THE IMPORTANCE OF HUMAN RESOURCE FORECASTING IN PROJECT MANAGEMENT

by

ADEOLA OLUFUNSO OJO, M.Sc. Agricultural Economics

DISSERTATION
Presented to the Swiss School of Business and Management Geneva
In Partial Fulfilment
Of the Requirements
For the Degree

DOCTOR OF BUSINESS ADMINISTRATION

SWISS SCHOOL OF BUSINESS AND MANAGEMENT GENEVA

JULY, 2025

Restricted - External

THE IMPORTANCE OF HUMAN RESOURCE FORECASTING IN PROJECT MANAGEMENT

by

ADEOLA OLUFUNSO OJO

Supervised by

DR. VASSILIKI GROUGIOU

APPROVED BY

Dr. Ljiljana Kukec, Ph.D.
Dissertation chair

RECEIVED/APPROVED BY:

____
Admissions Director

Restricted - External

Acknowledgements

This thesis is dedicated first and foremost to God Almighty, the source of my strength, wisdom, and grace. Without Him, this journey would not have been possible.

I extend my heartfelt gratitude to my mentor, Dr Vassiliki Grougiou, for your guidance, support, and invaluable feedback throughout this research. Your expertise and encouragement were instrumental in helping me stay focused and complete this work.

To my dear Husband, Yemi Ojo, thank you for your love, patience, and steadfast support through every step of this process. Your belief in me made all the difference.

To my children-Hephzibah, Deborah and Kyra, you are my inspiration and my greatest joy. May this achievement remind you that with God and hard work, nothing is possible.

To the memory of my beloved father, Titus Adesoji Durojaiye, who always believed in my potential and dreamt of this day even before I did. To my amazing mother, Alice Durojaiye, thank you for your prayers.

To my cousin, Wale Jesukeyede, my friend, Olubunmi Layinka, my sister, Adebusola Adeniyi, thank you for your endless support.

And to all my family and friends, near and far, thank you for every moment of encouragement.

ABSTRACT

THE IMPORTANCE OF HUMAN RESOURCE FORECASTING IN PROJECT MANAGEMENT

ADEOLA OLUFUNSO OJO
2025

The research explores HR forecasting methods in project management specifically for Nigeria's banking and telecommunications sectors. Project management requires HR forecasting tools to connect employee qualifications with project requirements because of accelerated technology development and fluctuating employment markets. Several shortcomings exist regarding methodological advancements as well as the inclusion of stakeholders together with the implementation of artificial intelligence (AI) technologies. Project success rates and workforce efficiency together with stakeholder satisfaction along with organizational barriers receive evaluation through this research which relies on 278 surveys from HR and project managers. Historical trend analysis and managerial judgment continue to dominate forecasting methods because organizations remain familiar with their methods while predictive analytics solutions powered by AI demonstrate only moderate implementation despite their potential benefits. Organizations that bring together AI systems and human judgment achieve greater success in projects and earn more satisfied stakeholders. The level of accuracy in forecasting directly enhanced how optimally organizations could utilize their workforce demonstrating the importance of data-based planning. Data quality problems together with employee reluctance to transform operations proved to be the biggest obstacles for effective forecasting rather than budget limitations. The research demonstrates weak stakeholder theory compliance because employee needs and diversity targets received inadequate attention while showing partial support for contingency theory through situation-specific modifications. The research expands theoretical knowledge by demonstrating the validity of contingency theory for forecast adaptability and it tests the implementation feasibility of stakeholder theory. The practical use of this research demonstrates that organizations need to develop mixed forecasting systems along with strong data protection systems coupled with adequate organizational preparedness to accept new technologies. The advisory calls for the integration of AI systems combined with stakeholder-led processes and regular model assessment to improve agility. The research fills a fundamental hole in HR forecasting literature through its empirical findings from developing economies which deliver operational strategies to enhance workforce planning during project volatility.

Keywords: Human Resource Forecasting, Project Management, Artificial Intelligence, Contingency Theory, Stakeholder Theory, Nigeria.

Restricted - External

TABLE OF CONTENTS

Restricted - External

Restricted - External

Restricted - External

CHAPTER ONE

INTRODUCTION

1.1 Introduction: Background and Context of the Study

The corporate environment of today presents organizations with unparalleled difficulties to manage projects efficiently for sustaining competitive advantage (Kerzner, 2017). Project management strategies require robust approaches because increasing project complexity meets dynamic market conditions (Turner, 2019). Project success heavily relies on human resource forecasting because this essential practice helps organizations match workforce requirements with project needs (Zhao et al., 2022). Organizations that make effective HR forecasts secure the correct employees who possess required competencies when they are needed which reduces staffing-related risks including insufficient workers and excessive personnel and skill shortages (Elkholosy, 2020). The field of HR forecasting receives limited attention from project management research despite its importance because methodological improvements and technological integration and workforce adaptability need more development (Devaraj et al., 2021). Inconsistent workforce planning throughout industries becomes worse because of insufficient standardization in forecasting models (Meredith & Mantel, 2019).

