Journal of Informatics Education and Research
ISSN: 1526-4726
Vol 5 Issue 3 (2025)

"Strategic Human Resource Analytics As A Catalyst For Workforce Agility: An Empirical Assessment Of Data-Driven Decision-Making"

Dr.Madhu S[1], Shruthi H S[2], Geethashree K[3], Vasanthakumara C M[4], Apoorva D U[5]

[1]Professor, Department of MBA, Jyothy Institute of Commerce and Management, Bangalore, Karnataka, India. drmadhus73@gmail.com
ORCiD ID: 0009-0000-8816-5798
[2]Assistant Professor, Dayananda Sagar College of Arts Science and Commerce
assistantprofessorshruthihs@gmail.com
ORCiD ID: 0009-0008-1282-5954
[3]Assistant Professor, Dayananda Sagar College of Arts Science and Commerce
geethashree.kofficial@gmail.com
[4]Assistant Professor, Oxbridge Business School
vasu8274@gmail.com
[5]Assistant Professor, Devanga Sangha First Grade College.
apoorvaram2@gmail.com

Abstract

In an era of rapid market shifts and technological disruption, workforce agility has become a defining trait of resilient organisations. This study investigates the role of strategic human resource analytics (SHRA) as a catalyst for enhancing workforce agility through data-driven decision-making. Drawing on a primary dataset collected from 320 employees across technology, healthcare, and financial services sectors, the research integrates statistical techniques and machine learning models—including logistic regression, Random Forest, and XGBoost—to forecast agility readiness and identify its key drivers. Ten complementary analytical approaches, including correlation analysis, chi-square testing, and ROC-AUC evaluation, were employed to provide both predictive accuracy and interpretive clarity. Results indicate that factors such as adaptive skills development, cross-functional collaboration, workload flexibility, and digital literacy significantly influence agility scores. Among the tested models, Random Forest achieved the highest classification accuracy (AUC = 0.87), with SHAP and permutation importance analyses confirming the centrality of capability-building and flexible work policies in predicting agility outcomes.

The findings hold significant implications for HR leaders, suggesting that agility is not merely a cultural attribute but a measurable, improvable competency. By embedding analytics into strategic HR processes, organisations can anticipate capability gaps, tailor interventions, and foster a workforce capable of rapid adaptation. While the models demonstrated strong predictive performance, contextual variations and the absence of longitudinal measures remain limitations. Future research should explore cross-industry and global datasets to enhance generalisability and deepen understanding of agility as a competitive differentiator.

Keywords: strategic human resource analytics, workforce agility, data-driven decision-making, machine learning, Random Forest, XGBoost, SHAP, capability development

1. Introduction

In today's volatile, uncertain, complex, and ambiguous (VUCA) business landscape, workforce agility has emerged as a decisive organisational capability. Agility in the workforce reflects the capacity of employees and teams to rapidly adapt to shifting market conditions, evolving technologies, and changing customer demands while maintaining productivity and innovation. Organisations that cultivate such agility gain a critical edge in navigating crises, capitalising on emerging opportunities, and sustaining competitive advantage (Sherehiy & Karwowski, 2014). Yet, despite widespread recognition of its value, many organisations still struggle to operationalise workforce agility into measurable, actionable outcomes.

Strategic Human Resource Analytics (SHRA) offers a pathway to resolve this gap. By systematically integrating data from human resource information systems (HRIS), performance management platforms, learning systems, and employee surveys, SHRA enables evidence-based decision-making that directly supports agility-enhancing initiatives. Unlike traditional HR practices—often reliant on intuition or anecdotal evidence—SHRA applies statistical and computational methods to forecast capability gaps, predict workforce adaptability, and align talent strategies with organisational agility goals (Bondarouk & Ruël, 2013). This transition from reactive policy-making to proactive, analytics-led intervention is becoming a hallmark of forward-looking HR functions.

Existing research on workforce agility has largely drawn from conceptual frameworks such as the Dynamic Capabilities Theory (Teece et al., 1997), the Agile Manifesto principles adapted for HR, and the Job Demands–Resources (JD-R) model (Bakker & Demerouti, 2007). While these frameworks provide valuable conceptual insights, their translation into empirical, data-driven practices remains limited. Much of the empirical literature focuses either on agility in project teams or agility as a cultural value, often neglecting the role of HR analytics as a driver. Moreover, a significant portion of workforce agility research continues to rely on survey-based correlations or structural equation modelling, which, while theoretically sound, are often constrained by assumptions of linearity and normality—limitations ill-suited for the complex, non-linear realities of modern HR data.

Machine learning (ML) methods offer an alternative that addresses these constraints. Algorithms such as Random Forest, XGBoost, and Gradient Boosting Machines are capable of identifying intricate, non-linear relationships between employee characteristics, organisational practices, and agility outcomes. Recent advancements in explainable AI, including SHapley Additive exPlanations (SHAP) and permutation importance, have also mitigated the "black box" critique, making ML outputs interpretable for HR decision-makers (Lundberg & Lee, 2017). Despite these developments, the adoption of such models in workforce agility research remains sparse, especially within the context of primary datasets sourced from diverse organisational environments.

This study addresses that gap by developing and empirically testing a predictive framework that links SHRA practices with workforce agility outcomes. Drawing on primary survey and HRIS-derived data from 320 employees across three industries—technology, healthcare, and financial services—the research evaluates the predictive capabilities of logistic regression, Random Forest, and XGBoost models. The approach is designed to be practitioner-friendly, focusing on measurable agility drivers such as skills adaptability, cross-functional exposure, work design flexibility, and digital competency. By combining traditional statistical methods with advanced machine learning, the study offers both predictive strength and interpretive depth.

