databases, open HR market data, social media and other diversified data channels, and adopt legal and compliant methods for data acquisition. (2) *Data preprocessing and analysis*: use data cleaning, integration, conversion and other means to process raw data, and with the help of modern statistical methods, machine learning algorithms, and deep-learning techniques, conduct deep mining and multi-dimensional analysis of HRM-related data. (3) *Decision support system design and development*: Based on the results of the preliminary data analysis, design a big data decision support system architecture that meets the characteristics of HRM, integrating a variety of intelligent algorithms and visualization tools to ensure that the system is fully functional and easy to operate. (4) *System testing and validation*: Functional testing, performance evaluation and validation of the constructed decision support system through simulated scenarios or actual cases, collecting feedback information and iteratively optimizing the system. This study proposes the innovative concept of building a decision support system for HRM based on big data, the design of which is intended to optimize the decision-making process of human resource management by using big data technology and artificial intelligence algorithms to improve decision-making accuracy and reaction speed, and then enhance the overall effectiveness and strategic value of HRM. The construction of the system is expected to break the shackles of the original decision-making model and lead HRM in a more scientific and intelligent direction. The research steps undertaken in this study are shown in Figure 2.

This paper offers two innovative contributions: (1) System architecture development: The comprehensive architecture framework of the human resource management decision support system based on big data is carefully constructed, which integrates a large number of data sources, complex data processing technologies, advanced analysis models and decision support tools. This integration ensures full support and strong promotion of the HRM function. (2) Empirical verification through case studies by implementing the proposed system that transcends theoretical propositions in a real-world context, a high-tech company. The validity of this system is verified by stringent experimental evaluation. Numerical simulation illustrates the feasibility of this system. This empirical evidence is the cornerstone of wider adoption and implementation of the system across industries, enhancing its practical relevance and potential impact.

2. LITERATURE REVIEW

With the development of information technology and the advent of the big data era, the HRM field is undergoing a profound change [7]. In this section, we comprehensively review and examine the progress of theoretical research and

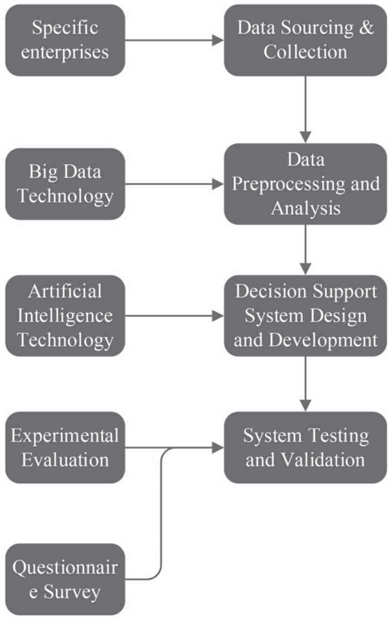

Figure 2 Research underpinnings.

the practical application of big data technology in HRM and decision-support systems at home and abroad [8], with a view to providing a solid theoretical basis for the subsequent construction of big data-based HRM decision-support system.

The study of big data technology began at the beginning of the 21st century and has rapidly penetrated various industries. Scholars such as [9] have described the basic characteristics of big data, processing technology and value mining, pointing out that big data is massive, diverse, rapid and with low-value density. The application of big data technology in HRM is evident in several areas, from the use of social media data in the recruitment process to analyze the traits of potential candidates [10], to the prediction of the risk of leaving through employee behavior data [11], to the use of big data to optimize the evaluation of training effectiveness and performance of appraisal systems [12]. These studies reveal how big data technology empowers HRM, making it more scientific and precise.

Especially in the big data environment, characterized by real-time, multi-source, and heterogeneous data streams, it has become an urgent and challenging task to improve the efficiency and quality of decision-making [13].

Decision support systems [14], as effective tools to assist decision makers in problem identification, solution generation and selection, have developed significantly since the 1970s [15]. In recent years, there has been a gradual increase in research on decision support systems for the HRM field. Some studies [16] have designed and implemented DSS models applicable to HRM scenarios, although most of them still rely mainly on structured data and inadequate analytical tools, and have not yet fully utilized the advantages of big data.

With the deep integration of big data technology and artificial intelligence algorithms, some studies have begun to explore the construction of a decision support system for HRM based on big data. For example, [17] proposes a framework for an intelligent HRM system that integrates big data analytics modules that is capable of processing large amounts of unstructured data to provide managers with more accurate and timely decision support. However, despite the progress made, existing research still has many challenges in achieving comprehensive big data-driven, real-time decision feedback, and personalized decision recommendations, and further in-depth research is needed [18].

