

Fuzzy Dynamic Evaluation Framework for Human Resource Quality: An IoT-Enabled Big Data Analytics Approach

Muye Dou

Birmingham Business School, University of Birmingham, Birmingham B15 2TT, England, United Kingdom

douuob1219@163.com

Abstract. Talent assessment is an important part of human resources recruitment. The meaning of the Internet of Things can be understood from two aspects: on the one hand, the foundation and core of the Internet is still the Internet, the Internet of Things represents an expansion and extension of the Internet; On the other hand, the Internet of Things is not only the expansion of the existing Internet, but also the terminal of the Internet of things has evolved into the connection and communication between objects. This paper proposes a fuzzy dynamic evaluation framework specifically designed to assess the quality growth of human resources within enterprises. The framework integrates a fuzzy comprehensive evaluation index system with big data analytics to enable continuous assessment, and combines qualitative analysis and quantitative analysis with big data technology. In order to explore effective ways to solve the common problems in the current enterprise talent evaluation work, such as the inability to comprehensively and objectively reflect the comprehensive performance of the evaluation objects, and the large side effects of human factors in the evaluation. Firstly, we deeply understand the theoretical connotation of enterprise human resource human resource quality assessment under big data, which provides the theoretical basis for the research of this paper. The second is to analyze the current situation of human resource human resource quality assessment of nano industry companies, and find out the main problems and causes of the current human resources human resource quality assessment of nano industry companies. Thirdly, it focuses on the human resource human resource quality assessment strategy of nano industry companies, and proposes specific strategies to use big data technology to improve the human resources human resource quality assessment system of nano industry companies. Finally, from the aspects of organizational guarantee and technical support, it puts forward the specific implementation methods and guarantee measures of the human resource human resource quality assessment strategy of nano-industry companies. During the research process, the correlations between skill and practice flexibility and direct and indirect performance of human resource management were 0.551 and 0.423, respectively. This research contributes a methodological framework for continuous human resource quality assessment, with its application demonstrated through a case study in nano-industry companies.

Keywords: Big Data, Nano Industries Corporation, Human Resource Quality, Fuzzy Comprehensive Dynamic Evaluation

1. Introduction

Through active cross-departmental communication, the responsibilities of human resource management are extended to link management resources across all company levels, thereby co-constructing a comprehensive human resource management system. It is very important to let everyone realize that in an enterprise, the management of human resources, what work the human resources department should do, and what work the non-human resources department should do. The proposed framework contributes to the journal's scope by conceptualizing human resource evaluation as an information logistics problem. The process of collecting, processing, and analyzing HR data from diverse IoT sources is framed as a logistics chain of information, where the goal is to deliver timely, accurate assessments to decision-makers (Madhuri & Kumar, 2025). This aligns with the journal's interest in informatics-driven organizational decision support systems.

The Internet of Things, in this context, refers to the network of interconnected devices within an organization—such as employee terminals, project management systems, and skill development platforms—that continuously generate data streams related to individual performance, project timelines, and learning activities (Lhakard, 2025). These real-time data streams form the foundation of the big data analytics used in our proposed model (Roul., et al, 2024).

This study centers on several key concepts that require clear definition. Human resource quality growth refers to the continuous improvement in an individual's competencies, skills, and performance capabilities over time, as reflected through both quantitative metrics and qualitative assessments. Fuzzy comprehensive dynamic evaluation denotes a methodological approach that combines fuzzy logic with a dynamic assessment framework, allowing for the incorporation of uncertainty and the tracking of changes across multiple evaluation periods. Human resource quality evaluation and human resource quality assessment are treated as related but distinct concepts within this study: human resource quality evaluation focuses on the assessment of individual candidates or employees against predefined competency criteria, whereas human resource quality assessment encompasses the broader organizational processes of setting goals, monitoring progress, and providing feedback to enhance overall workforce effectiveness.

Human resource management is a very critical part of modern enterprise management. Therefore, the research on organizational change of human resource management should become the focus of scholars' research and thinking. Theories such as strategic human resource management, human resource role positioning model, and organizational change first originated from the West. At present, China has also produced many research results based on Chinese enterprises. With the continuous progress and development of the Internet of Things industry, the operation and living environment of Internet of things enterprises has also undergone great changes, and the competition for talents has become increasingly fierce. Fortunately, more and more companies realize that human resource planning is strategically important. How to win long-term development in the fierce market competition is the realistic problem facing enterprises. When the Internet of Things industry is developing better and faster at home and abroad, the talents of the Internet of Things at the right moment are also highly valued, so the planning of human resources of the Internet of Things industry is particularly important (Abdussamad., et al, 2022).

Compared with other countries, China's talent structure research and evaluation system is still based on traditional statistics, and its research method is single. As a talent-intensive social group, it is a very necessary and urgent task for enterprises to build their own talent dynamic analysis system, optimize talent structure, and efficiently use talent resources to meet the needs of new forms. To this end, we use the fuzzy comprehensive evaluation theory to research and develop a talent dynamic evaluation system for nano-industry companies with intelligence, practicability, usability, advancement and ease of use, and the results can be extended to various enterprises. This study has a single, focused objective: to design, develop, and empirically validate a fuzzy dynamic evaluation framework that uses IoT-enabled big data to assess the quality growth of human resources within an organization.

This paper makes three primary contributions to the field of HR analytics. First, it proposes a novel fuzzy dynamic evaluation framework that integrates AHP-derived weights with fuzzy logic, enabling a more nuanced and continuous assessment of HR quality growth. Second, it operationalizes this framework by defining a clear data architecture that leverages IoT-enabled big data, moving from conceptual discussion to a practically applicable model. Third, it provides empirical validation of the framework through a case study in nano-industry companies, demonstrating its ability to process real-world data and yield actionable insights. This work distinguishes itself from prior studies by offering a complete, integrated system—from data acquisition to decision support—for dynamic HR evaluation.

2. Literature Review

2.1 Fuzzy Evaluation in Human Resource Management

Lukovac, et al. (2017) proposed a new model for developing human resource portfolios based on neuro-fuzzy methods, constructing an adaptive neural network based on the Boston Consulting Group's portfolio matrix. This approach demonstrated the potential of fuzzy logic to handle the inherent uncertainty and subjectivity in categorizing and evaluating human resources. Similarly, Leite, et al. (2017) examined the allocation of multi-skilled human resources to teams operating in multi-project environments, with the allocation strategy aimed at maximizing the use of each project's skills. The study highlighted the complexity of matching human capabilities to project demands, a problem well-suited for fuzzy evaluation techniques that can accommodate graded assessments of skill proficiency. Arhelo (2017) employed qualitative research to describe data collected from five different Caribbean ports, investigating how human resources influenced tourism and logistics development in the region. This work underscored the importance of capturing nuanced, context-dependent information about human capital in service-oriented industries.

