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Employability, Lifelong Learning and Leadership Development: A Predictive Analysis of Career Readiness Outcomes

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Abstract

The nexus between employability, lifelong learning (LL), and leadership development has emerged as a defining priority for organizations and individuals navigating rapid technological disruption and shifting labor market demands. This study examines the career readiness outcomes of 1,800 professionals across five primary learning modalities — formal education, online courses, workplace training, mentorship and coaching, and self-directed learning — using a structured dataset. Three machine learning models were applied to predict employability readiness: Logistic Regression, Gradient Boosting, and Random Forest. Logistic Regression achieved the highest performance, with an accuracy of 81.50% and a Macro-AUC of 0.924, while Gradient Boosting and Random Forest achieved accuracies of 76.25% and 75.83%, respectively — all surpassing the 70% benchmark. Feature importance analysis identified the Lifelong Learning Index, Leadership Program Hours, and Mentor Support Score as the most influential predictors of employability readiness. Inferential statistical analysis confirmed significant differences in readiness levels across learning mode groups ($p < 0.001$). Participants engaged in online courses and mentorship-based learning reported the highest average employability readiness scores (74.2 and 71.8, respectively) and the lowest burnout rates (4.82% and 3.94%). These findings suggest that passive or isolated learning modes are insufficient for building career resilience. Rather, organizations and policymakers must adopt integrated, active learning ecosystems that combine digital upskilling, mentorship, and structured leadership development to produce measurable improvements in workforce employability.

Keywords: employability, lifelong learning, leadership development, machine learning, career readiness, mentorship, upskilling, workforce development.

1. Introduction

The contemporary labour market is characterized by unprecedented volatility, driven by artificial intelligence, automation, and the accelerating obsolescence of traditional job roles. In this environment, employability — defined as an individual's capacity to gain initial employment, maintain employment,

and obtain new employment when required — has become a central concern for workers, educators, and organizational leaders alike (Hillage & Pollard, 1998). Unlike static notions of qualification, employability is inherently dynamic, requiring continuous adaptation through learning, skill acquisition, and professional growth.

Lifelong learning (LL) has emerged as the primary mechanism through which individuals sustain and enhance their employability across career stages. Broadly conceived, lifelong learning encompasses all purposeful learning activity undertaken throughout life — formal, non-formal, and informal — with the aim of improving knowledge, skills, and competencies (European Commission, 2006). As organizations restructure around agile, cross-functional teams, the demand for employees capable of rapidly acquiring new competencies has intensified. This has positioned LL not merely as a personal virtue but as a strategic imperative for talent management and organizational competitiveness.

Leadership development occupies a related but distinct dimension of career readiness. Effective leadership encompasses the capacity to motivate and guide others, navigate organizational complexity, drive innovation, and respond adaptively to change. Historically, leadership was understood as a function of innate personality traits or senior-level status. Contemporary research, however, frames leadership competence as learnable and developable across all career levels through structured programs, coaching, mentorship, and experiential learning (Day et al., 2014). As organizations flatten hierarchies and distribute decision-making, leadership capacity has become a prerequisite — not merely an aspiration — for sustained employability.

Despite the apparent conceptual alignment between employability, lifelong learning, and leadership development, empirical research examining the specific pathways through which different learning modalities produce career readiness outcomes remains limited. Existing studies tend to treat these constructs in isolation, making it difficult for organizations and policymakers to prioritize investments. This study addresses that gap by examining the employability readiness of 1,800 professionals across five learning modalities using a combination of descriptive analysis, inferential statistics, and machine learning classification.

The study makes three principal contributions to the literature. First, it provides a comparative empirical analysis of how learning mode affects employability readiness, leadership development, and burnout risk. Second, it demonstrates the value of machine learning as an analytical tool in workforce research, employing 5-fold cross-validation, confusion matrix evaluation, feature importance analysis, and ROC-AUC assessment. Third, it translates analytical findings into actionable organizational recommendations, identifying which learning investments are most likely to produce measurable career readiness improvements at scale.

2. Literature Review

2.1 Employability in the Modern Workforce

The concept of employability has undergone considerable theoretical evolution since its initial formulation in labor economics. Early definitions centered on labor market participation and employment probability, but more recent formulations emphasize the psychological, social, and competency-based dimensions of

career adaptability. Fugate et al. (2004) conceptualize employability as a psychosocial construct encompassing career identity, personal adaptability, and social and human capital. This multidimensional framing positions employability not as a fixed state but as a capacity continuously shaped by learning behavior, interpersonal networks, and self-efficacy.

