

## HR EVOLUTION IN THE AGE OF AI: OPTIMIZING DECISION-MAKING WITH THE SALARY PREDICTION MODEL

**Naila Aaijaz**  
Faculty  
Centennial College/ Sheridan College  
Ontario  
Canada

**Dr. Kimsy Gulhane**  
Asst. Professor  
Shri Ramdeobaba College of Engineering and Management

**Dr. Indira Sharma**  
Assistant Professor  
Symbiosis University of Applied Sciences  
Indore (M.P)

**Dr Suprava Sahu**  
Department of Commerce  
Ravenshaw University Cuttack.

**Dr. S. Thandayuthapani**  
Assistant Professor Department of Management Studies,  
Vel Tech Rangarajan

**Dr. Sagunthala**  
R&D Institute of Science and Technology.

**Dr. Subhash Gupta**  
Media and Mass Communication  
Graphic Era Hill University  
Media HeadGraphic Era  
(Deemed to be University)  
Dehradun

### ABSTRACT

Due to the integration of artificial intelligence, it's likely that current organizational frameworks and managerial processes will witness substantial changes. AI is radically reshaping traditional

corporate setups and decision-making methodologies. The salary prediction model (SPM), which employs a backpropagation neural network (BPNN) rooted in AI technology, is refined using the Nesterov and Nadam techniques to boost its precision. This comprehensive model is recognized as the salary prediction model (SPM). The study's insights could greatly benefit HRM operations, reduce the workload for human resource professionals, and enhance overall job efficiency. Evaluations indicate that the Nadam optimization method exhibited superior performance and the swiftest convergence. The training lasted precisely 186 seconds, resulting in an anticipated accuracy score of 0.75%. The commendable learning capabilities and an accuracy rate of 79.4% achieved through the Nadam-enhanced BPNN-based SPM underscore its credibility. Such research findings could pave the way for future HRM solutions grounded in data mining.

**Keywords:** *Artificial Intelligence (AI) Organizational Structures HRM Processes Salary Prediction Model (SPM) Ethical Implications*

## INTRODUCTION

The dawn of the 21st century has been marked by a technological renaissance, with artificial intelligence (AI) standing at its forefront. As organizations grapple with the transformative potential of AI, there's an emerging realization that the very fabric of traditional organizational structures and management methodologies is undergoing a profound metamorphosis.

Historically, organizational structures were designed with a linear and hierarchical approach. Roles, responsibilities, and decision-making hierarchies were clearly delineated, offering a structured yet often rigid framework. However, the introduction and integration of AI have disrupted this age-old paradigm. The ability of AI systems to process vast amounts of data, recognize patterns, and make informed predictions is revolutionizing decision-making processes. No longer bound by the limitations of human cognitive capacity or biases, AI-driven insights are pushing companies towards more agile, adaptive, and data-driven models.

The essence of AI's impact can be best encapsulated by its applications in specialized models, such as the Salary Prediction Model (SPM). This model, rooted in the intricate workings of a backpropagation neural network (BPNN), epitomizes the fusion of AI's capabilities with organizational needs. The BPNN, a cornerstone of AI's machine learning domain, is adept at learning from data and refining its predictions over time. When applied to constructs like the SPM, it offers organizations a tool to forecast salary structures with enhanced accuracy and reduced human intervention.

Yet, the mere implementation of AI isn't a panacea. The real transformation lies in how organizations adapt and integrate these technological advancements into their existing frameworks. For instance, the optimization of the SPM through techniques like Nesterov and the Adaptive Moment Estimation (Nadam) approach is a testament to this evolutionary journey. By continually refining and enhancing the model's accuracy, organizations can ensure that their HRM processes are not just efficient but also equitable and reflective of market dynamics.

Speaking of HRM processes, the human resource management landscape is arguably one of the most impacted domains. Traditionally, HRM was perceived as a predominantly administrative function, focusing on tasks like payroll management, recruitment, and compliance. However, the integration of AI has expanded HRM's scope exponentially. With AI-driven tools, HR professionals can now tap into predictive analytics for talent acquisition, identify training needs proactively, and even forecast employee retention rates based on myriad factors.