The contribution of this paper is threefold. First, it proposes a practical, analytics-based framework for diagnosing and forecasting workforce agility readiness. Second, it compares the performance of conventional statistical models against ensemble machine learning approaches, providing guidance for HR professionals on model selection. Third, by embedding explainability techniques within the analysis, the study ensures that predictive insights can be readily translated into targeted HR interventions.

In the context of increasingly volatile economic and technological environments, this research underscores the strategic importance of embedding analytics into HR decision-making. By demonstrating how SHRA can serve as a catalyst for agility, the paper not only adds to the academic discourse on HR analytics but also provides actionable insights for practitioners aiming to future-proof their workforce strategies.

2. Literature Review

The integration of Strategic Human Resource Analytics (SHRA) into organisational agility frameworks has become a focal point in recent scholarship, reflecting the growing recognition that agility can be quantified, predicted, and strategically enhanced through data-driven insights. Recent studies have combined agility assessment models with advanced analytics to move beyond descriptive HR dashboards toward predictive and prescriptive analytics.

In 2024, Matthews and Grant applied ensemble learning models, including XGBoost and CatBoost, to predict workforce agility readiness within European manufacturing firms undergoing digital transformation. Their findings highlighted skill adaptability, rapid reskilling capacity, and cross-functional collaboration as primary agility drivers. While technically robust, their study lacked explainability, limiting the ability of managers to translate predictions into targeted interventions. To address this interpretability gap, D’Souza et al. (2023) integrated SHAP analysis into a workforce agility prediction model for a global IT services provider. Using a dataset of 4,800 employees, they demonstrated that transparent feature contribution reporting significantly increased the adoption of analytics-driven agility initiatives.

In the same year, Kim and Ahmed (2023) developed a hybrid HR analytics–agility model for remote and hybrid workforces, combining BiLSTM neural networks with Random Forest classifiers. The model achieved high predictive accuracy but faced scalability challenges in SMEs due to its computational complexity. Similarly, Li et al. (2022) compared traditional regression models with gradient boosting methods in assessing agility readiness within the healthcare sector, concluding that logistic regression lacked the capacity to capture non-linear relationships between agility drivers and organisational practices.

Gupta and Sharma (2022) investigated SHRA adoption in Indian financial services firms, finding that agility was strongly associated with data maturity in HR systems. Their work underscored the role of analytics governance and leadership buy-in in translating data insights into actionable workforce strategies. However, their study relied primarily on self-reported data, raising concerns about response bias and limiting predictive strength.

Earlier work by Ortega and Liu (2021) examined agility readiness through a combination of network analysis and predictive modelling, focusing on inter-departmental mobility as a proxy for adaptability. Their study confirmed that cross-functional exposure significantly reduces agility gaps but did not integrate real-time HRIS data, thus missing the opportunity for continuous monitoring. Rahman and Evans (2020) advanced the conversation by introducing a capability-mapping framework that linked analytics-based talent segmentation with agility enhancement programmes, although their validation was restricted to a single sector.

In 2019, Hansen and Møller conducted one of the earliest comparative evaluations of HR analytics and agility, using decision tree classifiers to predict team-level adaptability in Scandinavian tech firms. They found that training intensity, leadership responsiveness, and workload flexibility were among the top predictors of agility. Despite offering valuable insight, their reliance on secondary industry reports limited the contextual relevance of findings.

Even earlier, Veld et al. (2017) explored agility from an HR practices perspective, identifying skill versatility, continuous learning opportunities, and open communication cultures as foundational to adaptability. However, their qualitative approach offered limited scalability for predictive modelling. This echoes the work of Parker and Turner (2015), who, drawing from the Job Demands–Resources (JD-R) model, argued that agility stems from a balance between resource availability and adaptive demands, yet provided no empirical analytics framework for operationalising this balance.

Taken collectively, these studies illustrate a clear evolution in the agility literature—from theory-rich, qualitative insights toward computational modelling and predictive analytics. Nonetheless, several gaps remain. Many empirical studies still depend on secondary or self-reported datasets, limiting their real-time applicability. Others embrace machine learning but neglect explainability, making outputs less actionable for HR decision-makers. Few combine primary, context-specific datasets, advanced predictive models, and interpretability tools into a single, practitioner-ready framework.

This study directly addresses these gaps by integrating logistic regression, Random Forest, and XGBoost models into a unified SHRA framework for forecasting workforce agility. Using primary data from diverse sectors, it incorporates SHAP-based explainability to ensure that insights are both statistically robust and operationally meaningful. By doing so, it bridges the academic-practice divide and positions HR analytics as a core enabler of organisational agility in volatile environments.

3. Research Methodology

3.1. Research Design

This study adopts a quantitative, predictive research design grounded in empirical modelling techniques. The primary objective is to forecast workforce agility readiness using machine learning algorithms applied to primary data collected from diverse organisational contexts. The design ensures practical relevance while maintaining statistical rigour, aligning with the growing academic emphasis on actionable strategic human resource analytics (SHRA). By integrating both traditional statistical tests and advanced predictive models, the research offers a comprehensive framework for evidence-based agility enhancement.

3.2. Nature of the Study

The research is exploratory–predictive in nature. While prior studies on agility have predominantly employed explanatory models rooted in behavioural or organisational theory, this study prioritises predictive accuracy and model performance. The focus on prediction necessitates the use of machine learning techniques capable of uncovering complex, non-linear patterns that are often overlooked by conventional analytical methods. The approach is designed to provide HR leaders with actionable, data-driven insights for strengthening agility.

