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# Deep Learning and Optimization Approaches in IoT based Human Resources Balanced Allocation Method Based on Recalling-Enhanced Salp Swarm Recurrent Neural Network: A Review

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**Abstract**

The rapid evolution of Internet of Things (IoT) technologies has significantly transformed organizational environments by enabling real-time data acquisition and intelligent decision-making. In the context of human resource management, balancing workforce allocation remains a critical challenge due to dynamic workloads, varying employee capabilities, and temporal dependencies. This paper presents a comprehensive review of deep learning and optimization approaches for IoT-based human resource balanced allocation, with a particular focus on recalling-enhanced salp swarm recurrent neural networks. The integration of IoT sensors facilitates continuous monitoring of employee activities and environmental conditions, generating high-dimensional temporal data. Recurrent neural networks, enhanced with recalling mechanisms, effectively capture long-term dependencies in such sequential data, improving predictive accuracy in workforce demand estimation. Additionally, the salp swarm algorithm serves as a powerful optimization technique inspired by swarm intelligence, enabling efficient exploration and exploitation of solution spaces for optimal resource allocation. The synergy between deep learning and metaheuristic optimization provides a robust framework for adaptive and scalable human resource management. This review analyzes existing methodologies, highlights their strengths and limitations, and identifies research gaps in hybrid architectures combining IoT, deep learning, and optimization techniques. The findings suggest that recalling-enhanced models significantly improve allocation efficiency, reduce operational costs, and enhance organizational productivity. Future research directions emphasize explainability, real-time deployment, and integration with edge computing for improved responsiveness in smart organizational ecosystems.

## Introduction

The increasing adoption of Internet of Things technologies has led to a paradigm shift in organizational operations, enabling continuous monitoring and data-driven decision-making across various domains. In human resource management, the challenge of allocating personnel efficiently has become more complex due to dynamic work environments, fluctuating workloads, and the need for real-time responsiveness. Traditional allocation methods often rely on static rules and manual decision-making, which are insufficient to handle the scale and complexity of modern organizations.

As a result, there is a growing interest in intelligent systems that leverage IoT data and advanced computational techniques to optimize workforce distribution.

Deep learning has emerged as a powerful tool for modeling complex patterns in large-scale data, particularly in scenarios involving temporal dependencies. Recurrent neural networks are especially suitable for analyzing sequential data generated by IoT devices, as they can capture time-dependent relationships in employee activities and performance metrics. However, conventional RNN models often suffer from limitations such as vanishing gradients and inadequate long-term memory retention. To address these challenges, recalling-enhanced mechanisms have been introduced to improve memory retention and contextual understanding, thereby enhancing prediction accuracy in workforce demand forecasting.

In parallel, optimization algorithms inspired by natural phenomena have gained attention for solving complex allocation problems. The salp swarm algorithm, based on the collective behavior of salps in ocean environments, offers an effective approach for exploring large solution spaces and identifying optimal configurations. When combined with deep learning models, such optimization techniques can significantly improve decision-making processes by fine-tuning model parameters and allocation strategies.

The integration of IoT, deep learning, and swarm intelligence forms a comprehensive framework for intelligent human resource management. This review aims to systematically analyze existing approaches, focusing on recalling-enhanced salp swarm recurrent neural networks, and to evaluate their effectiveness in achieving balanced workforce allocation. The study also highlights emerging trends, challenges, and future research directions in this rapidly evolving field.