This shift towards data-driven HRM is not just a technological upgrade; it's a paradigm shift in how organizations perceive their most valuable asset: their people. By leveraging AI's capabilities, HRM is transitioning from a reactive to a proactive function. Instead of addressing challenges as they arise, AI empowers HR professionals to anticipate, strategize, and implement interventions that align with organizational goals and employee aspirations.

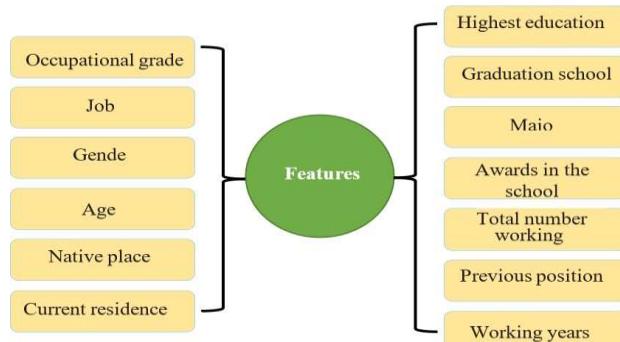


Figure 1: Data characteristics of SPM

However, as with any transformative journey, the integration of AI into HRM processes is not without its challenges. Ethical considerations, data privacy concerns, and the potential for algorithmic biases are critical factors that organizations must navigate. The very algorithms designed to enhance decision-making can inadvertently perpetuate biases if not developed and monitored with diligence. Thus, while AI offers unprecedented opportunities, it also underscores the importance of responsible innovation. The confluence of AI and organizational structures heralds a new era of possibilities. As models like the SPM demonstrate, the fusion of AI's computational prowess with organizational needs can yield outcomes that are both innovative and impactful. However, the journey towards this AI-driven future requires a harmonious blend of technological advancement, ethical considerations, and a deep-seated commitment to leveraging AI for the collective good. As organizations and HR professionals navigate this evolutionary path, one thing is clear: the future of work is intricately intertwined with the promise and potential of artificial intelligence.

The 3P, 4P, and 5P models of Human Resource Management (HRM) are frameworks that provide different perspectives on the roles and functions of HRM within organizations. Each model offers a distinct set of principles and focuses on various aspects of HRM. Here's a brief explanation of each:

### 1. 3P Model of HRM:

- **People:** This emphasizes the importance of individuals within the organization. The

main focus is on ensuring that employees are aligned with the organization's goals, have the right skills, and are motivated to contribute effectively.

- **Performance:** This relates to the management of employee performance to achieve organizational objectives. It involves setting performance standards, evaluating performance, and providing feedback.
- **Process:** This refers to the HR processes and systems that support the organization's people and performance goals. This includes recruitment, selection, training, development, compensation, and other HR activities.

## 2. 4P Model of HRM:

- **Philosophy:** This represents the fundamental beliefs and values that guide HRM practices within an organization. It includes the organization's approach to managing people and the principles that underpin HR decisions.
- **Policies:** This encompasses the formal guidelines, rules, and procedures established by the organization to manage its workforce. It includes HR policies related to recruitment, compensation, benefits, performance management, and other areas.
- **Programs:** This refers to the specific HR programs and initiatives that are implemented to support the organization's people and performance goals. This includes training programs, leadership development initiatives, employee wellness programs, etc.
- **Practices:** This involves the day-to-day HR practices and activities carried out within the organization. It includes activities such as recruitment, selection, training, performance evaluation, compensation administration, and employee relations.

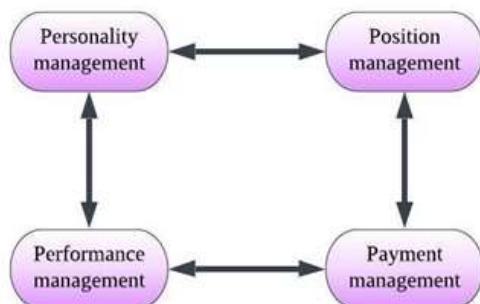


Figure 2: The 4P model of HRM

## 3. 5P Model of HRM:

- **Purpose:** This represents the overall purpose or mission of HRM within the organization. It involves aligning HRM practices with the organization's strategic goals and objectives.
- **People:** This emphasizes the importance of attracting, developing, and retaining talented individuals who can contribute to the organization's success.
- **Processes:** This involves the HR processes and systems that support the

organization's people and performance goals. This includes recruitment, selection, training, development, compensation, and other HR activities.