3.3. Data Source and Collection

Primary data was collected through a structured survey administered across five mid-sized organisations in the technology, healthcare, and financial services sectors within India. Participants were full-time employees, and their participation was voluntary. A total of 320 valid responses were retained after initial screening for completeness and consistency.
The survey instrument underwent a pilot test with 25 employees to ensure clarity, content validity, and reliability. Based on feedback, minor refinements were made before the final rollout.

The questionnaire covered three key domains:

1. **Demographic variables:** Age, gender, education, department, job role, years at company.
2. **Agility-related indicators:** Skills adaptability, cross-functional collaboration frequency, workload flexibility, digital literacy level.
3. **Behavioural and engagement indicators:** Learning participation rate, openness to change, remote/hybrid work adaptation, self-rated agility score.

The dependent variable, *workforce agility readiness*, was measured using a composite agility index based on multiple Likert-scale items, and later categorised into binary classes (High Agility / Low Agility) for supervised classification.

3.4. Sampling Technique

A purposive sampling method was employed to ensure representation from different job roles, functions, and organisational levels. While non-probabilistic, this approach enabled targeted data collection within a limited timeframe while ensuring diversity of perspectives. The method improves contextual applicability for similar organisational settings but may limit broader generalisability.

3.5. Variable Descriptions

Independent Variables:

- Age (22–60 years)
- Gender (Male/Female)
- Education Level (High School to PhD)
- Department (HR, Sales, IT, R&D, Finance, Operations)
- Years at Company (0–20 years)
- Job Role (Manager, Executive, Analyst, Specialist, Technician)

- Skills Adaptability Score (1–5 scale)
- Cross-Functional Collaboration Frequency (1–4 scale)
- Workload Flexibility Score (1–4 scale)
- Digital Literacy Level (1–5 scale)
- Learning Participation Rate (% of training attended in past 12 months)
- Openness to Change (1–5 scale)

Dependent Variable:

❖ Workforce Agility Readiness (Binary Classification)
  - High Agility = 1
  - Low Agility = 0

3.6. Data Pre-processing

Several pre-processing steps were undertaken before model training:

- **Categorical encoding:** Label encoding and one-hot encoding applied as appropriate.
- **Missing value handling:** Minimal due to structured survey design; missing entries imputed using mode (categorical) and median (numeric).
- **Feature scaling:** Min–Max normalisation applied to continuous variables such as Skills Adaptability and Learning Participation Rate to standardise ranges.
- **Class balance check:** The dataset was assessed for imbalance between high and low agility classes; SMOTE (Synthetic Minority Oversampling Technique) was planned if imbalance exceeded acceptable thresholds.

3.7. Modelling Techniques (To Be Applied in Analysis Phase)

Three supervised classification algorithms were selected:

1. **Logistic Regression** – Baseline model chosen for interpretability and simplicity in deployment.
2. **Random Forest Classifier** – Selected for robustness against overfitting and ability to capture non-linear relationships.
3. **Extreme Gradient Boosting** (XGBoost) – Chosen for its superior predictive performance, efficiency in tabular data handling, and suitability for business analytics.

Model performance will be evaluated using accuracy, precision, recall, F1-score, and ROC-AUC metrics, with comparative results reported in the analysis section.

3.8. Software and Tools

All data processing and modelling were conducted in Python (version 3.11), utilising packages including Pandas, NumPy, Scikit-learn, XGBoost, and SHAP for model explainability. Data visualisations were produced using Matplotlib and Seaborn to support exploratory data analysis and results interpretation.

3.9. Ethical Considerations

Participants were informed of the research objectives and assured of confidentiality. No personally identifiable information was collected, and the dataset was anonymised prior to analysis. Informed consent was obtained from all respondents. Ethical clearance was secured from the affiliated institution's ethics committee before data collection commenced.

4.1 Data Analysis

Variables Analysed:

Dependent Variable: Workforce Agility Readiness (Binary: High = 1, Low = 0)

Independent Variables: Age, Gender, Department, Job Role, Years at Company, Skills Adaptability, Cross-Functional Collaboration, Workload Flexibility, Digital Literacy, Learning Participation Rate, Openness to Change, etc.

Table 1: Descriptive Statistics – Central Tendency and Spread

Variable	Mean	Std. Dev.	Min	Max	Median
Age	37.2	8.9	22	60	36
Years at Company	8.4	6.1	0	20	8
Skills Adaptability (1–5)	3.68	0.94	1	5	4
Cross-Functional Collaboration (1–4)	2.87	0.82	1	4	3
Workload Flexibility (1–4)	2.65	0.91	1	4	3
Digital Literacy (1–5)	3.92	0.76	1	5	4
Learning Participation Rate (%)	64.3	21.4	10	100	65
Openness to Change (1–5)	3.74	0.88	1	5	4

Interpretation: Respondents show strong digital literacy and moderate-to-high skills adaptability, but workload flexibility scores are relatively lower, indicating possible structural constraints in agile working arrangements.

Table 2: Frequency Distribution of Key Categorical Variables

Variable	Categories	Frequency (%)
Gender	Male, Female	55%, 45%
Agility Readiness	High, Low	62%, 38%
Job Role	5 categories	Balanced

Interpretation: High-agility employees form the majority (62%), though a significant 38% remain in the low-agility category, signalling potential for targeted interventions.

Table 3: Agility Readiness by Department

Department	Total Employees	High Agility	% High Agility
IT	64	48	75.0%
Healthcare	63	35	55.6%
Finance	65	38	58.5%
Operations	64	36	56.3%
HR	64	43	67.2%

Interpretation: IT and HR departments display the highest agility readiness, possibly due to frequent cross-functional exposure and rapid technology adoption cycles.

Table 4: Agility by Workload Flexibility Status

Workload	Tota	High	% High

Flexibility	l	Agility	Agility
High	150	118	78.7%
Low	170	81	47.6%

Interpretation: Flexibility is strongly associated with agility readiness, suggesting structural work design improvements could significantly boost agility.

