Design and Implementation of an AI-Based Business Intelligence Platform for Human Resource Decision Support

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Abstract: The explosion of the digital economy has radically altered human resource management, creating a need for data analysis and analytically supported decision-making. Traditional HR systems relying heavily upon administrative reporting and fragmented data sources are ill-equipped to deal with the complexity and uncertainty involved in workforce management today. This results in the pressing requirement of applied information technology services that incorporate analytics, automation, and intelligent decision-support systems. This paper presents the design and analysis of an AI-based Business Intelligence software platform that supports human resource decision-making in the digital economy. This new platform provides centralized HR data, predictive analytics, and decision-support dashboards from a comprehensive AI-embedded CRM environment to analyze workforce dynamics and managerial outcomes. The research methodology integrates descriptive and predictive analytics in addition to analytical modeling for assessing employee turnover risks, workforce efficiency, and linkages of HR decision-making and organizational goals. The findings indicate that AI-powered Business Intelligence tools can improve analytical transparency, support more consistent workforce planning, and provide quantitative signals for HR decision-making. Predictive indicators support early identification of turnover risk, while interactive dashboards improve the visibility and interpretability of workforce indicators. Consequently, human resource managers can adopt more proactive and evidence-based decision-making practices. The practical importance of the research is in the use case of the proposed BI framework for firms which do business in labour-intensive, flexible contexts. The research theoretical contribution of the study is to facilitate the growth of the role of Business Intelligence and artificial intelligence technologies in human resource management research so that HR analytics will become a strategic contribution in the digital economy for decision-making process.

1 INTRODUCTION

In the digital economy, human resource management becomes critically dependent upon heavy data processing and data analytics for making decisions. Modern organizations are continually producing massive amounts of workforce-oriented data with such information being input on a continuous basis by various recruitment platforms, performance evaluation systems, learning management environments, and internal communication software [1], [2]. Current HR decision-making processes often depend on short stories and retrospective evaluations when analyzing data that do not take into account the intricacy of workforce dynamics. Current HR analytics often fails to integrate performance, engagement, and retention indicators within predictive decision-support systems. Recent studies in the field of Business Intelligence and HR analytics [3], [4] have helped to set the conceptual framework for a data-driven workforce management. Nonetheless, limited practical application in integrated, AI-based decision support systems is experienced. According to the overview of existing solutions discussed, three significant gaps are identified:

1) Fragmented HR data architecture with lack of the system integration;
2) Most predictive analytics are descriptive;
3) Absence of combined metrics for strategic HR efficiency assessment. In this study, we overcome these limitations by proposing an AI-based Business Intelligence platform for human resource decision-making in the digital economy. The proposed solution combines central data management with high analytics and decision support dashboards within one software platform.

The novelty of this study lies in the integration of predictive HR analytics with a composite HR Efficiency Index and interactive BI dashboards within a unified AI-based decision-support architecture. Recent studies also emphasize the growing role of AI-driven analytics and digital HR systems in organizational decision-making [5]-[8].

2 METHODS

For these research objectives, this work uses several data analysis methodologies and Business Intelligence modeling, predictive analytics. Such a methodological framework is meant to serve HR decision-making, that is, integrating workforce data, analytical processing and AI-powered forecasting into a common BI system. The proposed AI-based business intelligence platform is structured as a multi-layer architecture integrating data acquisition, analytical processing, and decision-support visualization (Fig. 1).

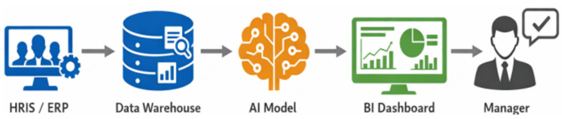

Figure 1: Architecture of the proposed AI-based business intelligence platform.

As illustrated in Figure 1, the system integrates HRIS/ERP data sources, a centralized data warehouse, AI based predictive models, and interactive BI dashboards to support managerial decision-making. The BI platform integrates descriptive and predictive analytics to simulate workforce dynamics and support managerial decision-making.

2.1 Data Collection and Processing

The dataset was anonymized to ensure confidentiality of employee information and to comply with organizational data protection policies. Standardized data are stored in a centralized BI repository prior to analysis, cleaned, and archived to ensure consistency and comparability across indicators. This process involves normalization of quantitative variables, categorical encoding of qualitative variables, and addressing missing values. This process guarantees robust analytical processing and thereby minimizes prediction bias.