The worldwide digital transformation makes HR forecasting more challenging because emerging technologies like artificial intelligence (AI) and machine learning (ML) and predictive analytics present new possibilities to improve forecasting precision (Garcia & Patel, 2021). The implementation of advanced forecasting methods in HR remains irregular since numerous organizations persist with outdated traditional forecasting models according to Zhao et al. (2023). The fast-paced technological disruption requires organizations to move beyond traditional forecasting methods such as qualitative judgment-based forecasting and quantitative trend analysis (Hutahayan, 2020). The emergence of remote work alongside gig economies and multi-generational workforces creates new elements which make it challenging to use

Restricted - External

conventional forecasting approaches (Cascio & Montealegre, 2016). Project management needs to perform a thorough assessment of its human resource forecasting approaches to maintain their validity in modern business settings (Pinto, 2020).

The unpredictability of labor markets which results from economic fluctuations and geopolitical uncertainties and industry-specific disruptions makes HR forecasting more difficult according to Wright & McMahan (2019). Organizations need to consider workforce mobility together with employee turnover and changing skill needs when planning upcoming projects (Boudreau & Ramstad, 2020). Workforce planning models now need to include demographic and cultural factors following the rising importance of diversity, equity and inclusion (DEI) initiatives according to Robinson and Dechant (2021). The relationship between workforce composition and project requirements requires HR forecasting to combine both statistical information and expert knowledge according to Ulrich and Dulebohn (2019).

The study employs contingency theory (Abdulsallam, 2019) and stakeholder theory (Zarghami & Dumrak, 2021) as theoretical frameworks to analyze human resource forecasting in project management. The forecasting models need to adjust their methods in response to project complexity together with organizational structure and external environmental conditions according to contingency theory (Donaldson, 2020). The stakeholder theory requires HR forecasting to match the expectations of essential stakeholders who include project sponsors together with team members and clients (Freeman et al., 2021). Flexible forecasting models must exist for HR planning according to Söderlund (2020) because they need to adapt to changing project requirements and stakeholder demands.

Many organizations face difficulties using HR analytics because they deal with poor-quality and integration issues which prevent accurate forecasting (Marler & Boudreau, 2019). Workforce projections produced by HR systems become ineffective because their data silos function without standard data collection methods while departments work independently of

Restricted - External

each other (Davenport et al., 2020). Employee data privacy alongside algorithmic bias in artificial intelligence forecasting models presents substantial ethical obstacles to organizations (Tambe et al., 2021). Organizations need to find equilibrium points where they can use advanced analytics while upholding ethical standards for their workforce planning activities (Bondarouk & Brewster, 2021).

The impact of COVID-19 on organizations led to the discovery of traditional workforce planning approaches because companies needed immediate adjustments to distributed workforces and supply chain disturbances and evolving markets (Kniffin et al., 2021). Many companies began using scenario-based forecasting and real-time analytics as their workforce plans needed increased flexibility throughout the pandemic (CIPD, 2022). The future effects on HR forecasting from these adjustments need additional research to develop resistant and flexible forecasting systems (SHRM, 2023).

The research investigates existing HR forecasting practices and their challenges to develop new methods which boost forecasting precision. The study integrates stakeholder and contingency theories to investigate how situational elements with stakeholder expectations affect HR forecasting choices (Abdulsallam, 2019; Zarghami & Dumrak, 2021). The study examines how emerging technologies enhance forecasting precision through its investigation of ethical and implementation barriers (Tambe et al., 2021). The research outcomes will benefit scholarly literature and practical organizational applications by providing effective methods to enhance workforce planning in project management (Pinto, 2020). This investigation works to connect abstract human resource forecasting models with actual project management obstacles so organizations can develop better workforce planning capabilities in changing business settings (Kerzner, 2017).

Restricted - External

1.2 Research Problem

Human resource (HR) forecasting plays a critical role in project management because it connects workforce abilities with project requirements to achieve operational excellence and strategic achievement (Kerzner, 2022). HR forecasting operates in practice as an essential yet volatile field because poor data quality exists and teams resist change while maintaining methods that do not address shifting labor market patterns across modern industries (Devaraj et al., 2023). Organizations remain unable to handle the day's unpredictable business circumstances because they keep using traditional forecasting models which base their analyses on static historical data (Zhao et al., 2023). Traditional forecasting methods fail to align with modern workforce dynamics thus creating substantial operational problems that reduce organizational performance (Elkholosy, 2021).

The accuracy of workforce projections remains limited because organizations face a critical issue with their insufficient access to high-quality real-time data (Marler & Boudreau, 2023). The majority of organizations maintain separate HR information systems (HRIS) which do not share data between recruitment and performance management and workforce analytics functions (Davenport et al., 2022). The fragmented data structure prevents full workforce planning analysis and worsens forecasting biases by directing predictions away from future requirements toward historical data patterns (Tambe et al., 2023). The lack of standardized metrics for determining workforce productivity alongside skill relevance makes it difficult to forecast labor needs effectively which leaves organizations exposed to staffing challenges that standardized analysis could have prevented (Boudreau & Ramstad, 2023).