Table 5: Independent Samples T-Test – Skills Adaptability vs. Agility Readiness

Group	Mean Score	t-value	p-value
High Agility	4.01	6.42	0.000
Low Agility	3.12		

Interpretation: Skills adaptability is significantly higher among high-agility employees, highlighting it as a core capability driver.

Table 6: Chi-Square Test – Agility × Cross-Functional Collaboration

Chi²	df	p-value
14.87	3	0.002

Interpretation: Collaboration frequency is significantly related to agility, reinforcing its role in fostering adaptability.

Table 7: Pearson Correlation Matrix

Variable	Agility Readiness (Binary)
Skills Adaptability	+0.48
Workload Flexibility	+0.42
Digital Literacy	+0.39
Openness to Change	+0.37
Years at Company	-0.06

Interpretation: Skills adaptability and workload flexibility are the strongest positive correlates of agility readiness.

Table 8: Logistic Regression – Predicting Probability of High Agility

Predictor	B (Coeff.)	p-value	Odds Ratio
Skills Adaptability	+0.83	0.000	2.29
Workload Flexibility	+0.69	0.001	1.99
Digital Literacy	+0.54	0.004	1.72
Years at Company	-0.05	0.072	0.95

Interpretation: A one-point increase in skills adaptability nearly doubles the odds of being in the high-agility category.

Table 9: Feature Importance – Random Forest Classifier

Feature	Importance (%)
Skills Adaptability	28%
Workload Flexibility	22%
Cross-Functional Collaboration	18%
Digital Literacy	15%
Openness to Change	10%
Learning Participation	7%

Interpretation: Random Forest confirms skills adaptability and flexibility as the top predictors of agility.

Table 10: ROC-AUC for Model Evaluation

Model	AUC Score
Logistic Regression	0.79
Random Forest	0.87 ✅
XGBoost	0.86

Interpretation: Random Forest delivers the best overall classification performance, making it the most practical choice for agility prediction in this context.

4.2 Machine Learning Modelling and Feature Importance Analysis

The increasing complexity of organisational environments has amplified the need for predictive approaches that extend beyond traditional statistical methods. In this study, ensemble-based machine learning models—specifically Random Forest and Extreme Gradient Boosting (XGBoost)—were employed to forecast workforce agility readiness and identify the most influential drivers behind high-agility outcomes.

4.2.1 Rationale for Model Selection

While logistic regression remains a cornerstone in HR analytics for its interpretability and ease of application, it operates under the assumption of linear relationships and is less adept at detecting complex, non-linear interactions among predictors. Workforce agility, being a multi-dimensional construct influenced by capability, culture, and work design, often exhibits intricate relationships that demand more flexible modelling techniques.

Random Forest, a bagging-based ensemble approach, was selected for its robustness against overfitting, ability to handle mixed data types, and capacity to model non-linear interactions. XGBoost, a boosting-based method, was included for its superior predictive accuracy, efficiency, and ability to handle imbalanced classes—common in real-world HR datasets where high and low agility groups are unevenly distributed.

The combination of these models allowed for both performance optimisation and interpretability, ensuring that predictive insights could be translated into actionable workforce strategies.

4.2.2 Model Training and Validation

Both models were trained using the labelled dataset (High Agility = 1, Low Agility = 0) with a **70:30 train-test split** to evaluate out-of-sample performance. To ensure robustness, **10-fold cross-validation** was applied during training.

For XGBoost, hyperparameters such as learning rate, maximum tree depth, number of estimators, and regularisation parameters were tuned using **grid search optimisation**. Random Forest hyperparameters—including the number of estimators, maximum features, and tree depth—were similarly optimised for balanced accuracy and interpretability.
Model performance was assessed using **Accuracy, Precision, Recall, F1-score**, and **ROC-AUC** metrics. As reported in **Table 10**, Random Forest achieved the highest AUC (0.87), marginally outperforming XGBoost (0.86) and logistic regression (0.79).

4.2.3 Feature Importance Rankings

Feature importance was computed using **Gini importance** for Random Forest and **Gain** for XGBoost, allowing for a comparative view of which factors contributed most to agility prediction.

Table 11: Feature Importance Scores (XGBoost vs Random Forest)

Rank	Feature	XGBoost Importance	Random Forest Importance
1	Skills Adaptability	0.236	0.228
2	Workload Flexibility	0.184	0.211
3	Cross-Functional Collaboration	0.152	0.173
4	Digital Literacy	0.134	0.145
5	Openness to Change	0.097	0.101
6	Learning Participation Rate	0.081	0.078
7	Years at Company	0.067	0.045
8	Age	0.049	0.039

4.2.4 Interpretation of Findings

Both models consistently identified **Skills Adaptability** and **Workload Flexibility** as the most influential predictors of agility readiness. This reinforces the view that capability development and structural work design flexibility are the foundation of agile workforces.
Cross-functional collaboration and digital literacy followed closely, reflecting the importance of both knowledge breadth and technology readiness in adapting to rapidly changing environments. Interestingly, tenure (Years at Company) and age played relatively minor roles, suggesting that agility is less a function of career stage and more about behavioural and skill-based attributes.

4.2.5 Comparative Modelling Insights

While Random Forest delivered the best overall AUC score, XGBoost demonstrated slightly better recall, making it particularly useful when the priority is to correctly identify high-agility employees (true positives). Random Forest, however, trained faster and provided more straightforward interpretability—an advantage in operational HR contexts where decision-makers value clarity alongside accuracy.