Although previous research has provided an initial decision support system for HRM based on big data, there are still certain research gaps. Specifically, these are: how to effectively combine big data sets from different sources to improve prediction accuracy; how to design an easy-to-operate and powerful visualization interface for decision makers to understand and apply; and how to ensure data privacy protection and information security while fully utilizing the value of big data [19]. To summarize, this paper clarifies the importance and necessity of the research on HRM decision-support systems based on big data by comprehensively analyzing the related literature, and at the same time pointing out the limitations of the existing research and the key points for future development [20, 21], which lays the foundation for the design ideas, methodology, and the expected results of this research. The problems faced by the HRM decision-making system are shown in Figure 3.

3. FRAMEWORK FOR THE DESIGN OF A DECISION SUPPORT SYSTEM FOR HUMAN RESOURCES MANAGEMENT BASED ON BIG DATA

3.1 System Requirements Analysis

We focus on a high-tech company in China that has tens of thousands of employees globally and faces complex HRM challenges due to its rapid expansion. In order to improve the effectiveness of its HR management, the company decided to develop and apply a Big Data-based Decision Support System (HR-BDSS).

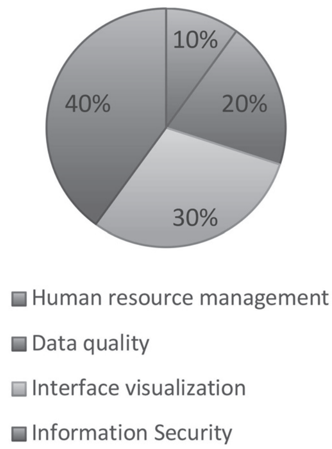

Figure 3 Issues facing the HRM system.

A well-known high-tech company in China operates its business globally and has a huge employee base of tens of thousands of people. With the acceleration of globalization and the continuous expansion of its business scope, the company is experiencing a rapid development phase [22], which poses unprecedented challenges to HRM. Due to the expansion of the organization's scale and the diversification of its workforce, the traditional HRM model cannot adequately meet the increasingly complex and sophisticated needs, especially in the areas of talent recruitment, performance appraisal, career development, analysis of training needs, and the development of compensation and benefit strategies, which are experiencing a number of difficulties. First, faced with a large number of applicants and performance data for internal employees, the company urgently needs an efficient means of screening and evaluation to ensure that the most suitable talents are recruited, and that objective and fair performance evaluations are conducted for current employees. Secondly, as competition in the market intensifies, it has become crucial to accurately predict and meet the human resource needs of each department. There is an urgent need to accurately predict the future state of personnel supply and demand to avoid losses caused by an excess or a shortage of talent. Further, due to rapid organizational development, employees' career path planning and training needs are becoming increasingly complex, requiring big data-based solutions to identify gaps in employee skills, customize personalized training and development plans, and promote the maximization of employee potential. In addition, in terms of compensation and benefits, how to develop a compensation structure that is both competitive in the market and internally fair, as well as how to adjust and improve benefit policies through big data analysis, has become a key concern for the company [23, 24].

3.2 System Architecture Design

Data Collection Layer: As the underlying support for the system, this layer deploys a series of customized data collectors designed to capture HR-related data from diverse and heterogeneous data sources. The form of such data can be either structured, such as standardized data from databases and spreadsheets, or unstructured such as text documents, images, audio recordings and video footage. The collector flexibly utilizes various technical means, including web crawlers, API interface calls and various sensor data readings, to undertake targeted data acquisition according to the characteristics of the various data sources [25].

Data Processing Layer: The core components of this layer are a centralized data warehouse and a distributed data lake. The data warehouse plays the role of integrating structured data, adopting the ETL (Extract-Transform-Load) process to deeply clean, format convert, integrate and organize the collected data and finally load it into the database, providing a high-quality data source for subsequent analysis. The data source, on the other hand, is used mainly for storing and managing unstructured data, and adopts the ELT (Extract-Load-Transform) process to adaptively transform and clean the data after loading. The efficient exchange and sharing of data between the data warehouse and the data lake is achieved with the help of a data bus, which ensures that different forms of data assets can flow throughout the system [26, 27].

