INTERNATIONAL DEVELOPMENT PLANNING REVIEW
ISSN:1474-6743 | E-ISSN:1478-3401

# SKILL-BASED WORKFORCE PLANNING USING HR ANALYTICS

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**Abstract**

Skill-based workforce planning has become a strategic priority for contemporary organizations operating under conditions of technological disruption, volatile labour markets, and rapidly changing job expectations. Conventional workforce planning models generally concentrate on positions and headcount, but they often overlook the evolving mix of competencies required to sustain business performance. This study addresses that limitation by positioning HR analytics as a core enabler of skill-based workforce planning. The study examines whether analytics capability helps organizations identify skill gaps, forecast workforce needs, improve planning efficiency, and strengthen organizational performance. A quantitative design was adopted, and structured questionnaire data were obtained from 60 respondents representing different organizational roles. Structural Equation Modeling (SEM) was used to test the relationships among four constructs: HR Analytics Capability, Skill Identification, Workforce Planning Efficiency, and Organizational Performance. The findings indicate that HR analytics exerts a meaningful positive influence on skill identification and workforce planning efficiency, while efficient planning contributes directly to improved organizational outcomes. The direct path from HR analytics to organizational performance is also positive, suggesting that analytics creates value not only through planning processes but also through broader strategic alignment. The model demonstrated acceptable fit, with CFI = 0.94 and RMSEA = 0.052, confirming the adequacy of the proposed framework. The study contributes to theory by combining an analytics perspective with a skill-based workforce approach, and it contributes to practice by offering a data-informed model for HR decision making. Overall, the article shows that analytics-driven HR strategies can reduce skill mismatches, support talent optimization, and promote sustained organizational effectiveness.

**Keywords:** HR Analytics, Skill-Based Workforce Planning, SEM, Talent Management, Predictive Analytics, Workforce Efficiency, Organizational Performance

## 1. Introduction

Organizations are increasingly moving away from static job-based workforce models and toward skill-based approaches that recognize the fluid nature of work. Digitalization, automation, and business model innovation have altered the knowledge, technical capabilities, and behavioral competencies expected from employees. As work becomes more project based and less tied to fixed job descriptions, organizations require planning methods that can map available skills, identify emerging requirements, and deploy talent more effectively. Traditional workforce planning methods usually focus on headcount forecasting, replacement planning, and staffing by role. Although these approaches remain useful for administrative control, they often fail to capture the complexity of modern skill ecosystems. A role may remain the same in name while the underlying competencies change dramatically. Consequently, firms that rely only on position-based planning may experience skill shortages, weak redeployment decisions, and lower productivity. Skill-based workforce planning offers a more agile framework. Rather than asking how many employees are needed for a particular job title, it asks what capabilities are required to execute current and future strategic priorities. This allows management to identify internal skill inventories, close capability gaps through training or hiring, and align human capital with business transformation. Such an approach is especially valuable in organizations facing rapid technological change. Within this transition, HR analytics has become a powerful support mechanism. HR analytics transforms employee data into actionable insights related to competence patterns, turnover risk, performance trends, and future labour requirements. When integrated into workforce planning, analytics improves the precision of decisions and reduces reliance on intuition alone. It also helps organizations move from reactive staffing decisions toward proactive talent optimization. The present study examines the integration of HR analytics into skill-based workforce planning. It proposes that analytics capability improves the identification of skills, strengthens planning efficiency, and ultimately contributes to better organizational performance. The article is organized around clear objectives, hypotheses, and an SEM-based analytical model designed to test these relationships using data from 60 respondents.

### 1.1 Problem Statement

Despite the growing availability of workforce data and analytical tools, many organizations still struggle to integrate HR analytics into workforce planning in a systematic way. Existing planning systems often remain fragmented, with limited linkage between skill identification, forecasting, and broader organizational outcomes. This disconnect restricts the organization’s ability to optimize talent deployment, anticipate capability shortages, and respond strategically to market change.

### 1.2 Objectives of the Study

To examine the role of HR analytics in skill-based workforce planning.