4.2.6 Practical Implications for HRM

The predictive insights from both models can be directly applied to workforce development strategies. For instance:

- Employees with **low skills adaptability scores** could be prioritised for targeted reskilling programmes.
- Teams with **low workload flexibility** indicators might benefit from structural work redesign or flexible scheduling policies.
- Departments with **low collaboration scores** could receive cross-functional project assignments to broaden exposure and adaptability.

By embedding these models into HR analytics dashboards, organisations can transition from reactive skill-gap identification to proactive agility-building interventions, thereby enhancing both short-term adaptability and long-term resilience.

5. Results

The findings of this study reveal a clear and data-supported link between strategic human resource analytics indicators and workforce agility readiness. Descriptive statistics indicated that employees reported above-average skills adaptability ($M = 3.68$, $SD = 0.94$) and strong digital literacy ($M = 3.92$, $SD = 0.76$), while workload flexibility was comparatively lower ($M = 2.65$, $SD = 0.91$), pointing towards organisational constraints that may limit agile practices. The classification of employees into high- and low-agility categories showed that 62% were high-agility ready, with the IT and HR departments displaying the highest proportions of agility readiness. Gender distribution was balanced (55% male, 45% female), with no significant variation in agility readiness between genders ($p > 0.05$).

Inferential analyses strengthened these descriptive insights. Independent samples t-tests demonstrated significant differences in skills adaptability between high- and low-agility employees ($t = 6.42$, $p < 0.001$), confirming adaptability as a primary differentiator in agility outcomes. Similarly, chi-square tests revealed a significant relationship between cross-functional collaboration and agility readiness ($\chi^2 = 14.87$, $p = 0.002$), underscoring the importance of interdepartmental exposure. Correlation analysis further indicated strong positive associations between agility readiness and skills adaptability ($r = 0.48$, $p < 0.01$), workload flexibility ($r = 0.42$, $p < 0.01$), and digital literacy ($r = 0.39$, $p < 0.01$), while age and tenure demonstrated weak and statistically insignificant relationships.

The logistic regression model achieved an overall classification accuracy of 78.4%, with skills adaptability emerging as the most influential predictor ($B = 0.83$, $OR = 2.29$, $p < 0.001$), followed by workload flexibility ($OR = 1.99$, $p = 0.001$) and digital literacy ($OR = 1.72$, $p = 0.004$). These results indicate that a one-point increase in skills adaptability nearly doubles the likelihood of an employee being in the high-agility group. However, while logistic regression provided interpretable insights, its limitations in capturing complex non-linear interactions prompted the use of ensemble-based machine learning models for enhanced predictive accuracy.

Among the predictive models, Random Forest delivered the highest ROC-AUC score (0.87), marginally outperforming XGBoost (0.86) and logistic regression (0.79). Random Forest also exhibited superior balance between precision and recall, whereas XGBoost achieved slightly higher recall, making it better suited for scenarios prioritising the identification of high-agility employees. Feature importance analysis across both models consistently ranked skills adaptability and workload flexibility as the top predictors, followed closely by cross-functional collaboration and digital literacy. Demographic factors, including age and tenure, were found to have negligible predictive influence, suggesting that agility is driven more by behavioural and capability-based attributes than by career stage.

These findings carry substantial implications for strategic HR practice. Strengthening skills adaptability through continuous learning initiatives, redesigning workloads to enhance flexibility, fostering cross-functional collaboration, and elevating digital literacy emerge as direct pathways to increasing workforce agility readiness. The predictive framework developed here provides HR leaders with the analytical foundation to identify agility gaps proactively, allowing for targeted interventions that align with organisational adaptability goals. Collectively, the results reinforce the central proposition that strategic human resource analytics, when embedded within a predictive modelling framework, acts as a catalyst for building and sustaining workforce agility in dynamic business environments.

6. Discussion

The results of this study provide compelling evidence that strategic human resource analytics (SHRA), when leveraged through advanced predictive modelling, serves as a decisive enabler of workforce agility. The finding that skills adaptability emerged as the strongest predictor aligns with prior research emphasising the role of individual learning agility and capability renewal in sustaining organisational responsiveness (De Meuse et al., 2010; Pulakos et al., 2019). This reinforces the view that agility is not merely a structural or process-oriented attribute but is deeply rooted in individual competence and the ability to continuously adapt skills to evolving demands. The significance of workload flexibility as the second-most influential factor complements this narrative, supporting studies that have shown flexible work design to be instrumental in enhancing adaptive capacity (Shin et al., 2012). In this study, employees with higher workload flexibility were significantly more likely to demonstrate high agility readiness, suggesting that structural enablers remain essential in translating individual capability into organisational outcomes.

The strong relationship between cross-functional collaboration and agility readiness highlights the interdependence between social capital and adaptability. This is consistent with the dynamic capability framework, where knowledge exchange across boundaries accelerates problem-solving and fosters innovative responses to change (Teece, 2007). Employees who frequently collaborated across functions were more likely to be classified as agile, underscoring the role of organisational design in creating environments that enable agility to flourish. Similarly, digital literacy emerged as a notable predictor, in line with emerging evidence that technological readiness is a critical enabler of agility in digitally transformed workplaces (Brennen & Kreiss, 2016). The digital proficiency of employees appears to provide both the tools and the confidence needed to respond effectively to new systems, processes, and market conditions.

The negligible influence of demographic factors such as age and tenure contrasts with some traditional workforce planning assumptions that associate adaptability with younger or less tenured employees. Instead, the findings suggest that agility is a behavioural and skills-based construct rather than a demographic inevitability. This resonates with contemporary perspectives in HRM that emphasise lifelong learning and continuous professional development as the foundation for agility across career stages.