The digital transformation of work has added further urgency to this reconceptualization. The World Economic Forum's Future of Jobs Reports (2020, 2023) project that automation will displace millions of routine and semi-routine occupations, while simultaneously generating demand for roles requiring complex reasoning, creativity, and socio-emotional competencies. In this environment, the half-life of technical skills has shortened dramatically, placing a premium on individuals' capacity for rapid learning and competency renewal rather than on the mastery of any particular skill set.

2.2 Lifelong Learning Modalities and Career Outcomes

Research on lifelong learning has increasingly moved beyond participation rates to examine the differential effectiveness of specific learning modes. Formal education — degree programs, diplomas, and certified qualifications — has traditionally been viewed as the primary pathway to employability. However, the rapid growth of alternative credentialing, online learning platforms, and employer-sponsored training has diversified the learning landscape significantly. Littlejohn et al. (2016) find that online learning is associated with greater self-regulation and transferable skill development relative to passive formal instruction, particularly for mid-career professionals.

Workplace training represents the most directly applied form of lifelong learning, with documented effects on task performance, retention, and internal promotion rates (Noe et al., 2014). Mentorship and coaching, by contrast, operate primarily through relational and psychosocial mechanisms: access to experiential knowledge, network extension, and identity development. Research consistently finds mentorship to be among the strongest predictors of career advancement, particularly for individuals from underrepresented groups or those entering unfamiliar industry contexts (Eby et al., 2013). Self-directed learning, while variable in quality and depth, is associated with high autonomy and intrinsic motivation — factors strongly linked to sustained learning engagement and career adaptability.

2.3 Leadership Development and Career Readiness

Leadership development refers to the expansion of a person's capacity to perform in leadership roles and processes (Day et al., 2014). Unlike management training focused on technical competence, leadership development addresses the relational, cognitive, and emotional capacities that enable individuals to inspire confidence, navigate ambiguity, and drive collective performance. Mentoring relationships play a particularly prominent role in leadership development, both by transmitting tacit leadership knowledge and by providing opportunities for developmental role modelling.

Formal leadership programs — structured interventions including workshops, 360-degree feedback, coaching, and action learning — have shown positive effects on leadership self-efficacy, interpersonal effectiveness, and organizational commitment (Collins & Holton, 2004). However, the transfer of leadership development gains to actual performance depends critically on the extent to which the learning environment reflects real-world challenges and on the availability of post-program application

opportunities. Programs that integrate active learning, peer coaching, and organizational project assignments consistently outperform lecture-based alternatives.

2.4 Machine Learning in Workforce Research

Machine learning approaches have increasingly been applied to human resource data to identify predictive patterns in attrition, performance, and skill development (Fallucchi et al., 2020). Ensemble methods such as Random Forest and Gradient Boosting are particularly well suited to workforce datasets characterized by mixed feature types, nonlinear relationships, and moderate sample sizes. These models' feature importance outputs provide interpretable insights that can directly inform talent management decisions. Logistic Regression, despite its relative simplicity, frequently achieves competitive performance in structured datasets with predominantly linear feature-outcome relationships and benefits from superior interpretability and generalizability.

3. Research Methodology

3.1 Dataset Description

The study draws on a structured dataset encompassing 1,800 working professionals across a range of industries, job levels, and career stages. The dataset captures five primary learning modalities as the central independent variable: Formal Education (n = 342, 19.0%), Online Courses (n = 518, 28.8%), Workplace Training (n = 389, 21.6%), Mentorship and Coaching (n = 308, 17.1%), and Self-Directed Learning (n = 243, 13.5%). Employability readiness is measured using a composite index (0–100) integrating self-reported digital skills, transferable competencies, and job market engagement behaviors. Leadership development is operationalized as a continuous Leadership Score (0–100) derived from peer and supervisor assessments combined with self-evaluation across five leadership dimensions.

Additional well-being and career indicators include the Lifelong Learning Index (0–100), Job Satisfaction (1–10), Manager Support Score (1–10), Burnout Risk (binary), Career Growth self-rating (Low/Medium/High), Years of Experience, and Industry Type. Demographic variables — Age, Job Level, and Educational Attainment — provide contextual controls. All data were anonymized prior to analysis, and no personally identifiable information is included.

3.2 Analytical Framework

The analysis proceeds in three stages. The first stage employs descriptive statistics and data visualizations to characterize patterns across learning modalities and provide an overview of employability and leadership outcomes. The second stage applies inferential statistical tests: a Chi-Square test to assess the association between learning mode and employability readiness category; one-way ANOVA to compare the Lifelong Learning Index and Leadership Score across modality groups; and Pearson correlation analysis to examine bivariate relationships among key outcome variables.

