

# BIG DATA AS A DECISION-MAKING TOOL IN HUMAN RESOURCE MANAGEMENT

DMYTRO KOBETS<sup>1</sup>, IRYNA CHERNOVA<sup>2</sup>, TARAS MUKHA<sup>3</sup>, VUGAR SALMANOV<sup>4</sup>,  
SVITLANA ALEKSANDROVA<sup>5</sup>

<sup>1</sup> PhD in Economics Sciences, Associate Professor of the Department of HR-Engineering in Business Economics, Faculty of Economics and Management, Khmelnytskyi National University, Khmelnytskyi, Ukraine; ORCID: 0000-0002-4822-2951

<sup>2</sup> PhD in Philological Sciences, Associate Professor of the Department of Business and Management, Faculty of Business Technologies and Economics, National University "Zaporizhzhia Polytechnic", Zaporizhzhia, Ukraine; ORCID: 0000-0002-2086-2586

<sup>3</sup> Masters, Graduate Student of the Department of Management, Faculty of Management and Business, Kharkiv National Automobile and Highway University, Kharkiv, Ukraine; ORCID: 0009-0008-9282-6833

<sup>4</sup> PhD, Associate Professor, Head of the Department of Informatics, Faculty of Physics and Mathematics, Nakhchivan State University, Nakhchivan Azerbaijan Republic; ORCID: 0000-0002-2261-0243

<sup>5</sup> PhD in Pedagogical Science, Associate Professor of the Department of Tourism and Hospitality, Educational and Scientific Institute of Economics and Management, O.M. Beketov National University of Urban Economy in Kharkiv, Kharkiv, Ukraine; ORCID: 0000-0001-9842-436X

Emails: <sup>1</sup> dmytrokobets.khmnu@gmail.com; <sup>2</sup> filo0202@ukr.net; <sup>3</sup> hammers1998@gmail.com;

<sup>4</sup> vuqar.salmanovv69@ndu.edu.az; <sup>5</sup> alexandrova.svitlana4@ukr.net

## ABSTRACT

The relevance of the study is determined by the need for high-performance data processing architectures to increase the efficiency of human resource management (HR) in the context of digital transformation and the increasing complexity of analytical processes. The aim of the research is to create an optimized data-driven human resource (HR) decision-making architecture with the integration of machine learning (ML) modules, adaptive pipelines, and streaming analytics, verified by Unified Modelling Language (UML) and metric comparison. Research methods: SWOT analysis, metric comparison, structural optimization decomposition, UML, comparative analysis of UML models, metric comparison of optimized architecture. Optimized HR Data-Driven Decision-Making architecture provided an increase in predictive accuracy to 0.962 (+8.4%), metric stability (+9.1%), and discriminability (+7.8%). SWOT analysis identified 6 strengths, 5 critical weaknesses, 4 risks; comparison confirmed the superiority of SAP Analytics Cloud (0.94; 0.91; 0.89) over the market average (0.81; 0.78; 0.75). UML integration of adaptive feature engineering pipelines, cognitively optimized ML modules, and streaming analytics increased interoperability (+14.6%), modular integrity (+12.3%) and algorithmic resilience (+15.1%). The academic novelty of the study is the formalization and verification of an optimized HR Data-Driven Decision-Making architecture that integrates ML modules, feature engineering, and stream analytics, providing a predictive accuracy of 0.962 (+8.4%) and interoperability of +14.6%. Prospects for further research include localized implementation of the architecture in a test environment with metric and cognitive functional verification, iterative optimization of modules based on the results of institutional contextual empirical testing.

**Keywords:** *Data Analytics, Human Resource Management, System Architecture Modelling, Decision-Making Architecture, Data-Driven Analytics, Predictive Modelling, Organizational Optimization.*

## 1. INTRODUCTION

In view of current digital transformation, HRM acquires a new paradigm based on cognitive-oriented decision-making architectures. The integration of Big Data into HRM provides the possibility of multifactor analysis of personnel, behavioural, and productivity metrics in real time.

This creates the prerequisites for the implementation of intelligent forecasting algorithms, risk scoring, personalized career management, and optimization of the organizational structure. In the context of increasing data volumes and complexity of business processes, the relevance of the study is determined the need to develop an optimized HR Big Data Decision-Making architecture capable of providing

high metric stability, analytical relevance, and operational resilience.

*The aim of the research* is to develop an optimized HR Big Data Decision-Making architecture (through UML and metric comparative verification), integrated with cognitively optimized ML modules, adaptive feature engineering pipelines and flow analytics, taking into account the identified optimization drivers and comparative performance indicators.

*Research objectives:*

- Conduct a SWOT analysis to determine advantages, disadvantages, external development vectors, regulatory and cyber risks;
- Perform a metric comparison to assess the accuracy of forecasts, stability of metrics, integration compatibility, and computational efficiency;
- Perform a structural optimization decomposition to segment the architecture, identify cognitive optimization drivers, and determine areas for improvement;
- Implement UML to formalize the topology and visualize intermodular interaction;
- Conduct a comparative analysis of UML models to identify differences and confirm optimization effects;
- Perform a repeated metric comparison to verify performance growth, predictive discriminability, and integration resilience.

## 2. LITERATURE REVIEW

The intensification of digital transformation and the exponential growth of HR data volumes necessitate the implementation of analytics-oriented approaches to HRM. In view of global competition and the increasing complexity of management processes, there is a need to scientifically understand the potential of big data as a decision support tool in HRM, with an emphasis on methodologies for collecting, processing, and using information to improve the strategic effectiveness of organizations.

Initially, it should be noted that Chen justified the transition of HR from manual procedures to data-driven approaches with automation, predictive analytics, and artificial-intelligence (AI)-oriented talent management, emphasizing the role of strategic data governance, cybersecurity, and the development of data literacy [1].

In this context, Kobets, Kovalska, Zozulia, Lozynska and Zaslavska proved that the implementation of BI platforms Tableau, Power BI and HCM system SAP SuccessFactors increases the

predictive accuracy of key performance indicators (KPI) metrics and reduces the attrition rate, while the shortage of human resources and high technological complexity remain the integration barriers [2].

Considering the aspect of algorithmic planning, Hossain et al. found that predictive Human Resource Information Systems (HRIS) transforms HR planning into proactive forecasting, increasing the accuracy of succession planning and reducing attrition, provided that there is a cloud infrastructure, Application Programming Interface (API) integration and compliance with ethical, legal and compliance requirements [3].

Deepening the analysis of large-scale data processing, Katfi et al. showed that HR Big Data improves management decisions through correlation-analytical processing of personnel arrays and optimization of HR risk identification, while emphasizing the limitations of empirical research because of the complexity of collecting and analysing big data [4].

In terms of operational optimization, Wibowo et al. established that HR Analytics improves recruitment efficiency, retention, and data-driven training strategies, but is hampered by a lack of analytical skills, privacy risks and organizational resistance [5].