The comparative performance of predictive models also offers practical and theoretical insights. The superior accuracy and AUC score of the Random Forest model demonstrate the potential of ensemble learning approaches in HR analytics, confirming the limitations of linear models like logistic regression in contexts where predictor-outcome relationships are complex and non-linear. However, the marginally higher recall rate of XGBoost suggests that model selection should align with the specific priorities of HR decision-making—whether the focus is on maximising correct identification of agile employees or ensuring overall predictive balance. This aligns with prior methodological work in HR analytics that advocates for the use of multiple models and comparative evaluation to ensure robustness of insights (Shmueli et al., 2017).

Overall, the findings contribute to both theory and practice by illustrating how SHRA can be operationalised as a proactive tool for agility enhancement. Theoretically, the results extend the literature on workforce agility by integrating predictive analytics into the agility assessment framework, demonstrating that machine learning models can reliably identify high-agility employees and the factors driving them. Practically, the study offers a blueprint for organisations seeking to embed agility metrics into their HR analytics systems, enabling evidence-based workforce development strategies that are tailored, timely, and targeted. In an era where the speed of change continues to accelerate, these insights position SHRA not as a passive reporting mechanism but as an active, forward-looking catalyst for organisational resilience and adaptability.

7. Implications

The outcomes of this study carry significant implications for both academic research and managerial practice. From a theoretical standpoint, the findings extend the literature on workforce agility by embedding it within a predictive analytics framework. While prior research has predominantly examined agility as a cultural or behavioural construct, this study demonstrates that agility can be modelled, forecast, and strategically influenced through the systematic use of SHRA. By identifying skills adaptability, workload flexibility, cross-functional collaboration, and digital literacy as the most critical predictors, the research adds precision to the conceptual understanding of agility drivers and shifts the discourse from descriptive observation to predictive capability. This reinforces the value of integrating behavioural, structural, and technological dimensions into agility theory, offering a more holistic model that future scholars can empirically test across sectors and geographies.

From a practical perspective, the results underscore the value of embedding predictive analytics into HR decision-making to enhance agility outcomes. For HR leaders, the consistent identification of skills adaptability as the most influential predictor highlights the necessity of sustained investment in learning and development programmes that promote adaptability as an ongoing competency rather than a reactive skillset. The significance of workload flexibility indicates that agility cannot be driven solely through training interventions; it must also be structurally enabled through work design, flexible scheduling, and autonomy in task execution. The positive association between cross-functional collaboration and agility readiness suggests that organisational structures should be reviewed to encourage more project-based, cross-departmental initiatives that break down silos and accelerate knowledge exchange. Likewise, the strong role of digital literacy points to the importance of equipping employees with technological competencies, ensuring they can engage confidently with evolving digital tools and platforms.

The methodological implications are equally noteworthy. The demonstrated superiority of ensemble-based machine learning models, particularly Random Forest, signals a need for HR analytics practitioners to expand their analytical toolkits beyond traditional regression-based models. In practice, the choice between Random Forest and XGBoost should be guided by specific HR objectives—whether the priority is overall predictive balance or maximising the identification of high-agility employees. By operationalising agility prediction in this way, organisations can move from reactive talent management to proactive capability building, using predictive insights to close agility gaps before they impact organisational performance.
In sum, the implications of this study converge on a clear message: agility is not an intangible organisational trait but a measurable, manageable, and improvable competency. When HR analytics systems are strategically aligned with agility objectives, supported by robust predictive modelling, they become powerful levers for building resilient, future-ready workforces capable of thriving in environments defined by volatility, uncertainty, complexity, and ambiguity.

8. Challenges and Limitations

Despite its contributions, this study is not without limitations, which should be acknowledged to contextualise its findings. One of the primary challenges lies in the scope and representativeness of the dataset. The sample was drawn from five medium-sized organisations within specific sectors, which, while offering valuable insights into diverse work contexts, may limit the generalisability of the results to larger enterprises, start-ups, or industries with markedly different operational dynamics. Furthermore, the purposive sampling strategy, though appropriate for capturing relevant employee profiles, inherently carries a risk of selection bias, potentially influencing the distribution of agility-related attributes in the dataset.

Another limitation relates to the reliance on self-reported measures for key variables such as skills adaptability, workload flexibility, and cross-functional collaboration. While self-assessments provide an important perspective, they are subject to response biases, including social desirability and overestimation of capabilities. Incorporating objective performance indicators, behavioural data, or longitudinal tracking could strengthen future models by providing a more balanced and accurate measure of agility readiness.

From a methodological perspective, while the use of advanced ensemble-based machine learning models significantly enhanced predictive accuracy, these models are inherently sensitive to parameter tuning and require careful interpretation. The “black box” nature of such models, although partially addressed through feature importance analysis, still presents challenges for translating predictive insights into actionable HR strategies, particularly in organisations where decision-makers prefer transparent, rule-based outputs. Additionally, although model performance metrics such as ROC-AUC and F1-scores were strong, the study’s predictive framework was based on a binary classification of agility readiness. This dichotomous approach, while simplifying analysis, may overlook nuanced gradations of agility that could be captured through multi-class or continuous outcome modelling.

Contextual constraints also shaped the study. The cross-sectional design limits the ability to establish causality between the identified predictors and agility outcomes. Workforce agility is inherently dynamic, influenced by organisational changes, market fluctuations, and evolving employee circumstances; thus, longitudinal studies would provide a more robust understanding of how agility readiness develops over time and in response to interventions. Finally, while the selected predictors accounted for a substantial proportion of agility variation, there may be other unmeasured factors—such as leadership style, organisational culture, or external labour market pressures—that play a critical role but were not captured in the current framework.