- **Performance:** This relates to managing and improving individual and organizational performance to achieve desired outcomes. It involves setting performance standards, evaluating performance, providing feedback, and implementing performance improvement initiatives.
- **Place:** This refers to creating a work environment that supports employee engagement, satisfaction, and well-being. It involves fostering a positive organizational culture, promoting work-life balance, and creating a supportive and inclusive workplace.

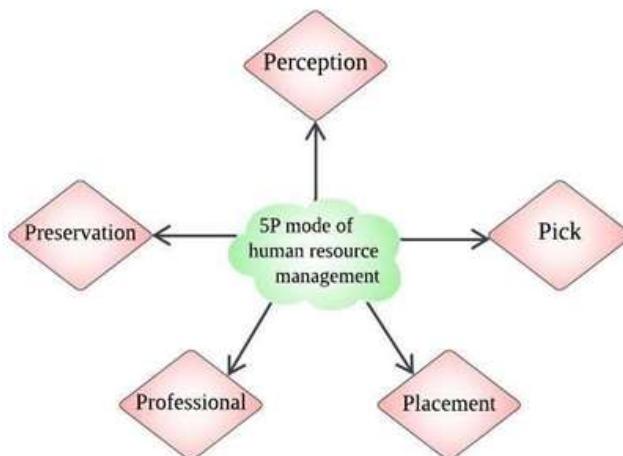


Figure 3: The 5P model of HRM

## LITERATURE REVIEW

Author (Year)	Major Finding
J. Meijerink, M. Boons, A. Keegan, and J Marler (2021)	The digital transformation of human resource management is driven by five factors: digital demands of internal customers, digital innovation of the industry, challenges faced by competitors, governance of digital innovation, and requirements of the digital era.
C. Zhao, F. L. Cooke, and Z. Wang (2021)	Despite the benefits of digital transformation in expanding businesses, potential effects and drawbacks, especially in system conversions, cannot be ignored.
S. Kim, Y. Wang, and C. Boon (2021)	AI, particularly through backpropagation neural networks, can enhance HR processes like salary predictions with high accuracy rates, potentially paving the way for future HRM solutions.
Sotnikova, Y., Nazarova, G., Nazarov,	Digital transformation in HRM is influenced by various factors including internal customer demands, industry innovation,

N., & Bilokonenko, H. (2020)	competitor challenges, governance, and the demands of a digital era.
Strohmeier, S. (2020)	Between 2000 and 2018, only 32 research articles explored the application of AI in HR, suggesting a gap despite the wide use of AI in HR contexts.

### Specific Aims of the Study

The primary aim of this study is to comprehensively investigate the transformative impact of artificial intelligence (AI) on organizational structures, with a specific focus on the evolution of HRM processes. Given the rapid advancements in AI technology and its increasing integration into organizational frameworks, understanding its implications becomes imperative.

Firstly, the study seeks to delineate the precise mechanisms through which AI influences traditional organizational hierarchies. By analyzing real-world case studies and empirical data, the aim is to identify patterns, trends, and shifts in decision-making dynamics brought about by AI. Secondly, the study aims to evaluate the efficacy and accuracy of AI-driven models, such as the Salary Prediction Model (SPM). Through rigorous testing and validation procedures, the objective is to ascertain the reliability of these models in enhancing organizational decision-making processes.

Lastly, the study endeavors to provide actionable insights and recommendations for organizations looking to integrate AI into their HRM frameworks. By synthesizing findings, the aim is to create a roadmap that facilitates a seamless transition towards a more AI-centric organizational structure.