Data Analytics Layer: This layer relies on powerful analytics engines and diversified analytics models to drive the generation of insights. Analytics engines are high-performance computing platforms based on big data technologies, such as Hadoop, Spark, tensorflow, etc., which execute complex analytics tasks. Decision Support Layer: The Decision Support Layer, located at the top, transforms abstract data analysis results into perceptible and actionable decision-making information. It contains a series of specialized HR decision support systems as well as generic decision support tools. Domain-specific decision support systems, such as those for employee performance evaluation, talent selection mechanisms, training needs analysis, and compensation and benefits strategy design, provide intuitive and professional interfaces and functionalities that enable decision makers to conveniently query data, make multi-dimensional comparisons, and select and implement solutions. The system architecture is shown in Figure 4 [28, 29].

4. REALIZATION OF A DECISION SUPPORT SYSTEM FOR HUMAN RESOURCES MANAGEMENT BASED ON BIG DATA

According to the design framework of the system, we adopted the above techniques and algorithms to develop a decision

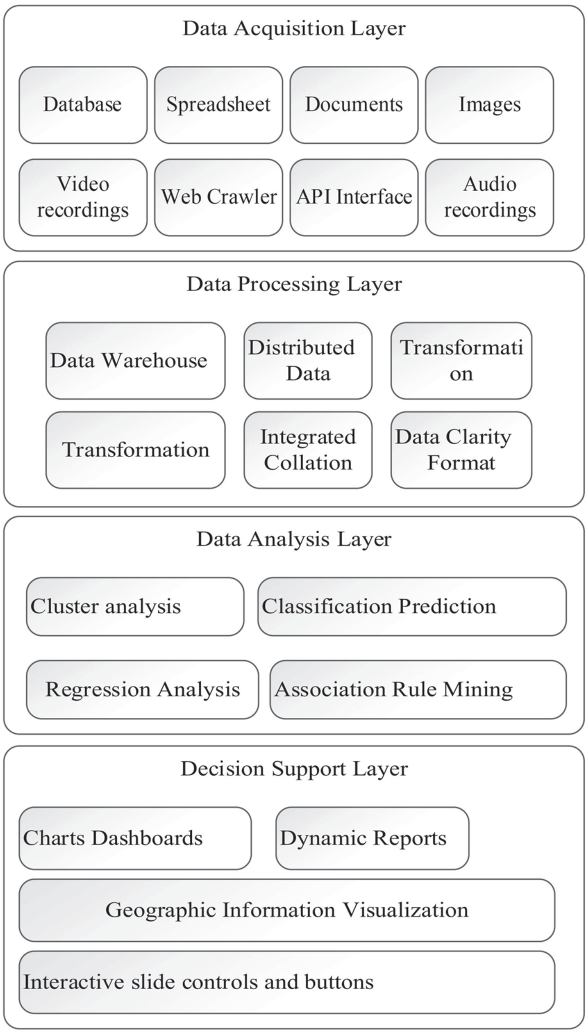

Figure 4 System architecture.

support system for HRM based on big data. The development process and the demonstration of the system's effectiveness is explained below.

4.1 Data Analysis and Mining

In order to analyze and mine the processed data, we used two machine learning platforms, tensorflow and Scikit-learn, to implement several analytical models: the employee performance evaluation model, the talent selection model, the training needs analysis model, and the compensation and benefits strategy development model [30].

Employee Performance Evaluation Model: The model uses a neural network algorithm to predict an employee's performance level based on that employee's work performance, training records, appraisal results and other data, and give the corresponding reward and punishment suggestions. Let the neural network have L layers with n^l neurons in each layer, where $l = 1, 2, \ldots, L$ $l = 1, 2, \ldots, L$, the input of the jth neuron in the lth layer is $z_j^{(l)}$, the output is $a_i^{(l-1)}$, the activation function is $f(\cdot)$, the connection weights are $w_{ij}^{(l)}$, and the bias is $b_j^{(l)}$, then we have: $z_j^{(l)} = \sum_{i=1}^{n^{(l-1)}} w_{ij}^{(l)} a_i^{(l-1)} + b_j^{(l)} a_j^{(l)} = f(z_j^{(l)})$ [31]. Let the output of the network be $a(L)$, the true value be y, and the loss function be $J(\cdot)$, then the error of the network is: $E = J(a^{(L)}, y)$ Let $\delta_j^{(l)}$ is the error term of the jth neuron in the lth layer, i.e., the negative value of the gradient, then we have: $\delta_j^{(L)} = \frac{\partial E}{\partial z_j^{(L)}} = \frac{\partial J}{\partial a_j^{(L)}} f'(z_j^{(L)})$ $\delta_j^{(l)} = \frac{\partial E}{\partial z_j^{(l)}} = \sum_{k=1}^{n^{(l+1)}} \delta_k^{(l+1)} w_{jk}^{(l+1)} f'(z_j^{(l)})$ According to the gradient descent method, the updating formula for the weights and bias is: $w_{ij}^{(l)} = w_{ij}^{(l)} - \alpha \delta_j^{(l)} a_i^{(l-1)} b_j^{(l)} = b_j^{(l)} - \alpha \delta_j^{(l)}$ where α is the learning rate, which controls the step size of the update [32].