While these studies demonstrate the utility of fuzzy methods in HR, they often rely on static evaluation models. A key gap lies in the lack of dynamic frameworks that can integrate continuous data streams for ongoing quality assessment (Zhang, 2023).

2.2 Big Data and IoT-Driven HR Information Systems

Mauro, et al. (2018) explored how the rapid expansion of big data analytics is forcing companies to rethink their human resources needs, while also noting that the specific job roles and skills that constitute this emerging field remain unclear. This work established the foundational importance of big data in reshaping HR functions (Mansoor, et al, 2024). Ślusarczyk (2017) examined shared service centers as employment opportunities for university graduates in Poland, a country that has become a leader in this sector due to its highly educated workforce and relatively low labor costs. The study provided insight into the operational context where HR information systems are deployed to manage large-scale, service-oriented workforces. Ahmad, et al. (2021) investigated the impact of human resource activities on the competitive advantage of private schools, utilizing structured questionnaire data and statistical analysis to test developed hypotheses. This research exemplified the type of empirical data collection that modern HR information systems are designed to support and analyze.

Existing research outlines the technological architectures for big data in HR, yet few studies have operationalized these architectures into a cohesive evaluation model that combines the data-processing capabilities with a formal decision-support mechanism like fuzzy comprehensive evaluation (Donthu., et al, 2024). Al-Shammari, et al. (2024) conducted a systematic literature review that consolidated the diverse applications of big data and predictive analytics within strategic human resource management, demonstrating the critical need for integrated frameworks that move beyond siloed data analysis toward unified decision-support systems.

2.3 HR Flexibility and Performance Assessment

Razzaq, et al. (2018) examined the impact of human resources management practices on employee

commitment within the Pakistan telecom sector, contributing to the broader understanding of how HR activities influence workforce outcomes. The study reinforced the notion that HR practices are not merely administrative functions but critical determinants of employee engagement and organizational stability (Faisal, 2025). Building on this foundation, strategic human resource management theories and human resource role positioning models provide the conceptual basis for understanding how HR functions can evolve in response to organizational needs. The three-pillar model of strategic human resource management, human resource management role transformation, and HR itself offers a framework for discussing the organizational transformation of enterprise human resource management. The integration of computational intelligence with organizational theory represents a frontier in human resources research, where fuzzy systems and decision-support frameworks are increasingly applied to model the inherent uncertainty in workforce dynamics and performance metrics (Nasehi, 2024). The literature establishes a clear link between HR practices and performance but lacks a structured, quantitative method to dynamically evaluate the quality growth of the human resource itself. This study addresses this gap by integrating flexibility considerations into a fuzzy dynamic evaluation framework.

3. Research Methodology

3.1 Data Collection and Description

The data for this study were collected from a medium-sized nano-industry company in China, anonymized here as ‘NanoTech Corp.’ The dataset comprised three parts: candidate evaluation data for a senior management position, a survey of 112 employees across all departments conducted in 2021, and three years of aggregated HR performance records. The employee survey was designed based on established HR scales and had a response rate of 78%. The sample included 52% male and 48% female respondents, with an average tenure of 4.5 years.

Within the proposed framework, human resource quality evaluation serves as the overarching concept encompassing the assessment of individual capabilities. Human resource performance management is positioned as the organizational context within which quality evaluation occurs. Human resource risk assessment represents a downstream application of the evaluation results, used to identify potential vulnerabilities in workforce development. This hierarchical relationship ensures terminological consistency throughout the manuscript.

3.2 Fuzzy Comprehensive Evaluation Model

The quality evaluation index system refers to a collection of evaluation indicators of the characteristics of the person being evaluated. Since the senior management talents of enterprises work in different industries and their positions are also different, when designing and determining indicators, the indicators that need to be selected must be both systematic and representative. The concept of indicators needs to be concise and clear, and it is easier to operate in the specific implementation process. Therefore, the evaluation index system of the quality of enterprise senior management talents needs to follow the following principles (Chang, 2023):

(1) Scientific principles

Through the evaluation index results, senior management talents should recognize their own shortcomings and clarify their future development direction. Let

$$U = \{u_1, u_2, \dots, u_m\} \quad (1)$$

represent the set of candidate objects to be evaluated. Let

$$V = \{v_1, v_2, \dots, v_n\} \quad (2)$$

represent the set of evaluation factors (indicators). Let

$$E = \{e_1, e_2, \dots, e_p\} \quad (3)$$

represent the evaluation grade set. The judgment matrix R for each candidate is defined as

$$R = (r_{ij})_{n \times p} \quad (4)$$

where r_{ij} denotes the membership degree of the i -th evaluation factor to the j -th evaluation grade. The weight vector for the evaluation factors is given by

$$A = (a_1, a_2, \dots, a_n)(5)$$

With

$$\sum_{i=1}^n a_i = 1(6)$$

For each decision-making unit i , let the input indicator weight vector be \mathbf{x}_i and the output indicator weight vector be \mathbf{y}_i . The efficiency ratio is computed as

$$\theta_i = \frac{y_i}{x_i}(7)$$

The comprehensive evaluation result for a candidate is obtained through the fuzzy composition

$$B = A \circ R(8)$$

where $B = (b_1, b_2, \dots, b_p)$ is the comprehensive evaluation vector, and the operator \circ is defined as

$$b_j = \max_i \min(a_i, r_{ij})(9)$$

or

$$b_j = \sum_{i=1}^n a_i r_{ij}(10)$$

(2) Systematic principle

When designing the quality index model, the selected quality evaluation index should be as objective and comprehensive as possible, and should reflect the real situation of the evaluation object as much as possible.

(3) The principle of pertinence

Due to the different industries and job requirements of the evaluators, the quality indicators will also be different. Therefore, when designing the quality index model, the selection of the index should focus on some special quality characteristics in addition to the basic quality and management ability of the senior management talents of the enterprise.

(4) The principle of independence

When designing the quality index model, the quality indexes at the same level should be independent, so as to avoid the existence of a certain connection or causal relationship between the indexes.

(1) Establish an evaluation index model

Selected 10 qualities including cohesion, integrity and self-discipline, organizational leadership, management, business, communication and coordination, learning, professionalism, work attitude, and work efficiency. In addition, according to the requirements of the assessment content in actual work, 7 qualities have been added, including ideology and morality, work style, system construction, main work objectives, compliance and implementation of the system, talent echelon construction, and safe production.