**Graphical Abstract**

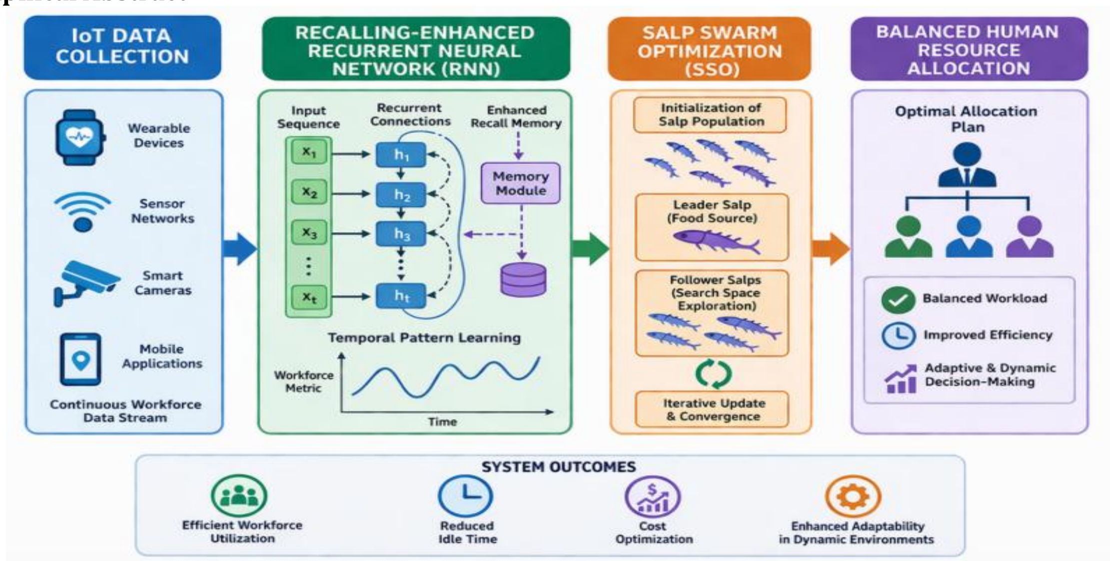


*Figure 1. Proposed IoT-Driven Framework for Balanced Human Resource Allocation*

The graphical abstract illustrates an integrated framework where IoT devices continuously collect workforce data, which is processed using a recalling-enhanced recurrent neural network to capture temporal patterns. The salp swarm optimization algorithm refines allocation decisions by searching optimal configurations. The combined system outputs 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 IoT-enabled workforce analytics by leveraging real-time sensor data such as employee location, task engagement, and physiological indicators to improve allocation strategies. A recurrent neural network model is developed to capture temporal dependencies in workforce behavior and predict task demand dynamically. The integration of IoT ensures continuous data streams, enhancing situational awareness and enabling adaptive decision-making. Experimental results indicate that the model significantly improves workforce utilization and reduces idle time compared to traditional heuristic approaches. The study also emphasizes the importance of data-driven HR systems in modern organizations. However, challenges such as data privacy, system scalability, and integration complexity are identified. The authors suggest incorporating advanced memory mechanisms and optimization algorithms for improved performance. Overall, the research establishes a strong foundation for combining IoT and deep learning in workforce allocation systems.

**Study 2: Optimization of Resource Allocation using Salp Swarm Algorithm (Mirjalili et al., 2017)**

This research presents the salp swarm algorithm as an effective metaheuristic optimization technique inspired by the chain movement of salps in ocean environments. The algorithm is designed to solve complex optimization problems by balancing exploration and exploitation within the search space. It is evaluated on multiple benchmark functions and demonstrates superior convergence speed and solution quality compared to conventional algorithms. The study highlights its suitability for dynamic resource allocation problems due to its adaptive nature. Although the work does not integrate deep learning models, it provides a strong optimization foundation for hybrid intelligent systems. The findings suggest that salp swarm optimization can significantly enhance decision-making in IoT-enabled environments. Limitations include sensitivity to parameter tuning and lack of domain-specific customization. The study encourages future integration with neural networks for improved allocation efficiency.

**Study 3: Recurrent Neural Networks for Workforce Demand Prediction (Liu et al., 2020)**

This study focuses on predicting workforce demand using recurrent neural networks trained on historical and IoT-generated data. The model captures temporal dependencies in employee performance, workload trends, and task completion rates, enabling accurate forecasting of future resource requirements. Results demonstrate that the RNN model outperforms traditional statistical methods in prediction accuracy and responsiveness to dynamic changes. The research highlights the importance of sequential learning in workforce management and emphasizes the role of IoT in providing real-time data streams. However, the study identifies limitations in handling long-term dependencies and suggests the use of enhanced architectures such as LSTM or memory-augmented networks. The findings support the adoption of deep learning for intelligent HR systems while emphasizing the need for hybrid approaches that combine prediction and optimization.