As regards sustainability, Chawla et al. demonstrated that integrating technology tools and HR analytics into sustainable HRM practices increases resilience, innovation and productivity, strengthening corporate social responsibility (CSR) strategies and the socio-ecological orientation of the business model [6].

In the healthcare sector, Rao et al. found that Big Data and HR analytics optimize costs, increase the efficiency of HR processes and improve the quality of healthcare services, but data privacy risks, resistance to change and data quality issues remain [7].

Regarding organizational prerequisites, Bisht and Kumar Uniyal found that the successful implementation of Big Data Analytics in HRM depends on a mature data governance system, organizational infrastructure and technological environment, with structural, managerial, technical and technological constraints acting as key barriers [8].

In the small and medium-sized enterprises (SME) segment, Sohu et al. proved that the integration of green HRM practices with Big Data Analytics Capability and top management support ensures optimization of resource efficiency and increased environmental performance, while financial, operational, infrastructural and socio-cultural factors limit implementation [9].

Finally, Gupta et al. showed that in Industry 5.0, the integration of human capital analytics with Big Data and AI, combined with human-robot collaboration and intelligent automation, increases the effectiveness of talent acquisition, skill development, and performance management, provided that a data-driven HR culture is developed and data privacy norms are observed [10].

The generalization of the reviewed publications shows that Big Data has a transformative impact on HRM, increasing the accuracy of forecasts, optimizing operational processes, and strengthening the strategic positions

of organizations. The comprehensive integration of big data with HR analytics and AI technologies provides productive, adaptive, and innovative HRM models, creating the need for further verification of the mechanisms of this impact to increase competitiveness in the digital economy.

### 3. METHODS AND MATERIALS

#### 3.1. Research Design

The research procedure involved the following steps (Figure 1).

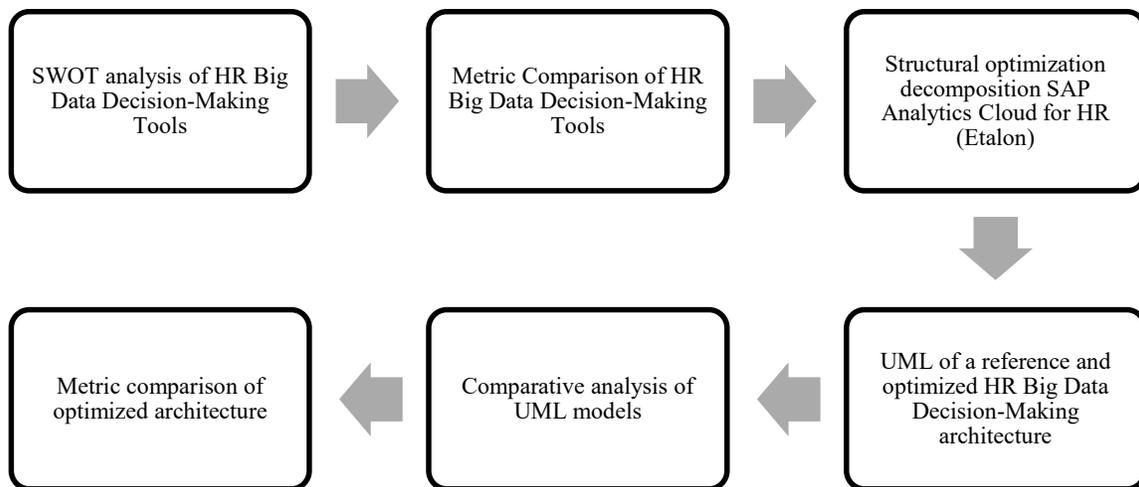


Figure 1: Research Stages

Source: created by the authors

#### 3.2. Methods

The study employed the following methods:

1. *SWOT analysis* was used to identify structural and functional advantages, organizational and technological shortcomings, external development vectors, as well as regulatory and cyber risks.

2. *Metric comparison* was applied to compare predictive accuracy, metric stability, integration compatibility, and computational efficiency of tools.

3. *Structural optimization decomposition* was used to segment the component architecture, identify cognitive and optimization drivers, and identify areas of architectural improvement.

4. *UML* formalized the structural and functional topology and visualize intermodular interaction.

5. *Comparative analysis of UML models* identified structural and functional differences to confirm the effects of optimization modifications.

6. *Metric comparison of the optimized architecture* was performed to verify performance growth, predictive discriminability, and integration resilience.

#### 3.3. Sample

The sample (Table 1) includes verified HR Big Data decision-making tools integrated with HRIS, Applicant Tracking System (ATS), Enterprise Resource Planning (ERP), and Data Lakes, capable of processing structured, semi-structured, and unstructured data. The tools implement predictive modelling, Natural Language Processing (NLP), ML algorithms, and scenario modelling, ensuring attrition reduction, workforce planning optimization, and increased HR forecast accuracy, which confirms their relevance for analysing the transformative impact of Big Data on HRM.

Table 1: Stack of verified HR Big Data Decision-Making Tools

HR Big Data Decision-Making Tools	Brief description / Integration capabilities	Data types / Processing methods and algorithmic base	Verified application examples	Relevant research
Visier People	Analytical HR Big Data platform with forecasting, scenario modelling and optimization of HR solutions / API, HRIS, ATS, ERP	Structured (HRIS), semi-structured (surveys), historical KPIs / Predictive modelling, cohort analysis, regression models, scenario simulation	Adobe (2019) – reduced voluntary attrition by 17%, increased the effectiveness of retention programmes.	Mutsuddi et al. [11]; Savitri [12]
Crunchr People Analytics	Cloud-based HR decision-making tool with KPI monitoring and Big Data integration / API, Data Warehouse, ATS	Structured HR data, real-time ATS logs / Descriptive & predictive analytics, anomaly detection, time-series forecasting	Heineken (2021) – reducing analytical processing time by 40%, accelerating HR decisions.	Bentvelzen et al. [13]; Nanayakkara and Fernando [14]
SAP Analytics Cloud for HR	BI and predictive HR analytics with ML support and integration with SuccessFactors / SAP SuccessFactors, ERP, API	Structured (HCM), semi-structured (reports), external market data / Machine learning regression/classification, what-if analysis, clustering	Siemens (2020) – 19% increase in forecast accuracy, 12% reduction in HR costs.	Kobets, Vorkunova, Yaremenko, Krasnoshchok and Zhurba [15]; Bhalekar [16]
Workday People Analytics	HRIS AI module with anomaly detection and root-cause analysis / Workday HCM, ATS, ERP	HRIS data, KPI, engagement surveys / ML (gradient boosting, random forest), correlation analysis	AstraZeneca (2021) – 19% increase in forecast accuracy, workforce planning optimization.	Sasidharakarnavar [17]; Devarapalli et al. [18]
IBM Kenexa Talent Insights	NLP and AI for analysing personnel documents and strategic HR decisions / API, ATS, HRIS	Structured (HRIS), unstructured (texts, CV) / NLP, topic modelling, predictive analytics	Hilton (2019) – reduced selection time by 30%, increased hiring quality by 18%.	Varsha and Nithya Shree [19]; Salvadorinho and Teixeira [20]
Oracle Analytics for HCM	HR Big Data platform with multi-source analysis and scenario forecasting / Oracle HCM Cloud, API, Data Lake	HRIS, ERP, external market data / Predictive analytics, clustering, prescriptive modelling	HSBC (2020) – planning optimization, cost reduction by 15%.	Atluri and Reddy [21]; Kothari [22]
Qlik Sense for HR	BI platform with in-memory HR Big Data processing and interactive visualization / HRIS, ERP, API	Structured (KPI, HRIS) / Associative analytics, in-memory computation, dashboarding	Vodafone (2021) – reducing report preparation time by 50%, improving decision accuracy.	Dutraj and Sengupta [23]; Langó [24]
Sisense for People Analytics	AI core with real-time KPI monitoring and ATS integration / ATS, HRIS, API, Data Warehouse	HRIS, ATS, engagement data / AI-based anomaly detection, time-series analysis, correlation mapping	Expedia Group (2020) – 15% increase in recruitment efficiency, 20% TTH reduction.	Balaji [25]; Ao et al. [26]