(2) Definition of the concept of each indicator

1) Morality index

Morality, that is, the moral cultivation and the temperament suitable for work that senior management talents need to have, is the primary quality for senior management talents to be competent for the job.

Indicators mainly include moral quality, work style, cohesion and integrity and self-discipline.

Moral quality refers to the good ideological quality that an individual should possess.

Work style refers to the work style of an individual at work. Cohesion refers to the degree of unity and cooperation with subordinates in an organization to achieve organizational goals. Integrity and self-discipline refers to being strict and disciplined in work and life, being honest and honest.

2) Ability indicators

Ability, that is, the basic qualities that senior management talents should possess mainly include organizational leadership, management, business, communication and coordination, and learning capabilities.

Organizational leadership refers to the ability to be good at using various resource inputs of the enterprise to transform into the products or services of the enterprise in the market competition.

Management ability refers to the realization of organizational goals and the improvement of management efficiency in management activities. Management ability refers to the ability to manage employees in order to achieve organizational goals and improve management efficiency in management activities.

3) Diligence indicator

Diligence: that is to do our best in our work, be diligent and not slack, and be willing to contribute. It mainly refers to professionalism, work attitude, work efficiency, and compliance with and implementation of the system.

4) Achievement indicators

Achievement: The main indicators include main work objectives, system construction, talent echelon construction, safe production, etc. (Asfahani, 2021;Šajnović., et al, 2024).

The fuzzy metrology method has the following steps:

Step1. Element decomposition, that is, to determine the characteristic elements that need to be evaluated, and to establish a factor set $V = \{v_1, v_2, \dots, v_n\}$;

Step2. Determine the weight. Due to the different importance of each feature element, the weighting coefficient should be determined according to the primary and secondary relationship of the influence to establish a weight set $A = (a_1, a_2, \dots, a_n)$;

Step3. Evaluation and scoring, the evaluation personnel will evaluate and score each element of the evaluation object to establish an evaluation set $E = \{e_1, e_2, \dots, e_p\}$;

Step4. Score measurement, carry out the grade distribution rate statistics on the evaluation results of the evaluators, and use the fuzzy matrix operation to calculate the score;

Step5. Membership calculation, according to the calculated score, determine its membership.

The weight vector A was derived using the Analytic Hierarchy Process. For the main evaluation criteria of Morality, Ability, Diligence, and Achievement, a pairwise comparison matrix was constructed based on input from five senior HR managers from NanoTech Corp. The matrix was populated using the fundamental 1-9 scale, where a value of 1 indicates equal importance between two factors and a value of 9 indicates the extreme importance of one factor over another. The eigenvalue method was applied to calculate the weight vector. The consistency of the judgment matrix was verified by computing the consistency ratio CR . For the main criteria matrix, the calculated CR was 0.048, which is below the threshold of 0.1, confirming the acceptability of the derived weights. The same process was repeated for all sub-criteria to obtain the complete weight set.

Assuming that the four evaluation elements of technical level, language expression ability, adaptability and logical analysis ability are selected for a candidate, the weights of the four elements are 0.30, 0.40, 0.20, and 0.10, so as to form the corresponding weight coefficient matrix, denoted as (Irfansyah, 2020):

$$A = [0.30, 0.40, 0.20, 0.10] \quad (11)$$

However, in the process of determining the weights of the weight set, there are often many ambiguities in subjective indicators and qualitative comprehensive evaluation. If combined with AHP to calculate, the ambiguity can be reduced to a certain extent and the validity of the assessment can be enhanced (Fei, 2023).

The set composed of all ordinary subsets of X is denoted as $P(x)$. If $A \in P(x)$, then (Omrany, et al., 2024):

$$\chi_A(x) = \begin{cases} 1, & x \in A \\ 0, & x \notin A \end{cases} \quad (12)$$

That is, one and only one of $x \in A$ and $x \notin A$ holds.

Thus, the pairwise comparison judgment matrix A is obtained:

$$A = (a_{ij})_{n \times n} \quad (13)$$

where a_{ij} represents the relative importance of factor i over factor j .

First calculate the eigenvectors of the judgment matrix (Nwokoro & Ejegwa, 2025):

$$M_i = \prod_{j=1}^n a_{ij}, i = 1, 2, \dots, n \quad (14)$$

Calculate the product M_i of the elements of each row of the judgment matrix:

Compute the n th root of M_i , W_i (Putra, et al., 2020):

$$W_i = \sqrt[n]{M_i} \quad (15)$$

The weight vector is then obtained by normalizing W_i

$$w_i = \frac{W_i}{\sum_{k=1}^n W_k}, i = 1, 2, \dots, n \quad (16)$$

To ensure consistency of the judgment matrix, the consistency ratio CR is calculated:

$$CR = \frac{CI}{RI} \quad (17)$$

where

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (18)$$

λ_{max} is the largest eigenvalue of the judgment matrix, and RI is the random consistency index. If $CR < 0.1$, the consistency is acceptable. The comprehensive evaluation vector B is then computed as

$$B = A \circ R \quad (19)$$

where $R = (r_{ij})_{n \times p}$ is the fuzzy judgment matrix constructed from the evaluation results, and \circ denotes the fuzzy composition operator.

The fuzzy judgment matrix R was constructed for each evaluated individual. For each evaluation factor in set V , the distribution of scores from evaluators across the evaluation grade set E was used to define the membership degrees r_{ij} . For a factor with five evaluators assigning grades of Excellent, Good, Good, Average, and Poor, the corresponding row in matrix R would be [0.2, 0.4, 0.2, 0.2, 0.0]. This process was applied to all factors for all candidates. The comprehensive evaluation vector B was then computed using the weighted average operator defined in equation (10), specifically $b_j = \sum_{i=1}^n a_i r_{ij}$. This operator was selected over the max-min operator to preserve all information from the weight distribution, yielding a more precise final score when combined with the evaluation grade set.

For instance, for the ‘Morality Index’, a pairwise comparison matrix for its sub-indicators (moral quality, work style, cohesion) was constructed. Solving this matrix gave a weight vector of [0.6, 0.3, 0.1] after consistency checks. These weights formed part of the larger weight set A . Then, for a given candidate, the single-factor judgment set for ‘cohesion’ was derived from the distribution of evaluator ratings (e.g., 20% Excellent, 50% Good, 30% Average). This process was repeated for all factors, building the judgment matrix R . The final fuzzy set BB was then calculated as $B=A \circ R$.