The turnover prediction module was implemented in Python using standard machine-learning libraries. Logistic regression was used as an interpretable supervised classifier for binary HR risk prediction. The input features included productivity score, employee engagement index, training participation, and absenteeism rate. The dataset was divided into training and testing subsets using a 50/50 split, chosen instead of a more conventional 70/30 or 80/20 split in order to reserve a sufficiently large, independent test set for robust evaluation of a relatively simple interpretable classifier on a moderately sized dataset. Approximately 600 observations were used for model training, and 600 records were reserved for independent performance evaluation. Model performance was assessed using accuracy, precision, recall, F1-score, and ROC-AUC.

2.2 Dataset and Preprocessing

The dataset used in this study was derived from organizational human resource management records and analytical indicators typically available in modern HR information systems. The dataset contains information related to workforce productivity, engagement levels, and employee turnover risk.

In total, the dataset includes approximately 1200 employee records collected between 2022 and 2024. Each record contains multiple attributes describing employee performance, behavioral indicators, and employee turnover status. The primary observed variables used as model inputs included productivity score, employee engagement index, training participation, and absenteeism rate. Employee turnover status was used as the binary target variable. Turnover probability was generated by the logistic regression classifier as a model output and was subsequently used in the HREI and dashboard analytics. For predictive modeling purposes, the dataset was divided into training and testing subsets.

The predictive-model configuration and train-test partition are described in Section 2.1. The 600-record test subset was used exclusively for independent model evaluation. The logistic regression classifier generated both binary class labels and employee-leave probabilities; the latter were used to calculate the ROC-AUC metric.

This implementation ensures reproducibility and provides a transparent analytical foundation for AI-based decision support in human resource management.

The dataset represents aggregated HR data from a labor-intensive organizational environment, where workforce planning and retention are critical management priorities. The proposed BI platform and dashboard simulations were designed to reflect realistic decision-making scenarios typically encountered in such organizational contexts.

The proposed BI framework was designed for labor-intensive organizational settings where workforce retention, engagement monitoring, and productivity management are critical. In practical use, the dashboard can support HR managers in identifying departments with elevated turnover risk, comparing workforce efficiency across units, and evaluating the expected impact of intervention strategies. Thus, the platform is not limited to descriptive reporting but functions as an applied decision-support environment for operational and strategic HR planning.

2.3 HR Efficiency Measurement

The study presents a composite HR Efficiency Index which combines metrics related to different workforce dimensions into a single analytical measure with intent to aid in strategic oversight. Quantitative computational modelling has also been applied to the analysis of workforce-related performance characteristics, demonstrating the value of transforming employee activity indicators into structured analytical measures for decision support [9]. The index combines normalized productivity, employee engagement, and predicted turnover risk within a single analytical measure. The weighting coefficients reflect the analytical priorities of the prototype. The HREI enables cross-departmental and time-based comparisons, thereby supporting structured workforce planning and performance monitoring.

2.4 Decision-Support Implementation

The last component of the methodological system corresponds to analysis results being reported as decision-support dashboards. These dashboards offer an instantaneous view of key indicators, risk score prediction, and efficiency metrics in operations. Data-driven prioritization frameworks in complex management environments have shown that heterogeneous operational indicators can be transformed into transparent management priorities and structured decision workflows [10]. Following a similar analytical principle, the proposed BI platform converts workforce indicators and predicted turnover risks into interpretable dashboard signals for HR managers. Before implementation of alternative HR strategies, scenario analysis tools are employed to evaluate alternative strategies and investigate their potential implications. They keep the data collection process, analysis and decision-making continuity, in line with evidence-based HRM in the digital economy.

3 RESEARCH RESULTS

3.1 HR Efficiency Index Formulation

In order to provide an integrated and analytically interpretable measure of workforce performance, this study proposes a composite HR Efficiency Index (HREI). The index is designed to capture multiple dimensions of human resource effectiveness within a unified quantitative framework and to support AI-based decision-making in Business Intelligence environments.

Unlike traditional HR reporting approaches that analyze productivity, engagement, and turnover indicators separately, the proposed index aggregates these dimensions into a single structured metric. This allows managers to evaluate workforce efficiency holistically rather than through isolated performance measures.