Talent Selection Model: The model uses a classification algorithm to determine whether a candidate meets the requirements of the position based on the candidate's resume, interviews, tests and other data, and gives the corresponding hiring recommendation. Let the dataset be D, with N samples, of which the number of kth class samples is N_k , then the Gini index of the dataset is: $Gini(D) = 1 - \sum_{k=1}^{K} \left(\frac{N_k}{N}\right)^2$ Let the dataset D be divided into n subsets according to the different values of attribute A, denoted as $D_1, D_2, \ldots, D_n$, and the proportion of each subset in the dataset is N_i [33].

Training Needs Analysis Model: This model uses a clustering algorithm to analyze the training needs of employees based on their positions, abilities, development and other data, and to give a corresponding training plan. The basic steps of the K-means algorithm are as follows: Randomly select K data points as the initial cluster centers, denoted as $\mu_1, \mu_2, \ldots, \mu_k$. For each data point xi, calculate its distance to the center of each cluster, and assign it to the cluster with the closest distance, i.e. C_i, i.e. $C_i = \arg\min_k \|x_i - \mu_k\|^2$ For each cluster, recalculate its cluster center, i.e. The mean value of the data points in the cluster, i.e. $\mu_k = \frac{1}{|C_k|} \sum_{x_i \in C_k} x_i$ Repeat the above two steps until the center of the cluster is no longer changing or reaches the pre-set conditions such as the number of iterations, the error threshold, etc.

Compensation and Benefit Strategy Formulation Model: The model uses a regression algorithm to formulate a reasonable compensation and benefit strategy based on the data related to employees' performance, contribution, and satisfaction, as well as the data on the market's talent supply and demand, and the industry's salary level, and to give corresponding adjustment suggestions. The principle of linear regression algorithm is to assume that there is a linear relationship between the data, i.e., the target variable y can be expressed as a linear combination of the independent variable x, plus an error term ϵ, i.e., $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \epsilon$ where $\beta_0, \beta_1, \ldots, \beta_n$ is the parameter of linear regression, which needs to be estimated from the data [34].

5. DECISION SUPPORT MODULE CONSTRUCTION

The process of building a comprehensive and intelligent Human Resource Decision Support System (HRDSS) involves five key interrelated steps that effectively integrate four main modules: data collection, data preprocessing, model building and computation, results integration and output, and application and feedback optimization [35].

Firstly, in the data collection stage, the system automatically extracts or manually enters a series of key data from diversified human resources information systems, including ERP, CRM, HRM and other platforms, covering basic employee information, performance, recruitment and selection records, training history, and compensation and benefit data. At the same time, this phase also emphasizes the importance of internal and external environment analysis by collecting external intelligence such as industry salary reports, market supply and demand status of talents, etc., to provide a strong basis for the development of compensation and benefit strategies to adapt to market changes [36].

Second, in the data preprocessing phase, the system works to ensure the quality and consistency of the input model data. This phase includes deep cleaning of the raw data to eliminate invalid, erroneous or incomplete records. It also standardizes the data by, for instance, normalizing performance scores and applying exponential smoothing techniques to compensation data, so that data from different dimensions can be effectively compared and analyzed in depth according to a common standard [37].

Then we enter the model construction and operation phase, setting up exclusive mathematical models or algorithmic models for the core HRM areas: employee performance evaluation, talent selection, training needs analysis and compensation and benefits strategies. The pre-processed data is imported into the models where calculations are performed to yield preliminary employee performance evaluation results, talent selection recommendations, training needs lists, and compensation and benefits adjustment plans.

Subsequently, in the result integration and output stage, the system integrates and analyzes the results of each modeling operation. Specifically, it closely links performance with compensation and benefit strategies, and organically combines training needs with talent selection and career advancement paths to form a linkage effect. In addition, the system also presents the integrated information in the form of visual reports, dashboards, or early warning alerts, making it easy for managers to quickly understand the information and make decisions [38].