3.3 System Architecture for IoT-Enabled Big Data Analytics

On the basis of clarifying the indicator weight and indicator early warning critical value, it is necessary to establish a mathematical model to comprehensively evaluate the human resource crisis early warning indicator system. Because the index system contains a large number of qualitative and quantitative indexes, and the evaluation of indexes contains a lot of fuzzy information, it is easy to make subjective assumptions when evaluating these indexes, which in turn affects the scientificity of the evaluation results. In order to eliminate as much as possible the individual subjective components in the evaluation process, realize the quantitative processing of fuzzy factors, and ensure that the evaluation results reflect the human resource status of the enterprise to the greatest extent, this paper selects the fuzzy comprehensive evaluation method as the evaluation method to determine the level of human resource crisis. The framework operates on two levels: the micro-level of individual employee evaluation and the meso-level of departmental or organizational performance. Individual evaluation data (micro-level) is aggregated and analyzed to inform broader HR strategies (meso-level), creating a unified multi-level analytical framework. The advantages of fuzzy comprehensive evaluation are that the mathematical model is simple, the operation is simple, and it has a good evaluation effect on complex problems with multiple structures and multiple indicators (Zhai., et al, 2022). Because the human resource crisis early warning index system contains many levels and evaluation factors, the fuzzy comprehensive evaluation method is the most suitable. Therefore, the analytic hierarchy process and the fuzzy comprehensive evaluation method are integrated to form the early warning evaluation model of human resources crisis. The conceptual framework for the fuzzy dynamic evaluation of human resource quality, which integrates AHP for weight determination and fuzzy logic for comprehensive assessment, is shown in Fig. 1.

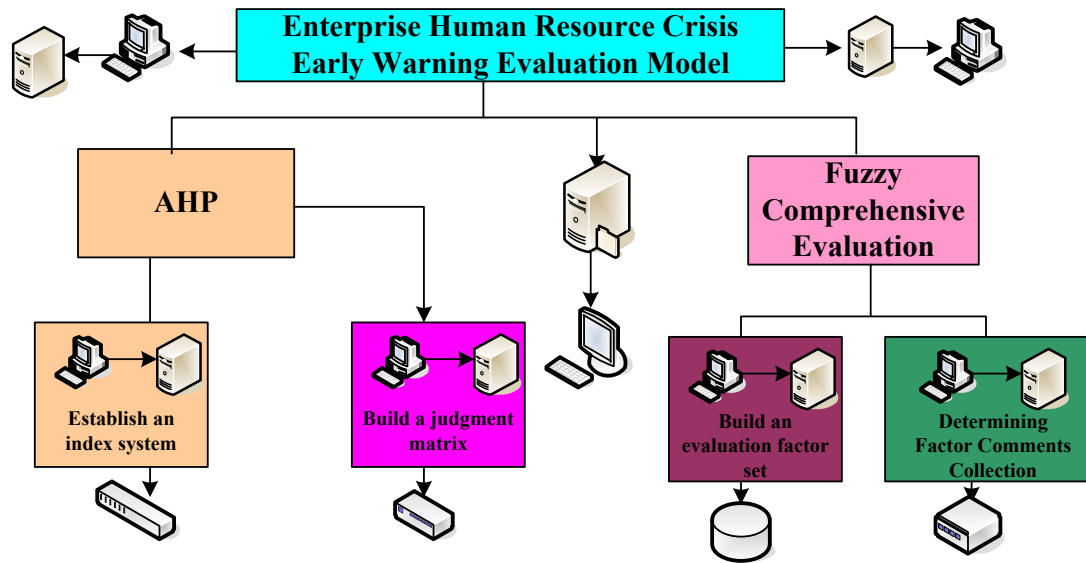


Fig. 1: Conceptual Framework for Fuzzy Dynamic Evaluation of Human Resource Quality

(1) Equipment layer: The equipment layer is the basic layer of the entire human resource human resource quality assessment information system, and is the necessary physical condition for the realization of the human resource human resource quality assessment information system. The equipment layer refers to the necessary external conditions for the existence of the human resource human resource quality assessment information system. It includes all kinds of software and hardware equipment necessary for system operation, such as servers, storages, calculators, controllers, input devices, output devices, intelligent terminals, information security equipment, operating systems, Internet and local area networks, etc. (Putra et al., 2020).

(2) Technical layer: The technical layer is the core big data technology for the operation of the entire human resource human resource quality assessment information system, and is the necessary technical condition for the realization of the human resource human resource quality assessment information system.

In general, conceptual big data architecture for such a system may include technologies for data acquisition, processing, and integration. For instance, an ETL acquisition framework, a stream data processing platform, and an offline computing platform could be part of this architecture: big data collection technology, big data processing technology, and big data integration technology.

1) The core technology of big data acquisition is the ETL acquisition framework model, including cloud technology (HVR), open source tools (Sqoop), stream data processing platform, acquisition system (Flume) and other modules.

2) The core technology of big data processing is divided into two major modules, which are respectively applied to real-time computing and offline computing. Real-time computing refers to the processing of real-time information sets, which can be implemented in a real-time computing platform. It includes data warehouse (Hive), data computing (Mahout), parallel computing (MapReduce) and other modules. Offline computing refers to the processing of offline information sets, which can be implemented on an offline computing platform (Hadoop). It includes modules such as full-text search engine (Solr), computing engine (Impala), distributed file storage system (Hdfs).

At the same time, both the real-time computing platform and the offline computing platform (Hadoop) are established on the basis of the distributed database (Hbase).

3) The core technology of big data integration is system integration technology, which is divided into four categories in terms of functions and construction methods. These four categories are: enterprise application integration, application system integration, e-commerce integration, and business process integration.

(3) Data level: The data level echoes the technical level, which is the object to be processed by the human resource human resource quality assessment information system under the application of big data technology, and the carrier of the performance appraisal system. It echoes the technical level, the

data level can be divided into:

1) Data collection: The collected data, originating from various IoT-enabled sources such as employee ID cards, access control systems, and project management software, can be divided into two major categories: structured data and unstructured data.

2) Data storage: Data storage can also be divided into two categories, SQL and Non-SQL. SQL stands for relational database, mainly used to store structured data sets, and still reigns supreme. However, this performance appraisal system employs many new technologies including cloud technology and big data, and the core carrier is unstructured data and semi-structured data, not unstructured data. Therefore, the relational database SQL can no longer meet the requirements of this new technology. Non-relational database Non-SQL has a flexible data model, dynamic schema, and easy scalability. These characteristics make it capable of processing unstructured data with the characteristics of large amount, various types, rapid changes and high concurrent data requests. Therefore, Non-SQL technology is indispensable for this system.