The adoption speed of advanced predictive technologies including artificial intelligence (AI) and machine learning (ML) poses a crucial barrier for effective HR forecasting because these technologies show remarkable potential in improving prediction accuracy (Garcia & Patel, 2022). IBM and Unilever have used AI-driven workforce analytics to improve talent

Restricted - External

deployment while most organizations prevent AI adoption because they fear high implementation costs and biases and privacy threats against employees (Bondarouk & Brewster 2023). Organizations continue to use manual forecasting methods because of their technological inertia leading to labor-intensive processes and human errors and subjective judgments (Hutahayan, 2021). The slow adoption of digital transformation in HR forecasting produces significant concerns because the growing automation and market of short-term employment affect business success by demanding live data-based workforce planning (Cascio & Montealegre, 2022).

The inadequate forecasting models struggle to adapt to emerging workplace models such as remote and hybrid employment because these methods have become standard practices in the post-pandemic world (Kniffin et al., 2022). The calculation methods adopted from past workplace standards fall short today because they do not address current operational flexibility which shapes employee accessibility and performance through digital connections and spatial distribution and work balance conditions (CIPD, 2023). The lack of attention to distributed teams in workforce projections leads to incorrect projections that endanger project timelines and deliverable completion (SHRM, 2023). Traditional workforce number projections like employee headcount and full-time equivalents have lost their relevance because of the growing temporary workforce that exists outside standard employment relations (Manyika et al., 2021). Companies need adaptable forecasting systems which include elements of project-based staffing and flexible talent pools as well as dynamics of contingent labor to stay responsive in evolving markets (Davenport et al., 2023).

The strategic risks which flawed HR forecasting creates impact organizational sustainability in the long term (Pinto, 2023). The implementation of incorrect workforce projections results in substantial financial issues because organizations must pay additional hiring expenses while dealing with overtime costs and penalties from delayed project deadlines (PMI, 2023). The

Restricted - External

consequence of poor forecasting becomes worse because it creates talent mismatches that result in underused or overwhelmed employees who experience decreased morale and higher turnover and loss of organizational knowledge (Ulrich & Dulebohn, 2023). The success of projects in knowledge-intensive industries depends on maintaining skilled personnel along with smooth expertise transfer because these outcomes prove particularly damaging (Wright & McMahan, 2023). Inaccurate HR needs forecasting prevents organizations from planning their workforce proactively which makes them have to respond instead of making proactive moves for talent gaps and leadership development and succession planning (Robinson & Dechant, 2022).

Although contingency theory and stakeholder theory create valuable theoretical foundations for these challenges the practical application of HR forecasting requires more development (Abdulsallam, 2023). The forecasting models used by organizations need to adapt to project complexity and market volatility according to contingency theory yet most organizations still use standardized forecasting approaches without considering contextual factors (Donaldson, 2023). According to stakeholder theory organizations need to match their workforce planning strategies with expectations from different groups such as staff members and business customers and shareholders thus current forecasting systems often lack built-in mechanisms for stakeholder input validation and model enhancement (Freeman et al., 2023). Research which unites academic understandings with practical implementations represents an absolute necessity because it enables organizations to establish forecasting systems that harmonize theoretical soundness with operational effectiveness (Söderlund, 2023).

HR forecasting faces additional complexity because of ethical considerations when organizations use AI and predictive analytics in workforce planning according to Tambe et al. (2023). The obvious manifestation of AI system biases in human resource forecasting sparks major ethical concerns because these automated systems favor some demographic groups over

Restricted - External

others thus compromising fairness standards in automated tools (Bondarouk & Brewster, 2023). Organizations must handle intricate legal and ethical challenges when collecting employee data for forecasting purposes because these activities fall under GDPR and CCPA privacy regulations (Marler & Boudreau, 2023). AI forecasting in HR encounters additional difficulties because of insufficient governance standards which puts organizations at risk for legal consequences and reputational harm (Tambe et al., 2022). The resolution of ethical challenges requires organizations to use technological progress alongside ethical principles which protect employee rights and maintain transparency (Davenport et al., 2023).

The study examines the fundamental issue between theoretical forecasting potential and practical project management applications because of the many challenges identified by Devaraj et al. (2023). Advanced forecasting techniques benefit organizations extensively based on academic studies yet their adoption persists slowly due to technical barriers and organizational resistance and ethical concerns according to Zhao et al. (2023). The current situation poses significant concerns because workforce agility and strategic talent management stand as key project success factors and organizational resilience components (Kerzner, 2023). The research examines various obstacles to HR forecasting and presents three combined solutions to create a dynamic forecasting discipline which combines data science with ethical governance standards (Pinto, 2023). The research findings will add to academic knowledge while offering practical solutions to professionals who need to enhance workforce planning and minimize risks along with project success in today's unpredictable business environment (Creswell & Creswell, 2023).

1.3 Purpose of Research

This research makes a dual impact on theoretical progress and practical innovation regarding human resource forecasting in project management by resolving longstanding gaps between workforce planning and organizational success (Kerzner, 2023). The research evaluates the

Restricted - External

practicality of contingency theory and stakeholder theory for modern HR forecasting while offering tested frameworks for better forecasting accuracy and talent allocation and project risk mitigation (Devaraj et al., 2023). Through its combination of theoretical strength and practical solutions this research both deepens academic scholarship and gives practitioners the ability to handle complex workforce challenges to develop resilient project management approaches (Pinto, 2023).

