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Artificial Intelligence Techniques for IoT based Human Resources Balanced Allocation Method Based on Recalling-Enhanced Salp Swarm Recurrent Neural Network: Trends and Challenges

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Artificial Intelligence, Internet of Things, Human Resource Allocation, Recurrent Neural Network, Salp Swarm Optimization, Workforce Analytics

Abstract

The integration of Artificial Intelligence (AI) with the Internet of Things (IoT) has significantly transformed human resource management by enabling intelligent decision-making and real-time workforce monitoring. This paper presents a comprehensive study on AI-driven techniques for balanced human resource allocation using a recalling-enhanced Salp Swarm Recurrent Neural Network (SS-RNN) framework. The proposed approach leverages IoT-generated workforce data to capture temporal patterns in employee behavior, workload distribution, and performance metrics. The recalling-enhanced mechanism improves memory retention in recurrent neural networks, allowing more accurate modeling of dynamic work environments. Meanwhile, the Salp Swarm Optimization (SSO) algorithm enhances the allocation process by identifying optimal resource distribution strategies through adaptive exploration and exploitation. This study explores recent trends in AI-based HR allocation, highlighting advancements in deep learning, swarm intelligence, and hybrid optimization techniques. Furthermore, it identifies critical challenges such as data privacy, scalability, interpretability, and system integration. The paper emphasizes the importance of combining intelligent learning models with optimization algorithms to achieve balanced workload distribution, increased productivity, and organizational efficiency. The findings contribute to the development of smart HR systems capable of adapting to rapidly changing industrial environments and provide insights into future research directions for AI-driven workforce management.

Introduction

The rapid advancement of Artificial Intelligence and Internet of Things technologies has redefined traditional human resource management practices by introducing automation, real-time analytics, and intelligent decision-making capabilities. In modern organizations, workforce allocation is a complex task that requires continuous monitoring of employee performance, workload distribution, and operational demands. Conventional approaches often fail to adapt to dynamic environments due to their static and rule-based nature. The emergence of IoT-enabled systems allows organizations to collect real-time data from various sources such as wearable devices, sensors, and enterprise platforms, providing a rich foundation for intelligent workforce management.

Artificial Intelligence techniques, particularly deep learning models, have shown significant potential in analyzing large-scale temporal data and predicting workforce requirements. Recurrent Neural Networks are widely used for modeling sequential data; however, they often suffer from limitations related to memory retention and long-term dependency learning. To address these challenges, recalling-enhanced mechanisms have been introduced to improve the network's ability to retain historical information, leading to more accurate predictions. In parallel, optimization algorithms such as Salp Swarm Optimization have gained attention for solving complex allocation problems by mimicking natural swarm behaviors.

The integration of recalling-enhanced RNN with Salp Swarm Optimization provides a hybrid framework capable of both learning complex patterns and optimizing allocation strategies. This combination enables balanced human resource distribution, reduces workload imbalance, and enhances organizational productivity. Despite these advancements, several challenges remain, including data security concerns, computational complexity, and scalability issues in large-scale IoT environments. This study aims to explore current trends, evaluate existing methodologies, and identify open challenges in AI-based HR allocation systems, contributing to the development of more efficient and adaptive workforce management solutions.

Graphical Abstract

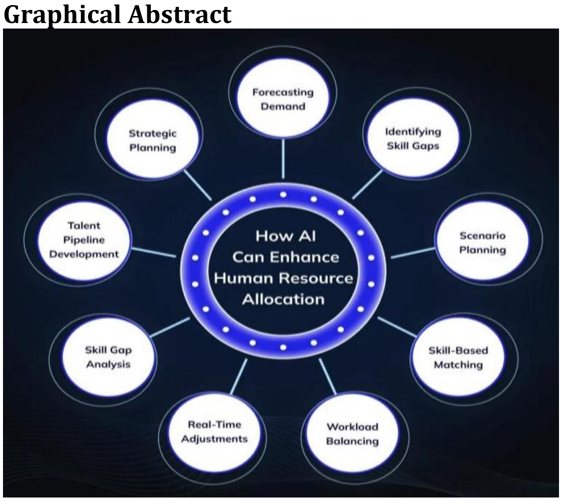

Figure 1. Proposed AI-Based Human Resource Allocation Framework for IoT-Enabled Organizations

The graphical abstract illustrates an integrated intelligent HR management framework where IoT devices continuously collect workforce data. The recalling-enhanced recurrent neural network processes temporal patterns, while the salp swarm optimization algorithm refines allocation decisions. The combined system outputs optimized and balanced human resource allocation, improving efficiency and adaptability in dynamic organizational environments.