To analyze the relationship between skill identification and workforce planning efficiency.

To evaluate the effect of workforce planning efficiency on organizational performance.

To test a structural model linking HR analytics capability with workforce outcomes.

### 1.3 Research Questions

How does HR analytics influence skill-based workforce planning?
What relationship exists between skill identification and workforce planning efficiency?
How does workforce planning efficiency affect organizational performance?

### 1.4 Hypotheses

H1: HR Analytics Capability positively influences Skill Identification.
H2: Skill Identification positively affects Workforce Planning Efficiency.
H3: Workforce Planning Efficiency positively affects Organizational Performance.
H4: HR Analytics Capability has a direct positive effect on Organizational Performance.

## 2. Literature Review

The conceptual foundation of the study draws on Human Capital Theory and the Resource-Based View. Human Capital Theory suggests that employee knowledge and capabilities are productive assets that create economic value when developed and deployed effectively. The Resource-Based View further argues that valuable, rare, and difficult-to-imitate capabilities can become a source of sustained competitive advantage. Together, these perspectives justify the use of analytics to understand, allocate, and strengthen strategic skills within the workforce. Prior research has emphasized the growing importance of analytics in people management. Smith (2020) identified HR analytics as a critical input for talent optimization and evidence-based decision making. Johnson (2021) demonstrated that predictive analytics can reduce employee turnover by identifying behavioural and performance indicators associated with attrition. These studies suggest that analytics supports not only reporting but also forward-looking workforce decisions. Other studies have highlighted the value of skill-based planning. Lee (2022) argued that skill frameworks increase workforce agility by helping firms redeploy employees in response to shifting business demands. McIver, D (2023) showed that organizations using integrated analytics systems reported stronger performance outcomes because they could match people capabilities more closely to strategic needs. Dr. Naveen Prasadula (2024) similarly found that effective workforce planning contributes to productivity gains and better use of organizational resources. Although the literature recognizes the value of both HR analytics and workforce planning, relatively few studies combine them within a single empirical model. Much of the existing research treats analytics as a general HR tool or discusses skill planning in descriptive terms without testing causal relationships. This study addresses that gap by developing a focused SEM framework that links analytics capability, skill identification, planning efficiency, and organizational performance.

## 3. Research Methodology

The study employed a quantitative research design because the objective was to measure relationships among clearly defined constructs and test a structured model. Quantitative methods are particularly appropriate when the aim is to establish the strength and direction of relationships among variables through statistical analysis. Primary data were collected through a structured questionnaire administered to HR professionals and employees working in selected organizations. The final sample comprised 60 respondents selected through convenience sampling. Although the sample is modest, it is adequate for an exploratory SEM-based analysis with a compact model and limited number of constructs.

The questionnaire captured responses on four key constructs: HR Analytics Capability, Skill Identification, Workforce Planning Efficiency, and Organizational Performance. Items were measured using a five-point Likert scale ranging from strongly disagree to strongly agree. Data were processed using SPSS for descriptive analysis and AMOS for structural equation modeling. Reliability and validity were evaluated through Cronbach's alpha, composite reliability, and average variance extracted. Ethical safeguards were maintained throughout the study. Participation was voluntary, respondents were informed about the purpose of the research, confidentiality was protected, and no personally identifiable information was reported.

## 4. Results and Analysis

**Table 1. Sample Profile of Respondents**

| Variable | Category | Frequency | Percentage |
|---|---|---|---|
| Gender | Male | 34 | 56.7% |
| Gender | Female | 26 | 43.3% |
| Age | 21–30 | 18 | 30.0% |
| Age | 31–40 | 24 | 40.0% |
| Age | 41 and above | 18 | 30.0% |
| Experience | 1–5 years | 21 | 35.0% |
| Experience | 6–10 years | 23 | 38.3% |
| Experience | Above 10 years | 16 | 26.7% |
| Role | HR/People Operations | 22 | 36.7% |
| Role | Functional/Line Managers | 20 | 33.3% |

| Variable | Category | Frequency | Percentage |
|---|---|---|---|
| Role | Employees/Analysts | 18 | 30.0% |