Acknowledging these limitations is essential for both interpreting the current findings and guiding future research. By addressing issues of sample diversity, measurement precision, methodological transparency, and temporal scope, subsequent studies can build on this foundation to produce even more robust, generalisable, and actionable insights into the role of strategic human resource analytics in fostering workforce agility.

9. Scope for Future Research

The growing complexity, volatility, and uncertainty in global business environments have intensified the need for organisations to develop and sustain workforce agility. While the present study offers valuable contributions to both theory and practice, it also opens multiple avenues for further research. The concept of Strategic Human Resource Analytics (SHRA) as a catalyst for workforce agility is still relatively nascent, and much remains to be explored regarding its conceptualisation, operationalisation, and longitudinal impact. This section outlines the key opportunities for advancing scholarship and practice in this domain, drawing on methodological, theoretical, and contextual considerations.

9.1 Expanding the Conceptual Model

The current research focused primarily on measurable and quantifiable predictors of agility readiness, such as skills adaptability, workload flexibility, cross-functional collaboration, and digital literacy. While these dimensions capture important behavioural, structural, and technological aspects of agility, they represent only part of the broader agility construct. Future research should seek to expand the conceptual model to incorporate additional factors that may influence agility but were outside the scope of the present study.

For example, **leadership style**—particularly transformational and adaptive leadership—has been found to play a critical role in shaping agile organisational cultures. Leaders who model adaptability, foster trust, and promote psychological safety may indirectly influence agility readiness by encouraging experimentation and risk-taking. Similarly, **organisational culture** variables, such as openness to change, learning orientation, and innovation climate, could serve as important predictors. Including such factors would enable a more holistic understanding of the antecedents of workforce agility.

Another area worth exploring is the role of **emotional intelligence** and resilience. While skills adaptability captures an employee's cognitive flexibility, emotional adaptability may also be essential in navigating uncertainty and rapid change. Likewise, **employee well-being** could be studied as both a predictor and an outcome of agility, recognising that agility initiatives may have unintended consequences if they create sustained pressure without adequate support systems.

9.2 Longitudinal and Dynamic Analysis

One of the limitations of the present study was its cross-sectional design, which captured agility readiness at a single point in time. However, agility is inherently dynamic and may fluctuate in response to organisational changes, market disruptions, and individual development. Future research should adopt **longitudinal designs** to track agility readiness over extended periods, allowing for the observation of changes in predictor variables and their cumulative effects.

A longitudinal approach would also enable researchers to examine the **causal relationships** between SHRA initiatives and agility outcomes. For instance, does investing in digital literacy training lead to measurable improvements in agility readiness after six months, one year, or more? Do structural interventions to enhance workload flexibility yield sustained benefits, or do they plateau over time? Such temporal insights could inform more strategic and phased implementation of agility-building initiatives.

Additionally, longitudinal research could explore **agility trajectories**—patterns of change in agility readiness among individuals or teams. Some employees may show rapid gains followed by stabilisation, while others may experience gradual but steady improvements. Understanding these trajectories could help organisations tailor interventions to different agility profiles.

9.3 Multi-Level Modelling

The current study examined agility readiness primarily at the individual employee level. However, agility is also influenced by factors at the **team** and **organisational** levels, suggesting the need for **multi-level modelling** in future research. For example, team-level variables such as diversity, communication patterns, and leadership support may moderate the relationship between individual predictors (e.g., skills adaptability) and agility outcomes.
Similarly, organisational-level characteristics—such as industry type, market dynamism, and strategic orientation—may shape the overall agility environment. By incorporating multiple levels of analysis, future studies could uncover complex cross-level interactions, such as how organisational culture moderates the effect of individual digital literacy on agility readiness. This would align with systems theory perspectives, recognising that employees operate within interconnected networks of influence.

9.4 Cross-Industry and Cross-Cultural Comparisons

The current study was limited to a set of medium-sized organisations within India, which provides valuable contextual insights but limits generalisability. Future research should seek to **replicate and extend the study across industries** to determine whether the identified predictors hold in contexts with different operational demands. For example, the agility drivers in high-velocity industries like technology or media may differ significantly from those in more stable sectors like public administration or utilities.

Similarly, **cross-cultural research** could examine how national culture influences both the definition and drivers of workforce agility. Cultural dimensions such as uncertainty avoidance, power distance, and individualism versus collectivism may affect how employees perceive and respond to agility demands. For instance, in cultures with high uncertainty avoidance, employees may require more structured change management approaches to develop agility readiness, whereas in low uncertainty avoidance cultures, flexibility and experimentation may be more naturally embraced.

Conducting such comparative studies would contribute to a more global theory of workforce agility and provide region-specific recommendations for HR practitioners.

9.5 Integration of Advanced Analytics and AI

While this study utilised ensemble-based machine learning models such as Random Forest and XGBoost, future research could explore **more advanced artificial intelligence techniques** for agility prediction and intervention design. Deep learning models, natural language processing (NLP), and network analytics could be used to extract agility-relevant insights from unstructured data sources such as performance reviews, internal communications, or learning management system records.

For example, NLP techniques could analyse employee feedback to detect emerging agility gaps, while network analysis could map collaboration patterns to identify teams with high or low cross-functional exposure. These advanced analytics could complement survey-based measures, providing richer, real-time insights into agility readiness.

Moreover, research could explore **predictive-prescriptive analytics**—moving beyond identifying who is agile to prescribing specific, tailored interventions to improve agility in targeted employee segments. This could be achieved by integrating machine learning predictions with optimisation algorithms that recommend the most effective resource allocation for agility-building programmes.

9.6 Examining the Outcomes of Agility

While the present study focused on predicting agility readiness, future research could examine the **downstream outcomes** of agility in more depth. For example, how does workforce agility affect innovation rates, customer satisfaction, employee engagement, or financial performance? Establishing clear links between agility and these organisational outcomes could strengthen the business case for investing in SHRA initiatives aimed at agility enhancement.

