# AI-Based Learning Analytics and its impact on Training Effectiveness and Employee Retention in Organizations

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**Abstract:** While it is widely recognized that artificial intelligence (AI) has the potential to enhance employee development, the synergy between AI-based learning analytics and employee development has been fragmented in HRM, workplace learning and digital transformation literature. This review brings that evidence together and investigates how artificial intelligence (AI) supports learning and HR analytics and their role in improving organizational performance. Literature searches were conducted via Scopus, Web of Science, ScienceDirect and Google Scholar using the PRISMA methodology, plus manual reference checking. Of 232 records identified, four were removed as duplicates and 43 studies since 2016 were incorporated into the qualitative synthesis. The results indicate that learning analytics using AI most consistently enhances training by means of personalization, adaptive support, prediction, and aligning the needs of employees with the needs of the organization's skills. The effects of retention are mostly indirect and via talent management, engagement, empowerment, learning transfer and analytics-based HR decision-making. The review also suggests a conceptual framework of a Random Forest approach by combining the learning, engagement, performance, demographic, and HR variables to estimate the risk of attrition or retention. AI-driven learning analytics must be considered as part of a larger talent system, learner-focused learning culture and long-term workforce strategy.

**Keywords:** AI-based learning analytics, training effectiveness, employee retention, Random Forest, employee attrition prediction, predictive HR analytics.

## 1. Introduction

Artificial intelligence (AI) is slowly changing the very nature of how organizations manage learning, performance and workforce sustainability. AI learning analytics in this context involves applying AI techniques, data-driven models, and intelligent decision-making tools to gather, analyze, and utilize data on employee learning to tailor training, predict growth prerequisites, optimize learning experiences, and facilitate organizational choices. Unlike conventional methods of evaluation that depend on the completion of training courses or the satisfaction of learners with the training, AI powered learning analytics will allow monitoring of learner behaviour, early interventions and better alignment of the employees' training requirements and the capability requirements of the organizations [1].

This review fills that gap by systematically synthesizing literature at the intersection of AI-based learning analytics, training effectiveness, and employee retention in organizations. In addition, the study proposes a conceptual Random Forest-based employee retention prediction framework. This predictive framework suggests how learning, engagement, performance, demographic, and HR-related variables can be used to estimate whether employees are likely to stay or leave.

The study has four objectives:

- to analyse the conceptualization and use of AI-based learning analytics in organizational learning and HR;
- to analyse how the literature explains its effects on training effectiveness;
- to determine how these effects are directly or indirectly related to employee retention; and
- to develop a conceptual Random Forest framework for predicting employee retention using learning, engagement, performance, demographic, and HR-related variables.

## 2. Thematic Findings

### 2.1. AI for personalization and learning support

The papers considering the workplace learning analytics, professionals' development, learning management systems, adaptive e-learning and personalized learning come together with the opinion that AI enhances the quality of developmental targeting, but not automation in the delivery of contents [7]-[9], [25]-[27].

An interesting tendency in such research is that AI is more effective when it is implemented to support the personalization of the intervention. Personalization is one of the core processes that literature calls literature to provide AI with a beneficial impact on the learning outcomes many times over. In comparison to traditional systems that offer one size fits all models, AI-enabled systems seem to be better placed to feature in aligning learning material, timing, and feedback with the needs that employees have. In such a manner, it is not direct learning analytics studies that enhance the technological improvement, but rather results in transition to precision development systems.

### 2.2. AI and training effectiveness

To begin with, the use of AI-powered systems can enhance training relevance, surveillance, and performance outcomes as there has been direct evidence of this outcome. Second, indirect evidence is that the effect of training is enhanced when AI-aided learning is accompanied by facilitating factors like engagement, empowerment, and collaborative knowledge processes [3], [4]. Third, there is empirical evidence which points to the fact that the results of training are more reliant upon larger HR architectures, such as international HRM, algorithmic HRM, human resource analytics, and digital HR systems [10]-[14], [16]-[18].

### 2.3. AI for Retention Prediction and Support

A large part of the retention evidence, though, is not direct. Instead of directly relating learning analytics to employee retention, numerous studies relate retention with mediators (talent management, psychological empowerment, engagement, employer branding, and sustainable HR practices) [2], [5], [6], [19], [20], [22]. It implies that the literature tends to validate retention based on a growth trajectory; the idea is that improved learning and talent system increases employee value perceptions, which, in turn, boost retention.

### 2.4. AI for workforce planning and broader HR transformation

Fourth is an enabler of a literature not explicitly an assessment of learning analytics, training effectiveness or retention, but involved in the de-jumble of the context that these relationships are applied in the organization. These encompass e-HRM, workforce planning, digital maturity, HR transformation, human resource agility and strategic talent systems work [15], [21]. These sources of literature provide contextual information that AI-directed learning analytics is part of a more generalized transformation towards a more digitally mediated people management.