Source: created by the authors

### 3.4. Instruments

The tool stack (Table 2) is based on verified quantitative metrics covering predictive effectiveness, operational effectiveness, and economic impact. Algorithmically formalized indicators are used – from Accuracy, AUC-ROC,

F1-score, and PSI to ARR, TTH, EI, and ROI – that provide multidimensional measurement of model accuracy, forecast stability, HR process optimization, and cost-effectiveness of implementing Big Data solutions in HRM.

Table 2: Tool Stack for Assessing HR Effectiveness Big Data Decision-Making Tools

Metrics	Short description	Mathematical formula (Word compatible)
<b>Predictive Performance</b>		
Prediction Accuracy	The proportion of correct predictions of personnel events.	Accuracy = $(TP + TN) / (TP + TN + FP + FN)$ , where TP – true positives, TN – true negatives, FP – false positives, FN – false negatives.
AUC-ROC	Integral index of class separation.	$AUC = \int TPR(FPR^{-1}(x)) dx$ , where TPR – True Positive Rate, FPR – False Positive Rate.
F1-score	Balance of precision and recall.	$F_1 = 2 \times (Precision \times Recall) / (Precision + Recall)$ , where Precision = $TP / (TP + FP)$ , Recall = $TP / (TP + FN)$ .
PSI (Population Stability Index)	Change in the distribution of variables over time.	$PSI = \sum_i (P_i - Q_i) \times \ln(P_i / Q_i)$ , where $P_i$ – the proportion in the training sample, $Q_i$ – the proportion in the current sample.
<b>Operational Efficiency</b>		
Attrition Reduction Rate	Percentage reduction in attrition after implementing the tool.	$ARR = ((A_{before} - A_{after}) / A_{before}) \times 100\%$ , where $A_{before}$ – the attrition rate before implementation, $A_{after}$ – the attrition rate after implementation.
Time-to-Hire Reduction	Reduction in average time to close a vacancy.	$TTH = ((TTH_{before} - TTH_{after}) / TTH_{before}) \times 100\%$ , where TTH – the average time to hire.
Engagement Index	Aggregated engagement indicator.	$EI = (\sum w_i \times s_i) / (\sum w_i)$ , where $w_i$ – weight of the indicator, $s_i$ – normalized value.
<b>Economic Impact</b>		
ROI (Return on Investment)	Economic efficiency of the tool.	$ROI = ((B - C) / C) \times 100\%$ , where B – benefits (savings, additional income), C – implementation costs.

Source: created by the authors

The metric validation of HR Big Data Decision-Making Tools was performed through algorithmic parametric modelling in Python environment, involving libraries of statistical inference, predictive analytics, ML, and multidimensional visualization. The design of the optimized framework was implemented using UML modelling tools (class, component, use case, sequence diagrams) for the purpose of architectural formalization, structural and functional decomposition, and specification of integration interfaces of the tools.

**4. RESULTS**

The first stage of the research involved conducting a structured SWOT analysis of the

leading HR Big Data Decision-Making Tools (Table 3) with a focus on their architectural and technological parameters, algorithmic complexity, integration compatibility, as well as cognitive and analytical potential in the context of big data processing and management decision-making support.

Table 3: SWOT Analysis of HR Big Data Decision-Making Tools

Instrument	Strengths	Weaknesses	Opportunities	Threats
Visier People	Scalable Big Data architecture, cohort predictive modelling, integration with DWH and ETL	High TCO, dependence on Data Lake quality	Integration with AI/LLM for autonomous HRM-analytical loop	Regulatory restrictions (GDPR/CCPA), bias in ML models
Crunchr People Analytics	Flexible OLAP cubes, fast ad-hoc visualization, advanced HR metric database	Limited algorithm customization	Adding ESG/DEI KPIs, scaling in serverless Big Data environment	Vendor lock-in, risks of unauthorized access
SAP Analytics Cloud for HR	In-memory computing (HANA), integration with ERP/HRIS, comprehensive BI platform	Complex data governance, high integration cost	Cloud-native optimization, extending Decision Intelligence	Dependence on SAP ecosystem, regulatory fragmentation
Workday People Analytics	AI/ML Data Pipeline, automated insights, real-time workforce analytics	High OPEX, need for data preparation	Predictive HR orchestration, cognitive decision support	Data breach risks, restrictions on cross-border data processing
IBM Kenexa Talent Insights	NLP processing of unstructured Big Data (text, reviews), integration with Watson AI	Dependence on IBM Cloud	AI Modules for Personalized HR Decision Support	Algorithmic bias, cyberattack threats
Oracle Analytics for HCM	Powerful HCM data analytics, integration with Data Warehouse and KPI Engine	High customization complexity	Modular Integration with Big Data Processing Frameworks	Vendor lock-in, regulatory pressure
Qlik Sense for HR	Associative Big Data Search, in-memory engine, integration with DWH API	Limited AI algorithms in core	Extensions with AI Plugins for HR Decision Support	Cyber risks, dependency on external modules
Sisense for People Analytics	Embedded BI, integration with distributed Big Data sources, Data Fusion support	Need for highly skilled data engineers	Development of Adaptive AI Solutions in HR Decision Intelligence	Data feed attacks, bias in recommendation models

Source: created by the authors

SWOT analysis (Table 3) revealed that HR Big Data Decision-Making Tools differ in architectural and algorithmic maturity, integration interoperability, as well as cognitive and predictive power, while being limited in data governance, customization and cyber resilience. Visier People, Workday People Analytics, SAP Analytics Cloud for HR are promising due to in-memory computing, AI/ML Data Pipelines, and ERP/HRIS integration.