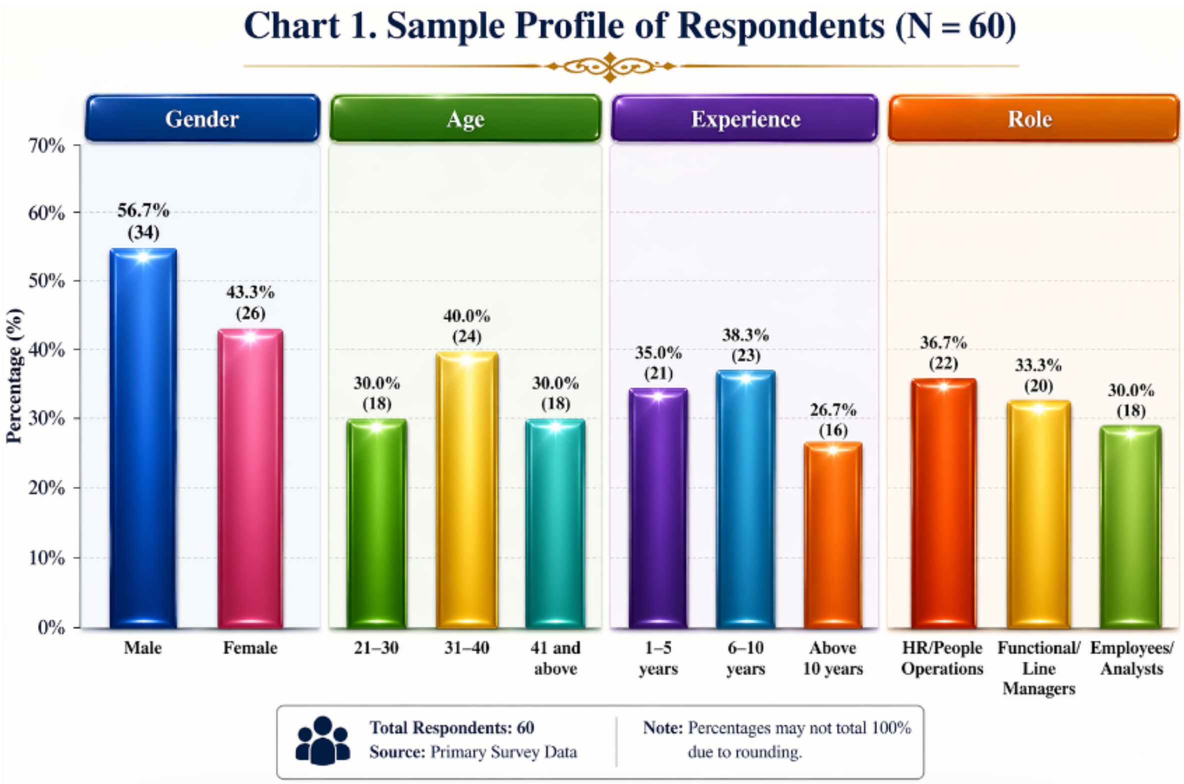
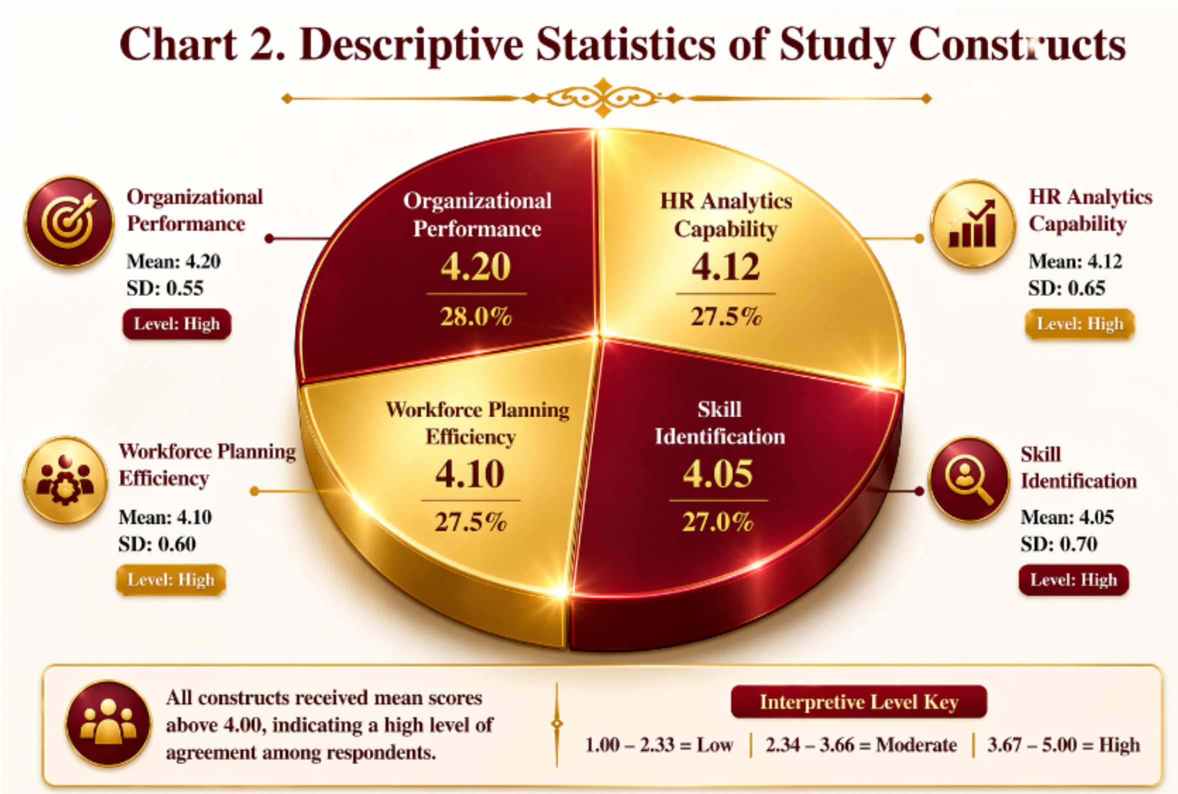