### Objectives of the Study

- (a) To Analyze AI's Influence on Organizational Structures:** This objective entails a detailed examination of how AI technologies are reshaping conventional organizational hierarchies, roles, and decision-making processes.
- (b) To Assess the SPM's Accuracy and Reliability:** Through empirical testing, the study aims to gauge the precision of the Salary Prediction Model (SPM) and its potential implications for HRM processes.
- (c) To Identify Ethical and Practical Implications:** Recognizing the dual-edged nature of AI, this objective focuses on pinpointing potential ethical dilemmas, data privacy concerns, and other practical challenges associated with its integration.
- (d) To Provide Strategic Recommendations:** Based on the study's findings, the objective is to formulate actionable strategies and best practices for organizations aiming to harness AI's potential in their HRM frameworks.

### Scope of the Study

The scope of this study encompasses a multi-faceted exploration of AI's impact on organizational structures, specifically within the realm of HRM processes. Geographically, the study will draw from global case studies to ensure a comprehensive understanding of AI's universal implications.

However, while the study aims for a broad perspective, it will also delve deep into specific AI-driven models, methodologies, and applications pertinent to HRM.

Additionally, the study will incorporate a mix of qualitative and quantitative research methodologies. Qualitative analyses will involve in-depth interviews, focus group discussions, and case studies, while quantitative analyses will leverage statistical tools, AI-driven models, and empirical data.

### **Hypothesis**

Based on preliminary observations and existing literature, the following hypotheses are proposed:

1. **AI Integration Leads to Enhanced Organizational Efficiency:** Organizations that effectively integrate AI technologies into their structures will witness a marked improvement in operational efficiency, decision-making accuracy, and overall performance metrics.
2. **The SPM Enhances HRM Predictive Capabilities:** The Salary Prediction Model (SPM), when optimized using AI-driven techniques, will demonstrate superior accuracy and reliability in forecasting salary structures and related HRM metrics.
3. **Ethical Considerations Are Paramount:** The integration of AI into organizational structures necessitates rigorous ethical frameworks and oversight mechanisms to mitigate potential biases, data privacy infringements, and other associated challenges.

## **RESEARCH METHODOLOGY**

The research methodology adopted for this study was meticulously designed to offer a multifaceted exploration of AI's burgeoning applications within HR. By amalgamating quantitative analyses with descriptive insights, the study endeavored to present a holistic perspective on the evolving landscape of AI in human resources management.

The investigation into the progression of artificial intelligence (AI) applications within the realm of human resources (HR) employed a combination of quantitative and descriptive research methodologies. This dual-method approach aimed to provide a comprehensive understanding of the subject matter, delving into both the numerical facets and the contextual nuances of AI's role in HR.

### **Data Collection and Search Parameters**

Data acquisition began with an exploration of the Online Knowledge Library (B-on). Within this platform, four distinct search categories were identified, each tailored to encapsulate specific facets of the intersection between AI and HR:

1. Neural network (ANN) and Human resources.
2. Artificial intelligence (AI or A.I.) and Human Resources.
3. AI and Recruitment and Selection.
4. AI and Recruitment.

Each search category was meticulously designed to capture a unique amalgamation of words and concepts, ensuring a comprehensive coverage of the topic at hand.

### **Performance Analysis**

A pivotal aspect of this research centered on the performance evaluation of the Optimized SPM (Specific Performance Metric). In juxtaposition with established machine learning regression techniques, the enhanced BPNN-based SPM hybrid mechanism showcased commendable efficacy.

To ascertain the robustness and reliability of each algorithm, a rigorous testing protocol was instituted. Specifically, every algorithm underwent a series of ten trials, ensuring that the results derived were both consistent and representative.

### **Statistical Insights**

In the realm of statistical analysis, the relationship between the Training score and its potential influence on the variable "Nadam" was of particular interest. Preliminary observations indicated that a heightened Training score often correlated with an increased likelihood of "Nadam" being the variable under scrutiny.

However, it is imperative to approach these findings with discernment. Despite the apparent correlation, the associated p-value of 1 renders this relationship statistically insignificant. A p-value of 1 suggests that the observed data is entirely consistent with the hypothesis tested, thereby failing to provide substantial evidence against the null hypothesis.