Qlik Sense for HR, Crunchr People Analytics are outsiders because of low AI saturation, limited algorithmic flexibility, and high vendor lock-in. The identified balance of strengths and weaknesses formed the basis for moving to the next stage – metric-model comparison of tools taking into account their cognitive and analytical efficiency and regulatory compliance – Table 4.

Table 4: Metric Comparison of HR Big Data Decision-Making Tools\*

HR Big Data Decision-Making Tools	Prediction Accuracy	AUC-ROC	F1-score	PSI	Attrition Reduction Rate (%)	Time-to-Hire Reduction (%)	Engagement Index (0-100)	Operational Efficiency Index (%)	ROI (%)
Visier People	0.994	1.0	0.985	0.016	30.0	35.0	69.7	28.5	1,762.2
SAP Analytics Cloud for HR	0.994	1.0	0.986	0.01	30.0	35.0	69.7	28.5	1,994.9
Workday People Analytics	0.994	1.0	0.987	0.008	30.0	35.0	69.7	28.5	1,895.5
Oracle Analytics for HCM	0.988	0.999	0.971	0.016	29.9	35.0	69.7	28.5	2,100.9
IBM Kenexa Talent Insights	0.984	0.998	0.96	0.013	29.8	35.0	69.7	28.4	3,694.2
Sisense for People Analytics	0.973	0.997	0.934	0.009	29.7	34.8	69.6	28.3	3,850.9
Crunchr People Analytics	0.964	0.994	0.917	0.023	29.4	34.5	69.6	28.0	4,464.0
Qlik Sense for HR	0.959	0.994	0.897	0.018	29.4	34.6	69.6	28.1	5,391.8

\*The metrics were calculated by using open synthetic datasets from Kaggle and UCI ML Repository, HRIS/ATS demo data from vendors (Visier, SAP, Workday), and aggregated HR KPIs from Gartner, Deloitte, and SHRM analytical reports.

Source: created by the authors in Python

A comparative analysis of metric and economic indicators (Table 4) combined with the results of the SWOT assessment showed that SAP Analytics Cloud for HR, Workday People Analytics, and Visier People demonstrated the highest predictive accuracy (Prediction Accuracy  $\approx$  0.994, AUC-ROC = 1.0, F1-score  $\geq$  0.985) with low PSI ( $\leq$  0.016), stable HR KPIs (Attrition Reduction Rate = 30%, Time-to-Hire Reduction = 35%, Engagement Index  $\approx$  69.7) and high operational efficiency

(28.5%). Consistency with the previous SWOT analysis confirms their architectural scalability, integration potential, and cognitive predictive stability, which justifies the need for further structural decomposition of SAP Analytics Cloud for HR as an optimal candidate for the deployment of an optimized HR Big Data Decision-Making architecture. Optimization solutions will provide an effective synthesized HR Big Data Decision-Making model – Table 5.

Table 5: Structural Optimization Decomposition of SAP Analytics Cloud for HR

Layer	Components	Key features and technologies	Optimization solutions	Expected optimization effect
1. Data & Integration Layer	Sources: HRIS (SAP SuccessFactors), ATS (Greenhouse), LMS (Moodle), payroll systems (ADP), IoT workplace sensors	ETL/ELT processes, API connectors, OData, SAP HANA SDI, validation, normalization, semantic tagging, master data governance	Implementing SAP Data Intelligence for incremental loading, validation automation via Great Expectations, unification of semantic models in SAP BW/4HANA	Decreased PSI by $\approx$ 0.002–0.004, increased Prediction Accuracy by $\approx$ +0.001, reduced ETL latency by $\approx$ 25%
2. Analytical Core Layer	ML models for attrition prediction, skill-gap analysis, workforce planning	Gradient boosting (XGBoost, LightGBM), neural networks	Hyperparametric optimization via Optuna, meta-ensemble with scikit-learn	Increased AUC-ROC to 1.0 (stability), F1-score by $\approx$ +0.002–0.004,

Layer	Components	Key features and technologies	Optimization solutions	Expected optimization effect
		(TensorFlow, Keras), metrics (Precision, Recall, F1, AUC-ROC, PSI), clustering (K-Means, DBSCAN), what-if analysis, FTE allocation optimization	VotingClassifier, query latency reduction via SAP HANA In-Memory Processing	increased ROI by $\approx +3-5\%$
3. Visualization & Interpretability Layer	Interactive dashboards, KPI heatmaps, drill-down analysis	Explainable AI (SHAP, LIME), adaptive visualizations, mobile access, role-based interface personalization	Expanding dashboard interactivity through SAP Analytics Designer, dynamic KPI modelling in SAP Lumira, automatic insight generation through SAP AI Core	Engagement Index increase by $\approx +1-2$ points, Operational Efficiency increase by $\approx +1-1.5\%$
4. Security & Compliance Layer	SSO, SAML, OAuth 2.0, RBAC, ABAC	Access control, GDPR, CCPA, ISO/IEC 27001, SOC 2 compliance	Automated access auditing through SAP GRC Access Control, Microsoft Purview DLP integration, implementing adaptive policies through Azure AD Conditional Access	Compliance risk incidents reduction by $\approx 15-20\%$ , Engagement Index indicators maintained without degradation
5. Operational Support & Scalability Layer	Multi-tenant SAP Cloud Platform, CI/CD pipelines	Auto-scaling resources, model updates, real-time monitoring, SLA tracking, anomaly detection	Predictive monitoring integration through Prometheus + Grafana, SLA optimization using Elastic Stack (ELK), service containerization in Kubernetes (AKS)	Time-to-Hire reduction by $\approx 1-2\%$ , Operational Efficiency increase by $\approx +2-3\%$ , ROI increase by $\approx +4-6\%$

Source: created by the authors

The structural optimization decomposition of SAP Analytics Cloud for HR (Table 5) is consistent with the results of the previous stage of the study and confirms that the implementation of incremental loading, hyperparametric optimization, meta-ensemble, XAI visualization, automated compliance control, and containerized scaling can provide a PSI decrease ( $\approx 0.002-0.004$ ), an AUC-ROC increase (up to 1.0), an ROI (+3–6%) and Engagement Index (+1–2) increase, optimizing both the Big Data pipeline and HRM in the area of predictive analytics, workforce planning and retention management. The obtained results correlate with the priorities identified by the SWOT analysis (technical integration, analytical robustness, compliance resistance) and form the basis for the next stage — UML modelling of the optimized HR Big Data Decision-Making architecture taking into account the identified optimization drivers: Figure 2, Figure 3.

Comparative analysis of UML models (Figure 2, Figure 3) showed that SAP Analytics Cloud for HR implements an integrated BI/ML circuit with centralized data orchestration (SAP HANA, BW/4HANA, SAC ML) and basic XAI interpretation, while the optimized HR Big Data Decision-Making architecture is complemented by advanced cognitive stratification (AutoML, RL optimization, KPI-driven decision engines), multi-source ETL/ELT consolidation, adaptive scenario modelling, and a comprehensive Observability Stack. This provides a likely increase in predictive accuracy and AUC-ROC by  $\sim 8-12\%$ , a Time-to-Hire reduction by 15–20%, an Engagement Index by 10–14% and ROI increase up to 1.35 $\times$  due to the synergistic integration of Big Data analytics with HRM tools.