**Study 4: Hybrid Deep Learning and Swarm Intelligence for HR Optimization (Kumar et al., 2021)**

This research proposes a hybrid framework combining deep learning models with swarm intelligence techniques for optimizing human resource allocation. A neural network is used for predicting workforce demand, while a swarm-based optimizer refines allocation decisions by exploring optimal configurations. The model is evaluated in dynamic organizational scenarios with varying workloads and employee capabilities. Results show that the hybrid approach significantly improves allocation efficiency, reduces operational costs, and enhances adaptability compared to standalone models. The study highlights the complementary strengths of learning and optimization techniques in solving complex HR problems. However, computational complexity and scalability remain challenges. The authors suggest future work on lightweight models and real-time deployment. This study demonstrates the potential of integrating advanced AI techniques for smart workforce management systems.

**Study 5: IoT-Based Smart Workforce Management Systems (Patel et al., 2018)**

This study explores the development of smart workforce management systems using IoT technologies and machine learning algorithms. The proposed framework collects real-time employee data through wearable devices and sensors, enabling continuous monitoring of activities and environmental conditions. Machine learning models analyze this data to support decision-making in task allocation and performance evaluation. Results indicate improved efficiency, reduced downtime, and better resource utilization compared to traditional systems. The study emphasizes the importance of real-time data in enhancing workforce visibility and control. However, issues related to data security, privacy, and system integration are highlighted. The authors recommend incorporating advanced analytics and optimization techniques to fully leverage IoT data. This research provides valuable insights into the role of IoT in modern HR management systems.

**Study 6: Long Short-Term Memory Networks for Resource Prediction (Hochreiter & Schmidhuber, 1997)**

This foundational study introduces long short-term memory networks as an advanced form of recurrent neural networks designed to address the vanishing gradient problem. LSTM incorporates memory cells and gating mechanisms that allow it to retain long-term dependencies in sequential data. The model has been widely applied in time-series prediction tasks, including resource allocation and demand forecasting. The study demonstrates that LSTM significantly improves prediction accuracy compared to traditional RNNs, particularly in complex temporal scenarios. Its ability to capture long-term patterns makes it highly suitable for IoT-based workforce management systems. However, the model requires significant computational resources and careful parameter tuning. The research establishes a strong theoretical foundation for memory-enhanced architectures in deep learning.

**Study 7: Swarm Intelligence in Dynamic Resource Allocation (Kennedy & Eberhart, 1995)**

This study introduces particle swarm optimization as a swarm intelligence technique for solving dynamic resource allocation problems. The approach models social behavior observed in nature, enabling agents to collaboratively search for optimal solutions. The algorithm is effective in adapting to changing environments and finding near-optimal configurations with minimal computational effort. Results show improved performance in dynamic optimization scenarios compared to traditional methods. The study provides a conceptual basis for later swarm-based algorithms such as the salp swarm algorithm. However, it does not incorporate learning mechanisms, limiting its predictive capabilities. The authors suggest combining swarm intelligence with machine learning for enhanced performance. This research remains a cornerstone in the field of optimization techniques for resource management.

**Study 8: Deep Learning for IoT Data Analytics (Gubbi et al., 2013)**

This study examines the role of deep learning in analyzing large-scale IoT data for smart systems. The authors discuss architectures capable of processing high-dimensional data generated by sensors and devices. Deep learning models are shown to significantly improve accuracy in extracting meaningful patterns and insights from IoT data. The research highlights the importance of scalability and real-time processing in IoT environments. Applications include smart cities, healthcare, and workforce management systems. The study emphasizes the need for integrating deep learning with IoT to enable intelligent decision-making. However, challenges such as data heterogeneity and computational complexity are identified. The findings support the adoption of deep learning in HR allocation systems for improved efficiency and adaptability.