1.4. Significance of the Study

The theoretical findings of this study transform project management scholarship regarding human resources forecasting by introducing new conceptual approaches. The research extends contingency theory through Donaldson (2023) by showing that different project circumstances including agile versus waterfall methods and short-term versus long-term assignments and high-risk versus low-risk initiatives require unique human resources forecasting techniques (Abdulsallam, 2023). The application of contingency theory to human resources forecasting lacks understanding when organizations face quick technological changes and employee movement patterns (Söderlund, 2023). The research determines particular project factors such as volatility along with stakeholder complexity and technological dependency which impact forecasting success and develops an improved theoretical model to classify forecasting methods as reactive, predictive or adaptive according to situation requirements (Zhao et al., 2023). The research advocates for a tailored forecasting methodology that takes project-specific variables into account because it challenges standardized approaches that currently prevail in HR forecasting literature (Elkholosy, 2023).

This research enhances stakeholder theory (Freeman et al., 2023) through its examination of how HR forecasting resolves stakeholder conflicts between project sponsors and team members and clients and regulatory bodies (Zarghami & Dumrak, 2023). Traditional forecasting models currently choose organizational goals above incorporating stakeholder perspectives which

Restricted - External

causes project direction and achievement to diverge (PMI, 2023). The research establishes a stakeholder-weighted forecasting system that uses quantitative methods to merge stakeholder needs such as client skill requirements and employee work preferences and regulatory workforce mandates within the forecasting framework (Robinson & Dechant, 2023). The study uses empirical testing across diverse industries to prove how stakeholder-based forecasting enhances both project success and employee contentment and client confidence while respecting regulatory requirements thus delivering practical tools for managing stakeholder conflicts (Ulrich & Dulebohn, 2023).

The research fills an essential void in literature by performing detailed investigations of artificial intelligence (AI) and machine learning (ML) effects on HR forecasting while providing factual evidence about their operational boundaries and ethical concerns (Garcia et al., 2023). AI-driven analytics for workforce planning received attention in research by Tambe et al. (2023) but there is a lack of systematic analysis comparing AI-accelerated forecasting to conventional techniques and a nonexistent focus on algorithmic decision-making transparency (Bondarouk & Brewster, 2023). The present study investigates actual cases of AI decision support tools which have succeeded or failed by examining how factors such as data quality and algorithmic clarity and user adoption capability affect their results (Marler & Boudreau, 2023). The analysis highlights the need for human involvement to evaluate and correct algorithmic outcomes because AI alone does not fix forecasting problems (Davenport et al., 2023). The research contributions develop theoretical AI knowledge in HR while defining proper practices for AI implementation in project management according to Boudreau and Ramstad (2023).

1.5. Research Purpose and Questions

The study presents practical knowledge which enables organizations to redesign their human resource forecasting systems to overcome widespread project success-limiting inefficiencies

Restricted - External

(Kerzner, 2023). The framework provides organizations with an immediate practical tool that guides forecasting accuracy improvement through a unified process combining data analytics and stakeholder engagement with contingency planning (Devaraj et al., 2023). The framework delivers specialized tools for project management forecasting that combine workforce dashboards with scenario planning templates and competency mapping matrices to facilitate immediate staffing strategy adjustments (Pinto, 2023). The forecasting agility index within the framework enables organizations to measure their ability to respond to labor market disruptions through skills training programs and temporary staffing resources (Hutahayan, 2023). The research presents clear forecasting explanations and adaptable tools which enable project managers to transition from fire-based response to planned workforce management (Cascio & Montealegre, 2023).

The research presents an evidence-based method for AI and predictive analytics adoption in HR forecasting that tackles both technical and cultural obstacles to implementation (Garcia et al., 2023). The research utilizes successful AI implementations at Siemens and Accenture to present a step-by-step approach for integration which includes initial pilot projects employing ML to forecast project-specific turnover risks followed by the expansion into enterprise-wide forecasting solutions (Tambe et al., 2023). The research presents both common implementation errors and their remedies through explainable AI interfaces that display algorithmic reasoning to non-technical stakeholders (Bondarouk & Brewster, 2023). The study establishes ethical deployment checklists for AI which help organizations meet their obligations regarding data privacy regulations as well as fairness requirements (Davenport et al., 2023). The research provides essential knowledge to organizations with limited HR analytics capabilities which want to use technology for strategic business gains (Wright & McMahan, 2023).

The research presents specific measures to address the three main risks in HR forecasting which primarily involve understaffing and overstaffing and skill deficits (Rezvani & Khosravi, 2023).

Restricted - External

The research conducts extended project studies across different industries to detect initial warning signs such as decreasing employee engagement metrics and timing differences between project schedules and recruitment periods which indicate upcoming workforce deficits (SHRM, 2023). The approach recommends "talent pipelining" strategies for understaffing situations because organizations should identify and develop future candidates for essential roles before actual workforce needs materialize (Ulrich & Dulebohn, 2023). The proposed solution for overstaffing includes dynamic redeployment algorithms which move excess talent into adjacent projects or upskilling initiatives according to Boudreau and Ramstad (2023). The study presents its most groundbreaking solution for skill shortages through a "skills futures" model which employs AI to forecast upcoming competency requirements and collaborates with educational institutions to fill gaps ahead of time (Manyika et al., 2023). The techniques receive additional support from cost-benefit assessments which help organizations select their workforce planning investment priorities (PMI, 2023).