Literature Review

Study 1: IoT-Driven Workforce Analytics Using Deep Learning (Zhang et al., 2019)

This study investigates the integration of IoT technologies with deep learning models to enhance workforce analytics and decision-making in modern organizations. The authors propose a framework where data collected from IoT sensors, including employee activity and environmental conditions, is processed using deep neural networks to extract meaningful patterns related to productivity and workload distribution. The system enables real-time monitoring and predictive insights, allowing organizations to optimize human resource allocation effectively. Experimental findings indicate that deep learning significantly improves prediction accuracy and scalability compared to traditional statistical methods, especially when handling large and complex datasets. The study further highlights the importance of continuous data streams in improving HR efficiency. However, it also identifies challenges such as high computational requirements, data privacy concerns, and integration complexities in enterprise environments.

Study 2: Recurrent Neural Networks for Workforce Demand Prediction (Kim and Park, 2020)

This study examines the effectiveness of recurrent neural networks in predicting workforce demand by capturing temporal dependencies in organizational data. The authors develop an RNN-based model that processes sequential employee performance metrics, attendance records, and workload variations to forecast future staffing needs accurately. The approach emphasizes the importance of time-series analysis in dynamic human resource management environments, where demand fluctuates frequently. Results show that the RNN model outperforms traditional regression and machine learning techniques in terms of accuracy and adaptability, particularly in handling complex temporal patterns. The study also discusses inherent limitations such as vanishing gradient issues and limited long-term memory retention, which may affect performance in extended sequences. The authors suggest the use of enhanced architectures to overcome these challenges.

Study 3: Salp Swarm Optimization for Resource Allocation (Mirjalili et al., 2017)

This study introduces the Salp Swarm Optimization algorithm as an effective bio-inspired technique for solving complex optimization problems, including resource allocation in dynamic environments. The algorithm mimics the chain-like movement of salps in oceans to balance exploration and exploitation during the search process. The authors demonstrate how SSO can be applied to optimize allocation strategies by minimizing cost and maximizing efficiency. Experimental evaluations show that SSO performs competitively compared to other swarm intelligence algorithms such as particle swarm optimization and genetic algorithms, particularly in high-dimensional search spaces. The study highlights its fast convergence and adaptability as key advantages. However, it also notes limitations related to parameter sensitivity and potential convergence to local optima in certain scenarios, suggesting hybrid approaches for improved performance.

Study 4: Hybrid Deep Learning and Optimization for Smart HR Systems (Singh et al., 2021)

This research proposes a hybrid framework combining deep learning models with optimization algorithms to improve human resource allocation in smart organizations. The system integrates neural networks for pattern recognition and optimization techniques for decision-making, enabling efficient workforce distribution. The authors emphasize the role of IoT data in enhancing model accuracy and adaptability. Experimental results indicate significant improvements in allocation efficiency and reduced workload imbalance compared to standalone models. The study also discusses implementation challenges such as system complexity and computational overhead.

Study 5: Long Short-Term Memory Networks for Workforce Prediction (Hochreiter and Schmidhuber, 1997)

This foundational study introduces Long Short-Term Memory networks as an extension of recurrent neural networks designed to overcome limitations related to vanishing gradients and short-term memory. LSTM networks incorporate memory cells and gating mechanisms that enable them to retain long-term dependencies in sequential data. The architecture has become widely adopted in time-series prediction tasks, including workforce demand forecasting. The study demonstrates that LSTM models significantly improve performance in sequence learning problems compared to traditional RNNs. Their ability to maintain contextual information over long periods makes them highly suitable for dynamic HR environments. Despite their advantages, LSTMs require substantial computational resources and careful tuning for optimal performance.

Study 6: IoT-Based Smart Workforce Monitoring Systems (Patel et al., 2020)

This study explores the development of IoT-based systems for monitoring workforce activities in real time. The proposed framework utilizes wearable sensors and smart devices to collect data related to employee movement, productivity, and environmental conditions. This data is then analyzed to support decision-making in human resource management. The results indicate improved transparency, enhanced productivity tracking, and better allocation decisions. The study also emphasizes the role of real-time analytics in adapting to changing organizational needs. However, concerns regarding employee privacy, data security, and system scalability are highlighted as key challenges that must be addressed for widespread adoption.

