A Study on the Transformative Effects of Artificial Intelligence Technology on Human Resource Management Models

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Abstract: *The penetration of artificial intelligence technology into the field of human resource management is gradually reshaping the operational logic of traditional management models. Following the progressive logic of "deconstruction-transition-evolution," this study systematically deduces the transformative path of artificial intelligence technology on human resource management models. First, at the level of deconstruction, the study analyzes the substitution boundaries of algorithmic decision-making, the trend toward disaggregation in job analysis, and the mechanism of performance weight redistribution. Second, at the level of transition, the study elucidates the morphological reconstruction of management models from linear processes to dynamic networks, the migration path of managerial authority in human-machine collaboration, and the logic of setting elastic thresholds under real-time data stream feedback. Finally, at the level of evolution, the study deduces the nonlinear improvement in matching accuracy in automated recruitment, the knowledge emergence effect triggered by intelligent recommendation systems, and the correction mechanism of turnover prediction models on human capital retention curves. Overall, through theoretical deduction, this study reveals that artificial intelligence technology does not simply replace the existing functions of human resource management; instead, it reshapes the endogenous logic of management models through the three-tier progressive path of deconstruction, transition, and evolution. This research aims to provide actionable theoretical propositions and an analytical framework for subsequent empirical testing.*

Keywords: *Artificial Intelligence Technology; Human Resource Management; Deconstruction Logic; Morphological Transition; Efficiency Evolution*

Introduction

The human resource management model has long faced the constraints of response delays and rigid rules in the process of digitalization. Traditional methods, which rely on fixed job descriptions, periodic assessments, and linear process designs, struggle to adapt to the rapid changes in the internal task structure of organizations. The introduction of artificial intelligence technology provides new possibilities for overcoming this dilemma. From algorithmic decision-making to data-driven analysis, and from human-machine collaboration to real-time feedback regulation, intelligent systems demonstrate regulatory capabilities in multiple management links that differ from traditional tools. Exploring the transformative effects of artificial intelligence technology on human resource management models not only helps clarify the boundary between technological substitution and human judgment but also provides a theoretical reference for organizations to design more flexible management frameworks. This study focuses on three levels, namely "algorithmic substitution boundary-morphological transition of models-efficiency evolution," and demonstrates the logical relationship of progressive layering and sequential driving among them: technology first deconstructs existing management modules, deconstruction leads to morphological transition, and transition ultimately brings about the nonlinear evolution of efficiency. Through a systematic analysis of this progressive process, this study addresses the deficiencies of existing theories in explaining dynamic management scenarios.

1. Deconstruction Logic of Artificial Intelligence Technology on Human Resource Management Models

1.1 Substitution Boundaries of Algorithmic Decision-Making in Human Resource Management Modules

Not all decision-making links in the field of human resource management are suitable for completion by algorithms. The delineation of substitution boundaries depends on the degree of rule-based formalization of the task itself and the clarity of the feedback loop. For example, in highly structured modules such as initial resume screening, abnormal attendance identification, and standardized test scoring, the mapping relationship between inputs and outputs is relatively fixed. Algorithms can train high-precision classification or regression models using historical data, thereby achieving decision-making substitution. In contrast, in unstructured scenarios such as employee emotional counseling, value judgment, and complex negotiations, machines struggle to capture subtle contextual cues and tacit knowledge, and thus the substitution boundary often stops at the level of auxiliary suggestions. In other words, for tasks where "the basis of judgment can be clearly articulated," algorithms are more likely to take over; for tasks that rely on "intuition and experience," current technology cannot yet achieve direct substitution[1].

Furthermore, the dynamic adjustment of substitution boundaries is also constrained by both technological maturity and organizational acceptance. On the one hand, although deep learning provides accurate predictions in a black-box state, its lack of interpretability makes it difficult to fully entrust high-stakes decisions such as recruitment, hiring, and promotion nominations to algorithms. On the other hand, the managed subjects (i.e., employees) perception of fairness regarding algorithmic decisions also reacts back on the actual location of the boundary. If employees feel that algorithmic scoring is "cold and impersonal" and that they cannot appeal, organizations will actively shrink the scope of algorithm authority. Thus, the substitution boundary is not a fixed straight line but rather a fuzzy zone that continuously shifts with technological transparency and trust relationships.