This study brings practical value through strategic organizational development which includes both sustainability initiatives and organizational adaptability features (Kniffin et al., 2023). The research shows that strategic goal alignment of HR forecasting enables workforce planning to advance from a tactical HR practice into a fundamental business resilience driver (CIPD, 2023). The "forecasting maturity model" from this research helps organizations compare their predictive analytics capabilities with industry leaders so they can build their forecasting skills from basic headcount planning to advanced predictive analytics (Marler & Boudreau, 2023). The study places equal importance on ethical forecasting and inclusive approaches which enable organizations to achieve their ESG targets through diverse talent representation and equitable workforce practices (Robinson & Dechant, 2023). The study shifts HR forecasting from project management tool status to essential strategic foundation which ensures long-term organizational sustainability (Freeman et al., 2023).

Restricted - External

1.6 Research Objectives

The broad objective of the study is to evaluate the effectiveness of human resource (HR) forecasting techniques in project management and develop an optimized framework that integrates contingency theory, stakeholder theory, and AI-driven analytics to enhance workforce planning accuracy and project success. The specific objectives includes to:

1. measure the relationship between HR forecasting method sophistication and project success rates
2. evaluate the impact of forecasting accuracy on workforce efficiency
3. assess stakeholder satisfaction with different forecasting approaches
4. examine barriers to effective forecasting implementation

1.7. Research Questions

1. What is the correlation between the level of technological adoption in HR forecasting and project success metrics?
2. How strongly does HR forecasting accuracy predict workforce utilization efficiency?
3. What differences exist in stakeholder satisfaction levels between organizations using different HR forecasting methods?
4. What are the most significant organizational factors limiting HR forecasting effectiveness?

1.8. Research Hypotheses

H1: Organizations using AI-enhanced forecasting methods report significantly higher project success rates than those using traditional methods

H2: Higher forecasting accuracy positively correlates with improved workforce utilization rates

H3: Organizations using integrated forecasting approaches report higher stakeholder satisfaction than those using single-method approaches

Restricted - External

H4: Data quality issues and resistance to change emerge as the strongest negative predictors of forecasting effectiveness

1.9 Limitations of the Study

While this research provides valuable insights into HR forecasting in project management, several limitations must be acknowledged that may affect the interpretation and generalizability of the findings.

1. The study focuses exclusively on Nigeria's banking and telecommunications sectors, which, while highly dynamic and relevant, may limit the applicability of the findings to other industries. The banking and telecom sectors are characterized by rapid technological adoption, stringent regulatory oversight, and high workforce mobility—factors that may not be representative of slower-paced industries such as manufacturing or agriculture. Consequently, the results may not fully generalize to sectors with different operational dynamics, labor structures, or project management approaches. Future research could expand the scope to include other industries to enhance external validity.
2. The study relies on survey questionnaires, which introduce the risk of self-reporting biases (Dillman et al., 2014). Respondents—particularly HR managers and project leaders—may overstate forecasting accuracy or underreport implementation challenges due to social desirability bias or organizational image concerns. Additionally, recall bias may affect responses, as participants may inaccurately remember past forecasting outcomes or project performance metrics. While anonymity was ensured to mitigate some of these biases, the subjective nature of survey data remains a limitation. Future studies could incorporate objective HR records or project management software data to validate self-reported findings.

Restricted - External

3. The research was conducted within a limited timeframe (September 2023–May 2025), which restricted the ability to conduct a longitudinal analysis of HR forecasting trends over multiple project cycles. A longer study period could have provided deeper insights into how forecasting effectiveness evolves with changing market conditions, technological advancements, or workforce trends. Additionally, seasonal variations in workforce demand (e.g., year-end financial reporting in banking or network upgrades in telecom) may not have been fully captured. Future research could adopt a multi-year approach to examine long-term forecasting reliability.
4. The study employs a cross-sectional rather than experimental design, meaning it captures data at a single point in time rather than tracking changes over time. As a result, while correlations between forecasting methods and project success can be identified, causal relationships cannot be definitively established. For instance, while AI-driven forecasting may correlate with higher project success rates, other unmeasured factors (e.g., organizational culture, leadership quality) could also influence outcomes. Future research could use quasi-experimental or longitudinal designs to strengthen causal inferences.
5. The findings are influenced by Nigeria's unique economic, regulatory, and labor market conditions, which may differ from those in other emerging or developed economies. Factors such as talent availability, digital infrastructure maturity, and regulatory compliance burdens could vary significantly across regions, affecting the transferability of the study's recommendations. Comparative studies across different countries could help determine which findings are universally applicable versus context-dependent.

Despite these limitations, the study offers critical insights into HR forecasting practices in high-growth sectors, providing a foundation for future research to address these constraints through expanded samples, mixed-method designs, and longitudinal analyses.

Restricted - External

1.10. Delimitations of the Study

A focused approach has been chosen for this study through deliberate boundary limitations which determine its practical scope.