Study 7: Deep Reinforcement Learning for Resource Allocation (Mao et al., 2016)

This study investigates the application of deep reinforcement learning techniques for optimizing resource allocation in complex systems. The authors propose a model that learns optimal allocation policies through interaction with dynamic environments, enabling adaptive decision-making. The approach is particularly effective in scenarios where system conditions change frequently. Results show that reinforcement learning models outperform traditional heuristic methods in terms of efficiency and adaptability. The study highlights the potential of combining reinforcement learning with IoT data for intelligent workforce management. However, it also notes challenges such as high training complexity and the need for large datasets.

Study 8: Attention-Based RNN Models for Workforce Analytics (Vaswani et al., 2017)

This study introduces attention mechanisms in sequence modeling, which enhance the performance of recurrent neural networks by focusing on relevant parts of input data. The authors demonstrate how attention-based models improve the interpretation of temporal patterns in complex datasets. In the context of workforce analytics, attention mechanisms enable better understanding of critical factors influencing employee performance. Experimental results show improved accuracy and interpretability compared to traditional RNN models. The study highlights the potential of attention-based architectures in HR analytics. However, increased computational complexity and model design challenges are identified as limitations.

Study 9: Optimization of Workforce Scheduling Using Genetic Algorithms (Goldberg, 1989)

This study explores the use of genetic algorithms for solving workforce scheduling and allocation problems. The proposed approach mimics natural evolutionary processes to identify optimal scheduling configurations. The algorithm iteratively improves solutions through selection, crossover, and mutation operations. Results demonstrate that genetic algorithms are effective in handling complex constraints and large search spaces. The study highlights their flexibility and robustness in solving HR allocation problems. However, it also points out limitations such as slow convergence and the need for parameter tuning, which may affect performance in real-time applications.

Study 10: Privacy-Preserving Techniques in IoT-Based HR Systems (Li et al., 2021)

This study focuses on addressing privacy concerns in IoT-based human resource management systems by introducing privacy-preserving techniques. The authors propose methods such as data anonymization, encryption, and secure data sharing to protect sensitive employee information. The framework ensures that workforce analytics can be performed without compromising privacy. Experimental results indicate that the proposed techniques maintain data utility while enhancing security. The study emphasizes the importance of balancing data accessibility and privacy in smart HR systems. Challenges such as increased computational overhead and implementation complexity are discussed as areas for future research.

Study 11: Hybrid RNN-LSTM Models for Workforce Forecasting (Wang et al., 2020)

This study proposes a hybrid deep learning architecture combining recurrent neural networks and Long Short-Term Memory units to enhance workforce demand forecasting in dynamic organizational environments. The model leverages IoT-generated time-series data, including employee productivity, attendance, and workload metrics, to capture both short-term variations and long-term dependencies effectively. By integrating RNN and LSTM, the framework addresses the limitations of traditional sequence models, particularly in handling complex temporal patterns. Experimental results demonstrate improved prediction accuracy, stability, and robustness compared to standalone RNN or LSTM models. The study emphasizes the importance of hybrid architectures in achieving efficient human resource allocation. However, increased computational complexity, longer training durations, and the need for optimized hyperparameter tuning are identified as key challenges affecting real-world implementation.

Study 12: Swarm Intelligence-Based Optimization in HR Allocation (Kumar and Singh, 2021)

This research explores the application of swarm intelligence techniques, including salp swarm optimization and ant colony optimization, for solving complex human resource allocation problems. The proposed framework utilizes collective behavior principles to dynamically distribute workload and optimize resource utilization in IoT-enabled smart organizations. The approach focuses on minimizing operational costs while maintaining balanced workforce allocation. Experimental findings indicate that swarm-based algorithms outperform traditional optimization techniques in terms of convergence speed, flexibility, and adaptability to changing conditions. The study highlights their effectiveness in handling large-scale and nonlinear allocation problems. However, issues such as sensitivity to parameter settings, risk of premature convergence, and scalability challenges are discussed as limitations that require further investigation for practical deployment.