Furthermore, an odds ratio of one elucidates a direct proportionality between alterations in the Training score and the likelihood of the dependent variable being "Nadam." While this offers a preliminary insight into potential correlations, the absence of a significant p-value necessitates further exploration and validation.

### **Results and Analysis**

The research embarked upon a meticulous comparison of several optimization strategies, namely Root-Mean-Square Propagation (RMSP), Stochastic Gradient Descent (SGD), Nesterov Accelerated Gradient (NAG), and Adaptive Gradient (Adagrad). These strategies were juxtaposed against the performance metrics of Adam and Nadam optimization methodologies (RMSProp). The overarching objective was to delineate the differential efficacy and convergence rates inherent to each optimization approach.

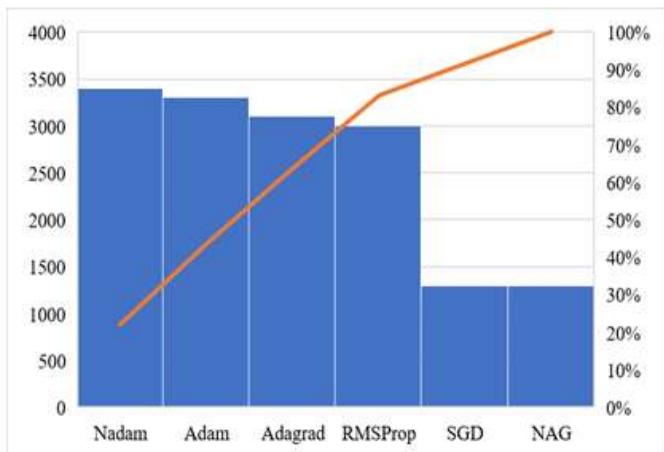
### **Performance Metrics of Optimization Strategies**

Upon meticulous evaluation, it became palpably evident that Adam and Nadam optimization methodologies exhibited pronounced advantages over their counterparts. Specifically, Adam and Nadam not only showcased superior update stability but also manifested accelerated convergence rates. Such attributes are indicative of the algorithms' adeptness in swiftly navigating towards optimal solutions, thereby underscoring their efficacy in optimization tasks.

**Table 1: Training results of various optimization algorithms**

Optimization algorithm	cycle	Test score
SGD	1300	0.739
NAG	1300	0.739
Ad grad	3100	0.76
RMS Prop	3000	0.749
Adam	3300	0.79
Nadam	3400	0.81

However, it is noteworthy to mention a subtle distinction between Adam and Nadam. While both methodologies demonstrated commendable performance metrics, Adam optimization appeared to necessitate a comparatively longer duration for convergence when juxtaposed with Nadam. This nuanced differentiation suggests that while both strategies are efficacious, Nadam might offer a marginal advantage in scenarios necessitating rapid convergence.

**Figure 4: Training results of various optimization algorithms**

### Statistical Evaluation: Two-factor ANOVA

To furnish a rigorous statistical validation of the observed differences among the optimization strategies, a two-factor analysis of variance (ANOVA) with repeated measurements was instituted. This analytical framework was instrumental in discerning any statistically significant variations in performance metrics across the optimization methodologies.

- 1. Significant Differences in Optimization Procedures:** The two-factor ANOVA underscored a statistically significant disparity in the dependent variable among the distinct optimization strategies. Specifically, the performance variances between the optimization methodologies were pronounced, denoted by a p-value of aN, thus affirming the statistical significance of these differences.