The research study examines only project-based industries by focusing on banking and telecommunications sectors within Nigeria while excluding non-project-driven sectors including manufacturing, agriculture and retail. The excluded sectors maintain operational workflows that differ fundamentally from project-focused structures which results in distinctive HR forecasting needs regarding workforce scalability and skill requirements and temporal needs. The research concentrates on banking and telecom industries because project management plays an essential role in their business operations to ensure that practical findings directly benefit organizations that need dynamic workforce planning. The results will not apply to industries featuring stable labor requirements because of this study's delimitation.

This research exclusively investigates organizations with 250+ employees which means it does not include small businesses along with startups. The research focuses on organizations with structured HR forecasting processes and dedicated project management offices and sufficient workforce analytics capabilities because they generally have larger sizes. The forecasting methods used by small businesses tend to be informal because they have restricted funding and fewer employees. The study maintains strong internal validity for its target demographic by excluding small businesses yet acknowledges that the methods presented do not address forecasting needs of the significant portion of Nigeria's economy which comprises small businesses.

The research study analyzes only established HR forecasting techniques without considering spontaneous workforce evaluation methods. The selected boundaries guarantee methodological consistency yet disregard different workforce planning strategies which arise from organizations with minimal bureaucratic HR structures.

Restricted - External

The study's boundaries are defined by these delimitations which establish parameters for future research to examine excluded sectors and organization sizes and different forecasting approaches.

1.11. Assumptions of the Study

The research builds its framework and data interpretation through key assumptions which form its base. These foundational premises both direct research exploration and establish essential constraints that researchers need to recognize during analysis of study results.

1. The study bases its analysis on the belief that participants from surveyed organizations will give truthful responses about their human resources forecasting methods and project evaluation results. The validity of the study's findings depends on participants revealing truthful data about forecasting effectiveness as well as organizational performance and challenges because data collection uses self-reported measures. The research results may be affected by two possible biases including social desirability bias which leads respondents to exaggerate their forecasting achievements and recall bias that stems from limited recall abilities. Anonymity features in the survey design along with validated Likert-scale questions help participants feel comfortable giving honest responses.
2. Also, the study was based on the assumption that successful HR forecasting stands as a vital project success factor which affects delivery timing and budget management along with workforce performance. The study premise matches findings from Kerzner (2022) and Pinto (2023) but fails to address situations where external elements such as economic turbulence or regulatory adjustments dominate workforce planning effects on project accomplishments. The study implements controls for contextual variables yet it positions HR forecasting as the main variable which might diminish other influential elements.

Restricted - External

3. The research assumes that technological innovations including AI and machine learning will permanently transform workforce planning thus necessitating their integration into HR forecasting systems for competitive purposes. The advancement of digital technology (Davenport et al., 2023) supports this prediction yet it does not apply to sectors that avoid technological adoption because of cultural barriers or monetary limitations. This research concentrates on organizations that use predictive analytics because they are actively working with these methods yet avoids organizations that stick to conventional forecasting approaches.

The research uses these assumptions as essential organizational structures yet they also identify conditions that may affect the findings' validity. Research should investigate these assumptions through empirical testing to establish their general application.

1.12. Definition of Key Terms

To ensure clarity and consistency throughout this study, the following key terms are operationally defined based on authoritative sources:

Human Resource Forecasting (HRF): The systematic process of estimating future workforce requirements by analyzing project demands, skill gaps, and labor market trends to ensure optimal staffing

Project Management (PM): The application of knowledge, methodologies, and tools to initiate, plan, execute, and close projects while meeting predefined objectives of scope, time, cost, and quality.

Predictive Analytics: The use of historical data, artificial intelligence (AI), machine learning (ML), and statistical algorithms to identify patterns and predict future workforce trends, such as attrition risks or skill shortages

Restricted - External

Contingency Theory: A management framework positing that organizational strategies, including HRF, must adapt to situational variables like project complexity, market volatility, and technological disruption

Stakeholder Theory: A paradigm emphasizing that HRF should balance the expectations of diverse stakeholders (e.g., employees, clients, regulators) to achieve project success.

AI-Driven Forecasting: The application of artificial intelligence (e.g., neural networks, natural language processing) to automate and optimize workforce demand-supply predictions.

Workforce Utilization Efficiency: A metric measuring the percentage of employees effectively deployed on projects without underuse or overuse, calculated as (Actual Productive Hours / Available Hours) × 100

Project Success: A multidimensional construct assessed through on-time completion rates (±10% of deadline), budget adherence (±5% of forecasted costs), and stakeholder satisfaction scores (≥4/5 Likert scale).

Skill Mismatch: The discrepancy between employees' competencies and project requirements, quantified as the percentage of roles filled by underqualified or overqualified personnel.

Gig Economy Workforce: A labor market characterized by short-term, freelance, or contract-based engagements, measured by the proportion of contingent workers in project teams.

Data Quality: The reliability, accuracy, and completeness of HR data used for forecasting, assessed via error rates in workforce records and missing data percentages.

Change Management: Structured approaches to transitioning organizations from traditional to AI-enhanced HRF, evaluated by employee adoption rates and resistance levels.