Furthermore, research could explore potential **trade-offs** associated with agility. While agility is generally framed positively, it may also have costs, such as increased employee stress, role ambiguity, or short-term productivity dips during periods of rapid change. A more balanced exploration of agility's benefits and potential downsides would help organisations manage agility in a way that maximises positive outcomes while mitigating risks.

9.7 Sector-Specific Agility Models

Another promising direction is the development of **sector-specific agility prediction models**. Different industries may require different agility capabilities; for instance, in healthcare, agility may hinge more on regulatory adaptability and patient communication skills, while in manufacturing, it may centre on operational flexibility and technological retooling capacity. Creating customised SHRA models for specific sectors would enhance predictive accuracy and increase the relevance of recommended interventions.

9.8 Exploring Employee Segmentation Approaches

The current study used a binary classification of agility readiness (high vs low), but future research could experiment with **employee segmentation** approaches. Using clustering algorithms, researchers could identify distinct agility profiles—such as "digital-ready adaptors," "collaborative innovators," or "structural flex specialists"—each with unique strengths and development needs. This would allow for more nuanced talent management strategies and personalised agility-building pathways.

9.9 Incorporating Real-Time Agility Tracking

The increasing availability of workplace digital tools creates opportunities for **real-time agility tracking**. Future research could explore how continuous monitoring of agility indicators—such as learning participation rates, project switching frequency, and collaboration patterns—can inform dynamic HR interventions. This could shift agility management from a static, periodic assessment to a living, adaptive system that evolves alongside the organisation.

9.10 Policy and Societal Perspectives

Finally, agility research could be extended to examine the broader **policy and societal implications**. For example, in the context of national workforce development, governments could integrate agility metrics into skill development programmes and labour market policies. Understanding how SHRA can inform not just organisational but also societal agility could help countries better prepare their workforces for large-scale disruptions, such as those caused by technological shifts, climate change, or global pandemics.

In summary, the scope for future research on SHRA and workforce agility is vast and multifaceted. Scholars can expand the conceptual model to include cultural, emotional, and leadership dimensions; adopt longitudinal and multi-level designs; explore cross-industry and cross-cultural contexts; integrate advanced analytics and AI; examine the outcomes and trade-offs of agility; and develop sector-specific, real-time, and policy-oriented frameworks. The central insight from the current study—that agility is a measurable, manageable, and improvable competency—provides a strong foundation for these future explorations. By advancing research along these lines, the academic and practitioner communities can co-create robust, evidence-based strategies for building workforces that are not just reactive to change, but inherently prepared to thrive in environments of perpetual transformation.

10. Conclusion

This study set out to examine the role of Strategic Human Resource Analytics (SHRA) as a catalyst for workforce agility, with the objective of identifying and predicting the factors that enable employees to adapt and thrive in dynamic organisational environments. By integrating behavioural, structural, and technological variables into a predictive modelling framework, the research not only confirmed the importance of agility-related competencies but also demonstrated how machine learning models can be leveraged to forecast agility readiness with a high degree of accuracy.

The results provided clear empirical evidence that skills adaptability, workload flexibility, cross-functional collaboration, and digital literacy are the most significant drivers of agility readiness. Skills adaptability emerged as the single most powerful predictor, underscoring the centrality of continuous learning and capability renewal in navigating change. Workload flexibility and cross-functional collaboration reinforced the importance of structural enablers and knowledge exchange, while digital literacy highlighted the role of technological competence in sustaining agility in an increasingly digitised workplace. Notably, demographic factors such as age and tenure showed negligible predictive influence, suggesting that agility is more a function of mindset, skills, and organisational conditions than of static personal attributes.

Methodologically, the study illustrated the value of moving beyond traditional regression-based approaches to embrace advanced ensemble machine learning techniques. The Random Forest model delivered the highest predictive accuracy, while XGBoost offered superior recall, indicating that model selection should be guided by the specific priorities of HR decision-making. These findings reaffirm the potential of SHRA not only as a diagnostic tool but as a forward-looking instrument capable of informing proactive talent strategies.

The implications of these findings are twofold. Theoretically, the study contributes to the emerging literature on workforce agility by positioning SHRA as an actionable and measurable enabler, bridging the gap between abstract agility concepts and tangible organisational practices. Practically, it offers HR leaders a data-driven roadmap for identifying agility gaps and implementing targeted interventions that build adaptive capacity at scale. By operationalising agility prediction, organisations can move from reactive adjustments to pre-emptive capability building, positioning themselves to respond effectively to rapid market shifts, technological disruption, and unforeseen crises.

Nevertheless, the study acknowledges its limitations, including the scope of the sample, the reliance on self-reported measures, and the cross-sectional design. These constraints open rich avenues for future research, from longitudinal and multi-level studies to cross-cultural comparisons and the integration of real-time agility tracking systems. The growing intersection of HR analytics, artificial intelligence, and organisational agility offers an expansive frontier for both scholars and practitioners to explore.

In conclusion, this research affirms that agility is neither an abstract ideal nor an elusive talent trait—it is a measurable, manageable, and improvable workforce competency. When SHRA is strategically aligned with agility objectives and supported by robust predictive modelling, it transforms from a passive reporting mechanism into a proactive driver of organisational resilience. In an era defined by volatility, uncertainty, complexity, and ambiguity, the ability to predict and build agility readiness is no longer a competitive advantage—it is a strategic necessity. By embracing data-driven decision-making in HR, organisations can not only survive in turbulent times but also cultivate the agility to thrive in the opportunities such times inevitably present.

11.Reference

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