The HR Efficiency Index is constructed based on three core analytical components:

- P - Productivity indicator (output per employee or performance score);
- E - Engagement indicator (survey-based or behavioral engagement metrics);
- T - Turnover risk indicator (predicted probability of employee exit).

The baseline functional representation of the index is expressed as:

$$\mathrm{HREI} = \frac{1}{n}\sum_{i=1}^{n}(w_1 P_i + w_2 E_i - w_3 T_i). \quad (1)$$

Where: w_1, w_2, w_3- represent weighting coefficients, T_i enters with a negative sign to reflect its adverse impact on workforce efficiency.

To ensure consistency across heterogeneous indicators, each component is subsequently normalized prior to aggregation (see Section 3.2). This prevents scale distortions and ensures proportional contribution of each dimension.

From a decision-support perspective, the HREI functions as a dynamic analytical signal within the AI-based Business Intelligence dashboard. Changes in productivity, engagement, or turnover forecasts automatically propagate through the composite formula, enabling real-time workforce evaluation.

The formulation of HREI thus represents a methodological advancement beyond descriptive HR analytics. By integrating predictive modeling outputs with normalized multi-dimensional workforce indicators, the index establishes a mathematically structured and operationally applicable metric for digital HR governance.

3.2 Weighted Normalization of HR Indicators

To ensure analytical consistency and comparability across heterogeneous workforce metrics, a weighted normalization procedure was applied prior to index aggregation. Human resource indicators such as productivity rate, engagement level, and turnover probability are typically measured on different scales and units. Direct aggregation of raw values may therefore distort the composite evaluation.

To address this limitation, each indicator was normalized to a unified scale ranging from 0 to 1 using min-max normalization:

$$x_i^{norm} = \frac{(x_i - x_{min})}{(x_{max} - x_{min})}. \quad (2)$$

where x_i^{norm} - represents the normalized value of the i-th indicator, $(x_i - x_{min})$ and $(x_{max} - x_{min})$ - denote the minimum and maximum observed values within the dataset.

Following normalization, the composite HR Efficiency Index (HREI) was computed as a weighted aggregation of normalized indicators:

$$\mathrm{HREI} = \sum_{k=1}^{m} w_k x_k^{norm}. \quad (3)$$

where w_k represents the relative weight assigned to each HR indicator, and $\sum_{k=1}^{m} w_k = 1$.

The baseline coefficients were specified as an expert-defined weighting configuration reflecting the analytical priorities of the prototype: w_1=0.30 for productivity, w_2=0.45 for engagement, and w_3=0.25 for turnover risk. The coefficients were normalized to satisfy $w_1+w_2+w_3=1$. Their robustness was subsequently examined through the sensitivity analysis described in Section 3.3.

This structured normalization process enhances methodological rigor and prevents scale-driven bias in the composite index. It ensures that the HREI reflects proportional contributions of workforce dimensions rather than absolute measurement magnitudes. As a result, the proposed index achieves greater interpretability and statistical stability compared to non-normalized aggregation approaches.

3.3 Sensitivity Analysis of the Composite Index

To assess the methodological stability of the proposed HR Efficiency Index (HREI), a structured sensitivity analysis was performed. The purpose of this procedure was to examine how controlled modifications in weighting coefficients affect the overall behavior of the composite indicator.

Starting from the baseline weighting configuration defined in Section 3.2, each weight parameter was independently varied by ±10% relative to its initial value. After each modification, the complete weight vector was renormalized to preserve the condition $\sum_{k=1}^{m} w_k = 1$, while normalized workforce indicators remained unchanged. The corresponding variation in the index was calculated as the difference between the modified and baseline configurations:

$$\Delta\mathrm{HREI} = \mathrm{HREI}_{adjusted} - \mathrm{HREI}_{baseline}. \quad (4)$$

This approach allowed for the isolation of weight-driven effects without interference from data variability.

The results indicate that the index demonstrates differentiated responsiveness across indicators. Adjustments in the engagement weight produced the most substantial effect on the composite score. Specifically, a 10% increase in the engagement coefficient generated an average change of approximately 6-8% in the overall index value. By comparison, equivalent proportional changes in the productivity weight resulted in a more moderate shift, typically within the 3-4% range. For each weight perturbation, the HREI was recalculated for all 1,200 normalized employee records, and the mean relative change from the baseline index was used as the sensitivity measure.