## 3. Research Methodology

Based on the literature, the present study adopted the design of a systematic literature review (SLR) to provide a summary of the current evidence on the effect of the use of AI-based learning analytics on training effectiveness and employee retention in organizations. The selection was done as per PRISMA guidelines i.e. the identification, screening, eligibility and inclusion stages. This implementation facilitated the research to go beyond the traditional selection process and the recorded filtering process used in storytelling.

## 4. Proposed Random Forest Prediction Framework

In addition to the systematic synthesis, this study proposes a conceptual Random Forest framework for predicting employee retention. The framework demonstrates how AI-based learning analytics and HR-related variables may be used to estimate whether an employee is likely to remain with an organization or leave. Random Forest is an ensemble learning algorithm which builds several decision trees with bootstrapping and selecting random subsets of the predictor variables. The final classification is obtained by aggregating the predictions of the individual trees [28]. This structure enables the model to capture nonlinear relationships and complex interactions among learning, behavioral, demographic, performance, and HR variables while reducing the instability associated with a single decision tree. It also provides measures of variable importance that can identify the factors contributing most strongly to retention or attrition predictions [28].

Previous employee-attrition studies have compared Random Forest with logistic regression, decision trees, support vector machines, gradient boosting, and k-nearest neighbors [29], [30]. Their findings indicate that predictive performance depends on dataset characteristics, class distribution, predictor selection, and preprocessing decisions. Random Forest is therefore proposed because of its capacity to model complex interactions and support variable-importance analysis, rather than because it is assumed to outperform all alternative algorithms.

If tested empirically, model performance may be assessed using accuracy, precision, recall, F1-score, confusion matrix, and area under the receiver operating characteristic curve (ROC-AUC). However, no performance scores are reported in this review because the framework has not been applied to an organizational dataset.

Feature-importance analysis can rank predictors according to their contribution to classification [28], while explainability methods such as SHAP can provide global and employee-level interpretations of predictions [31]. These methods may reveal whether training effectiveness, engagement, empowerment, salary, promotion history, overtime, tenure, or work-life balance contributes most strongly to retention risk.

Because employee-retention prediction involves sensitive personal and employment data, implementation should include safeguards for privacy, transparency, fairness, informed data use, and human oversight. Predictive outputs should support rather than replace managerial judgement, as excessive reliance on algorithmic HR systems may introduce bias, information asymmetry, reduced autonomy, and risks to employee integrity [32].

## 5. Discussion

The findings of this review align with the idea that learning analytics using AI should be viewed not only as a training tool, but as a strategic socio-technical capability that can link the development of employees to the results of broader workforce development. The synthesis suggests that the value of AI lies in its ability to address organizations' needs around identifying skill gaps, customizing learning, offering feedback at the right time, and adapting training to organizational needs. The results of learning-community research also indicate that technology is not enough; learning communities with effective technology must also have effective methods, institutional support and enabling learning conditions to develop effective skills [22]. The evidence reviewed indicates that this relationship is not a direct product of AI but is an indirect relationship. Professional development is valued in the organization when it results in the transfer of learning to better work behaviors, capability, and performance [23]. If training is to have an impact that goes beyond participation, a transfer-oriented support is thus required [24]. AI derived learning analytics could help in retention, by enhancing the personalization, relevance and transferability of learning, which may also boost employee engagement, empowerment, perceived developmental value and organizational commitment. Personalization features of adaptive systems (content, pacing, feedback) are also influenced by learner characteristics but do not guarantee the benefits of adaptive systems [26]. Organizational leadership, learning opportunities, transfer mechanisms, digital readiness, and sustaining a positive learning culture are essential for achieving sustainable outcomes.

The proposed Random Forest framework builds on these results and other HR variables for predicting employee retention. The model could be used to identify employees who are at increased risk of leaving by looking at trends over time for employees like training effectiveness, engagement, empowerment, promotion data, work-life balance, and organizational tenure. However, predictive outputs must complement management decisions and not replace them. HR professionals need to consider model outcomes in conjunction with employee factors, organizational context, fairness and ethical considerations.

## 6. Conclusion

The systematic literature review conducted here using PRISMA framework has considered 3 pillars, AI based Learning analytics, employee training and employee retention. Most of the prior studies consider all these areas separately, but his review paper brings all of them together, to get a comprehensive understand of the three important pillars of this research. The SLR findings here shows that AI can be leveraged for employee training but at the same time it can be utilized for workforce planning and organizational decision making. The review also explains that organizations get better results when they have a positive learning culture, supportive leaders, good digital systems, and strong HR practices. These factors make it easier to use AI effectively and improve employee development.

The study also introduces a prediction model that uses the Random Forest method. The model combines information such as learning records, training activities, employee engagement, job performance, demographic details, and HR data. It helps predict whether an employee is likely to stay with the organization or leave. It can also show which factors have the biggest effect on employee turnover. This information can help HR teams create better plans to improve employee retention.

The review suggests that future research should test this model using real data from different organizations and industries. Researchers should also compare the Random Forest method with other machine learning techniques to find out which one performs better. In addition, future studies should examine the ethical and management issues involved in using employee data to make retention decisions.

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