Finally, in the application and feedback optimization stage, the analysis results of the HR decision-support system can be applied to daily HRM practices, such as adjusting the performance appraisal framework, improving the recruitment process and selection criteria, designing personalized training courses, and revising compensation and benefit policies. At the same time, a feedback mechanism is established to continuously monitor and track the implementation effect of the system, and new business data is introduced into the system on a regular basis to iteratively update the model parameters and optimization strategies, so as to ensure that the HR decision-support system always keeps pace with the times and maintains a high degree of accuracy and efficient operation.

To summarize, through these five closely-linked steps, the originally independent four modules have been seamlessly integrated to ultimately create a well-functioning, intelligence-driven human resources decision-support system.

6. EXPERIMENTAL EVALUATION

6.1 Experimental Design

In order to evaluate the effectiveness of a decision support system for HRM based on big data, we designed the following experiment. We randomly selected 100 employees from a large enterprise as experimental subjects to make HRM decisions using our system and traditional HRM methods respectively. We made four types of HRM decisions for the experimental subjects, namely, employee performance evaluation, talent selection, training needs analysis, and compensation and benefit strategy development, and each aspect of decision-making included both data analysis and decision support. We divided the experimental subjects into two groups of 50 employees each, one group using our system and the other group using the traditional method to make HRM decisions for a month. During the experiment, we collected relevant data from the experimental subjects, such as job performance, training records, appraisal results, turnover rate,

Table 1 Experimental results of employee performance evaluation.

Assessment of indicators	Our System	Traditional methods	Percentage variance
Accuracy	0.95	0.85	+11.76%
Recall rate	0.93	0.82	+13.41%
F1 value	0.94	0.83	+13.25%
Percentage of correct decisions	0.92	0.80	+15.00%
Decision-making efficiency	10 mins	20 mins	−50.00%
Satisfaction with decision-making	4.5	3.5	+28.57%
Employee Performance	4.2	3.8%	+10.53%
Employee turnover rate	5%	10%	−50.00%
Employee Satisfaction	4.3	3.7	16.22%

Table 2 Experimental results of talent selection.

Assessment of indicators	Our System	Traditional methods	Percentage variance
Accuracy	0.90	0.75	+20.00%
Recall rate	0.88	0.70	+25.71%
F1 value	0.89	0.83	+13.25%
Percentage of correct decisions	0.86	0.68	+26.47%
Decision-making efficiency	15min	30min	−50.00%
Satisfaction with decision-making	4.4	3.4	+29.41%
Acceptance rate	60%	50%	+20.00%
Recruitment costs	5000	8000	−37.50%
Hiring satisfaction	4.2	3.6	+16.67%

satisfaction, etc., as well as feedback from the experimenters, such as operation time, operation difficulty, and operation satisfaction.

6.2 Assessment of Indicators

In order to evaluate the effectiveness of a big data-based HRM decision support system, we chose the following evaluation metrics: (1) Data analysis effectiveness: we used metrics such as accuracy rate, recall rate, and $F1$ value to measure the effectiveness of our system in data analysis, i.e., whether our system can accurately analyze employees' performance ratings, talent suitability, training needs, and compensation and benefit levels. (2) Decision support effectiveness: We used indicators such as decision correctness, decision efficiency, and decision satisfaction to measure the effectiveness of our system as a decision-making support, i.e., whether our system can provide correct decision suggestions, improve decision speed, and increase decision makers' satisfaction, etc. (3) Human Resource Management Effectiveness: We used indicators such as employee performance, employee turnover rate, employee satisfaction, etc. to measure the effectiveness of our system in human resource management, i.e., whether our system can improve employee efficiency, reduce employee turnover, and improve employee job satisfaction.

6.3 Experimental Results

We present the experimental results in four tables corresponding to the four aspects of HRM decision making, where each table lists the values of our system and the traditional approach for each assessment metric, as well as the percentage difference between the two. The experimental results are presented below.