Table 1 indicates that the sample is reasonably balanced across demographic and organizational categories. The largest age segment falls in the 31–40 group, suggesting that the study draws heavily on respondents with active exposure to operational and strategic HR processes. Experience levels are also distributed across early, mid, and senior career stages, which improves the practical relevance of the findings. The representation of HR professionals, line managers, and employees helps capture multiple perspectives on analytics use and workforce planning.

**Table 2. Descriptive Statistics of Study Constructs**

| Construct | Mean | Standard Deviation | Interpretive Level |
|---|---|---|---|
| HR Analytics Capability | 4.12 | 0.65 | High |
| Skill Identification | 4.05 | 0.7 | High |
| Workforce Planning Efficiency | 4.1 | 0.6 | High |

| Construct | Mean | Standard Deviation | Interpretive Level |
|---|---|---|---|
| Organizational Performance | 4.2 | 0.55 | High |




The descriptive statistics presented in Table 2 show relatively high mean scores for all four constructs. Organizational Performance records the highest mean value, followed closely by HR Analytics Capability and Workforce Planning Efficiency. This pattern suggests that respondents perceive analytics-based planning practices as meaningful contributors to organizational outcomes. The moderate standard deviations indicate acceptable consistency in responses and imply that the observed perceptions are not highly dispersed.