Algorithmic Bias: Systemic errors in AI-driven forecasting that disadvantage specific demographic groups, measured through disparity audits in hiring or promotion predictions.

Restricted - External

Hybrid Work Models: Employment arrangements blending remote and on-site work, operationalized as the percentage of project teams working flexibly.

Workforce Agility: An organization’s capacity to rapidly reskill or redeploy employees in response to project shifts, quantified by average training time for new competencies.

1.13. Conclusion

The essential framework for this study has been established by defining critical background information and presenting the problem statement together with research significance and objectives and investigation scope of human resource forecasting (HRF) in project management. Advancing business environments with dynamic workforce requirements present complex challenges to forecasting human resources forecasting in addition to technological transformations and changing labor forces and stakeholder requirements. The research objectives focused on resolving HRF accuracy problems and methodological constraints and technological implementation barriers by using empirical data. The chapter defined both the study's limitations and assumptions which established its specific research boundaries. The established groundwork enables this research to bring significant value to academic research and business-based practices. With a thorough review of literature in the following chapter existing theoretical models and empirical work joins empirical findings and developmental patterns in Human Resource Management and project management to sustain the research approach. A strong theoretical base will support the upcoming research methodology together with analytical framework.

Restricted - External

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The literature review is an essential segment of academic research as it establishes the scholarly context for the study. It synthesizes existing knowledge, identifies gaps, critically evaluates contributions, and provides a framework for the current research. In the context of this study on the importance of human resource (HR) forecasting in project management, the literature review performs several crucial functions. It clarifies key concepts, presents theoretical frameworks, evaluates traditional and modern forecasting techniques, and explores the interplay between HR forecasting and project management success. Furthermore, it critically examines sector-specific challenges, particularly within the Nigerian banking and telecom industries, while identifying barriers and post-COVID-19 shifts in HR forecasting practices.

The significance of conducting a comprehensive literature review lies in its ability to anchor the research in an established academic discourse. It enables the researcher to build on prior studies rather than reinventing the wheel. As Machi and McEvoy (2016) suggest, a well-structured literature review helps define the problem space and justifies the need for the present investigation. It also enables a critical appraisal of theoretical models, guiding the selection of the most appropriate analytical lenses for the research.

This chapter begins with conceptual clarifications of key terms, including human resource forecasting and project management. It then presents the theoretical underpinnings of the study, focusing on contingency theory and stakeholder theory. This is followed by a historical overview of HR forecasting, an evaluation of traditional and modern forecasting techniques, and a comparative analysis of their applications. The chapter further explores the integration of HR forecasting with project management, delves into industry-specific issues in Nigeria, and identifies organizational, technological, and environmental barriers to effective HR

Restricted - External

forecasting. It concludes with a review of empirical studies, identification of research gaps, and a summary that ties together the themes and justifies the research direction.

2.2 Conceptual Clarifications

2.2.1 Project Management

Project management is defined by the application of existing knowledge, techniques, tools, and skills to deliver projects within scope, time, quality, and cost constraints as stipulated by PMI (2021). Project management is based on the use of organized methodologies to ensure that temporary efforts are planned, implemented, and managed to successfully deliver unique deliverables (Kerzner, 2017). As organizations are confronted by more and more complex, multi-component projects in continually changing environments, the strategic significance of project management has moved from a peripheral to a primary engine of organizational success.

Along with the five major process groups such as initiation, planning, execution, monitoring and controlling, and closing, the PMBOK Guide becomes an important resource in learning about the basics of project management. response These process groups are underpinned by ten knowledge domains including integration, scope, time, cost, quality, resource, communication, risk, procurement and stakeholder management. All these areas of knowledge are critical for the success of the project and require a synergistic application of the technical competencies, leadership skills, and resource planning.

Human resource management is the heart of the entire project process. Human resource management from team formation to the strategic allocation of tasks during execution and measurement of project performance at conclusion is essential to deliver projects on time and at cost and quality expectations (Turner, 2019). Project human resource management normally involves the processes of team planning, hiring, skill building, and teamwork dynamics management. Acknowledging the crucial connection between people’s ability and project

Restricted - External

outcomes, there is a much greater focus on strategic workforce planning in project management (Meredith & Mantel, 2019).

The project management frequently fails to match the staff capabilities with the changing needs of the projects. With the various complexities, duration, risk, and expertise required by projects, there is a need for organizations to embrace responsive and dynamic HR strategies (Pinto, 2020). Effective alignment requires predicting the needs of staff and at the same time identifying the needed expertise, experience, and soft skills for each stage of a project. Project failures, as pointed out by Zwikael and Globerson (2006), are frequently due to an improper match between team capability and project expectation, underscoring the critical role of effective HR forecasting.

Because of their temporary and cross-functional nature, project teams pose unique challenges for the traditional human resource planning process. Project teams are different from fixed organizational groups because they are formed and dissolved depending on particular project needs and members are often drawn from various departments or from outside partnerships (Söderlund, 2011). The dynamic nature of project teams complicates HR forecasting by requiring the consideration of both internal talent movements and the existence of external contract workers. In industries such as Nigerian banking and telecom where there is frequent project start up and changing priorities, poor workforce planning may result in resource shortage, project lag and financial mismanagement (Okereke & Nwachukwu, 2015).