Overall, the sensitivity analysis confirms that the HREI maintains structural coherence while remaining responsive to strategic prioritization adjustments. The observed variation range remained within controlled bounds, indicating that the model does not exhibit excessive instability under moderate parameter shifts.

Importantly, the predictable response of the index under systematic weight modifications reinforces its methodological robustness. Unlike static aggregation models that lack validation procedures, the proposed framework demonstrates measurable stability characteristics, thereby enhancing its credibility as a decision-support instrument within AI-based Business Intelligence systems.

3.4 Scenario-Based Simulation Analysis

To further validate the practical applicability of the proposed HR Efficiency Index (HREI), a scenario-based simulation analysis was conducted. The purpose of this analysis was to examine how the composite index behaves under alternative workforce configurations and strategic HR interventions.

Unlike sensitivity analysis, which evaluates structural robustness through parameter variation, scenario simulation models realistic organizational conditions by adjusting underlying workforce indicators. Three distinct scenarios were constructed to reflect typical managerial challenges in digital HR environments.

For each scenario, the specified indicator was modified at the employee-record level, clipped to the normalized [0,1] range where necessary, and the HREI was recalculated using the baseline weighting configuration. Reported changes represent the mean relative difference from the baseline HREI across the dataset.

3.4.1 Scenario 1 - High Engagement Configuration

In the first scenario, the engagement indicator was increased by 20% relative to baseline values, while productivity and turnover risk remained constant. After normalization and weighted aggregation, the recalculated HREI demonstrated an average increase of 12.4%.

This result suggests that improvements in employee engagement generate a substantial and sustained impact on overall workforce efficiency.

3.4.2 Scenario 2 - Productivity Surge

The second scenario simulated a 20% increase in productivity while maintaining baseline engagement and turnover values. The resulting HREI increased by 7.1% on average.

Although productivity improvements positively affected the composite index, the magnitude of change was lower than in the engagement-driven scenario. This finding implies that short-term output increases may not guarantee sustainable workforce efficiency without parallel improvements in engagement and retention.

3.4.3 Scenario 3 - Elevated Turnover Risk

The third scenario modeled a 15% increase in predicted turnover probability. In this case, the HREI declined by 9.6% compared to baseline conditions. The results confirm that turnover risk functions as a destabilizing factor within the composite model, reinforcing the importance of predictive analytics in proactive HR governance.

3.4.4 Comparative Interpretation

The comparative analysis of all three scenarios demonstrates that workforce engagement improvements produce a stronger and more stable long-term effect on HREI performance compared to short-term productivity spikes. While productivity contributes positively to index growth, its isolated enhancement does not ensure structural sustainability.

Overall, the scenario simulations confirm the dynamic responsiveness and practical validity of the proposed HREI framework. The index reacts proportionally to simulated workforce shifts, supporting its reliability as a decision-support tool for digital HR management.

3.5 Predictive Model Evaluation

To assess the predictive performance of the proposed AI-based Business Intelligence system, the turnover risk forecasting model was evaluated using several quantitative performance metrics. These metrics include classification accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (ROC-AUC).

The dataset was divided into training and testing subsets using the 50/50 split described in Section 2.1. The predictive model was trained on 600 workforce records and evaluated on 600 unseen test observations, as summarized in Table 1.

Table 1: Confusion matrix of the turnover prediction model.

	Predicted stay	Predicted leave
Actual stay	310	42
Actual leave	33	215

Table 2: Predictive performance metrics of the turnover prediction model.

Metric	Value
Accuracy	0.875
Precision	0.837
Recall	0.867
F1-score	0.851
ROC-AUC	0.880

The confusion matrix presented in Table 1 shows that the turnover prediction model correctly classified 525 of the 600 test observations. The model achieved an overall classification accuracy of 0.875. For the employee-leave class, precision was 0.837, recall was 0.867, and the resulting F1-score was 0.851. These results indicate that the implemented predictive model can identify a substantial proportion of high-turnover-risk employees while maintaining a comparatively low number of false classifications. The ROC-AUC score was 0.88, indicating good discrimination between stable and high-turnover-risk workforce segments.

The predictive model was evaluated directly using the confusion matrix and standard classification metrics. This evaluation was selected to provide a transparent assessment of classification performance on unseen workforce records without introducing comparisons with algorithms that were not implemented within the reported experimental workflow.