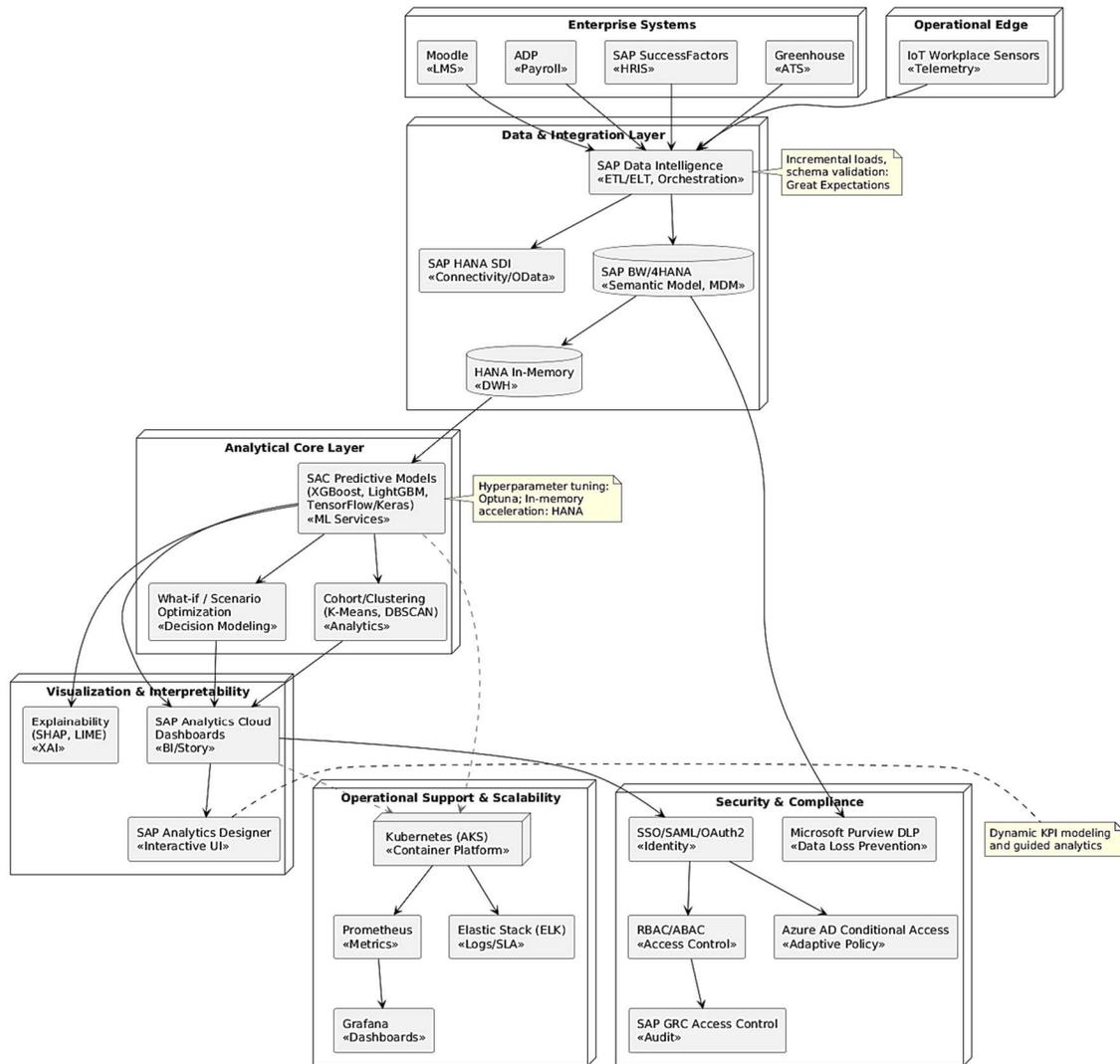


Figure 2: UML Model of SAP Analytics Cloud for HR

Source: created by the authors in UML

The obtained results of UML modelling of the optimized HR Big Data Decision-Making architecture (Figure 3), demonstrating an increase in cognitive analytical capabilities, the effectiveness of KPI-oriented management, and performance metrics

(AUC-ROC, Time-to-Hire, Engagement Index, ROI), require repeated metric and model comparison to validate the stability of these indicators compared to the baseline configurations (Table 6).