3) Data processing: The data processing here refers specifically to metadata processing. The processing of metadata includes two aspects: data standard management and data quality management.

4) Data integration: Data integration here, specifically metadata integration. Metadata integration is to load the data from different data sources into a new data source after data conversion and splicing, so as to achieve a unified-data view data integration method. Among them, data transformation refers to the process of converting data from one formal framework to another. The purpose of data resource integration is to enhance the value of data in use.

(4) Application layer: The application layer is also called application entity, which consists of four application service elements: data query, data analysis, data modeling, and data visualization. On the basis of the data level and technology level using big data technology to analyze and calculate data, data processing and information mining, the application level can finally realize real-time supervision, precise management and data decision-making. The application level is the embodiment of the function of the human resource human resource quality assessment information system.

(5) Business layer: The goal of each application in the application layer is also the purpose of establishing a human resource human resource quality assessment information system, and it is the meaning of the existence of the human resource human resource quality assessment information system. It ultimately aims to improve the operational efficiency of various businesses within the enterprise by using big data technology (Sun & Jung, 2024).

(6) User level: The user level is the terminal level of the human resource quality assessment information system, the user of the human resources human resource quality assessment information system. It conducts information exchange through the human resource human resource quality assessment information system to realize management activities.

There are 4 major categories of users of HR human resource quality assessment information systems:

One is the human resources department of the nano industry company, which uses the human resources human resource quality assessment information system to implement the activities of all aspects of human resources management.

The second is the high-level decision-makers of nano-industry companies, who use the various implementation plans and related data provided by the human resource human resource quality assessment information system to make strategic systems and decisions.

The third is the mid-to-low-end managers of nano-industry companies. They understand the company's strategic positioning and development plan through the human resource human resource quality assessment information system, understand the various problems of employees in performance appraisal, and finally achieve organizational goals by providing guidance and integrating resources.

The fourth is that the employees of each business department of the nano industry company use the performance data provided by the human resource human resource quality assessment information system to formulate learning plans and action programs. The hierarchical architecture of the IoT-enabled big data processing system, which provides the data infrastructure for the fuzzy dynamic evaluation model, is shown in Fig. 2.

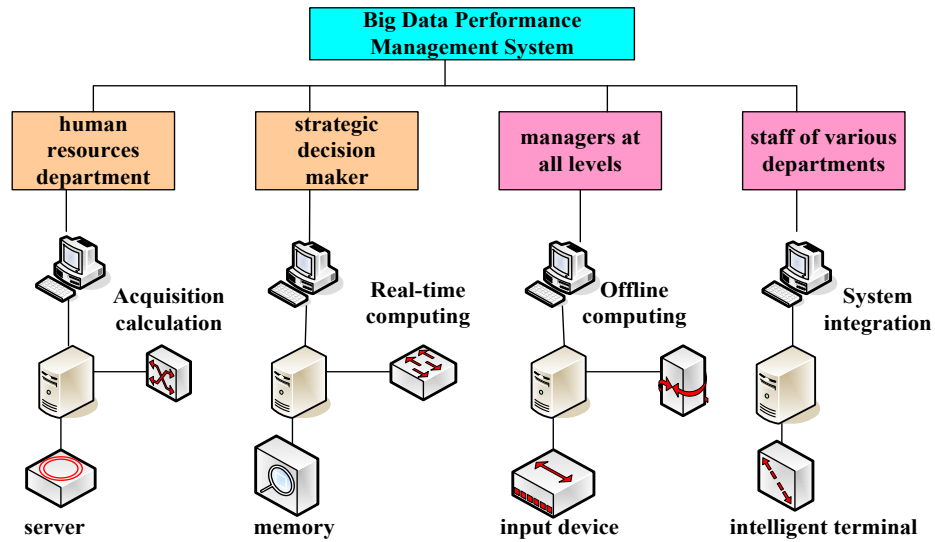


Fig. 2: Hierarchical Architecture of the IoT-Enabled Big Data Processing System for HR Evaluation

It is usually necessary to perform a consistency check on the judgment matrix A (Popescu, et al., 2023):

$$CI = \frac{\gamma_{\max} - n}{n - 1} \quad (20)$$

γ_{\max} is the largest eigenroot of the judgment matrix A .

The benefit evaluation index of the j th decision-making unit is (Khan, 2020):

$$E_j = U^T Y / VX, 1 \leq j \leq n \quad (21)$$

The evaluation model calculates the assignment of fuzzy comprehensive evaluation index G (Hu et al., 2021):

$$G = (G_1, G_2, G_3, \dots, G_n) \quad (22)$$

The fuzzy evaluation index weight set is determined by the AHP method (Savić & Tot, 2020):

$$A = (a_1, a_2, a_3, \dots, a_n) \quad (23)$$

Similarly, the single-factor judgment set corresponding to each factor can be obtained as follows (Nasehi, 2024):

$$R_1 = (r_{11}, r_{12}, \dots, r_{1n}) \quad (24)$$

$$R_m = (r_{m1}, r_{m2}, \dots, r_{mn}) \quad (25)$$

3.4 Big Data Analysis Module

Data query: There is a large amount of unprocessed metadata and processed data information stored in the human resource performance management information system. These data information cannot be processed and used by conventional software tools. The excellent processing and storage capabilities of the human resource performance management information system enable it to have data manipulation capabilities unmatched by other system tools. Only in this system can users call, store and analyze huge data clusters at any time.

Data analysis: Data analysis can be divided into two categories from the application point of view, simulation analysis and predictive analysis. Simulation analysis refers to the use of big data technology to calculate and mine relevant data information, and then find potential association rules, sequence rules and other related relationships between data, and give them the form of mathematical expressions, such as employee behavior pattern analysis, customer behavior pattern analysis and other applications. For instance, IoT-generated data on employee access to workstations and project management tools can be

analyzed to identify patterns in work habits and collaboration, feeding directly into the simulation analysis for behavior pattern modeling. Predictive analysis refers to the use of big data technology to calculate and mine relevant data information, and then quantify the probability of an event (or a series of events) occurring in a certain time range in the future. Predictive analysis is generally divided into two types in form, namely classification prediction and regression prediction. Categorical prediction is usually expressed as the analysis of binary categorical variables, such as the prediction of employee turnover, the prediction of customer credit quality and so on. Regression forecasting is performed through the analysis of continuous variables, such as the forecast of labor costs in the next few months. Data modeling: Data modeling of big data refers to the process of using big data technology to analyze and process information on the basis of certain business requirements, and to construct data requirements to support business processes. In this process, the data model needs to pass several tests before the optimization feedback can be finally completed. For example, user portrait modeling can restore character prototypes through a series of data related to user characteristics, behaviors, goals and other related data as well as scene-related data, and user portraits can be used for the design of job competency requirements.