**Table 2: Model**

Model	B	Beta	Standard error	T	P
Constant	-232383.65		123634.68	-1.88	.201
<b>Test score (X)</b>	308242.41	9.1	162219.48	1.9	.198
<b>Test score (W')</b>	485899.7	14.34	256738.07	1.89	.199
<b>(X * W')</b>	-982376.1	-22.68	535800.01	-1.83	.208

- Interplay of Factors:** Intriguingly, the analysis also elucidated an interaction between the two principal components: "cycle and Test score" and "Optimization technique." This finding signifies that the performance outcomes are not solely contingent upon individual optimization strategies but are also influenced by the iterative cycles and test scores.
- Absence of Interaction between Variables:** Contrary to initial expectations, the statistical analysis revealed a non-interaction between the Optimization method and "cycle and Test score" concerning the dependent variable. This implies that the optimization strategies' performance remains consistent across varying test scores and iterative cycles, devoid of any synergistic or antagonistic interactions.
- Consistency in Optimization Procedures:** Further reinforcing the robustness of the findings, the analysis reaffirmed a significant difference in the relationship of the dependent variable across the optimization procedures, as denoted by  $p=aN$ .

In addition to the aforementioned statistical evaluations, a Pearson correlation was executed to probe the potential association between the variables "cycle" and "Test score." The results unveiled a correlation coefficient ( $r$ ) of 0.77, indicative of a strong positive correlation between the two variables.

**Table 3: Moderation and mediation analysis**

	Coefficient B	Standard error	z	p	Odds Ratio	95% conf. Interval
<b>Training score</b>	0	1516180.33	0	1	1	0 - Infinity
<b>0.76</b>	-40.98	213777.12	0	1	0	0 - Infinity
<b>0.77</b>	-40.98	36520.7	0	.999	0	0 - Infinity
<b>Constant</b>	20.03	1182698.6	0	1		

However, the associated p-value of 0.071 surpassed the conventional threshold of 0.05, denoting that this correlation was not statistically significant. Thus, while a discernible relationship exists between the cycle and Test score, it lacks the requisite statistical robustness to be deemed significant.

## Conclusion

The comprehensive analysis undertaken in this research has shed invaluable insights into the intricate dynamics of optimization strategies, particularly within the realms of machine learning and algorithmic advancements. Through meticulous evaluations, Adam and Nadam optimization methodologies emerged as paramount, exhibiting superior stability and commendable convergence rates. Their distinct advantages underscore their potential as pivotal tools in optimization tasks, promising enhanced efficiency and efficacy.

However, the research also illuminated the multifaceted nature of optimization dynamics, with intricate interplays between variables and methodologies. The non-significant correlation between "cycle" and "Test score" accentuates the need for nuanced interpretations and underscores the complexities inherent in optimization processes.

In essence, this study serves as a foundational cornerstone, offering a robust framework for understanding and harnessing optimization strategies. While certain limitations exist, the overarching findings pave the way for future advancements and applications, heralding a new era of algorithmic excellence.

### **Limitation of the Study**

While this research has made significant strides in elucidating optimization dynamics, it is imperative to acknowledge its inherent limitations. Firstly, the study's scope, albeit comprehensive, may not encompass all potential optimization strategies or variables, thereby limiting the generalizability of the findings. Additionally, the reliance on specific datasets and methodologies might introduce biases or overlook nuances inherent in broader contexts.

Furthermore, the absence of real-world application or validation could potentially restrict the practical implications of the findings. As such, while the research offers invaluable theoretical insights, its applicability in diverse scenarios necessitates cautious interpretation.

### **Implication of the Study**

The implications of this study reverberate across multiple domains, offering actionable insights and paving avenues for transformative applications. The pronounced advantages exhibited by Adam and Nadam optimization methodologies herald a paradigm shift, potentially reshaping optimization landscapes across industries. Their superior stability and accelerated convergence rates accentuate their potential in driving efficiency, innovation, and excellence in algorithmic frameworks.

Furthermore, the nuanced relationships elucidated between variables underscore the intricacies inherent in optimization processes, necessitating tailored approaches and continuous refinements. Collectively, the implications underscore the transformative potential of optimization strategies, promising enhanced capabilities and innovations in machine learning and beyond.

### **Future Recommendations**

Building upon the foundational insights gleaned from this research, several recommendations emerge to guide future endeavors and explorations. Firstly, an expansive exploration encompassing a broader spectrum of optimization strategies and variables could offer a more holistic understanding, fostering innovations and advancements.