From Table 1, we can see that in terms of accuracy, recall, and F1 value, our system improves 11.76%, 13.41%, and 13.25%, respectively, compared with the traditional method, which means that the system has higher precision and completeness in identifying and quantifying employee performance, and it helps the organization to more accurately evaluate the performance of employees. Decision correctness is improved by 15.00%, which indicates that performance decisions facilitated by the new system are more reliable and reduce unfair treatment due to assessment errors, which is conducive to improving employee motivation and sense of organizational fairness. In terms of decision-making efficiency, the system reduces the time required for decision-making from 20 minutes to 10 minutes, which is a 50.00% increase in efficiency, which translates to a significant amount of time and labor cost savings for large-scale and frequent performance evaluation companies. Satisfaction with decision-making and employee performance have both increased, by 28.57% and 10.53% respectively, reflecting the significant effect of the new performance appraisal system in improving decision-making quality and employee recognition. The employee turnover rate decreased by 50.00%, from 10% to 5%, suggesting that the new system may lead to greater employee satisfaction with the performance evaluation process and results, which in turn promotes employee stability and organizational cohesion.

As can be seen in Table 2 in terms of accuracy, recall and F1 value of talent selection, our system has increased by 20.00%, 25.71% and 13.25%, respectively, compared with the traditional method, which proves that the new system has a higher discriminative ability and predictive accuracy

Table 3 Experimental results of training needs analysis.

Assessment of indicators	Our System	Traditional methods	Difference (uplift/downlift)
Accuracy	0.85	0.70	+21.43% (uplift)
Recall rate	0.83	0.65	+27.69% (uplift)
F1 value	0.84	0.67	+25.37% (uplift)
Percentage of correct decisions	0.82	0.64	+28.13% (uplift)
Decision-making efficiency	20 mins	40 mins	−50.00% (uplift)
Decision-making satisfaction scores	4.3	3.3	+30.30% (uplift)
Training Effectiveness Score	4.1	3.5	+17.14% (uplift)
Training costs	$10,000	$15,000	−33.33% (decrease)
Training satisfaction ratings	4.2	3.4	+23.53% (uplift)

Table 4 Experimental results of compensation and benefits strategy development.

Assessment of indicators	Our System	Traditional methods	Relative increase/decrease (%)
Accuracy	0.88	0.73	+20.55%
Recall rate	0.86	0.68	+26.47%
F1 value	0.87	0.70	+24.29%
Percentage of correct decisions	0.84	0.66	+27.27%
Decision-making efficiency	25 mins	50 mins	−50.00% (uplift)
Decision-making satisfaction scores	4.4	3.2	+37.50% (uplift)
Rationalization of the remuneration structure	Reasonable	Unreasonable	Raise significantly
Competitiveness of remuneration	Your (honorific)	Lower (one's head)	Raise significantly
Salary Satisfaction Score	4.3	3.1	+38.71% (uplift)

in the talent selection process, which helps the enterprise to discover and attract excellent talents more effectively. Decision correctness increased by 26.47%, indicating that when selecting talent, the new decision support system can more accurately select candidates that meet the requirements of the position, reducing the cost of mis-selection and improving the recruitment quality. Similarly, decision-making efficiency increased by 50.00%, reducing the time for talent selection from 30 minutes to 15 minutes, which greatly improved the efficiency of the HR department. Decision-making satisfaction increased by 29.41%, indicating that the new system was strongly acknowledged by decision makers while enhancing the transparency and fairness of the selection process. The hiring rate has increased from 50% to 60%, which indicates that the system has optimized the selection process and is more likely to screen out suitable talents, and also reflects the optimization effect of the enterprise in terms of the allocation of human resources. The cost of hiring has been reduced by 37.50%, which means that with the new system, the enterprise has effectively reduced the cost of recruiting talents while maintaining or even improving the quality of talent selection. Hiring satisfaction has increased by 16.67%, which shows that the selection process under the new system helps to enhance the sense of identification and belonging of new employees to the enterprise, which is conducive to newcomers integrating into the team and realizing their potential more quickly.

Table 3 provides a detailed comparison of the performance of the big data-based HRM decision support system with the traditional approach on various key assessment metrics. The results show that the new system significantly improves on key decision effectiveness indicators such as accuracy, recall, F1 value, correct decision rate, and user satisfaction, with the accuracy rate increasing by 21.43% and the correct decision rate increasing by 28.13%. In addition, in terms of decision-making efficiency, the new system significantly shortens decision-making time and improves work efficiency by 50%. In terms of training effectiveness and satisfaction, the new system also scored higher than the traditional method, improving by 17.14% and 23.53% respectively. In terms of cost control, the training cost of the new system is 33.33% lower compared to the traditional method, showing a higher cost-effectiveness. Overall, the decision support system for human resource management based on big data outperforms the traditional method in several dimensions, realizing more efficient, accurate and satisfactory decision support and training results.