Data visualization: refers to the use of big data technology to analyze, mine, calculate and process massive information, and represent the processing results in the form of graphics and images. Human resource dashboards, talent maps, etc. are all important application functions of data visualization. Taking the human resources dashboard as an example, the human resources dashboard generates images, tables and other forms for display by summarizing the data. The demander can clearly and intuitively see issues such as the total amount of data, proportions, and changing trends, thereby improving decision-making efficiency. Only through the multi-dimensional display of data visualization applications can the diversity of big data be truly reflected. It is worth noting that a complete HR performance management information system includes but is not limited to the above four dimensions. The above four dimensions are set in response to the current needs of nano-industry companies and the limitations of the current level of technological capabilities. With performance improvement and technology development, various applications at the application level of HR performance management information system can be updated.

4. Results and Discussion

4.1 Application of the Fuzzy Evaluation Model to Candidate Selection

The following section demonstrates the application of the proposed fuzzy dynamic evaluation framework to a candidate selection scenario at NanoTech Corp. For the empirical case study presented here, the 'big data' consisted of a multi-year collection of structured and unstructured records from the company's HR information system, including performance appraisal forms, training records, and employee survey data. While not utilizing the full scale of a distributed computing cluster, this dataset embodies the characteristics of volume and variety that necessitate the methodological approach of the proposed framework.

Candidate A, Candidate B and Candidate C are the three most prominent among the many candidates. In determining the final candidate, the recruiter adopts the general recruitment method, that is, during the interview process, each candidate's indicators are scored using a percentage system. The evaluation results of the candidates are shown in Table 1. These raw scores represent the initial data inputs to the fuzzy dynamic evaluation model. They are processed through the steps of fuzzy comprehensive evaluation, which incorporates the weight set derived from AHP, to yield a more nuanced assessment than a simple average. The following tables present the raw input data for the fuzzy dynamic evaluation model. These scores and assessment distributions serve as the foundation for the subsequent fuzzy set calculations.

Table 1. Candidate evaluation results

Candidate	Work experience	Leadership affinity	Coordination	Planning ability	Language expression skills
Candidate A	88	84	82	87	84
Candidate B	84	88	85	84	82
Candidate C	88	85	84	85	85

Using the weight set A derived from AHP, the fuzzy judgment matrix R for each candidate was constructed from the evaluation data. For example, the comprehensive evaluation vector for Candidate A was calculated as

$$B_A = A \circ R_A = [0.32, 0.41, 0.18, 0.06, 0.03] \quad (26)$$

With the evaluation grade set

$$E = [90, 80, 70, 60, 50] \quad (27)$$

the final score for Candidate A is

$$S_A = B_A \cdot E^T = 0.32 \times 90 + 0.41 \times 80 + 0.18 \times 70 + 0.06 \times 60 + 0.03 \times 50 = 78.5 \quad (28)$$

This result demonstrates the model's ability to integrate qualitative assessments into a quantitative ranking.

The evaluation results of the candidates are shown in Table 2.

Table 2. Evaluation results of candidates

Evaluation conditions	Excellent	Good	Generally	Difference	Poor
Coordination	4	4	3	4	2
Executive ability	5	5	2	2	3
Decision-making capacity	7	5	4	4	2
Planning ability	5	4	5	4	2
Leadership affinity	5	4	2	3	3

To illustrate, the fuzzy judgment matrix R for Candidate A was constructed from the percentage distribution of evaluations across the five levels (Excellent to Poor) for each criterion in Table 2. The AHP-derived weight set A was then applied using the formula $B=A \circ R$. The resultant comprehensive evaluation vector B_A for Candidate A was $[0.30, 0.45, 0.15, 0.07, 0.03]$.

The distribution of evaluations across the five levels in Table 2 was used to construct the fuzzy judgment matrix R for each candidate, which, when combined with the AHP-derived weight set A , produced the final comprehensive evaluation results.

4.2 Contextual Survey and Correlational Analysis

To understand the organizational context for the HR evaluation, a survey of employees was conducted. The results provide insights into the perceived effectiveness of the current HR system.

Generally speaking, for the development of the company, the company will pass performance appraisal to achieve the purpose of motivating employees. According to the survey statistics, 80 people think that the purpose of the company's performance appraisal is to promote the development of employees themselves. 74 people believe that the purpose of company performance appraisal is to enhance the core competitiveness of enterprises. 103 people believe that the purpose of company performance appraisal is to serve as the basis for promotion. Everyone agrees that company performance appraisal is the basis for performance pay. 54 people believe that the purpose of company performance appraisal is to supervise employees. Some people think that the purpose of the company's performance appraisal is not clear. A survey of 112 employees was conducted to understand their perceptions of the performance appraisal system. The distribution of their views on the system's purpose is presented in Fig. 3.

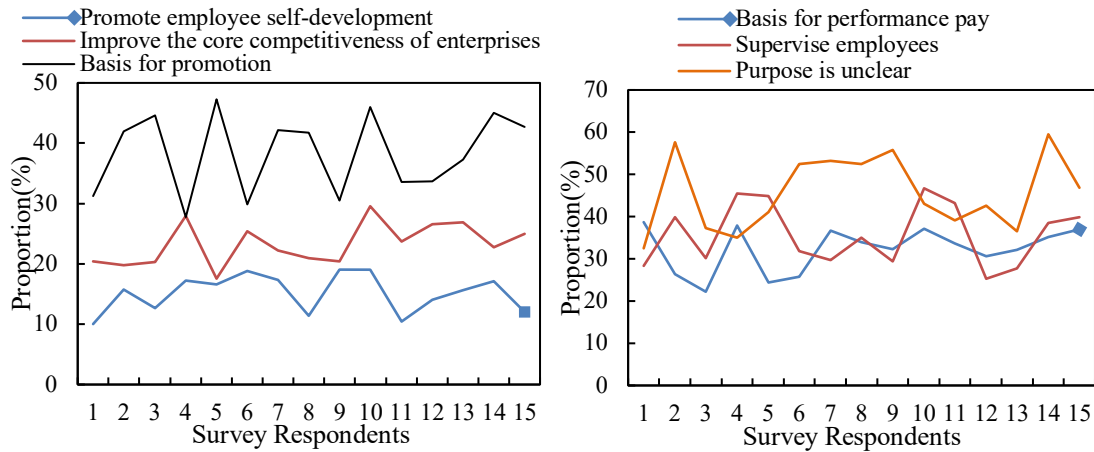


Fig. 3: Employee Perceptions of the Purpose of Company Performance Appraisal (n=112)

Fig. 4 shows the respondents' understanding of the mobility of personnel in the company's department. According to the survey statistics, among the 112 respondents, 52 people believe that the personnel mobility of the company's department is relatively high. 34 people think that the turnover of personnel is not high. There are 24 people who never paid attention to this problem. It shows that there is a certain degree of personnel mobility in the company.