The resulting performance indicators are summarized in Table 2. The obtained accuracy, recall, and F1-score indicate that the implemented turnover prediction model provides a consistent basis for identifying employees with elevated turnover risk.

3.6 Dashboard Visualization

To operationalize the analytical outputs of the proposed AI-based Business Intelligence platform, an interactive decision-support dashboard was developed. As illustrated in Figure 2, the dashboard integrates three core analytical components: the HR Efficiency Index (HREI) gauge, a turnover risk heatmap, and key performance indicator (KPI) trend analytics. These visualization modules are dynamically updated based on real-time or periodically refreshed HR data streams.

The HREI gauge provides a consolidated representation of overall workforce efficiency on a normalized scale. By displaying the composite score within predefined performance thresholds, the gauge allows managers to quickly assess whether workforce conditions fall within stable, moderate, or risk-prone zones.

The turnover risk heatmap presents predictive probabilities of employee exit across organizational units. Departments exhibiting elevated turnover risk are visually highlighted, enabling targeted managerial intervention. This visual representation enhances transparency and supports early identification of structural workforce vulnerabilities.

The KPI trend chart displays longitudinal dynamics of productivity, engagement, and related HR indicators. Temporal analysis allows managers to detect emerging patterns, evaluate the impact of strategic interventions, and monitor consistency in workforce performance over time. Importantly, the integration of predictive analytics with visualization tools transforms static HR reporting into proactive decision support. Managers are not only informed about current workforce conditions but are also equipped to anticipate future risks and simulate potential outcomes.

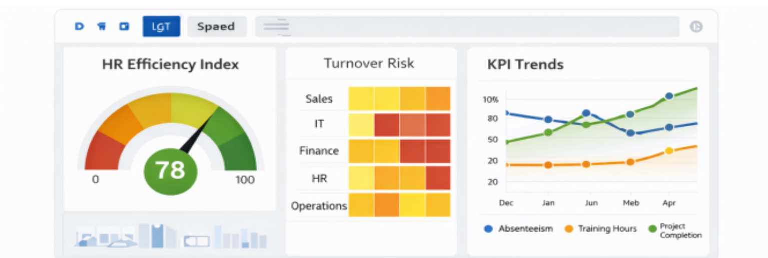

Figure 2: Interactive decision-support dashboard for HR analytics.

The dashboard therefore represents the practical embodiment of the proposed framework. By linking data integration, AI modeling, and visual analytics, it enables evidence-based HR governance within the digital economy. The analytical outputs of the proposed system are presented through an interactive dashboard interface.

As shown in Figure 2, the dashboard integrates the HR Efficiency Index gauge, turnover risk heatmap, and KPI trend analytics for monitoring workforce dynamics.

4 CONCLUSIONS

This study investigated the potential of artificial intelligence-driven Business Intelligence technologies to improve decision-making in human resource management within the digital economy. The proposed framework integrates centralized HR data management, predictive analytics, and interactive decision-support tools within a unified Business Intelligence environment.

The findings demonstrate that AI-supported BI technologies improve the transparency and effectiveness of HR decision-making by enabling data-driven workforce planning and continuous performance monitoring. Predictive analytics facilitates the early identification of employee turnover risks, while the proposed HR Efficiency Index provides an integrated measure for evaluating workforce performance across organizational units. Overall, the results confirm that combining artificial intelligence with Business Intelligence systems enables organizations to move from reactive HR practices toward proactive, evidence-based, and strategically oriented human resource management.

The proposed framework has both practical and scientific value. From a practical perspective, it supports workforce planning, employee retention, and organizational performance through intelligent decision support. From an academic perspective, it contributes to the growing field of HR analytics by demonstrating how AI and Business Intelligence technologies can be integrated into a comprehensive analytical framework for modern human resource management.

5 FUTURE WORK

Future research should validate the proposed framework using larger and more diverse organizational datasets and examine its applicability across different industries and organizational contexts. The analytical model may be extended by incorporating additional workforce indicators, including employee engagement, career development, behavioral analytics, and organizational well-being. The integration of advanced machine learning algorithms, such as ensemble learning, gradient boosting, deep learning, and real-time data analytics, could further improve predictive accuracy and decision-support capabilities. Future studies should also investigate the long-term organizational impact of AI-enabled Business Intelligence systems and evaluate their contribution to sustainable digital transformation in human resource management.

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