

# ARTIFICIAL INTELLIGENCE AND PREDICTIVE ANALYTICS IN EMPLOYEE RETENTION: A DECISION SUPPORT APPROACH

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## Abstract

Employee retention has become a strategic concern for commercial enterprises because avoidable turnover can increase recruitment costs, disrupt organizational knowledge, and weaken workforce continuity. This study develops an integrated decision-support framework linking artificial intelligence (AI)-enabled human resource practices, predictive analytics capability, employee data quality, AI-supported career development, organizational support for AI, employee engagement, and employee retention. The framework follows a quantitative survey design and combines descriptive statistics, reliability analysis, exploratory factor analysis, correlation, multiple regression, mediation analysis, PLS-SEM-oriented measurement assessment, and machine-learning validation. A dataset of 250 responses is used only to demonstrate the structure and presentation of statistical analysis; it is not claimed to represent actual field observations. The results indicate acceptable internal consistency, positive associations among the principal constructs, significant predictive relationships, and stronger predictive performance for nonlinear machine-learning models than the regression baseline. The study positions AI and predictive analytics not as replacements for managerial judgement but as decision-support mechanisms for identifying retention risks, targeting interventions, and improving evidence-based workforce planning.

*Keywords: artificial intelligence; predictive analytics; employee retention; employee engagement; HR analytics; machine learning; decision support; human resource management.*

## 1. Introduction

Employee turnover is increasingly treated as a strategic workforce issue rather than only an operational human resource problem. Commercial enterprises operate in environments where employee expectations, skill requirements, work arrangements, career opportunities, and organizational structures change rapidly. Consequently, managers require timely evidence about the factors associated with employees' intention to remain with an organization.

Artificial intelligence and predictive analytics can strengthen this process by transforming historical and current workforce information into decision-support insights. Instead of relying exclusively on annual surveys or managerial intuition, organizations can combine employee profiles, engagement indicators, career information, performance patterns, learning participation, and other ethically governed workforce data to identify potential retention risks. Predictive systems can **then** support targeted interventions such as career development, manager coaching, recognition, workload review, and learning opportunities.

However, analytical capability alone does not guarantee employee retention. Data quality, employee trust, organizational support, responsible AI practices, and the quality of human interpretation can influence whether AI-supported recommendations are useful. This study therefore adopts an integrated socio-technical perspective and examines both the explanatory relationships among HR constructs and the predictive usefulness of analytics.

The research is designed to provide a statistically rich framework that can be implemented with SPSS, SmartPLS, R, or Python. The numerical tables in this article are and must be replaced by actual survey output before academic or journal submission.

## 2. Review of Literature and Theoretical Background

### 2.1 Artificial Intelligence in Human Resource Management

AI in HRM refers to computational techniques used to support activities such as recruitment, workforce planning, learning recommendations, performance analysis, employee-service automation, and workforce risk assessment. Its value for retention lies in the ability to identify patterns across multiple indicators and provide managers with timely information for intervention. At the same time, responsible deployment requires attention to transparency, privacy, bias, accountability, and employee perceptions of fairness.

### 2.2 Predictive Analytics Capability

Predictive analytics capability represents an organization's ability to collect, prepare, model, interpret, and operationalize workforce information for future-oriented decisions. A mature capability includes analytical skills, appropriate technologies, reliable data, model validation, and managerial ability to convert predictions into actions. In retention management, this capability can support early identification of employees who may be at elevated turnover risk.

### 2.3 Employee Data Quality

Predictive systems depend on the quality and completeness of their underlying data. Accurate, timely, consistent, and relevant employee information can improve the usefulness of analytical outputs. Conversely, incomplete or biased data may produce unreliable recommendations. Data quality is therefore treated as an organizational capability that can influence confidence in AI-supported HR decisions.

### 2.4 AI-Supported Career Development

Career development is an important retention mechanism because employees may remain longer when they perceive meaningful opportunities to learn, progress, and apply their capabilities. AI can personalize learning recommendations, identify skill gaps, suggest development

pathways, and connect employees with suitable internal opportunities. Such applications may strengthen employees' perceptions that the organization invests in their long-term growth.

## 2.5 Organizational Support for AI

Organizational support for AI includes leadership commitment, resources, training, governance mechanisms, and communication surrounding AI-enabled HR practices. Supportive implementation can reduce uncertainty and help employees understand how analytical systems are used. It can also strengthen managerial adoption and the likelihood that predictive insights are translated into appropriate retention interventions.

## 2.6 Employee Engagement

Employee engagement captures employees' psychological and behavioral connection with their work and organization. Engaged employees may demonstrate stronger involvement, commitment, and willingness to contribute. In this framework, engagement is positioned as a potential mechanism through which AI-enabled HR practices and organizational support influence retention.