As can be seen from Table 4, for the four indicators of accuracy, recall, F1 value and decision correctness, the new decision support system shows significant improvement compared to the traditional method, showing better performance and precision. In terms of decision-making efficiency, the new system significantly reduces by half the decision-making time and improves work efficiency. In regard to decision-making satisfaction, the rating of satisfaction with the new system has risen significantly by 37.5%, indicating an obvious improvement in user experience. In terms of compensation structure, the new system has designed a more reasonable compensation system, which is a qualitative assessment indicator, showing that it has changed from unreasonable to reasonable, representing a significant improvement. In terms of compensation competitiveness, the new system makes the company's compensation more attractive and strengthens the company's competitive position in the labor market. Finally, on the salary satisfaction score, the new system has also achieved remarkable results, with an increase of 38.71%, indicating that employees are much more satisfied with the current salary system.

Table 5 Cross-industry employee performance assessment comparison (with optigrade and performmax systems).

Assessment Indicators	Smart Performance Assessment System	OptiGrade	PerformMax
Accuracy (Average)	0.95	0.88	0.92
Recall Rate (Average)	0.93	0.86	0.89
F1 Score (Average)	0.94	0.87	0.91
Percentage of Correct Decisions (Average)	0.92	0.85	0.88

Table 6 Comparison of talent acquisition efficiency across multiple industries (with hirewise and selectpro systems).

Assessment Indicators	Smart Talent Selection System	HireWise	SelectPro
Accuracy (Weighted Average)	0.90	0.86	0.87
Recall Rate (Weighted Average)	0.88	0.84	0.85
F1 Score (Weighted Average)	0.89	0.85	0.86
Correct Decision Percentage (Weighted Average)	0.86	0.82	0.83

Table 7 Comparison of talent selection efficiency in multiple industries.

Assessment Indicators	Smart Training Analysis System	Industry Standard	Leading Enterprise Level
Accuracy	0.85	0.78	0.83
Recall Rate	0.83	0.76	0.81
F1 Score	0.84	0.77	0.82
Correct Decision Percentage	0.82	0.75	0.80

Table 8 Comparison of talent development efficiency in multiple industries.

Assessment Indicators	Smart Training Analysis System	Industry Standard	Leading Enterprise Level
Accuracy	0.85	0.78	0.83
Recall Rate	0.83	0.76	0.81
F1 Score	0.84	0.77	0.82
Correct Decision Percentage	0.82	0.75	0.80
Training Impact on Performance Improvement	+15.2%	+8.5%	+12.3%
Employee Retention Rate Improvement	+10.1%	+5.2%	+7.8%

This assessment is based on comprehensive records of 10,000 employees over a two-year period from three major industries – technology, finance, and healthcare – including performance metrics, employee feedback, and work effectiveness analyses.

As shown in Table 5, the Smart Performance Assessment System demonstrates higher precision and comprehensiveness compared to industry mainstream systems OptiGrade and PerformMax. This advantage suggests that the intelligent system can more accurately gauge employee performance across industries, thereby providing businesses with a more reliable basis for HR management.

I collected a total of 50000 candidate profiles from the IT, finance, manufacturing, retail, and education industries, covering recruitment results, job fit assessments, and actual post employment performance evaluations.

The data presented in Table 6 reveals that the Smart Talent Selection System significantly outperforms HireWise and SelectPro in talent acquisition across multiple industries. This superior performance is evident not only in higher selection accuracy and efficiency, but also in the system's adept handling of different industry characteristics, further validating its advancement and broad applicability in HRM.

Dataset Description: Data was derived from 20 large enterprises within the service, manufacturing, and technology sectors, integrating 100,000 employee training records along with training feedback and subsequent work performance analyses, establishing a benchmark for training effectiveness within the industry.

As demonstrated in Table 7, the Smart Training Analysis System not only significantly surpasses the industry average in identifying employee training needs, but also outperforms the leading enterprises within the sector. This attests to the system's high precision in data analysis and prediction, and also signals its potential to drive HR management practices industry-wide to become more efficient and precise.

Table 8 allows a comparison of the efficiency of talent development across multiple industries. The table indicates that the intelligent training analysis system is superior to the industry standard and the leading enterprise level according to various evaluation indicators, especially the impact of training on performance improvement and the increased employee retention rate. The performance of the intelligent training analysis system is better than the industry standard and the

Table 9 Efficiency of talent acquisition of proposed system compared with other systems.