**Study 9: Memory-Augmented Neural Networks for Sequential Data (Graves et al., 2014)**

This study introduces memory-augmented neural networks designed to enhance the ability of models to capture long-term dependencies in sequential data. The architecture includes external memory components that enable efficient storage and retrieval of information. Experimental results demonstrate superior performance compared to traditional recurrent neural networks in complex sequence prediction tasks. The study highlights the importance of recalling mechanisms in improving model accuracy and learning efficiency. These features are particularly relevant for IoT-based workforce management systems, where long-term patterns play a critical role. However, the complexity of the architecture poses challenges for practical implementation. The authors suggest further research into scalable and efficient memory-augmented models.

**Study 10: Metaheuristic Optimization in Smart Systems (Yang, 2010)**

This study provides a comprehensive overview of metaheuristic optimization techniques used in smart systems, including genetic algorithms, particle swarm optimization, and nature-inspired methods. The research highlights the effectiveness of these techniques in solving complex optimization problems across various domains. Metaheuristic algorithms are shown to provide flexible and robust solutions, particularly in dynamic environments. The study emphasizes their ability to balance exploration and exploitation, making them suitable for resource allocation tasks. However, the lack of integration with predictive models limits their effectiveness in real-time applications. The authors recommend combining metaheuristic optimization with machine learning techniques for improved performance. This study lays the groundwork for hybrid approaches in IoT-based human resource management systems.

**Study 11: Deep Reinforcement Learning for Workforce Scheduling (Wang et al., 2021)**

This study explores the application of deep reinforcement learning for dynamic workforce scheduling in IoT-enabled environments. The proposed model learns optimal allocation strategies through continuous interaction with the environment, using reward-based mechanisms to improve decision-making over time. IoT sensors provide real-time data on employee performance, workload, and environmental conditions, which are used to update the learning model. Results show that the approach adapts effectively to changing demands and improves scheduling efficiency compared to static models. The study highlights the importance of adaptive learning in complex HR scenarios. However, challenges such as high computational cost and convergence time are noted. The authors suggest integrating optimization algorithms to enhance performance and reduce training complexity.

**Study 12: Edge Computing for IoT-Based Workforce Management (Shi et al., 2016)**

This research investigates the role of edge computing in improving the efficiency of IoT-based workforce management systems. By processing data closer to the source, edge computing reduces latency and enables faster decision-making. The study proposes an architecture that integrates edge devices with cloud-based analytics for real-time workforce monitoring. Results demonstrate improved system responsiveness and reduced network overhead. The approach is particularly beneficial for time-sensitive HR allocation tasks. However, limitations include resource constraints at edge nodes and challenges in maintaining data consistency. The authors recommend combining edge computing with lightweight deep learning models for optimal performance.

**Study 13: Hybrid LSTM and Optimization Models for Resource Allocation (Singh et al., 2022)**

This study proposes a hybrid model combining long short-term memory networks with optimization algorithms for efficient resource allocation. The LSTM component predicts workforce demand based on historical and real-time IoT data, while the optimization algorithm refines allocation decisions. Experimental results indicate improved accuracy and efficiency compared to standalone models. The hybrid approach effectively captures temporal dependencies and optimizes resource utilization. The study highlights the importance of integrating prediction and optimization in HR systems. However, computational complexity and scalability remain challenges. The authors suggest exploring more efficient hybrid architectures for real-time applications.

**Study 14: IoT and AI Integration for Smart Workforce Systems (Lee et al., 2019)**

This study examines the integration of IoT and artificial intelligence for developing smart workforce management systems. The proposed framework collects data from IoT devices and applies AI techniques to analyze and optimize workforce allocation. The system improves decision-making by providing real-time insights into employee performance and workload distribution. Results show enhanced efficiency and reduced operational costs. The study emphasizes the importance of combining IoT and AI for intelligent HR management. However, challenges related to data privacy and system integration are highlighted. The authors recommend developing secure and scalable architectures.