## 2.7 Employee Retention

Employee retention refers to an organization's ability to maintain a stable workforce and encourage employees to continue their employment. Retention can be influenced by career opportunities, organizational support, job experiences, recognition, development, work conditions, and perceived fairness. Predictive analytics provides a mechanism for integrating these factors into a decision-support process.

## 3. Conceptual Framework and Hypotheses

The proposed framework contains five explanatory constructs—AI Adoption in HR (AIHR), Predictive Analytics Capability (PAC), Employee Data Quality (EDQ), AI-Supported Career Development (ACD), and Organizational Support for AI (OSA)—one mediating construct, Employee Engagement (EE), and one outcome construct, Employee Retention (ER).

The conceptual logic is: AI-enabled HR practices and analytical capabilities improve the organization's ability to understand employee needs and risks; these capabilities can strengthen engagement; and stronger engagement can contribute to retention. Direct relationships are also proposed because AI-enabled practices may improve retention through better decisions and more responsive HR interventions.

- H1: AI adoption in HR positively influences employee retention.
- H2: Predictive analytics capability positively influences employee retention.
- H3: Employee data quality positively influences employee retention.
- H4: AI-supported career development positively influences employee retention.
- H5: Organizational support for AI positively influences employee retention.
- H6: Employee engagement positively influences employee retention.
- H7: Employee engagement mediates the relationship between AI-enabled HR practices and employee retention.

## 4. Methodology

### 4.1 Research Design

A quantitative, cross-sectional survey design is proposed. The target population comprises employees working in commercial enterprises where digital HR systems, analytics, or AI-enabled HR practices are used or are being introduced. A five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree can be used for construct items.

### 4.2 Sampling and Sample Size

For the proposed model, approximately 250–400 usable responses would provide a practical basis for multivariate analysis. An a priori power analysis should be conducted before actual data collection. The tables below use  $N = 250$  solely to demonstrate the statistical presentation.

### 4.3 Measurement Dimensions

| Construct                             | Suggested dimensions                                                     |
|---------------------------------------|--------------------------------------------------------------------------|
| AI Adoption in HR (AIHR)              | Usefulness, integration, automation, decision support                    |
| Predictive Analytics Capability (PAC) | Analytical skills, forecasting, model use, decision integration          |
| Employee Data Quality (EDQ)           | Accuracy, completeness, timeliness, consistency                          |
| AI-Supported Career Development (ACD) | Personalized learning, skill-gap identification, career recommendations  |
| Organizational Support for AI (OSA)   | Leadership support, resources, training, governance                      |
| Employee Engagement (EE)              | Vigor, involvement, dedication, organizational connection                |
| Employee Retention (ER)               | Intention to stay, organizational commitment, reduced turnover intention |

## 5. Statistical Analysis Plan

The proposed sequence is: data screening → descriptive statistics → missing-value and outlier assessment → reliability analysis → exploratory factor analysis → correlation analysis → multicollinearity diagnostics → multiple regression → mediation analysis → PLS-SEM measurement and structural assessment → effect-size and predictive-relevance assessment → machine-learning validation. This layered approach distinguishes explanatory relationships from out-of-sample predictive performance.

### 6.1 Respondent Profile ()

| Category   | Group         | Frequency | Percentage |
|------------|---------------|-----------|------------|
| Gender     | Male          | 142       | 56.8       |
| Gender     | Female        | 108       | 43.2       |
| Age        | Below 25      | 46        | 18.4       |
| Age        | 25–35         | 98        | 39.2       |
| Age        | 36–45         | 64        | 25.6       |
| Age        | Above 45      | 42        | 16.8       |
| Experience | Below 5 years | 80        | 32.0       |
| Experience | 5–10 years    | 94        | 37.6       |

|            |                |    |      |
|------------|----------------|----|------|
| Experience | Above 10 years | 76 | 30.4 |
|------------|----------------|----|------|

## 6.2 Descriptive Statistics and Reliability

| Construct                       | Mean | SD   | Cronbach's $\alpha$ |
|---------------------------------|------|------|---------------------|
| AI Adoption in HR               | 3.71 | 0.72 | 0.91                |
| Predictive Analytics Capability | 3.62 | 0.76 | 0.90                |
| Employee Data Quality           | 3.68 | 0.70 | 0.88                |
| AI-Supported Career Development | 3.55 | 0.79 | 0.89                |
| Organizational Support for AI   | 3.49 | 0.81 | 0.90                |
| Employee Engagement             | 3.74 | 0.68 | 0.92                |
| Employee Retention              | 3.66 | 0.73 | 0.93                |

All reliability coefficients exceed the commonly used threshold of 0.70, indicating acceptable internal consistency for demonstration purposes.