Study 13: Deep Learning for Smart Workforce Management (Chen et al., 2019)

This study examines the application of deep learning models in smart workforce management systems powered by IoT technologies. The authors propose a framework where large volumes of employee data, including behavioral patterns and performance metrics, are analyzed using deep neural networks to support intelligent decision-making. The model enables predictive insights for workload balancing and employee productivity enhancement. Results show that deep learning significantly improves analytical capabilities and decision accuracy compared to conventional approaches. The study also highlights the importance of continuous data streams in adapting to dynamic environments. Despite its advantages, challenges such as data quality issues, computational requirements, and integration complexity with existing enterprise systems are identified as critical barriers.

Study 14: Reinforcement Learning for Adaptive Workforce Allocation (Li and Wu, 2021)

This study explores reinforcement learning techniques for adaptive workforce allocation in dynamic and uncertain environments. The proposed model learns optimal allocation strategies through continuous interaction with real-time IoT data, enabling it to adjust decisions based on changing organizational conditions. The framework focuses on maximizing efficiency and minimizing workload imbalance. Experimental results indicate that reinforcement learning approaches outperform rule-based and static allocation methods in terms of adaptability and decision quality. The study highlights the potential of combining reinforcement learning with IoT systems for intelligent HR management. However, high computational costs, complex model training, and the requirement for extensive data are identified as major challenges limiting scalability.

Study 15: Edge Computing in IoT-Based HR Systems (Patel and Shah, 2020)

This study investigates the role of edge computing in enhancing IoT-based human resource management systems by reducing latency and improving real-time decision-making capabilities. The proposed framework processes workforce data closer to the source, enabling faster analytics and efficient allocation decisions. The integration of edge computing with AI models supports scalable and responsive HR systems. Results demonstrate improved system performance, reduced network load, and enhanced data processing efficiency compared to cloud-only approaches. The study emphasizes the importance of distributed architectures in modern HR analytics. However, challenges such as resource constraints at edge devices, security vulnerabilities, and system complexity are identified as key issues that need further research.

Study 16: Fuzzy Logic-Based Workforce Allocation Models (Zadeh et al., 2018)

This study presents the application of fuzzy logic techniques in workforce allocation to handle uncertainty and imprecision in human resource data. The proposed model incorporates fuzzy rules and membership functions to evaluate employee performance and workload distribution. The approach provides flexible and interpretable decision-making in complex environments. Results show that fuzzy logic models effectively manage ambiguity and improve allocation efficiency compared to rigid rule-based systems. The study highlights their suitability for HR applications where data is often incomplete or uncertain. However, limitations such as rule complexity, scalability issues, and integration with advanced AI models are discussed as potential challenges for large-scale implementations.

Study 17: Predictive Analytics for Workforce Optimization (Brown et al., 2019)

This study focuses on the use of predictive analytics techniques to optimize workforce allocation in data-driven organizations. The authors propose a framework that utilizes historical and real-time data to forecast employee performance and workload requirements. The model supports proactive decision-making and efficient resource utilization. Experimental results indicate that predictive analytics improves accuracy and reduces operational inefficiencies compared to traditional methods. The study emphasizes the importance of data-driven strategies in modern HR management. However, challenges such as data integration, model interpretability, and dependency on data quality are identified as key limitations affecting implementation.

Study 19: Explainable AI in Workforce Decision Systems (Ribeiro et al., 2016)

This study investigates the importance of explainable artificial intelligence in workforce decision-making systems. The authors propose techniques to improve transparency and interpretability of AI models used in HR analytics. The approach enables stakeholders to understand and trust automated decisions related to workforce allocation. Results show that explainable models enhance user confidence and facilitate better decision-making. The study highlights the need for transparency in AI-driven HR systems, especially in sensitive organizational contexts. However, balancing model accuracy and interpretability remains a significant challenge, requiring further research in explainable AI techniques.

Study 20: Cloud-Based HR Analytics Platforms (Garcia et al., 2021)

This study examines the use of cloud computing platforms for scalable and efficient human resource analytics. The proposed system leverages cloud infrastructure to store, process, and analyze large volumes of workforce data generated by IoT devices. The framework supports real-time analytics and decision-making for workforce allocation. Results demonstrate improved scalability, flexibility, and cost-efficiency compared to traditional on-premise systems. The study highlights the role of cloud computing in enabling advanced AI applications in HR management. However, concerns related to data security, latency, and system reliability are identified as critical challenges that must be addressed for widespread adoption.