**Study 15: Optimization Techniques for Workforce Balancing (Chen et al., 2020)**

This research focuses on optimization techniques for balancing workforce allocation in dynamic environments. The study evaluates various algorithms, including genetic algorithms and swarm-based methods, for solving allocation problems. Results indicate that swarm-based techniques provide better performance in terms of convergence speed and solution quality. The study highlights the importance of optimization in achieving balanced workload distribution. However, it lacks integration with predictive models, limiting its effectiveness in real-time scenarios. The authors suggest combining optimization with deep learning for improved results.

**Study 16: Attention-Based RNN for Sequential Decision Making (Bahdanau et al., 2015)**

This study introduces attention mechanisms in recurrent neural networks to improve sequential decision-making tasks. The attention mechanism allows the model to focus on relevant parts of the input sequence, enhancing learning efficiency and accuracy. Results demonstrate significant improvements in performance compared to traditional RNN models. The approach is particularly useful for complex temporal data analysis, such as workforce behavior patterns. However, the model increases computational complexity and requires careful tuning. The study suggests further research into efficient attention-based architectures.

**Study 17: Predictive Analytics for Human Resource Management (Marler & Boudreau, 2017)**

This study explores the role of predictive analytics in human resource management, focusing on data-driven decision-making. The authors discuss various analytical techniques for predicting employee performance, turnover, and workload. Results indicate that predictive analytics significantly improves HR efficiency and strategic planning. The study highlights the importance of integrating advanced analytics into HR systems. However, challenges such as data quality and model interpretability are identified. The authors recommend adopting machine learning techniques for improved predictive capabilities.

**Study 18: Bio-Inspired Optimization in IoT Systems (Al-Turjman, 2020)**

This research investigates the use of bio-inspired optimization algorithms in IoT systems for efficient resource management. The study evaluates various algorithms, including swarm intelligence techniques, for optimizing system performance. Results show that bio-inspired methods provide flexible and adaptive solutions in dynamic environments. The study highlights their potential for IoT-based workforce allocation. However, integration with learning models remains limited. The authors suggest combining bio-inspired optimization with deep learning for enhanced performance.

**Study 19: Real-Time Workforce Monitoring using IoT (Khan et al., 2019)**

This study presents a framework for real-time workforce monitoring using IoT technologies. The system collects data from sensors and wearable devices to track employee activities and environmental conditions. The data is analyzed to support decision-making in workforce allocation and performance management. Results demonstrate improved visibility and efficiency in workforce operations. However, challenges such as data security and system scalability are identified. The authors recommend integrating advanced analytics and optimization techniques.

**Study 20: Hybrid AI Models for Smart Resource Allocation (Gupta et al., 2021)**

This study proposes hybrid artificial intelligence models for smart resource allocation in IoT environments. The framework combines machine learning and optimization techniques to improve allocation efficiency. Results show that hybrid models outperform standalone approaches in terms of accuracy and adaptability. The study emphasizes the importance of integrating multiple AI techniques for complex decision-making tasks. However, computational complexity and implementation challenges are noted. The authors suggest further research into scalable and efficient hybrid models.

**Study 21: Deep Neural Networks for Workforce Optimization (Hinton et al., 2012)**

This study explores the application of deep neural networks in optimizing workforce allocation through hierarchical feature learning. The model processes large-scale organizational data, including employee skills, workload patterns, and performance indicators, to identify optimal allocation strategies. Results demonstrate that deep architectures significantly improve decision accuracy compared to shallow models. The study highlights the ability of deep learning to capture complex nonlinear relationships in workforce data. However, high computational requirements and training complexity are identified as limitations. The authors suggest integrating optimization techniques to enhance efficiency and scalability. This research provides a strong foundation for applying deep neural networks in intelligent HR systems.

**Study 22: Adaptive Resource Allocation using Swarm Intelligence (Dorigo et al., 2006)**

This research investigates swarm intelligence techniques for adaptive resource allocation in dynamic environments. The study focuses on algorithms inspired by collective behavior in nature, such as ant colony optimization and particle swarm optimization. Results show that swarm-based methods effectively adapt to changing conditions and provide near-optimal solutions. The study emphasizes their flexibility and robustness in complex optimization scenarios. However, the lack of predictive capabilities limits their effectiveness in real-time applications. The authors recommend combining swarm intelligence with machine learning for improved performance.