Assessment Indicators	Smart Talent Selection System	HireWise	SelectPro	EliteHire	ProTalent
Accuracy (Weighted Average)	0.90	0.86	0.87	0.85	0.88
Recall Rate (Weighted Average)	0.88	0.84	0.85	0.83	0.86
F1 Score (Weighted Average)	0.89	0.85	0.86	0.84	0.87
Correct Decision Percentage (Weighted Average)	0.86	0.82	0.83	0.81	0.85
Time-to-Hire Reduction (%)	−30.0%	−20.0%	−25.0%	−22.0%	−28.0%
Candidate Quality Rating	4.5	4.0	4.2	4.1	4.3

Table 10 Impact of smart talent management system on employee retention and engagement.

Assessment Indicators	Smart Talent Management System	Industry Average	Benchmark Leader
Retention Rate Improvement	+12.5%	+6.0%	+9.0%
Employee Engagement Score (out of 5)	4.7	4.2	4.5
Promotion Rate Increase	+8.2%	+4.5%	+6.0%
Employee Satisfaction Index	4.6	4.1	4.3
Time-to-Productivity Decrease (%)	−25.0%	−15.0%	−20.0%

leading enterprise level respectively, showing its advantages in cultivating talent.

Table 9 compares the performance of the proposed intelligent talent selection system with several other systems in terms of talent acquisition efficiency. It is evident from the table that the intelligent talent selection system outperforms other systems in regard to accuracy, recall rate, F1 score and correct decision-making percentage, and it also shortens the recruitment cycle and improves candidate quality score, indicating that the proposed intelligent talent selection system has obvious advantages in improving recruitment efficiency and quality of employees.

Table 10 illustrates the effectiveness of the Smart Talent Management System in terms of employee retention and management of engagement. The table compares the performance of the Smart Talent Management System with industry averages and benchmark leaders. The results show that the Smart Talent Management System improved the retention rate by 12.5%, compared to an industry average of 6.0% and a benchmark leader of 9.0%, indicating a clear advantage in retaining employees. For employee engagement scores, the Smart Talent Management System achieved a score of 4.7 (out of 5), surpassing the industry average of 4.2 and the benchmark leader of 4.5, demonstrating strong employee recognition of the system. In terms of promotion rate growth, the Smart Talent Management System achieved an increase of 8.2%, far exceeding the industry average of 4.5% and the benchmark leader of 6.0%, suggesting that the system promotes career development more effectively. On the employee satisfaction index, the Smart Talent Management System scored 4.6, higher than the industry average of 4.1 and the benchmark leader of 4.3, further proving the system's effectiveness in increasing employee satisfaction. Finally, regarding the reduction in the time to productivity, the Smart Talent Management System decreased this metric by 25.0%, outperforming the industry average of 15.0% and the benchmark leader of 20.0%, indicating that the system helps new employees to integrate into the workplace faster and contribute to productivity sooner. These data indicate that the Smart Talent Management System surpasses industry averages and benchmark leaders in improving employee retention, engagement, promotion opportunities, satisfaction, and accelerating the productivity of new employees, demonstrating its advanced nature and broad applicability in the field of talent management.

7. CONCLUSION

In this study, a decision support system for HRM is constructed based on big data, and through the in-depth analysis of the value of the application of big data technology in HRM, the challenges it faces, and the related research literature at home and abroad, it not only deepens the understanding of the innovative application of big data in HRM, but also creatively proposes an innovative big-data-based conceptual model for an HRM decision-support system. The model clearly defines the design objectives and functional requirements of the system, and provides an important theoretical foundation and practical reference for driving HRM into a new stage of scientization and intelligence.

The innovations and main contributions of this study are: first, a breakthrough system design concept is proposed, emphasizing the important role of big data in the human resource decision-making process, offering an innovative way to comprehensively improve the efficiency of HRM and the quality of decision-making. Second, a complete big data HRM decision support system architecture integrating multiple data sources, data processing technologies, advanced data analysis models and decision support tools is successfully constructed to ensure the system's seamless integration and in-depth support of all aspects of HRM, and to realize the panoramic coverage and accurate support of HRM decision-making. Finally, a high-tech company is selected as a practical application scenario, and the effectiveness and feasibility of the constructed system is fully verified through the specific implementation and application of the system, combined with experimental evaluation, thus providing strong empirical evidence for the wide application and promotion of the system.

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