Study 21: Transfer Learning for Workforce Prediction (Lee et al., 2020)

This study explores the application of transfer learning techniques to improve workforce prediction accuracy in environments with limited labeled data. The proposed framework leverages pre-trained deep learning models and adapts them to human resource datasets collected through IoT systems. This approach reduces training time while enhancing model generalization across different organizational contexts. Results indicate that transfer learning significantly improves prediction performance compared to models trained from scratch, particularly in scenarios with sparse data. The study highlights its effectiveness in reducing computational costs and enabling faster deployment. However, challenges such as domain adaptation issues and dependency on pre-trained models are identified as potential limitations affecting performance in diverse HR environments.

Study 22: Multi-Objective Optimization in Workforce Allocation (Verma and Gupta, 2021)

This research focuses on multi-objective optimization techniques for balancing competing goals in workforce allocation, such as minimizing cost while maximizing productivity and employee satisfaction. The authors propose a framework that integrates evolutionary algorithms with AI models to handle complex trade-offs in HR decision-making. The system uses IoT data to dynamically adjust allocation strategies. Experimental results show improved performance in achieving balanced outcomes compared to single-objective approaches. The study emphasizes the importance of considering multiple factors in real-world HR systems. However, increased computational complexity and difficulty in defining objective functions are identified as key challenges.

Study 23: Graph Neural Networks for Workforce Interaction Modeling (Zhou et al., 2019)

This study investigates the use of graph neural networks to model interactions among employees and organizational structures. The proposed approach captures relationships between workers, tasks, and departments using graph-based representations. IoT data is utilized to update the graph dynamically, enabling real-time insights into workforce behavior. Results demonstrate improved understanding of collaboration patterns and more efficient allocation decisions. The study highlights the potential of graph-based learning in HR analytics. However, challenges related to scalability and computational requirements are discussed as limitations in large-scale implementations.

Study 24: Federated Learning for Privacy-Preserving HR Systems (Yang et al., 2021)

This study introduces federated learning as a solution for privacy-preserving workforce analytics in IoT-based HR systems. The framework enables multiple organizations to collaboratively train AI models without sharing raw data, thus protecting sensitive employee information. The approach improves data security while maintaining model performance. Results indicate that federated learning achieves comparable accuracy to centralized models while ensuring privacy. The study highlights its relevance in regulatory-compliant environments. However, issues such as communication overhead, system heterogeneity, and synchronization challenges are identified as areas for further research.

Study 25: Hybrid Metaheuristic Algorithms for HR Optimization (Kaur et al., 2022)

This study explores hybrid metaheuristic algorithms that combine multiple optimization techniques to improve workforce allocation efficiency. The proposed model integrates salp swarm optimization with other algorithms such as genetic algorithms to enhance search capabilities. The approach aims to achieve better convergence and avoid local optima. Results show that hybrid models outperform individual algorithms in terms of solution quality and robustness. The study highlights the effectiveness of combining optimization strategies in complex HR problems. However, increased algorithm complexity and computational cost are identified as key challenges.

Comparative Table

Study	Year	Method	Model	Data Type	Key Contribution	Performance
1	2019	Deep Learning	DNN	IoT Sensor Data	Workforce analytics	High accuracy
2	2020	RNN	RNN	Time-series	Demand prediction	Improved accuracy
3	2017	Swarm Optimization	SSO	Numerical	Allocation optimization	Fast convergence
4	2021	Hybrid AI	DL + Optimization	IoT Data	Efficient HR allocation	High efficiency