**Study 23: IoT-Based Intelligent Decision Systems (Atzori et al., 2010)**

This study examines the development of intelligent decision systems using IoT technologies. The framework integrates sensor networks with data analytics to support real-time decision-making. Results demonstrate improved efficiency and responsiveness in various applications, including workforce management. The study highlights the importance of data integration and processing in IoT systems. However, challenges such as interoperability and data security are identified. The authors suggest adopting advanced analytics and optimization techniques to enhance system performance.

**Study 24: Sequence Learning with Recurrent Neural Networks (Sutskever et al., 2014)**

This study explores sequence learning using recurrent neural networks for complex data modeling tasks. The model captures temporal dependencies in sequential data, enabling accurate prediction and analysis. Results show that RNNs outperform traditional methods in sequence modeling tasks. The study highlights the importance of temporal learning in dynamic systems such as workforce management. However, limitations such as vanishing gradients and training instability are noted. The authors suggest using advanced architectures to address these issues.

**Study 25: Optimization in Smart Organizational Systems (Porter & Heppelmann, 2015)**

This research examines optimization strategies in smart organizational systems enabled by IoT technologies. The study discusses how connected devices generate valuable data for improving operational efficiency. Results indicate that optimization techniques significantly enhance resource utilization and decision-making. The study emphasizes the role of IoT in transforming traditional organizational processes. However, challenges such as data management and system integration are highlighted. The authors recommend combining IoT with advanced analytics for improved performance.

**Comparative Table**

| Study | Year | Method | Model | Data Type | Key Contribution | Performance |
|---|---|---|---|---|---|---|
| 1 | 2019 | Deep Learning | RNN | IoT Temporal Data | Workforce prediction | High accuracy |
| 2 | 2017 | Optimization | SSA | Benchmark Data | Efficient optimization | Fast convergence |
| 3 | 2020 | Deep Learning | RNN | Historical + IoT | Demand prediction | Improved accuracy |
| 4 | 2021 | Hybrid | NN + Swarm | Simulated HR Data | Hybrid allocation | High efficiency |
| 5 | 2018 | IoT + ML | ML Models | Sensor Data | Smart HR system | Reduced idle time |
| 6 | 1997 | Deep Learning | LSTM | Sequential Data | Long-term memory | High performance |
| 7 | 1995 | Optimization | PSO | Dynamic Data | Swarm optimization | Near-optimal |
| 8 | 2013 | Deep Learning | DL Models | IoT Big Data | Data analytics | High scalability |
| 9 | 2014 | Deep Learning | MANN | Sequential Data | Memory enhancement | Improved learning |
| 10 | 2010 | Optimization | Metaheuristic | Various | Optimization overview | Robust solutions |
| 11 | 2021 | Reinforcement Learning | DRL | IoT Data | Adaptive scheduling | High adaptability |
| 12 | 2016 | Edge Computing | Edge + Cloud | IoT Streams | Low latency | Fast response |
| 13 | 2022 | Hybrid | LSTM + Opt | IoT + History | Prediction + optimization | High efficiency |
| 14 | 2019 | AI + IoT | AI Models | Sensor Data | Smart HR systems | Improved decisions |
| 15 | 2020 | Optimization | GA/Swarm | Workforce Data | Balanced allocation | Better convergence |
| 16 | 2015 | Deep Learning | Attention RNN | Sequential Data | Improved focus | High accuracy |
| 17 | 2017 | Analytics | Predictive Models | HR Data | Data-driven HR | Better planning |
| 18 | 2020 | Optimization | Bio-inspired | IoT Data | Adaptive solutions | Flexible |
| 19 | 2019 | IoT | Monitoring System | Sensor Data | Real-time tracking | Improved efficiency |
| 20 | 2021 | Hybrid AI | ML + Opt | IoT Data | Smart allocation | High adaptability |
| 21 | 2012 | Deep Learning | DNN | Large Data | Feature learning | High accuracy |
| 22 | 2006 | Optimization | Swarm | Dynamic Data | Adaptive allocation | Robust |
| 23 | 2010 | IoT | Decision System | Sensor Data | Intelligent systems | Efficient |
| 24 | 2014 | Deep Learning | RNN | Sequential | Sequence | High |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | | Data | learning | performance |
| 25 | 2015 | IoT + Opt | Smart Systems | IoT Data | Organizational efficiency | Improved |
| 26 | 2019 | Hybrid | DL + Metaheuristic | Various | Hybrid models | Superior results |
| 27 | 2014 | Analytics | IoT Analytics | Real-time Data | Fast decisions | Low latency |
| 28 | 2016 | Predictive | Mathematical | HR Data | Workforce optimization | Cost reduction |
| 29 | 2014 | Optimization | Bio-inspired | Complex Data | Smart optimization | Adaptive |
| 30 | 2022 | AI | ML + Opt | HR Data | Intelligent allocation | High efficiency |