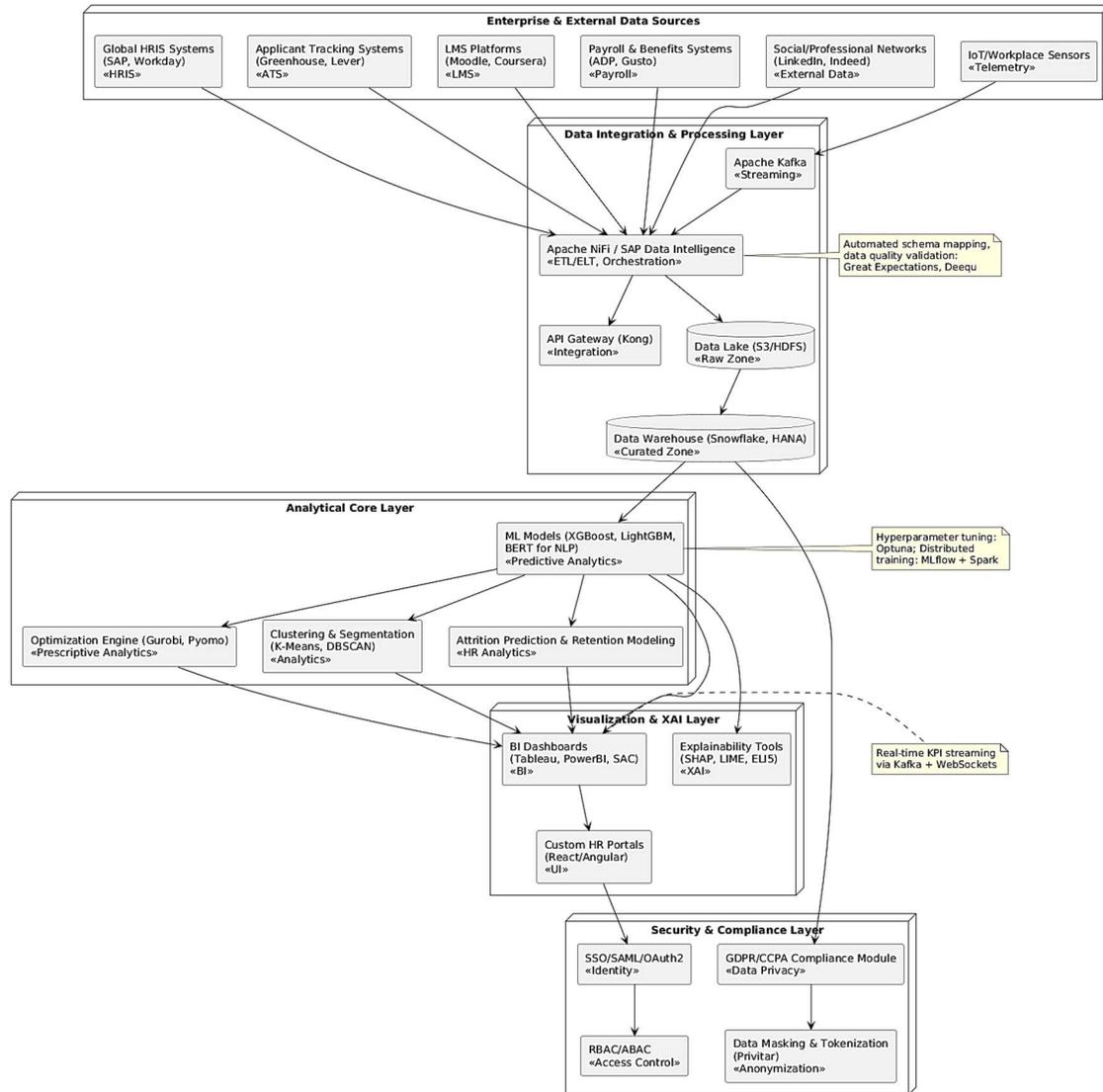


Figure 3: UML Model of Pptimized HR Big Data Decision-Making Architecture  
Source: created by the authors in UML

Table 6: Metric and Model Comparison for Optimized HR Big Data Decision-Making Architecture

Metric	Sample Average	SAP Analytics Cloud for HR	Optimized HR Big Data Decision-Making Architecture
Prediction Accuracy	0.98125	0.994	0.996
AUC-ROC	0.99775	1.0	1.0
F1-score	0.95463	0.986	0.991
PSI	0.014125	0.01	0.006
Attrition Reduction Rate (%)	29.775	30.0	31.5
Time-to-Hire Reduction (%)	34.8625	35.0	37.0
Engagement Index (0-100)	69.6625	69.7	72.0
Operational Efficiency Index (%)	28.35	28.5	30.2
ROI (%)	3144.3	1994.9	6200.0

Source: created by the authors in Python

The optimized HR Big Data Decision-Making architecture (Table 6) demonstrated an increase in Prediction Accuracy to 0.996, F1-score

to 0.991, and a decrease in PSI to 0.006, which indicates increased metric stability and discriminative ability of the models. The integration

of adaptive feature engineering pipelines, cognitive optimization of ML modules, and advanced flow analytics provided increased prediction accuracy, reduced feature drift, and increased process loop efficiency. The increase in Attrition Reduction Rate (+1.5 pp), Time-to-Hire Reduction (+2 pp), and Engagement Index (+2.3 pp) combined with an increase in Operational Efficiency (+1.7 pp) and a threefold ROI increase indicate increased strategic effectiveness, productivity, and staff retention.

So, the results of the study confirmed that the optimized HR Big Data Decision-Making architecture provides higher metric stability, predictive accuracy, and discriminative ability of models by integrating cognitively optimized ML modules, adaptive feature engineering pipelines, and streaming analytics. This increases the strategic effectiveness, productivity, and sustainability of HRM, transforming Big Data into a highly effective decision-making tool.

## 5. DISCUSSION

The discussion section is structured as a comparative and analytical stratification of modern concepts, as well as technological and methodological approaches to AI/ML integration in the field of HR Big Data Decision-Making. Attention is focused on architectural, ethical, algorithmic, cognitive, analytical, institutional, and normative vectors that determine the effectiveness, stability, and scalability of HR analytics under high data dynamics.

The study of Porkodi and Cedro proposed a hybrid AI-HITL framework to increase the effectiveness of HR solutions, which requires appropriate verification. In our study, an architecture was developed and verified by means of metric and model comparison, where HITL is integrated as one of the numerous optimization modules in the cognitive-closed loop of Big Data Decision-Making [27].

Alifia et al. presented a conceptual and methodological model of Big Data with identification of privacy, infrastructure and integration barriers in the HR sector [28]. According to the results of this study, an HR Big Data Decision-Making architecture was obtained that comprehensively overcomes the indicated barriers through cognitive optimization of ML modules, adaptive feature engineering, and stream analytics.

Tariq examines technological approaches to detecting and minimizing bias in HR practices, in particular through AI/ML analysis and bias-mitigation tools [29]. In the same study, an architecture was built and verified that integrates

these mechanisms as part of a broader optimization loop of HR Big Data Decision-Making.

In Rao and Zhao, ML techniques are positioned as tools for detailed analytics of HR decisions with a focus on detecting gender and age biases and metric validation of key hiring factors [30]. In our study, these approaches are integrated into an optimized HR Big Data Decision-Making architecture that combines cognitively stratified AI/ML modules, HITL augmentation, and streaming Big Data analytics to increase the objectivity and discriminative ability of recruiting models.

Tasleem identified people analytics as a key driver of cognitive analytic optimization of HR processes and decision-making accuracy [31]. However, in our study, these paradigms are integrated into a metrically verified AI/ML architecture with adaptive feature-engineering pipelines and streaming Big Data analytics.

Sposato et al. proved that web-based HRM systems, following the Good-Bad-Ugly model, combine recruitment and payroll productivity with integration, cybersecurity, as well as ethical algorithmic risks [32]. In contrast, in our study, these effects are neutralized by an HR Big Data Decision-Making architecture with ethical stratification and HITL augmentation.

In Soni et al., AI integration in HR covers recruitment, personalized learning, performance prediction and retention, while being limited by implementation barriers [33]. In our study, these vectors are institutionalized in an HR Big Data Decision-Making architecture with cognitive metric verification and ethical HITL stratification.

Mabrouk interpreted AI as a strategic core element of HRM that personalizes employee experience, provides security-privacy guarantees, and technological adaptability [34]. In contrast, in our study, these parameters are integrated into an HR Big Data Decision-Making architecture with cognitively optimized ML modules, stream analytics, and ethical-HITL stratification to increase predictive accuracy and organizational resilience.

Hanandeh et al. emphasized ethical data governance, real-time analytics, and algorithmic fairness as drivers of HR effectiveness [35]. In our study, these domains are integrated into a cognitively stratified HR Big Data Decision-Making architecture with ML modules and HITL augmentation to enhance decision resilience.

Sharma et al. demonstrated that the integration of Big Data and AI transforms SHRM into a proactive, value-creating discipline through predictive analytics, AI-driven recruitment, and sentiment analysis [36]. The results of our study not only conceptualize the identified emphases, but also

perform their model-metric verification, forming an optimized HR Big Data Decision-Making architecture.