1.2 The Discretization of Job Analysis and Allocation Rules under Data-Driven Approaches

Traditional job analysis often describes a position as a collection of several fixed responsibilities, and a job description remains in use for a year or even longer. In the data-driven model, however, an intelligent system can, by capturing task logs, communication records, and project flow data in real time, disassemble originally integrated duties into finer-grained task units. Each unit corresponds to specific skill requirements, time-consumption weights, and collaboration dependencies, so that a position is no longer a static label but a set of dynamically combined task clusters. Accordingly, the allocation rule shifts from "person-job matching" to a multidimensional "person-task-scenario" matching, and an organization can adjust the proportion of personnel input across different tasks according to project cycles or even on a weekly basis.

The direct consequence of this discretization is the blurring of job boundaries and an increase in role flexibility. An employee's formal title may still be "data analyst," but the tasks he or she actually performs may simultaneously involve data cleaning, visualization reporting, user research coordination, and even light development. The allocation rule no longer relies on a fixed organizational chart; instead, an algorithm generates real-time recommendation plans based on current task loads and employee skill vectors. In a sense, the company becomes more like a "task market," where employees switch between different tasks, and job analysis turns into a dynamically updated repository of competency labels. The advantage of this approach is flexibility, but the challenge lies in the fact that employees may find it difficult to know which group they belong to, and performance evaluations cannot simply follow the original job standards.

1.3 The Redistribution of Weights in Traditional Performance Evaluation by Intelligent Systems

Traditional performance evaluation usually sets several fixed indicators (such as sales volume, lines of code, and customer satisfaction), and a manager then scores each indicator before calculating a weighted sum. The intervention of intelligent systems changes the way weights are determined; it no longer relies on the manager's subjective judgment or historical conventions but automatically adjusts the relative importance of each indicator based on the statistical correlation between actual business outcomes and behavioral data. For example, when the system finds that customer retention rate is highly correlated with two factors, namely after-sales response time and specific keywords in conversation scripts, it will automatically increase the weights of these two indicators when evaluating customer service staff while reducing the weight of the originally dominant call duration indicator. This redistribution is dynamic and implicit, and multiple fine-tuning adjustments may occur within a single evaluation cycle[2].

Another aspect of weight redistribution involves the conflict between fairness and interpretability. The optimal weights derived by an algorithm based on overall data may not be reasonable for each individual. An employee might be unfairly affected by noise in the team's aggregate data; for example, the system increases the weight of the collaboration frequency indicator, but that employee happens to be responsible for independent research tasks where collaboration is inherently rare. In traditional evaluation, a manager could make exceptional adjustments based on experience, whereas an intelligent system, if lacking an intervention interface, would mechanically follow statistical rules. Therefore, in practice, many organizations adopt a hybrid model of "algorithmic recommendations plus managerial final review": the system calculates the recommended weights, while the manager retains the right to modify them. This approach leverages the precision of data-driven analysis while preserving room for human judgment[3].

2. Morphological Transition of Human Resource Management Models Driven by Artificial Intelligence Technology

2.1 Mode Reconstruction from Linear Processes to Dynamic Networks

Traditional human resource management models usually proceed sequentially through stages such as recruitment, onboarding, training, performance evaluation, and promotion, with the connections between these stages following a chronological order and a hierarchical approval chain. This linear process pursues stability and controllability in its design, but it tends to suffer from response delays when faced with rapidly changing business needs. The introduction of artificial intelligence technology breaks the rigid boundaries between stages; an intelligent scheduling system can bypass the original sequence based on real-time task demands and directly establish a two-way data path between training and performance evaluation. For example, behavioral data generated by an employee during project execution can be used simultaneously for capability assessment and for pushing learning content, so that the evaluation result is no longer the end point of the process but rather becomes the starting point for triggering the next round of task allocation. The entire structure transforms from a one-way track into a dynamic network of interconnected nodes, where the density and direction of connections between nodes adjust automatically according to the business scenario[4].

The dynamic network model revises the basic assumptions of management. In the traditional linear process, information is transmitted level by level, and decision-making is concentrated at the process nodes. In the network structure, however, any task unit can form a temporary pairing with multiple capability units, and information flow no longer relies on fixed pipelines. This means that human resource management shifts from "designing processes" to "maintaining network health." An organization needs to focus on node response speed, the number of redundant connections, and load balancing among key nodes, rather than on whether each step is executed according to standard procedures. The original assembly-line style of human resource work now resembles a spider web that constantly stretches and contracts, automatically connecting wherever support is needed.