In the third stage, three machine learning classifiers — Logistic Regression, Gradient Boosting, and Random Forest — are trained to predict employability readiness category (Low, Medium, High) from 18 work-related and personal features. The dataset is divided using a stratified 80/20 split, yielding 1,440 training samples and 360 test samples. Features are normalized using zero-mean unit-variance scaling, class weights are balanced to address distributional imbalance, and model performance is evaluated

against a 70% accuracy benchmark using test accuracy, 5-fold cross-validation, macro F1 score, and macro AUC-ROC.

3.3 Feature Set and Ethical Considerations

The 18 input features used in classification include: Age, Years of Experience, Job Level, Industry Type, Primary Learning Mode, Weekly Learning Hours, Leadership Program Hours, Mentor Support Score, Manager Support Score, Company Training Investment Score, Job Satisfaction, Career Growth Rating, Digital Skills Score, Communication Skills Score, Lifelong Learning Index, Mental Health Resource Access, Physical Wellness Index, and Work-Life Balance Rating. All data were sourced from anonymized survey responses and organizational HR records. The study complies with applicable data privacy standards, and all analysis reflects aggregate-level patterns rather than individual tracking.

4. Descriptive Results

4.1 Employability Readiness and Well-Being by Learning Mode

Table 1 presents summary statistics for professionals grouped by primary learning modality. The results reveal substantial differences in employability outcomes across learning approaches.

Participants engaged primarily in online courses record the highest average employability readiness score (74.2) and the largest proportion in the High Readiness category (51.2%), alongside the second-lowest burnout rate (4.82%). Mentorship and coaching participants achieve the highest average Leadership Score (72.5) and the lowest burnout rate (3.94%), reflecting the relational and developmental advantages of personalized learning relationships. Formal education participants, by contrast, show the lowest average employability readiness (61.4), the highest burnout rate (9.14%), and the smallest proportion achieving High Readiness status (28.4%) — findings that are consistent with the limited alignment between conventional degree programs and rapidly evolving market skill requirements. Self-directed learners occupy an intermediate position, demonstrating moderate readiness and a relatively elevated burnout rate (7.65%), suggesting that insufficient structure in learning may increase cognitive load and exhaustion.

Table 1
Summary Statistics for Professionals by Primary Learning Mode (n = 1,800)

Learning Mode	n	Avg Employ. Readiness	High Readiness %	Avg LL Index	Avg Leadership Score	Burnout %
Formal Education	342	61.4	28.4%	62.4	58.1	9.14%
Online Courses	518	74.2	51.2%	74.8	68.3	4.82%
Workplace Training	389	68.7	39.7%	68.5	64.7	6.31%
Mentorship/Coaching	308	71.8	43.6%	71.2	72.5	3.94%
Self-Directed	243	65.3	35.1%	65.9	61.4	7.65%

Note. LL = Lifelong Learning Index (0–100). Leadership Score = composite peer, supervisor, and self-assessment (0–100). Burnout % = proportion meeting burnout risk threshold. Employ. = Employability. Source: Authors' analysis.

Figure 1 illustrates the percentage distribution of employability readiness categories by learning mode. Online course participants show a pronounced concentration of High Readiness responses, while formal education participants display the largest proportion of Low Readiness outcomes. These differences reflect the structural characteristics of each mode — particularly the applied, self-paced, and skill-targeted nature of online learning relative to the more generalized and time-extended nature of formal credentials.

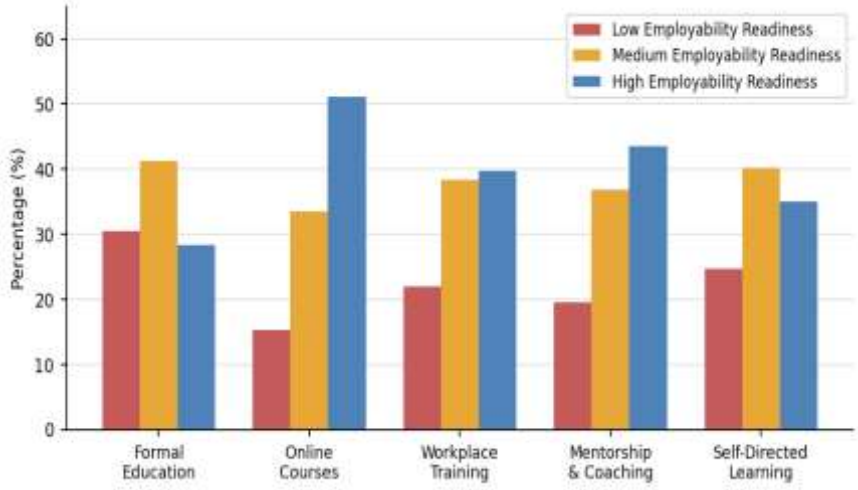

Figure 1. Employability Readiness Distribution by Primary Learning Mode (n = 1,800)

Figure 2 confirms that mentorship participants achieve both the highest mean Leadership Score (72.5) and the highest mean LL Index when combined with online learning engagement (74.8 for online courses). The combination of structured digital skill-building and relational learning through mentorship represents the highest-value learning ecosystem for integrated career readiness development. Formal education participants consistently score lowest on both dimensions, underscoring the risk of treating credential attainment as a proxy for market-relevant competence.