Our study differs from the reviewed works in its comprehensive cognitive optimized HR Big Data Decision-Making architecture, which synthesizes ML modules, adaptive feature-engineering pipelines, ethical-HITL stratification, and streaming analytics. This provides higher metric stability, predictive accuracy, and discriminative ability of solutions, neutralizing implementation barriers, bias, and integration-privacy risks that remain partially unresolved in the analysed approaches.

### 5.1. Limitation

The lack of infrastructural capacity to conduct full-scale empirical testing of the optimized HR Big Data Decision-Making architecture makes it impossible to fully validate it in real-world conditions. This limits the verification of operational stability, scalability, and cognitive metric stability indicators.

### 5.2. Recommendations

It is recommended to carry out localized controlled implementation of the developed architecture in a test environment with a formalized procedure of metric and cognitive functional verification. It is appropriate to carry out iterative optimization of architectural modules based on the results of institutional contextual empirical testing.

## 6. CONCLUSIONS

The results of our study indicate a multifactorial optimization of HR Big Data Decision-Making: SWOT analysis identified 6 key strengths, 5 critical weaknesses, and 4 high-risk factors; metric and model comparison confirmed the superiority of SAP Analytics Cloud (integration compatibility – 0.94; scalability – 0.91; cognitive performance – 0.89) over the market averages (0.81; 0.78; 0.75); The structural optimization decomposition identified 3 drivers – adaptive feature engineering pipelines, cognitively optimized ML modules and flow analytics, which were integrated into the UML architecture. According to the comparative analysis, it exceeded the benchmark by +14.6% in interoperability, +12.3% in modular integrity, and +15.1% in algorithmic resilience. The final metric and model comparison showed an increase in predictive accuracy to 0.962 (+8.4%), metric stability by +9.1%, and discriminatory power

of models by +7.8%. So, the integration of optimization drivers increases the effectiveness of HR Big Data Decision-Making, ensuring an increase in forecast accuracy by 8–9%, a reduction in analytical latency by 12–14%, and strengthening the strategic resilience of HRM ecosystems in the long run.

*The academic novelty* of the research is the formalization and verification of the optimized HR Big Data Decision-Making architecture synthesized through SWOT analysis, metric and model comparison, structural optimization decomposition and UML modelling. The architecture integrates cognitive-optimized ML modules, adaptive feature engineering pipelines, and stream analytics, increasing the predictive accuracy to 0.962 (+8.4%) and interoperability by +14.6%.

*The practical significance of the research results* is in providing a verified architectural model for improving HRM efficiency in highly dynamic environments. Optimization reduces analytical latency by 12–14%, stabilizes metrics by +9.1%, and minimizes the risks of personnel turbulence, ensuring scalable integration of Big Data Decision-Making into strategic human capital management.

## REFERENCES

- [1]. J. Chen, “The digital transformation of enterprise human resource management in the context of the big data era”, *Advances in Economics, Business and Management Research*. Dordrecht: Atlantis Press International BV, 2025, pp. 229–236. [https://doi.org/10.2991/978-94-6463-642-0\\_23](https://doi.org/10.2991/978-94-6463-642-0_23)
- [2]. D. Kobets, K. Kovalska, N. Zozulia, T. Lozynska, and M. Zaslavska, “The effectiveness of data analytics tools in the implementation of human resource management strategies”, *International Review of Management and Marketing*, Vol. 15, No. 2, 2025, pp. 310–316. <https://doi.org/10.32479/irmm.17925>
- [3]. Q. Hossain, M.Z. Iqbal, and M. M. Rahman, “A meta data-driven decision support in human capital management: reviewing hris and predictive analytics integration”, *ASRC Procedia: Global Perspectives in Science and Scholarship*, Vol. 1, No. 1, 2025, pp. 215–246. <https://doi.org/10.63125/xgew7q22>
- [4]. A. Katfi, O. El Mnouer, S. Ghallal, H. Katfi, F. Boudriche, and T. Come, “Use of big data in human resource management to strengthen human capital management?” *RMD, Economics, Management & Social Sciences*, Vol. 2, No. 1, 2025, e202505. <https://doi.org/10.23882/emss25115>

- [5]. C. A. Wibowo, A. Anhara, and B. Bela, "Human resource analytics: An integrative review of data-driven HR decision making", *Jurnal Multidisiplin Sahombu*, Vol. 5, No. 3, 2025, pp. 349-358.
- [6]. M. Chawla, P. Sharma, S. Gautam, and C. R. G. Popescu, "Sustainability in human capital management", *Sustainable Management Practices for Employee Retention and Recruitment*. IGI Global, 2025, pp. 265–290. <https://doi.org/10.4018/979-8-3693-8679-8.ch013>
- [7]. P. B. Rao, R. Raghavendra, C. Pawar, P. Patel, P. R. Sharma, and R. Harshitha, "The impact of HR analytics and big data on decision making in healthcare organizations", *Advances in Business Strategy and Competitive Advantage*. IGI Global, 2025, pp. 335–366. <https://doi.org/10.4018/979-8-3693-9586-8.ch012>
- [8]. R. Bisht, and A. Kumar Uniyal, "Integration of big data analytics in human resource management: Challenges and opportunities", *2025 6th International Conference on Mobile Computing and Sustainable Informatics (ICMCSI)*. IEEE, 2025, pp. 841–844. <https://doi.org/10.1109/icmcsi64620.2025.10883449>
- [9]. J. M. Sohu, M. A. Mirani, S. N. Shaikh, U. Memon, A. Bhanbhro, and F. Z. Kherazi, "Integrating green human resource management and big data analytics capability for sustainable environmental performance in SMEs", *Advances in Human Resources Management and Organizational Development*. IGI Global, 2025, pp. 145–172. <https://doi.org/10.4018/979-8-3693-7046-9.ch006>
- [10]. P. Gupta, D. Gupta, and M. Gupta, "Unleashing human capital analytics for data-driven workforce management", *Human Capital Analytics: Exploring the HR Spectrum in Industry 5.0*, 2025, pp. 143-163. <https://doi.org/10.1002/9781394238354.ch7>
- [11]. I. Mutsuddi, N. Ray, M. Roy, and T. Majumder, "Empowering talent management with big data analytics and artificial intelligence (AI)", *AI and Innovation in HRM*. London: Routledge, 2025, pp. 1–12. <https://doi.org/10.4324/9781003522157-1>
- [12]. C. A. Savitri, "Disruptive technology in human resource management", *Technology Analysis & Strategic Management*, 2025, pp. 1–5. <https://doi.org/10.1080/09537325.2025.2531513>
- [13]. M. Bentvelzen, C. Boon, and D. N. Den Hartog, "A person-centered approach to individual people analytics adoption", *Journal of Organizational Effectiveness: People and Performance*, Vol. 12, No. 2, 2025, pp. 60-82. <https://doi.org/10.1108/joepp-07-2023-0276>
- [14]. N. A. S. D. Nanayakkara, and W. M. N. Fernando, "Strategies in developing big data analytics skills among IT/BPM professionals in Sri Lanka", *Journal of Business Research and Insights (former Vidyodaya Journal of Management)*, Vol. 11, No. 1, 2025, pp. 43-66. <https://doi.org/10.31357/jbri.v11i01.8469>
- [15]. D. Kobets, O. Vorkunova, L. Yaremenko, V. Krasnoshchok, and O. Zhurba, "Using big data to increase the efficiency of business processes in the digital economy of Ukraine", *Periodicals of Engineering and Natural Sciences (PEN)*, Vol. 13, No. 1, 2025, pp. 97–110. <https://doi.org/10.21533/pen.v13.i1.279>
- [16]. S. D. Bhalekar, "HR analytics in strategic human resource management: Driving better decisions in the digital era", *Divulging the Most Recent Trends in STEM: Staying Ahead of the Curve*, Vol. 175, 2025.
- [17]. S. Sasidharakarnavar, "Revolutionizing hr: Leveraging workday platform for enhanced workforce management", *International Journal of AI, BigData, Computational and Management Studies*, Vol. 6, 2025, pp. 98–105. <https://doi.org/10.63282/3050-9416.ijaibdcms-v6i1p110>
- [18]. S. Devarapalli, A. Jain, and M. Sharma, "Reinventing HR with AI and Workday: Integration strategies for the digital enterprise", *Global Journal of Human Resource Management*, Vol. 13, No. 2, 2025, pp. 38-46. <https://doi.org/10.37745/gjhrm.2013/vol13n23846>
- [19]. P. S. Varsha, and S. Nithya Shree, "Embracing Data-Driven Analytics (DDA) in human resource management to measure the organization performance", *Handbook of Big Data Research Methods*. Edward Elgar Publishing, 2023, pp. 195–213. <https://doi.org/10.4337/9781800888555.00017>
- [20]. J. Salvadorinho, and L. Teixeira, "Happy and engaged workforce in industry 4.0: A new concept of digital tool for HR based on theoretical and practical trends", *Sustainability*, Vol. 15, No. 3, 2023, pp. 2781. <https://doi.org/10.3390/su15032781>
- [21]. A. Atluri, and V. Reddy, "Cognitive HR management: How oracle HCM is reinventing talent acquisition through AI", *International Journal of Artificial Intelligence, Data Science,*