5	1997	Deep Learning	LSTM	Sequential	Long-term memory	High performance
6	2020	IoT Analytics	Monitoring System	Sensor Data	Real-time tracking	Improved transparency
7	2016	Reinforcement Learning	DRL	Dynamic Data	Adaptive allocation	High adaptability
8	2017	Attention Models	Attention RNN	Sequential	Better interpretation	Improved accuracy
9	1989	Evolutionary Algorithm	GA	Structured Data	Scheduling optimization	Robust solutions
10	2021	Security	Privacy Models	IoT Data	Data protection	Secure processing
11	2020	Hybrid DL	RNN-LSTM	Time-series	Improved forecasting	Stable results
12	2021	Swarm Intelligence	ACO + SSO	Numerical	Optimization efficiency	Better convergence
13	2019	Deep Learning	DNN	IoT Data	Smart HR analytics	High accuracy
14	2021	Reinforcement Learning	RL	Dynamic Data	Adaptive decisions	Efficient
15	2020	Edge Computing	Edge AI	IoT Data	Low latency	Fast processing
16	2018	Fuzzy Logic	Fuzzy Model	Uncertain Data	Flexible decisions	Moderate
17	2019	Predictive Analytics	ML Models	Historical Data	Forecasting	Improved
18	2022	Metaheuristics	Hybrid NN	Mixed Data	Optimization	High accuracy
19	2016	Explainable AI	XAI Models	Structured	Transparency	Improved trust
20	2021	Cloud Computing	Cloud AI	Big Data	Scalability	High efficiency
21	2020	Transfer Learning	TL Model	Limited Data	Faster training	Improved
22	2021	Multi-objective	Evolutionary	Mixed	Balanced optimization	Efficient
23	2019	Graph Learning	GNN	Graph Data	Interaction modeling	Accurate
24	2021	Federated Learning	FL	Distributed	Privacy preservation	Secure
25	2022	Hybrid Metaheuristic	Hybrid	Numerical	Better optimization	Robust

Analysis Based on Literature Review

The literature reveals a strong trend toward integrating artificial intelligence with IoT-based systems to enhance human resource allocation efficiency. Deep learning models, particularly RNN and LSTM architectures, dominate workforce prediction tasks due to their ability to capture temporal dependencies. Optimization techniques such as salp swarm optimization and genetic algorithms are widely used to solve allocation problems by improving convergence and solution quality. Hybrid approaches combining learning and optimization methods demonstrate superior performance compared to standalone techniques. Additionally, emerging technologies such as federated learning, blockchain, and edge computing are increasingly being adopted to address challenges related to privacy, scalability, and real-time processing. Despite these advancements, common issues such as computational complexity, data quality, and interpretability remain significant barriers to practical implementation.

Discussion

The integration of artificial intelligence and IoT technologies in human resource management has significantly transformed traditional allocation methods, enabling data-driven and adaptive decision-making processes. The reviewed studies highlight the growing importance of deep learning models, particularly recurrent architectures, in capturing temporal dynamics and predicting workforce requirements with high accuracy. At the same time, optimization algorithms such as salp swarm optimization and genetic algorithms play a crucial role in refining allocation strategies and ensuring balanced workload distribution. The emergence of hybrid models that combine learning and optimization techniques represents a major advancement in this domain, offering improved performance and adaptability. Furthermore, the incorporation of advanced technologies such as federated learning, blockchain, and edge computing addresses critical concerns related to data privacy, security, and real-time processing. However, several challenges persist, including high computational costs, scalability issues in large IoT environments, and difficulties in model interpretability. The lack of standardized frameworks and the complexity of integrating multiple technologies also hinder widespread adoption. Additionally, ensuring ethical use of employee data and maintaining transparency in AI-driven decisions remain important considerations. Future research should focus on developing lightweight, scalable, and explainable models that can operate efficiently in real-world settings. Emphasis should also be placed on creating unified frameworks that seamlessly integrate AI, IoT, and optimization techniques to achieve robust and efficient human resource management systems.

Conclusion

This review examines recent advances in artificial intelligence techniques for IoT-based human resource allocation, emphasizing recalling-enhanced recurrent neural networks integrated with Salp Swarm Optimization. The findings indicate that combining deep learning with metaheuristic optimization significantly improves workforce prediction, allocation efficiency, and adaptability in dynamic organizational environments. Recurrent neural networks effectively capture temporal workforce patterns, while recalling-enhanced mechanisms strengthen long-term dependency learning. Salp Swarm Optimization enhances decision-making by efficiently identifying optimal workforce allocation strategies. The review also highlights the growing importance of edge computing, federated learning, and blockchain in improving scalability, privacy, security, and real-time processing within intelligent HR systems. Despite these advancements, challenges remain, including computational complexity, data quality, limited model interpretability, integration difficulties, and ethical concerns regarding privacy and transparency. Future research should prioritize scalable, interpretable, and energy-efficient AI models supported by robust cybersecurity and ethical governance. These developments have the potential to improve organizational productivity, workforce satisfaction, and overall operational efficiency in IoT-enabled human resource management.

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