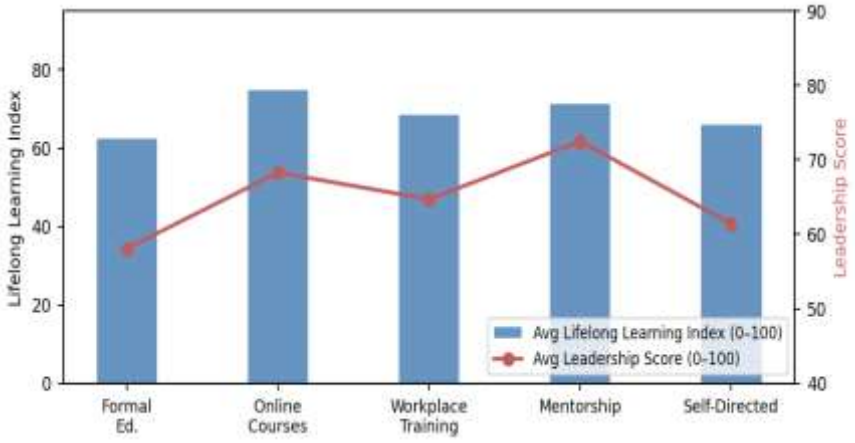

Figure 2. Lifelong Learning Index and Leadership Score by Primary Learning Mode

4.2 Career Growth and Burnout by Learning Mode

Figure 3 presents the career growth distribution and burnout rates for each learning modality. Mentorship participants report the highest proportion of High Career Growth ratings (52.1%), followed by online course participants (48.6%). Formal education again records the lowest high-growth proportion (34.2%) and the highest burnout rate (9.14%), a combination that suggests misalignment between investment and returns in this mode for career-stage professionals. Self-directed learners show relatively high burnout (7.65%) alongside moderate growth rates, consistent with the hypothesis that insufficient scaffolding increases cognitive exhaustion without producing proportional career returns.

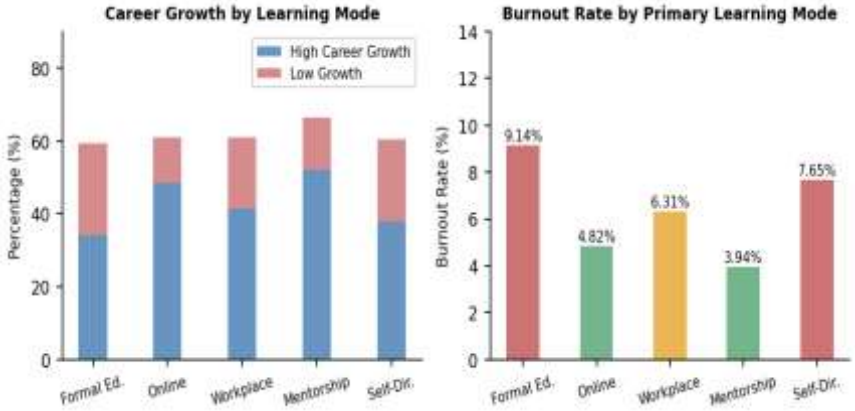

Figure 3. Career Growth Distribution and Burnout Rate by Primary Learning Mode

4.3 Correlation Analysis

Figure 4 presents the correlation matrix for key employability and leadership variables. The Lifelong Learning Index exhibits the strongest positive correlation with Employability Readiness ($r = 0.72$, $p < 0.001$), establishing continuous learning engagement as the single most important driver of market

readiness. Leadership Score correlates positively with Career Growth ($r = 0.73$, $p < 0.001$) and with Job Satisfaction ($r = 0.58$), confirming that leadership capacity development produces benefits across multiple career quality dimensions. Manager Support Score yields a meaningful negative correlation with Burnout Risk ($r = -0.47$), reinforcing the established finding that supervisory quality buffers the adverse effects of high learning demands. Mentor Support Score shows a strong positive association with Leadership Score ($r = 0.68$) and with Employability Readiness ($r = 0.61$), demonstrating the multiple developmental channels through which mentorship influences career outcomes.