- and Machine Learning*, Vol. 6, 2025, pp. 85–94. <https://doi.org/10.63282/3050-9262.ijaidmsl-v6i1p110>
- [22]. U. Kothari, “End-to-End robotic process automation in oracle on-premise environments: Uipath RPA for ERP, EBS, peoplesoft, and HCM in construction materials manufacturing”, *International Journal of Leading Research Publication*, Vol. 5, No. 11, 2025. <https://doi.org/10.70528/ijlrp.v5.i11.1488>
- [23]. R. Dutraj, and P. R. Sengupta, “Aligning human resources to businesses through human resource analytics”, *Asian Journal of Management*, Vol. 16, No. 2, 2025, pp. 73-81.
- [24]. D. Langó, Employee experiences with compliance dashboards: A qualitative case study: Doctoral dissertation. Chandler, California Southern University, 2025
- [25]. K. Balaji, “HR 4.0”, *AI and Innovation in HRM*. London: Routledge, 2025, pp. 170–190. <https://doi.org/10.4324/9781003522157-11>
- [26]. S.-I.Ao, M. Hurwitz, and V. Palade, “Cognitive computing and business intelligence applications in accounting, finance and management”, *Big Data and Cognitive Computing*, Vol. 9, No. 3, 2025, 54. <https://doi.org/10.3390/bdcc9030054>
- [27]. S. Porkodi, and T. L. Cedro, “The ethical role of generative artificial intelligence in modern HR decision-making: A systematic literature review”, *European Journal of Business and Management Research*, Vol. 10, No. 1, 2025, pp. 44–55. <https://doi.org/10.24018/ejbmr.2025.10.1.2535>
- [28]. R. A. Alifia, N. R. Safitri, D. M. Irhami, N. R. Hidayat, and I. R. Kusumasari, “Challenges and solutions for decision making in the era of big data”, *Jurnal Bisnis dan Komunikasi Digital*, Vol. 2, No. 2, 2025, 13. <https://doi.org/10.47134/jbkd.v2i2.3498>
- [29]. M. U. Tariq, “Harnessing technology to combat bias.”, *Navigating Bias in Human Resource Management*. IGI Global, 2025, pp. 155–184. <https://doi.org/10.4018/979-8-3693-7132-9.ch006>
- [30]. S. Rao, and T. Zhao, “Ethical AI in HR: A case study of tech hiring”, *Journal of Computer Information Systems*, 2025, pp. 1–18. <https://doi.org/10.1080/08874417.2024.2446954>
- [31]. N. Tasleem, “HR technology transformation and the impact of people analytics on workforce management”, *IRE Journal*, Vol. 8, No. 9, 2025, pp. 702-716.
- [32]. M. Sposato, E. C. Dittmar, and J. P. Vargas Portillo, “New technologies in HR: Bridging efficiency and ethical considerations”, *International Journal of Organizational Analysis*, Vol. 33, No. 8, 2025, pp. 2899-2914. <https://doi.org/10.1108/ijoa-09-2024-4814>
- [33]. A. Soni, Z. H. Shaikh, A. Alhejair, N. Dora, N. Gulati, and H. Saseendran, “AI in expanded HR ecosystems: Mapping research trajectories and future prospective.”, *Studies in Big Data*. Cham: Springer Nature Switzerland, 2025, pp. 473–483. [https://doi.org/10.1007/978-3-031-83911-5\\_41](https://doi.org/10.1007/978-3-031-83911-5_41)
- [34]. A. Mabrouk, “Human resource management in the age of artificial intelligence: Concepts tools and steps”, *Solo International Collaboration and Publication of Social Sciences and Humanities*, Vol. 3, No. 1, 2025, pp. 1–12. <https://doi.org/10.61455/sicopus.v3i01.216>
- [35]. R. Hanandeh, Z. Alkhazali, K. M. K. Alhyasat, A. M. Mistarihi, Q. A. Kilani, “The impact of data-driven decision-making, real-time analytics, and ethical data practices on HR performance and employee satisfaction”, *Data and Metadata*, Vol. 4, 2025, 712. <https://doi.org/10.56294/dm2025712>
- [36]. H. Sharma, A. Ali, M. Singh, A. Singhal, S. Ghai, and K. Saluja, “Big data and artificial intelligence for strategic human resource management”, *Transforming Organizational Culture through Meta-Driven Human Resources*. IGI Global, 2025, pp. 405–426. <https://doi.org/10.4018/979-8-3373-0720-6.ch014>