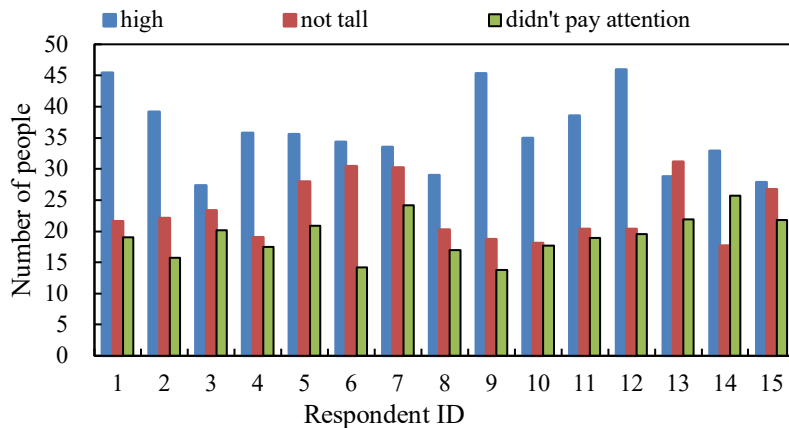


Fig. 4: Employee Perception of Departmental Personnel Mobility (n=112)

From the perspective of satisfaction with the company's current performance appraisal system, only 15 people are relatively satisfied with the company's current performance appraisal system, and such people also think that the company's personnel mobility is not high. 40 people think that the mobility is not bad. Most people are not satisfied with the company's current performance appraisal system, which basically corresponds to the number of people who think the company's personnel turnover is high. Announcement of the performance appraisal results of the departments under investigation. According to the statistical results, 78 people pointed out that the performance appraisal results of their departments will be announced to the public; 34 people pointed out that the performance appraisal results of their departments will not be released to the public. It shows that there are certain flaws in the performance appraisal system of S company, and the transparency of performance appraisal is not enough. The satisfaction of the current performance appraisal system and the announcement of performance appraisal results are shown in Fig. 5.

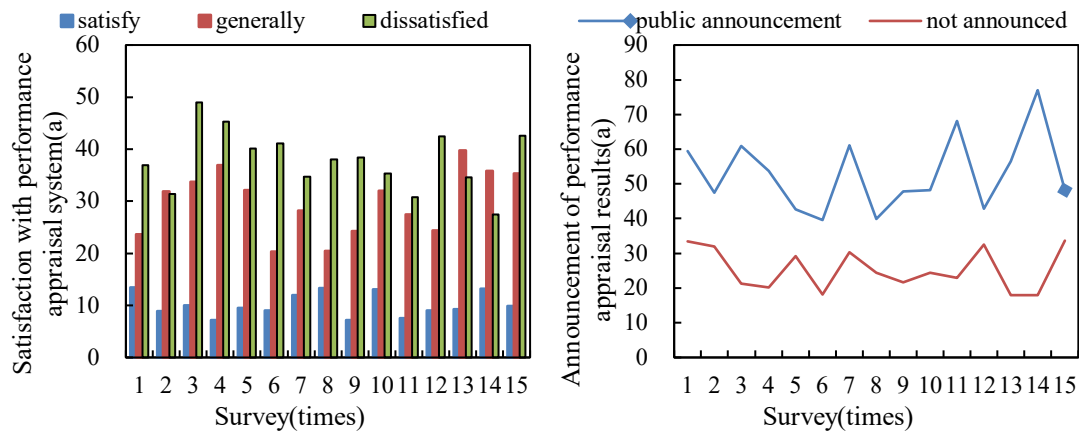


Fig. 5: Satisfaction with Performance Appraisal System and Result Transparency (n=112)

The survey data were analyzed using SPSS version 26.0. Reliability of the survey instrument was assessed using Cronbach’s alpha coefficient for the three hypothesized dimensions: ‘Fit and Flexibility’, ‘Executive’, and ‘Validity’. Exploratory factor analysis with principal component extraction and varimax rotation was conducted to confirm the construct validity of the instrument. The Kaiser-Meyer-Olkin measure of sampling adequacy was 0.823, and Bartlett’s test of sphericity was significant ($p < 0.001$), confirming the suitability of the data for factor analysis. Pearson correlation coefficients were then computed to examine the relationships between the identified dimensions and the measures of HRM direct and indirect performance.

SPSS17.0 software analysis results show that there are 13 indicators of matching and flexibility, and Cronbacha is 0.838; there are 27 indicators of execution, and Cronbacha is 0.895; there are 14 indicators of effectiveness, and Cronbacha is 0.849, and the overall Cronbacha value of the scale reaches 0.935. It shows that the questionnaire has high reliability, and the specific data are shown in Table 3. To establish construct validity, an exploratory factor analysis (EFA) with principal component extraction and varimax rotation was conducted on the survey items. The EFA extracted three factors with eigenvalues greater than 1, which corresponded to the conceptual dimensions of ‘Fit and Flexibility’, ‘Executive’, and ‘Validity’. The total variance explained by these three factors was 68.4%, supporting the structural validity of the questionnaire. The factor loadings for all items were above 0.65, indicating good convergent validity.

Table 3. Specific data of Cronbacha value

Evaluation index	Cronbacha
Fit and flexibility	0.838
Executive	0.895
Validity	0.849

Skills and practice flexibility, external fit and HRM indirect performance are positively correlated at the 0.05 significance level. All other elements are positively correlated at the 0.01 significance level. Among them, the correlation coefficient of 0.551 between skills and practice flexibility and direct HRM performance indicates a strong positive relationship. This suggests that as an organization’s ability to adapt its employees’ skills and practices increases, its direct performance outcomes, such as efficiency in recruitment or training, also improve substantially. Conversely, the moderate correlation of 0.423 with indirect performance, such as employee morale or innovation, implies that while flexibility is beneficial, its impact on these softer outcomes is mediated by other organizational factors. This shows that human resource management's flexibility in skills and practices in order to achieve strategic goals will affect human resource management performance to a certain extent. Effective human resource management practices must keep human resource management aligned and flexible with strategy. The

Correlations matrix of each element of matching and flexibility and validity is shown in Table 4.