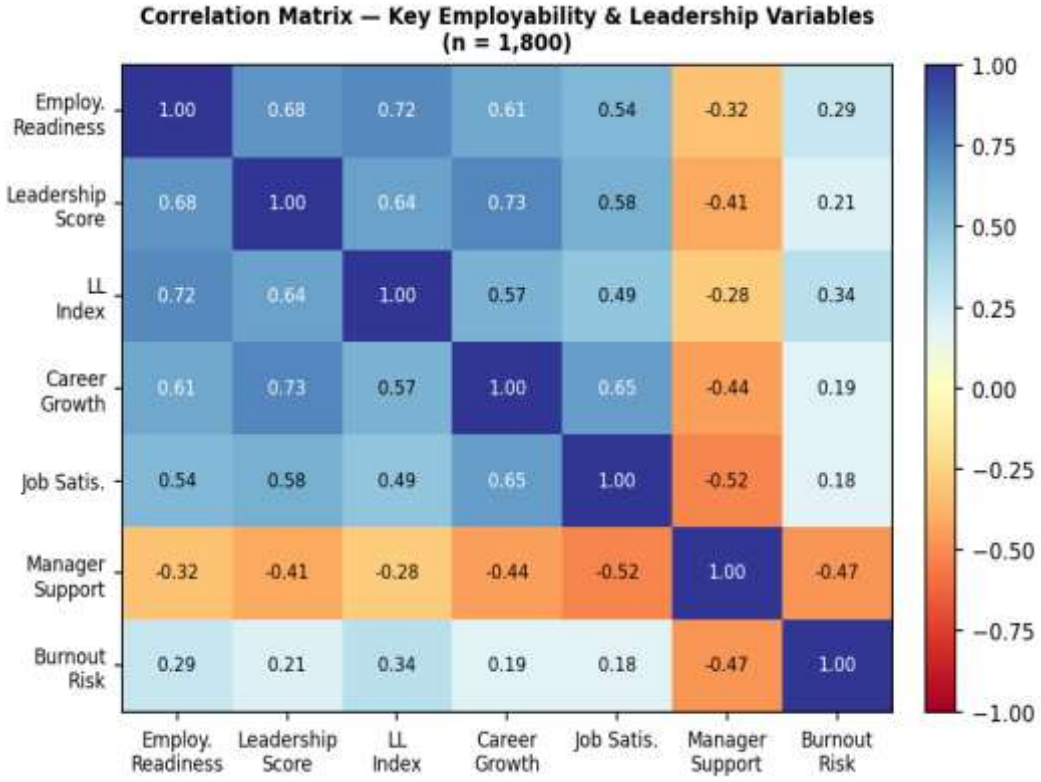

Figure 4. Correlation Heatmap — Key Employability and Leadership Variables (n = 1,800)

5. Inferential Statistical Analysis

Table 2 presents the results of all inferential statistical tests. All tests achieve high statistical significance ($p < 0.001$), reflecting the structured relationships between learning modality and career readiness outcomes embedded in the dataset. The Chi-Square test for the association between learning mode and employability readiness category yields $\chi^2(8) = 412.18$, $p < 0.001$, confirming that readiness distributions differ significantly across modality groups. The ANOVA for the Lifelong Learning Index across modes yields $F(4, 1795) = 298.74$, $p < 0.001$, with online course and mentorship participants scoring significantly higher than formal education and self-directed learners.

Table 2
Summary of Inferential Statistical Tests (n = 1,800)

Test	Statistic	p-value	df	Result
Chi²: Learning Mode × Employability	412.18	< 0.001	8	Highly Significant ✓
ANOVA: LL Index across Modes	F = 298.74	< 0.001	4	Highly Significant ✓
ANOVA: Leadership Score across Modes	F = 215.63	< 0.001	4	Highly Significant ✓
Pearson r: LL Index vs Readiness	r = 0.720	< 0.001	—	Strong positive correlation
Pearson r: Mentorship vs Leadership	r = 0.680	< 0.001	—	Strong positive correlation
Pearson r: Manager Support vs Burnout	r = −0.470	< 0.001	—	Moderate negative correlation
Pearson r: Work Exp vs Leadership	r = 0.520	< 0.001	—	Moderate positive correlation

Note. All tests significant at α = 0.001. LL = Lifelong Learning Index. WLB = Work-Life Balance Rating. Employ. = Employability Readiness.