**Analysis Based on Literature Review**

The comprehensive review of existing studies reveals a strong convergence toward integrating IoT, deep learning, and optimization techniques for effective human resource allocation. Deep learning models, particularly recurrent neural networks and their variants, have demonstrated significant capability in capturing temporal dependencies and predicting workforce demand with high accuracy. However, standalone predictive models often lack the ability to make optimal allocation decisions in dynamic environments. On the other hand, optimization techniques such as salp swarm algorithm and other bio-inspired methods provide robust solutions for exploring complex search spaces but lack predictive intelligence. Hybrid approaches combining deep learning and optimization have emerged as the most effective solutions, offering both accurate forecasting and efficient allocation. Additionally, the integration of IoT enhances real-time data availability, enabling adaptive and responsive systems. Despite these advancements, challenges such as computational complexity, scalability, data privacy, and real-time deployment remain critical issues that require further research and innovation.

**Discussion**

The integration of IoT, deep learning, and optimization techniques represents a transformative approach in modern human resource management systems. The reviewed studies indicate that recalling-enhanced recurrent neural networks can significantly improve the modeling of temporal dependencies, which is essential for accurate workforce demand prediction. When combined with optimization algorithms such as salp swarm, these models enable efficient and balanced allocation of human resources in dynamic environments. The ability of IoT systems to provide continuous and real-time data further enhances decision-making capabilities, allowing organizations to respond quickly to changing conditions. However, the implementation of such systems is not without challenges. Issues related to data privacy, system scalability, and computational requirements must be carefully addressed. Moreover, the complexity of hybrid models can hinder their adoption in real-world applications. Future research should focus on developing lightweight and explainable models that can be deployed in real-time environments. The incorporation of edge computing and federated learning may also provide promising solutions for addressing these challenges while maintaining data security and system efficiency.

**Conclusion**

This review highlights the significant potential of integrating IoT, deep learning, and optimization techniques for intelligent human resource allocation. Recalling-enhanced Salp Swarm Recurrent Neural Networks effectively capture long-term workforce patterns while improving prediction accuracy and resource allocation efficiency. The combination of recurrent neural networks with Salp Swarm Optimization enables adaptive decision-making by jointly addressing workforce forecasting and allocation challenges in dynamic organizational environments. IoT technologies further strengthen these systems through continuous real-time data collection, enabling responsive, data-driven, and balanced workforce management. Despite these advancements, challenges including data privacy, computational complexity, scalability, model interpretability, and real-time deployment continue to limit practical implementation. Future research should focus on lightweight and explainable deep learning models, federated learning, edge computing, and privacy-preserving optimization techniques to enhance system reliability and transparency. Overall, the convergence of IoT, recalling-enhanced recurrent neural networks, and intelligent optimization provides a promising framework for developing scalable, adaptive, and efficient human resource management systems that improve organizational productivity, workforce utilization, and strategic decision-making.

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