## 6.3 Correlation Matrix

| Variable | AIHR | PAC  | EDQ  | ACD  | OSA  | EE   | ER   |
|----------|------|------|------|------|------|------|------|
| AIHR     | 1.00 | .61  | .55  | .58  | .63  | .60  | .57  |
| PAC      | .61  | 1.00 | .59  | .56  | .65  | .62  | .64  |
| EDQ      | .55  | .59  | 1.00 | .52  | .57  | .54  | .53  |
| ACD      | .58  | .56  | .52  | 1.00 | .60  | .66  | .62  |
| OSA      | .63  | .65  | .57  | .60  | 1.00 | .68  | .65  |
| EE       | .60  | .62  | .54  | .66  | .68  | 1.00 | .72  |
| ER       | .57  | .64  | .53  | .62  | .65  | .72  | 1.00 |

## 6.4 Multiple Regression

| Predictor                       | $\beta$ | t    | p     | VIF  | Decision    |
|---------------------------------|---------|------|-------|------|-------------|
| AI Adoption in HR               | .14     | 2.62 | .009  | 2.01 | Significant |
| Predictive Analytics Capability | .20     | 3.61 | <.001 | 2.28 | Significant |
| Employee Data Quality           | .10     | 2.01 | .045  | 1.74 | Significant |
| AI-Supported Career Development | .17     | 3.18 | .002  | 2.12 | Significant |
| Organizational Support for AI   | .16     | 2.94 | .004  | 2.36 | Significant |
| Employee Engagement             | .31     | 5.86 | <.001 | 2.48 | Significant |

model summary:  $R = .806$ ;  $R^2 = .650$ ; Adjusted  $R^2 = .641$ ; Standard Error = .446; Durbin-Watson = 1.91. ANOVA: Regression SS = 122.64; df = 6; MS = 20.44;  $F = 102.79$ ;  $p < .001$ .

.001. Residual SS = 48.31; df = 243; MS = .199. Total SS = 170.95; df = 249.

## 6.5 Exploratory Factor Analysis

| Construct                       | Indicative loading range | KMO | Variance explained |
|---------------------------------|--------------------------|-----|--------------------|
| AI Adoption in HR               | .71–.88                  | .86 | 68.4%              |
| Predictive Analytics Capability | .70–.89                  | .88 | 71.2%              |
| Employee Data Quality           | .69–.86                  | .82 | 64.7%              |
| AI-Supported Career Development | .72–.90                  | .84 | 69.1%              |
| Organizational Support for AI   | .70–.88                  | .87 | 70.3%              |
| Employee Engagement             | .73–.91                  | .90 | 73.6%              |
| Employee Retention              | .75–.92                  | .91 | 75.1%              |

Factor results suggest that the proposed items form coherent dimensions. Actual factor retention should be determined from the real dataset using eigenvalues, scree plot, communalities, and factor loadings.

## 6.6 PLS-SEM Measurement Model ()

| Construct                       | Composite Reliability | AVE | Assessment |
|---------------------------------|-----------------------|-----|------------|
| AI Adoption in HR               | .92                   | .63 | Acceptable |
| Predictive Analytics Capability | .91                   | .62 | Acceptable |
| Employee Data Quality           | .89                   | .58 | Acceptable |
| AI-Supported Career Development | .90                   | .61 | Acceptable |
| Organizational Support for AI   | .91                   | .63 | Acceptable |
| Employee Engagement             | .93                   | .68 | Acceptable |
| Employee Retention              | .94                   | .70 | Acceptable |

For an actual PLS-SEM study, discriminant validity should also be examined using HTMT and appropriate cross-loading evidence.

## 6.7 Structural Model and Hypothesis Testing

| Hypothesis | Path                  | $\beta$ | t    | p     | Result    |
|------------|-----------------------|---------|------|-------|-----------|
| H1         | AIHR $\rightarrow$ ER | .14     | 2.62 | .009  | Supported |
| H2         | PAC $\rightarrow$ ER  | .20     | 3.61 | <.001 | Supported |
| H3         | EDQ $\rightarrow$ ER  | .10     | 2.01 | .045  | Supported |

|    |             |     |      |       |           |
|----|-------------|-----|------|-------|-----------|
| H4 | ACD<br>→ ER | .17 | 3.18 | .002  | Supported |
| H5 | OSA<br>→ ER | .16 | 2.94 | .004  | Supported |
| H6 | EE →<br>ER  | .31 | 5.86 | <.001 | Supported |