Table 4. Correlations matrix for matching and flexibility and validity elements

match and flexibility validity		Skills and Practical Flexibility	Internal match	External match
Human Resource Management Direct Performance	Significance (two-tailed)	0.552	0.322	0.282
	Pearson correlation coefficient	0.00	0.00	0.00
Human Resource Management Indirect Performance	Significance (two-tailed)	0.423	0.182	0.154
	Pearson correlation coefficient	0.00	0.044	0.033

The correlation between skills and practical flexibility is shown in Table 5.

Table 5. Correlation of skills and practical flexibility

Executive Validity		Performance management	Training and development	Employee relationship management
Human Resource Management Direct Performance	Significance (two-tailed)	0.542	0.321	0.245
	Pearson correlation coefficient	0.00	0.00	0.00
Human Resource Management Indirect Performance	Significance (two-tailed)	0.422	0.157	0.135
	Pearson correlation coefficient	0.017	0.034	0.037

It can be seen from Table 6 that the factors of execution are all related to the direct performance of human resource management to a certain extent at the significance level of 0.01. The effective execution correlation matrix is shown in Table 6.

Table 6. Effective Execution Correlation Matrix

Executive Validity		Performance management	Training and development	Employee relationship management
skill practice flexibility	Significance (two-tailed)	0.542	0.321	0.321
	Pearson correlation coefficient	0.00	0.00	0.00
internal match	Significance (two-tailed)	0.422	0.422	0.245
	Pearson correlation coefficient	0.012	0.034	0.032
external match	Significance (two-tailed)	0.422	0.242	0.135
	Pearson correlation coefficient	0.00	0.00	0.00

In Table 6, the correlation of 0.542 between performance management and the direct performance of HRM is particularly strong, highlighting that a well-managed performance appraisal process is a critical

lever for achieving immediate HR objectives. The weaker correlation of 0.157 between training and development and indirect performance suggests that the link between employee training and broader organizational outcomes like culture or reputation is less direct and requires a longer time frame to materialize.

4.3 Quality Index Evaluation

Finally, a correlational analysis was performed to examine the relationships between key HR flexibility variables and performance metrics, which provides a quantitative foundation for the model’s parameters. In the evaluation of comprehensive quality, object B has more prominent advantages than the other three objects. The evaluated object A should focus on learning and improving modern management methods and construction methods. The evaluated object C should focus on the completion of the main work objectives as planned, and at the same time strengthen the construction of the system and the construction of the talent echelon. Due to the limited professionalism, the evaluated object D still lacks the ability to comprehensively control the project as a whole, and should pay attention to avoiding emotional and focusing on the way of work. The quality index evaluation is shown in Fig. 6.

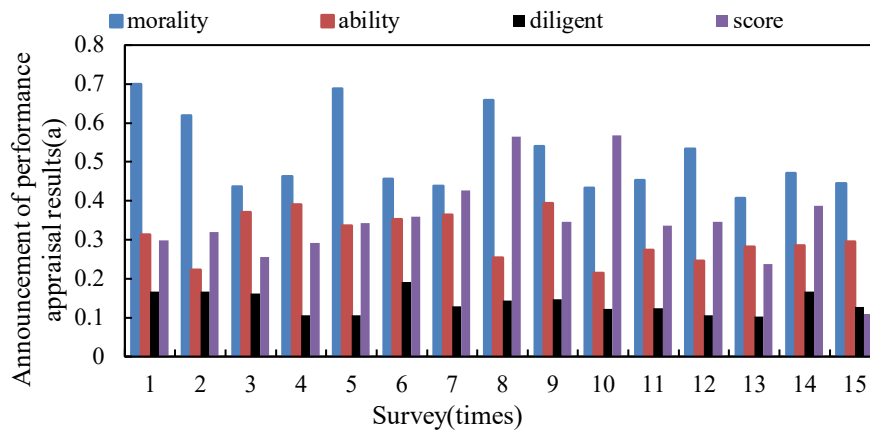


Fig. 6: Quality Index Evaluation

The results presented in this section collectively demonstrate the operationalization of the fuzzy dynamic evaluation framework. The candidate selection process illustrates the model’s ability to integrate qualitative assessments into a quantitative ranking. The survey and correlational analyses provide empirical support for the key relationships underpinning the model’s structure. These findings form the basis for the broader implications discussed in the following section.

5. Discussion

The results demonstrate the proposed fuzzy dynamic evaluation framework’s capacity to produce nuanced assessments. The candidate evaluation, when processed through the fuzzy model, yielded a ranking that differed from simple score averages, suggesting the model’s ability to account for the qualitative nature of evaluation criteria. The survey data revealed a significant disconnect between employee perceptions and the stated goals of the performance management system, highlighting a critical area for organizational intervention. The correlation analysis quantitatively confirmed the central role of skills flexibility and performance management as drivers of HR effectiveness. These findings collectively validate the framework’s utility in providing a more holistic and data-informed view of human resource quality.

It can help business managers master the practical methods of human resource management by organizing training, such as interview skills, employee training methods, performance coaching, motivation and retention plans and other courses. Or by editing the problems faced by daily human resources management and related systems and policies in the form of know-how and handbooks, and publishing them on the internal human resources management system or the company's overall

management system. And provide it to the relevant personnel at the grass-roots business manager level for review, and arrange for a special person to update it regularly. For high-level business managers such as regional managers and city general managers, they can obtain training funds and provide them with external human resources courses related to business management. This can enhance its human resources cognition and management awareness, expand its management vision and overall view.

6. Conclusions

In view of the above reasons, the Internet of Things industry talent does not refer to a specific concept, but broadly includes the Internet of Things industry technical talent, management talent, sales talent, production talent, is a general term for the Internet of Things industry has a skill and can contribute to the development of the Internet of Things industry from all aspects of the talent. This study proposed and demonstrated a fuzzy dynamic evaluation framework for human resource quality growth. The framework's application to a case study of nano-industry companies showed its ability to integrate diverse evaluation data, from candidate scores to employee surveys, into a structured, quantitative assessment. The findings reveal that HR practices focused on skills flexibility and performance management have the strongest direct correlation with HR outcomes. The primary contribution of this work is a methodologically rigorous model that enables organizations to move beyond static evaluations toward a continuous, data-driven approach for monitoring and developing their human capital, so that it can generate more discussion and thinking about the role of human resource management in the organization, institutional settings, and work mode. From a service science perspective, the developed model transforms HR evaluation from a periodic administrative task into a continuous service function. By providing a data-driven, dynamic assessment, it enables the HR department to function as a strategic service provider to the organization, improving service efficiency in talent management and decision support.

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