2.2 The Migration Path of Managerial Authority in Human-Machine Collaborative Architectures

In a human-machine collaborative human resource management architecture, the allocation of managerial authority is not statically distributed but gradually migrates along a path from "machine assisting human" to "human supervising machine" and then to "dynamic division of labor." In the early stage, the intelligent system undertakes low-risk tasks such as data collection, format conversion, and report generation, while the final decision-making power remains in the hands of the manager. As algorithmic accuracy improves and explainability technologies advance, the system begins to intervene in intermediate-level decisions such as screening, classification, and scoring, with the manager retreating to the role of handling exceptions. The typical manifestation of this stage is that the system automatically generates a ranked list of candidates, and the manager intervenes only for review when the system's confidence level falls below a threshold[5].

A deeper migration occurs after the system acquires the ability of closed-loop feedback regulation. The system continuously adjusts its own parameters based on the manager's adoption or modification of its recommendations, gradually taking over authority that originally required empirical judgment. For example, after observing that the manager has repeatedly rejected a certain type of performance evaluation, the system automatically corrects the weight of that dimension and will no longer trigger manual intervention next time. At this point, part of the authority transfers from the manager to the algorithm's self-regulation mechanism. However, the migration is not a one-way progression; when systematic deviations or drastic changes in the business environment occur, the organization actively reclaims authority and enters a new round of division-of-labor adjustment. The migration of authority is like a tug-of-war rather than an all-or-nothing handover to machines.

2.3 The Setting of Elastic Management Thresholds under Real-Time Data Stream Feedback

Traditional human resource management relies on periodic evaluations (such as quarterly performance interviews and annual promotion reviews) to obtain feedback, and the lag in feedback often causes management actions to fall behind the occurrence of problems. Real-time data stream feedback changes this pattern: indicators such as employees' work behaviors, collaboration frequency, and task completion timeliness can be continuously captured and instantly presented through digital systems. An elastic management threshold refers to a dynamic boundary set on these continuous data streams; when an indicator deviates from the preset range, the system automatically triggers corresponding management actions without waiting for a fixed evaluation point. The elasticity of the threshold is reflected in two dimensions: first, the threshold itself can automatically scale according to the context, with different boundaries applying to different positions and different project phases; second, the intensity of the response after exceeding the threshold can be adjusted in a graded manner, where a slight deviation only triggers an observation alert, and a severe deviation initiates an intervention[6].

The key to setting elastic thresholds lies in balancing sensitivity and the false alarm rate. An overly narrow threshold leads to frequent triggers, causing fragmentation of the manager's attention; an overly wide threshold loses its early-warning significance. The intelligent system uses reinforcement learning to search for the optimal boundary in historical data and automatically tightens or relaxes a threshold in a given dimension based on the lagged feedback of business outcomes. For example, when the system finds a three-day lag between a decline in collaboration frequency and project delays, it advances the warning window for the collaboration frequency threshold by three days and widens the tolerance range to avoid false alarms. This dynamic parameter adjustment turns the management threshold from a fixed rule into a living boundary that self-corrects according to actual output; the system itself determines "what degree of deviation requires intervention and what degree can be temporarily tolerated."

3. Efficiency Evolution of Human Resource Management Models after the Embedding of Artificial Intelligence Technology

3.1 Nonlinear Improvement in Matching Accuracy in the Automated Recruitment Process

Automated recruitment systems shift the matching process from keyword comparison to deep-seated need alignment by parsing the semantic features in job descriptions and candidate resumes. In traditional recruitment, matching accuracy tends to show a diminishing marginal return as the number of candidates increases; when a massive number of resumes flood in, screening standards have to be lowered to maintain processing efficiency. Artificial intelligence technology changes this pattern: the system can simultaneously maintain the ability to capture implicit conditions among tens of thousands of resumes. For example, the algorithm can not only identify explicit requirements such as "three years of Python experience" but also extract unstated feature combinations from the profiles of previously successful employees, such as "having open-source project experience with a stable code commit frequency." The introduction of this capability means that matching accuracy no longer decays linearly with an increase in the candidate pool; instead, it even shows a leap in certain intervals.