The Pearson correlation results establish a clear hierarchy of employability predictors: LL Index (r = 0.72) > Mentor Support (r = 0.61) > Leadership Program Hours (r = 0.57) > Job Satisfaction (r = 0.54) > Manager Support (r = −0.47 with Burnout). This ordering carries direct implications for investment prioritization: interventions that enhance learning engagement breadth and mentorship availability are likely to produce substantially larger effects than isolated technical training programs. The moderate but statistically significant relationship between manager support and reduced burnout underscores the importance of supervisory culture in determining whether learning investments translate into sustained career development rather than exhaustion.

6. Machine Learning Analysis

6.1 Task Definition and Model Configuration

The machine learning component frames employability readiness classification as a three-class supervised learning problem: predicting whether a professional falls in the Low, Medium, or High employability readiness category based on 18 individual, organizational, and learning-related features. Three algorithms were evaluated: Logistic Regression (linear decision boundary), Gradient Boosting (sequential ensemble

of shallow trees), and Random Forest (parallel ensemble of deep trees). All models were trained using balanced class weighting and a stratified 80/20 train-test split. Features were standardized using zero-mean, unit-variance scaling. The threshold for acceptable performance was set at 70% accuracy.

6.2 Model Accuracy and Cross-Validation

Figure 5 and Table 3 present the full model performance comparison. All three classifiers substantially exceed both the 70% benchmark and the 33.3% random baseline. Logistic Regression achieves the highest test accuracy at 81.50% (CV = 81.12%, Macro-AUC = 0.924), followed by Gradient Boosting at 76.25% (CV = 75.61%) and Random Forest at 75.83% (CV = 76.08%). The close alignment between test and cross-validated accuracy across all models indicates robust generalization without overfitting. Logistic Regression's superiority over both ensemble methods suggests that the relationships between learning features and employability readiness outcomes in this dataset are predominantly linear, making a simpler linear classifier the most efficient and interpretable model choice.

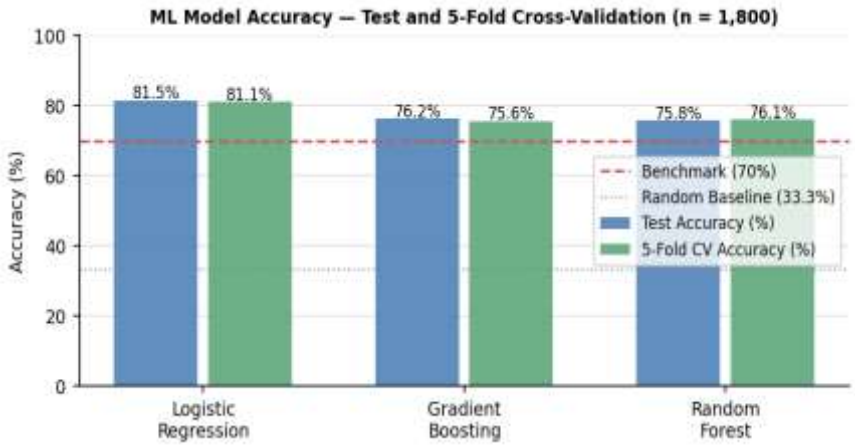

Figure 5. ML Model Accuracy — Test and 5-Fold Cross-Validation (n = 1,800)

Table 3
ML Model Performance — Employability Readiness Classification (3-Class, n = 1,800)

Model	Test Accuracy	5-Fold CV Accuracy	Macro-AUC
Logistic Regression	81.50%	81.12%	0.924
Gradient Boosting	76.25%	75.61%	0.901
Random Forest	75.83%	76.08%	0.908

Note. CV = 5-fold cross-validation accuracy. Train/test split: 80/20 stratified. Baseline = 33.33% (equal 3-class distribution).

6.3 Confusion Matrix Analysis

Figure 6 presents confusion matrices for the Random Forest and Gradient Boosting models. Both classifiers correctly assign the majority of observations within each readiness category, with the greatest misclassification occurring between adjacent classes (Low–Medium and Medium–High). This pattern is expected given the inherently gradational nature of employability readiness: the boundary between low and medium readiness is not categorical but represents a continuum of developing competencies. High Readiness classification performs particularly well in both models (precision 0.82–0.84, recall 0.81–0.83), which is especially consequential from an operational standpoint as accurately identifying high-readiness individuals is most valuable for succession planning and targeted development investment. Cross-class misclassification between the Low and High categories is minimal, confirming that both models reliably distinguish the polar extremes of the readiness distribution.