## 6.8 Mediation Analysis –

| Relationship   | Indirect effect | BootSE | 95% LLCI | 95% ULCI | Decision                |
|----------------|-----------------|--------|----------|----------|-------------------------|
| AIHR → EE → ER | .072            | .021   | .033     | .116     | Indirect effect present |
| PAC → EE → ER  | .091            | .024   | .048     | .143     | Indirect effect present |
| ACD → EE → ER  | .103            | .026   | .054     | .156     | Indirect effect present |
| OSA → EE → ER  | .118            | .029   | .063     | .176     | Indirect effect present |

## 6.9 Collinearity Diagnostics

| Predictor | Tolerance | VIF  |
|-----------|-----------|------|
| AIHR      | .498      | 2.01 |
| PAC       | .439      | 2.28 |
| EDQ       | .575      | 1.74 |
| ACD       | .472      | 2.12 |
| OSA       | .424      | 2.36 |
| EE        | .403      | 2.48 |

The VIF values are below 5, suggesting that serious multicollinearity is not evident in this demonstration model. Actual conclusions must be based on the observed dataset.

## 6.10 Machine-Learning Validation

| Model                     | R <sup>2</sup> / AUC | MAE | RMSE | Use                            |
|---------------------------|----------------------|-----|------|--------------------------------|
| Multiple Regression       | .65                  | .35 | .45  | Explanatory baseline           |
| Random Forest             | .72                  | .30 | .40  | Nonlinear predictive benchmark |
| Gradient Boosting         | .75                  | .28 | .38  | Predictive benchmark           |
| Support Vector Regression | .70                  | .31 | .41  | Alternative nonlinear model    |

The comparison suggests that ensemble machine-learning models may capture nonlinear patterns that are not fully represented by a conventional regression model. In an actual study, training/test separation or cross-validation, hyperparameter tuning, class-balance checks where relevant, and out-of-sample evaluation should be reported.

## 7. Discussion

The proposed framework integrates AI-enabled HR practices with predictive analytics and employee-level

outcomes. The regression results indicate that employee engagement has the strongest direct association with retention, followed by predictive analytics capability, AI-supported career development, organizational support for AI, AI adoption, and employee data quality. This ordering is rather than an empirical claim.

The framework emphasizes that predictive analytics should support managerial decision-making rather than automatically determine employee outcomes. A prediction of turnover risk should trigger a structured review of possible causes and an appropriate human response. For example, an organization may use analytical signals to identify whether an employee would benefit from career development, workload discussion, recognition, flexible arrangements, or manager intervention.

The mediation results provide a useful theoretical direction: AI-enabled practices may influence retention partly because they improve employees' engagement with the organization. This makes employee experience an important bridge between technology adoption and workforce outcomes.

## 8. Theoretical and Practical Implications

Theoretically, the study connects technology-enabled HR capability, employee experience, and retention within a single explanatory-predictive framework. It also distinguishes statistical explanation from predictive accuracy, allowing future researchers to assess whether significant relationships translate into useful predictions.

For managers, the framework can be used to develop retention dashboards, identify emerging workforce risks, personalize development opportunities, and evaluate the effectiveness of retention interventions. Organizations should establish governance processes covering privacy, access controls, transparency, bias monitoring, human review, and appropriate use of employee data.

For employees, responsible AI deployment should be communicated clearly. Employees should understand what categories of data are used, why analytics are applied, and how decisions involving them are reviewed. Predictive risk scores should not be treated as definitive judgements about individual employees.

## 9. Future Research Scope and Limitations

- Collect longitudinal employee data to examine whether predicted turnover risks translate into actual turnover over time.
- Compare AI-enabled HR practices across industries, organization sizes, and occupational groups.
- Test moderation by organizational culture, leadership style, remote-work intensity, or digital maturity.
- Use explainable AI methods to identify influential predictors while avoiding the assumption that algorithmic importance proves causality.
- Combine employee survey measures with appropriately anonymized HR records and validated turnover outcomes.

## 10. Conclusion

This article proposes an integrated decision-support framework for examining how artificial intelligence and predictive analytics can contribute to employee retention in commercial enterprises. The framework combines AI adoption,

predictive analytics capability, employee data quality, AI-supported career development, organizational support for AI, employee engagement, and employee retention. Its methodological design moves beyond simple descriptive analysis by combining reliability assessment, factor analysis, correlation, regression, mediation, PLS-SEM, and machine-learning validation. The central proposition is that AI becomes strategically valuable when analytical insight is converted into responsible and employee-centered managerial action. Future empirical research should validate the framework with real longitudinal data and transparent model evaluation.

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