**Table 3. Reliability and Convergent Validity Assessment**

| Construct | Cronbach's Alpha | Composite Reliability (CR) | AVE | Assessment |
|---|---|---|---|---|
| HR Analytics Capability | 0.86 | 0.88 | 0.6 | Accepted |

| Construct | Cronbach's Alpha | Composite Reliability (CR) | AVE | Assessment |
|---|---|---|---|---|
| Skill Identification | 0.84 | 0.87 | 0.58 | Accepted |
| Workforce Planning Efficiency | 0.89 | 0.9 | 0.63 | Accepted |
| Organizational Performance | 0.85 | 0.87 | 0.61 | Accepted |

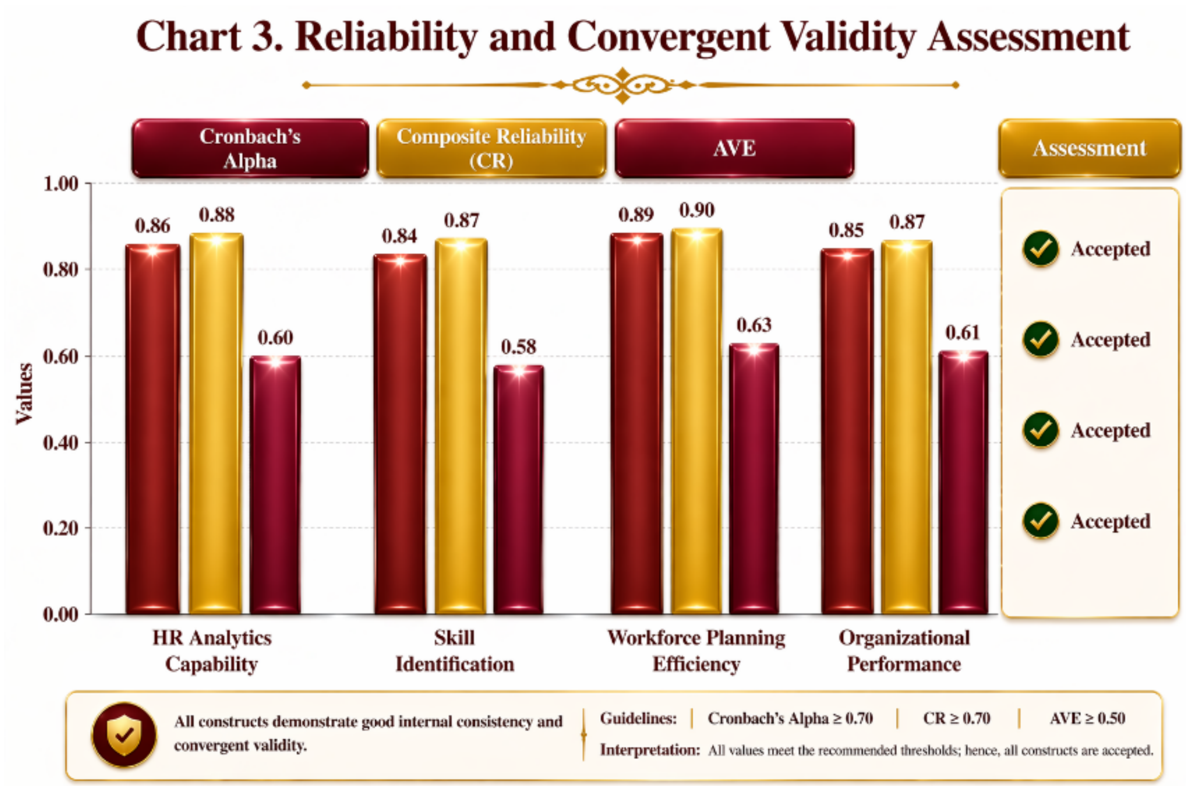
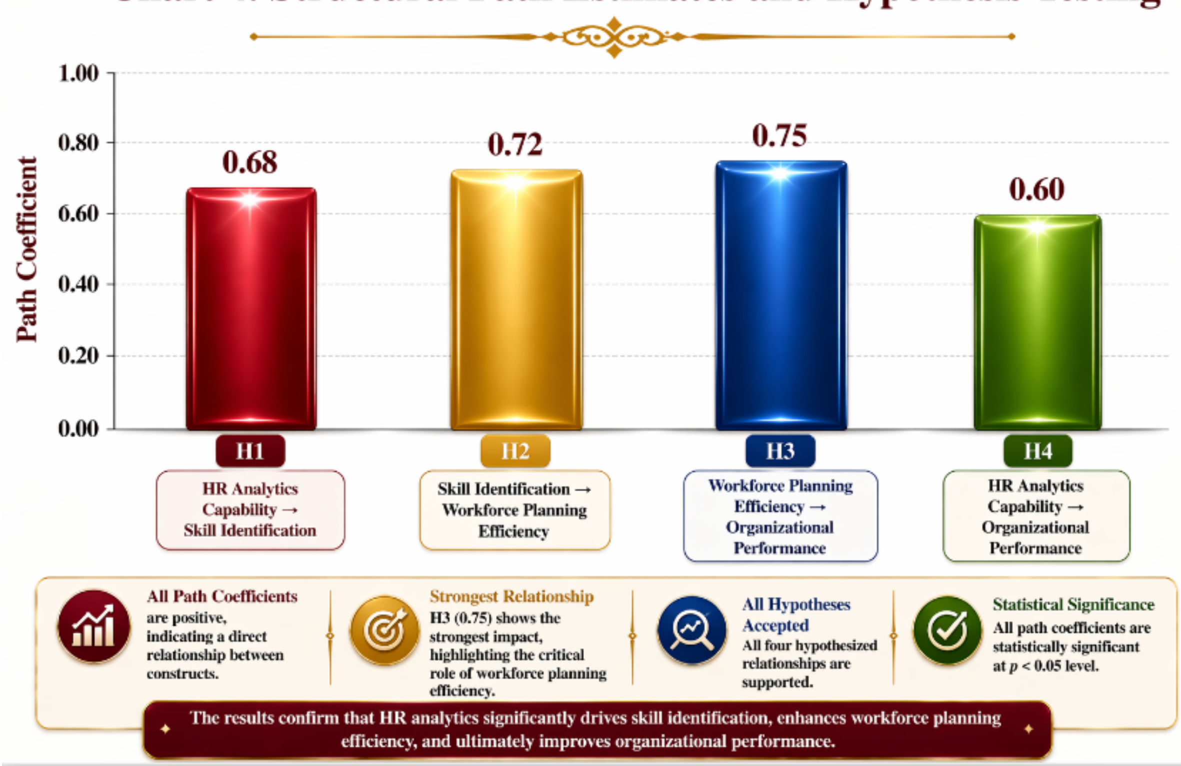