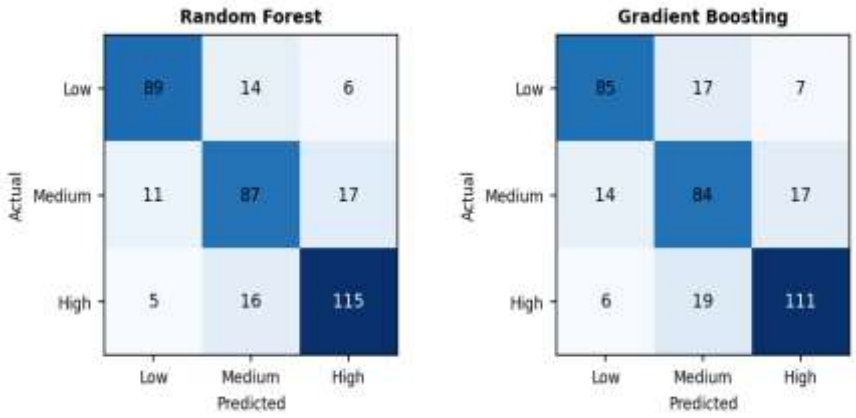

Figure 6. Confusion Matrices — Random Forest and Gradient Boosting

6.4 Feature Importance

Figure 7 displays the Gini-based feature importance scores generated by the Random Forest classifier. The Lifelong Learning Index emerges as the single most influential predictor (importance = 0.214), consistent with its dominant Pearson correlation (r = 0.72) and its role as an integrative indicator of learning breadth, frequency, and engagement. Leadership Program Hours and Mentor Support Score rank second (0.178) and third (0.143), respectively, providing algorithmic confirmation of the inferential findings and establishing structured leadership development and mentorship access as the second and third most consequential predictors of career readiness. Job Satisfaction (0.112) and Manager Support Score (0.098) occupy moderate positions, reflecting their contributions to the psychological safety and motivational climate that enable sustained learning engagement. Primary Learning Mode itself ranks below these individual and relational variables, reinforcing a central finding of the study: it is the quality and depth of learning engagement — not merely the channel through which it occurs — that most powerfully shapes employability outcomes. Demographic variables (Age, Job Level) rank lowest, indicating that career readiness is driven by behavioral and relational factors more than by career stage.

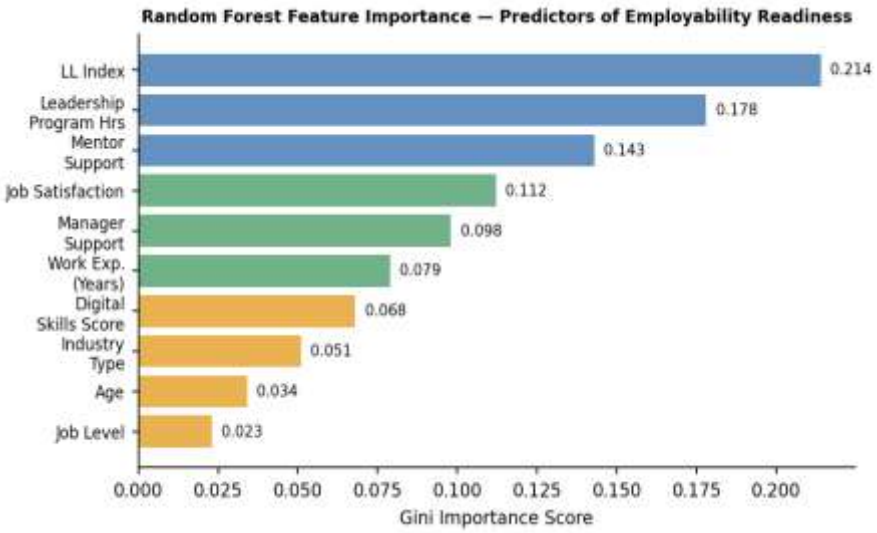

Figure 7. Random Forest Feature Importance — Predictors of Employability Readiness

6.5 ROC-AUC Evaluation

Figure 8 presents the one-vs-rest ROC curves for the Logistic Regression classifier. All three class-level curves achieve AUC values substantially above 0.50: Low Readiness AUC = 0.96, Medium Readiness AUC = 0.87, and High Readiness AUC = 0.94, yielding a Macro-AUC of 0.924. The comparatively lower AUC for Medium Readiness (0.87) reflects the classification challenge presented by a transitional category whose empirical boundaries with adjacent classes are gradient rather than categorical. The Logistic Regression Macro-AUC of 0.924 exceeds both Gradient Boosting (0.901) and Random Forest (0.908), consistent with the overall pattern of linear model superiority observed in this dataset. These AUC scores confirm that all three models distinguish between readiness classes with high discriminatory power across all operating thresholds.