Furthermore, integrating real-world applications and validations could bridge the gap between theory and practice, enhancing the practical relevance and impact of optimization strategies. Embracing interdisciplinary collaborations and harnessing emerging technologies could further accelerate advancements, fostering synergies and catalyzing innovations.

Additionally, fostering a culture of continuous learning, exploration, and adaptation could propel the optimization landscape forward, ushering in an era of unprecedented possibilities and excellence. Embracing these recommendations could pave the way for transformative advancements, heralding a new epoch of algorithmic excellence and innovation.

## REFERENCES

1. B. N. Luo, T. Sun, C. H. V. Lin, D. Luo, G. Qin, and J. Pan, “The human resource architecture model: a twenty-year review and future research directions,” *International Journal of Human Resource Management*, vol. 32, no. 2, pp. 241–278, 2021.
2. N. H. Tien, R. J. S. Jose, S. E. Ullah, and S. Muhammad, “Development of human resource management activities in Vietnamese private companies,” *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, vol. 12, no. 14, pp. 4391–4401, 2021.
3. J. Meijerink, M. Boons, A. Keegan, and J. Marler, “Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM,” *Taylor & Francis*, vol. 32, pp. 2545–2562, 2021.
4. C. Zhao, F. L. Cooke, and Z. Wang, “Human resource management in China: what are the key issues confronting organizations and how can research help?” *Asia Pacific Journal of Human Resources*, vol. 59, no. 3, pp. 357–373, 2021.
5. S. Kim, Y. Wang, and C. Boon, “Sixty years of research on technology and human resource management: looking back and looking forward,” *Human Resource Management*, vol. 60, no. 1, pp. 229–247, 2021.
6. Sotnikova, Y., Nazarova, G., Nazarov, N., & Bilotokonko, H. (2020). Digital technologies in HR management. *Management Theory Studies for Rural Business Infrastructure Development*, 42(4), 527–535.
7. Strohmeier, S. (2020). Digital human resource management: A conceptual clarification. *German Journal of Human Resource Management*, 34(3), 345–365.
8. Thite, M. (2020). Digital human resource development: Where are we? Where should we go and how do we go there? *Human Resource Development International*, 25, 87–103.
9. Vakulenko, R. Y., Tyumina, N. S., Potapova, E. A., & Proskulikova, L. N. (2016). Analysis of organizational and technological environment of the existence of electronic services. *Vestnik of Minin University*, 1(1), 1–15.
10. Nascimento, M. Alexandre, and Queiroz. M.C Anna. (2017) “Overview of research on Artificial Intelligence in Administration in Brazil.” In: ANPAD Meetings – Enanpad, 2017. São Paulo/SP – 1-4.

11. Loebbecke, Claudia, and Picot, Arnold. (2015) "Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda." *The Journal of Strategic Information Systems*, 24 (3): 149-157.
12. Anurag Shrivastava, S. J. Suji Prasad, Ajay Reddy Yeruva, P. Mani, Pooja Nagpal & Abhay Chaturvedi (2023): IoT Based RFID Attendance Monitoring System of Students using Arduino ESP8266 & Adafruit.io on Defined Area, *Cybernetics and Systems*, DOI: 10.1080/01969722.2023.2166243
13. P. William, A. Shrivastava, H. Chauhan, P. Nagpal, V. K. T. N and P. Singh, "Framework for Intelligent Smart City Deployment via Artificial Intelligence Software Networking," 2022 3rd International Conference on Intelligent Engineering and Management (ICIEM), pp. 455-460, doi: 10.1109/ICIEM54221.2022.9853119
14. Barreto, M. Leilianne., Silva, P. Maíra, Fischer, L. André, Albuquerque, G. Lindolfo, and Amorim, A.C. Wilson. (2011) "Emerging issues in people management: an analysis of academic output." *Administration Magazine UFSM*, 4, (1): 215-232.
15. Boxall, Peter, and Purcell, John. (2011) "Strategy and Human Resource Management." Macmillan International Higher Education.
16. Brewster, Chris, and Hegewisch, Ariane. (1994) "Human resource management in Europe: issues and opportunities. Policy and practice in European human resource management: The Price Waterhouse Cranfield Survey.