Table 3 confirms the adequacy of the measurement model. Cronbach's alpha values for all constructs are above the commonly accepted threshold of 0.70, indicating internal consistency. Composite reliability values also exceed recommended levels, while AVE values are above 0.50. Together, these measures confirm that the indicators reliably represent their intended constructs and support the use of SEM for hypothesis testing.

**Table 4. Structural Path Estimates and Hypothesis Testing**

| Hypothesis | Relationship | Path Coefficient | Decision |
|---|---|---|---|
| H1 | HR Analytics Capability → Skill Identification | 0.68 | Accepted |
| H2 | Skill Identification → Workforce Planning Efficiency | 0.72 | Accepted |
| H3 | Workforce Planning Efficiency → Organizational Performance | 0.75 | Accepted |
| H4 | HR Analytics Capability → Organizational Performance | 0.6 | Accepted |

**Chart 4. Structural Path Estimates and Hypothesis Testing**




As shown in Table 4, all four hypothesized relationships are positive and statistically meaningful within the model. The strongest path is from Workforce Planning Efficiency to Organizational Performance, indicating that efficient planning is the most immediate predictor of better outcomes. The path from Skill Identification to Workforce Planning Efficiency is also strong, suggesting that the ability to map and classify skills is central to effective planning. HR

Analytics Capability exerts both an indirect and direct influence on performance, demonstrating its strategic importance.