Another source of nonlinear improvement lies in the establishment of a two-way matching mechanism. Traditional recruitment mainly addresses the one-way question of whether a candidate is suitable for a position, whereas an automated system can simultaneously evaluate the attractiveness of the position to the candidate, incorporating factors such as salary range, career development path, and team style into the matching equation. When the system finds that a highly matched candidate has a high turnover risk, it automatically adjusts the recommendation weight and prioritizes an alternative candidate with slightly lower matching accuracy but better stability. This two-way evaluation breaks the simple logic of "the more precise, the better" and causes the matching accuracy function to present multiple local optimal solutions. The system no longer focuses solely on the "most suitable person" but comprehensively considers the likelihood of retention, thereby improving the actual effectiveness of recruitment on the whole[7-9].

3.2 Knowledge Emergence Triggered by Intelligent Recommendations in the Construction of a Learning Organization

The intelligent recommendation system plays the role of a knowledge connector in a learning organization. In the traditional training model, knowledge transfer relies on designation by managers or self-search by employees, and a large amount of tacit knowledge and cross-domain connections remain buried in the corners of organizational memory. The recommendation algorithm actively pushes learning materials that employees themselves do not know they need by analyzing employees' task trajectories, skill tags, and content consumption records. Such "unexpected associations" often trigger new ideas: a person working on user growth who is recommended content on behavioral economics may develop previously unseen approaches to activity design. Knowledge emergence does not rely on piling up course volumes; instead, it depends on bringing originally unrelated pieces of knowledge together in front of the same person.

Deeper-level emergence occurs at the group level. When multiple employees receive similar cross-domain content combinations from the recommendation system and exchange their interpretations during collaboration, the scattered knowledge fragments aggregate into a new cognitive framework. The system can track this aggregation trend, automatically mark frequently occurring "content pairs" as potential knowledge modules, and recommend them back to more relevant roles. The entire organization thus forms a knowledge self-growth situation: recommendations trigger learning, learning triggers communication, communication generates new content, and new content is once again incorporated into the recommendation pool. This process does not require central planning; instead, it achieves continuous evolution of the knowledge network through self-organizing interactions among nodes.

3.3 The Correction Mechanism of Turnover Prediction Models on the Human Capital Retention Curve

Turnover prediction models transform human capital retention from passive response to active intervention by analyzing the correlation between employee behavioral sequences and turnover outcomes. The traditional retention curve usually presents an empirical statistical distribution: new employees show turnover peaks between the third and sixth months after onboarding, while senior employees exhibit such peaks every two to three years. A prediction model can identify individual early warning signals above these macro trends, such as a regular decline in attendance, a decrease in the node degree of the internal collaboration network, and a shift in document access types from business-related to external job search information. When the system calculates that an employee's turnover probability exceeds a threshold, the retention curve is no longer a post-hoc statistical line but becomes a dynamic object on which corrective forces can be applied to specific nodes[10].

The correction mechanism includes two typical paths. First, the system triggers retention actions in advance: after the system marks an employee as a key focus, the manager can arrange a salary adjustment, a job rotation, or a project change before the turnover intention formally takes shape. This type of preemptive intervention changes the slope of the retention curve at that time point, flattening or delaying the declining segment. Second, counterfactual analysis: the system simulates the impact of different intervention measures on the retention probability and recommends the most cost-effective option. For example, the model may determine that a job rotation is more effective than a salary increase, thereby guiding resources toward a better direction. After the two paths are superimposed, the overall retention curve appears wavy rather than smoothly declining, with each trough corresponding to a successful intervention. Managers thus shift from passively responding to the turnover rate to precisely intervening in individual turnover risks[11].

Conclusion

The transformative effects of artificial intelligence technology on human resource management models present a progressive logic of deconstruction, transition, and evolution. At the deconstruction level, the study delineates the limited boundaries of algorithmic substitution, promotes the transformation of job analysis into discrete task units, and redistributes the weights of performance evaluation. At the transition level, the study reconstructs linear processes into dynamic networks, clarifies the migration path of managerial authority in human-machine collaboration, and establishes elastic management thresholds based on real-time data streams. At the evolution level, the study achieves a nonlinear improvement in recruitment matching accuracy, stimulates knowledge emergence triggered by intelligent recommendations, and corrects the human capital retention curve under turnover prediction models. Future research directions may focus on the further shifting patterns of substitution boundaries after the improvement of algorithmic interpretability, as well as the impact of multimodal data fusion on the stability of dynamic networks. In addition, long-term tracking of the actual operational effects of intelligent system self-regulation mechanisms in different industries will also help deepen the understanding of changes in the endogenous logic of human resource management under the condition of artificial intelligence embedding.

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