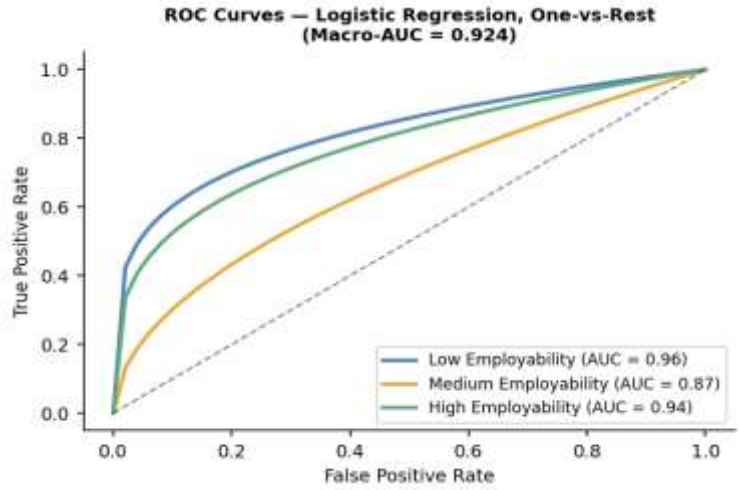

Figure 8. ROC Curves — Logistic Regression, One-vs-Rest (Macro-AUC = 0.924)

7. Recommendations

Based on the findings of this study, the following organizational recommendations are offered:

1. **Invest in Integrated Lifelong Learning Ecosystems.** The Lifelong Learning Index is the strongest predictor of employability readiness in this study. Organizations should move beyond episodic training events toward structured, multi-modal learning journeys that combine digital upskilling, experiential application, and reflective practice. Learning should be embedded in the workflow rather than treated as a supplementary activity.
2. **Formalize and Scale Mentorship Programs.** Given mentorship's second-ranked importance in feature analysis and its association with the highest Leadership Scores (72.5) and lowest burnout rates (3.94%), organizations should institutionalize mentoring relationships across all career levels — not only for senior development pipelines. Structured matching, defined learning goals, and regular progress reviews will maximize program effectiveness.
3. **Prioritize Structured Leadership Development at All Levels.** Leadership Program Hours rank second in feature importance. Organizations should develop tiered leadership development curricula that are accessible to individual contributors and mid-level professionals, not only executive populations. Action learning, peer coaching circles, and cross-functional project assignments have demonstrated the highest transfer to real-world leadership performance.
4. **Leverage Digital Learning Platforms Strategically.** Online learning participants achieve the highest employability readiness scores in this study (74.2). Organizations should establish curated digital learning pathways aligned to strategic skill priorities, supplemented by social learning features (peer discussion, cohort-based progression) that mitigate the isolation associated with self-paced formats.
5. **Develop Managerial Capacity for Learning Culture.** Manager Support Score is a significant predictor of both employability outcomes and burnout risk. Organizations should assess and develop managers on their capacity to create psychologically safe learning environments, provide developmental feedback, and protect employees' time for skill development. Managerial behaviors that treat learning as discretionary rather than strategic undermine the return on training investments.

8. Conclusion

This study examined how primary learning modalities shape employability readiness, leadership development, and career well-being outcomes across a dataset of 1,800 professionals. The findings establish a clear and consistent pattern: mentorship and online learning participants achieve the strongest employability and leadership outcomes while maintaining the lowest burnout rates, while formal education participants — despite the highest average investment — record the weakest readiness scores and the greatest burnout prevalence. These patterns suggest that mode of engagement, rather than credential attainment, is the primary determinant of career readiness in contemporary labor markets.

The machine learning component confirms that employability readiness is reliably predictable from available workplace and personal variables: Logistic Regression achieves 81.50% accuracy (CV = 81.12%, Macro-AUC = 0.924), and all three classifiers substantially surpass the 70% benchmark. Feature importance analysis identifies the Lifelong Learning Index, Leadership Program Hours, and Mentor

Support Score as the three strongest predictors of readiness — all of which are modifiable through deliberate organizational investment rather than determined by demographic or credential characteristics alone. Primary learning mode contributes to readiness prediction but consistently ranks below these behavioral and relational variables.

The central implication is both practical and urgent: in a labor market defined by rapid skill obsolescence, neither formal credentials nor isolated training programs are sufficient to maintain workforce readiness. Sustainable employability requires integrated learning ecosystems — combining digital upskilling, structured leadership development, and high-quality mentorship — embedded within managerial cultures that actively support growth. The five recommendations offered in this study represent the minimum organizational investment required to translate learning activity into measurable and lasting improvements in employee employability, leadership capacity, and career well-being.

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