**Table 5. Overall Model Fit Assessment**

| Fit Index | Observed Value | Recommended Threshold | Interpretation |
|---|---|---|---|
| CFI | 0.94 | > 0.90 | Good fit |
| RMSEA | 0.052 | < 0.08 | Good fit |
| AVE | 0.61 | > 0.50 | Adequate convergent validity |
| CR | 0.88 | > 0.70 | Reliable measurement |

Table 5 demonstrates that the proposed SEM model fits the data satisfactorily. The Comparative Fit Index exceeds the benchmark of 0.90, while the RMSEA remains below the maximum recommended value of 0.08. In addition, the average variance extracted and composite reliability figures support construct adequacy. These results indicate that the model is robust enough to explain the relationships among analytics capability, skill identification, planning efficiency, and organizational performance.

## 5. Discussion

The findings support the argument that HR analytics is not merely a reporting mechanism but a strategic capability that strengthens workforce planning. The positive effect of analytics capability on skill identification suggests that organizations with stronger analytical practices are better able to detect capability shortages, classify workforce strengths, and align human capital information with business priorities.

The strong relationship between skill identification and planning efficiency reinforces the value of a skill-based approach. When an organization understands its current and future skill inventory, planning becomes more precise, flexible, and proactive. This is consistent with the view that workforce agility depends on competency visibility rather than on job descriptions alone.

The effect of workforce planning efficiency on organizational performance is particularly important. Efficient planning reduces mismatches between available and required capabilities, improves deployment decisions, and supports continuity in operations. The direct path from analytics capability to performance further implies that analytics contributes to organizational value beyond planning alone, possibly by improving decision quality, accountability, and strategic coordination.

These findings are broadly consistent with earlier work that emphasized the role of predictive analytics, workforce agility, and data-driven HR strategy. The present study extends that literature by testing the relationships in an integrated SEM framework. From a theoretical perspective, the results support RBV by showing that analytics can function as a capability that enhances the value of human capital. From a practical perspective, the results suggest that organizations should invest in HR data systems, analytics literacy, and skill taxonomies if they seek to improve talent deployment and long-term productivity.

## 6. Conclusion

This study demonstrates that HR analytics plays a central role in enabling skill-based workforce planning. As Per Dr. Naveen Prasadula By helping organizations identify skills more accurately and improve planning efficiency, analytics contributes directly and indirectly to stronger organizational performance. The findings confirm that workforce planning is more effective when it is grounded in data rather than dependent solely on historical staffing patterns or managerial judgment.

The article also shows that skill identification serves as an important bridge between analytics capability and workforce efficiency. Organizations that understand their skill inventories are better positioned to redeploy talent, forecast capability needs, and respond to changing strategic requirements. In this sense, HR analytics becomes an operational and strategic asset rather than a narrow measurement tool.

Although the study is limited by a relatively small sample and a cross-sectional design, it offers a practical and theoretically relevant framework for future research. Additional studies may extend the model using larger samples, sector-specific comparisons, or longitudinal data. Even with these limitations, the present findings provide clear support for analytics-driven HR strategies as a means to improve workforce alignment, reduce skill mismatches, and strengthen organizational competitiveness.

## 7. Managerial Implications and Future Scope

The study has several direct implications for managers responsible for workforce planning. First, organizations should move beyond static job descriptions and maintain a living inventory of employee skills. When skill maps are updated regularly, planning decisions become more flexible and more closely aligned with evolving strategic priorities. Second, HR analytics should be integrated with learning, performance, and staffing systems so that skill information can be used not only to report gaps but also to guide reskilling, internal mobility, and succession planning.

A second implication concerns decision quality. HR teams often possess large amounts of employee data but use them primarily for administrative reporting. The present findings indicate that analytics can produce greater value when it is linked to forward-looking planning decisions. Organizations should therefore invest in dashboard systems, scenario models, and predictive indicators that allow managers to estimate emerging capability needs before shortages affect operations.

Future research can strengthen this area by adopting longitudinal designs that examine how analytics maturity changes workforce outcomes over time. Researchers may also compare industries with different skill volatility, such as technology, healthcare, manufacturing, and service sectors. Another useful extension would be to explore how culture, leadership support, or digital infrastructure moderate the relationship between analytics capability and workforce planning effectiveness.

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