In addition, the use of agile project management has altered the way organizations plan for their work force. Agile methodologies, represented by Scrum and Kanban, are concerned with iterative development, cross-team collaboration, and rapid change adaptation (Highsmith, 2009). As a result, HR planning must be more flexible and focused on empowerment, autonomy, and lifelong learning in teams. In agile environments, the HR forecasting should be flexible, multi-hypothesis, and be prepared for shifts in job functions. According to Serrador

Restricted - External

and Pinto (2015), if HR practices are aligned with agile values, then the adoption of agile methods greatly increases the success of projects.

Stakeholder engagement is an important part of project management and involves the strategic management of expectations and keeping open, effective communication with all stakeholders involved. For successful HR forecasting, the client demands, regulation, and cultural aspects must be considered, which define the make-up of the workforce and performance standards (Freeman et al., 2021). Failure to address these issues may provoke project resistance, undermine stakeholder trust and damage an organization's reputation.

Anticipating future needs of talent, identifying deficiencies, and planning for the necessary recruitment or training can help organizations avoid the chaos as a result of shortages or poor management of staffing resources (Elkholosy, 2020). Early and strategic human resource forecasting is critical for projects that depend on emerging technologies due to the rate of change in the competencies required (Garcia & Patel, 2021).

In spite of its essential role in project management, the application of HR forecasting is not always applied consistently. It is usual for project leaders to rely on established information and managerial hunches rather than using comprehensive forecasting techniques. As a result, managers often have excessively-sized workforces, wasted resources, and talent ill-suited for the goals of the project (Devaraj et al., 2021). Furthermore, lack of collaboration between HR and project teams frequently leads to fragmented workforce planning, thus decreasing project efficiency and success (Wright & McMahan 2019).

Effective project management requires a shift to overall talent strategies supported by accurate HR forecasting. In current projects, the management of human resources is as critical as the control of processes or technologies (Kerzner 2022). HR forecasting should seamlessly fit into the project governance framework in order to ensure consistency with project objectives,

Restricted - External

timelines and outcomes. To achieve this synergy seamless coordination among HR experts, project leaders, and the top organizational officials is needed.

2.2.2 Human Resource Forecasting

HRF is the strict process of predicting an organization's future demands and human resources, in terms of skill, quantity, and quality, within a given period (Armstrong & Taylor, 2020). It is a strategic guide to ensure that human resources are aligned to an organization's future operational and strategic goals. By using HR forecasting, organizations can have the alignment of the required headcount and skill sets with positions and timing (Bohlander & Snell, 2017).

HR forecasting is not just about calculating the number of people required. It entails assessing workforce characteristics, skills, turnover in staffing, industry patterns, economic environments, and impact of technological changes (Noe et al., 2019). This process is critical in developing recruitment strategies; determining future leaders; in the staff development process and in reacting to changes in the organization. Proper HR forecasting implementation helps businesses to stay ahead of gaps and redundancies in their workforce and limit exposure to risks that come with inadequate human capital.

HR forecasting also involves the evaluation of wider environments and preparation for potential scenarios to estimate changes in availability of workforce due to changes in labour markets, regulatory structures, learning systems, and sociocultural trends (Jackson, Schuler & Jiang, 2014). One of the noteworthy examples is changes such as remote working, new immigration rules, and international health emergencies such as COVID-19 that have required the development of more responsive and flexible approaches to workforce planning.

This approach links the existing skills in a company with the skills it will need to accomplish its future goals. Its relevance is a pure cause of how effective organizations are at competing and succeeding, particularly in fast-changing fields such as technology, healthcare, and finance. Overvaluation of accurate forecasting can result in companies that have poorer performance,

Restricted - External

higher employee departures, and skill shortages, all of which reduce competitive capability (Cascio & Boudreau, 2016).

2.2.3. Types of Human Resource Forecasting

Human Resource Forecasting can be described as qualitative, quantitative, or as more recently, including AI techniques. The appropriateness of each approach to forecasting differs greatly depending on such factors as organizational context, availability of data, and corporate strategy, determining which of the approaches is finally implemented.

2.2.3.1. Qualitative HR Forecasting

Mostly, qualitative techniques rely on the interpretations of knowledgeable people and personal views to predict human resource demands. These approaches work best in situations where conditions are changing rapidly or where there is a lack of reliable data because of uncertainty (Dessler, 2020). Qualitative forecasting is likely to be employed by SMEs, nascent enterprises and industries where innovation is being pursued at a high speed.

The Delphi Technique is one of the most frequently used qualitative forecasting approaches. A collective forecast is achieved through iterative combination of separate forecasts submitted by a group of specialists. This approach minimizes the influence of powerful individuals, which enables group wisdom to guide the formation of the forecast (Wright, 2011).

A second approach involves the input of line managers and HR staff who examine departmental plans, forecast retirements and estimate likely skill shortages to establish future staffing needs. This technique is agile and considers hidden knowledge and non-formal information such as projected attrition or organizational spirits.

However, there are some inherent disadvantages of qualitative forecasting. It can be biased by overconfidence and confirmation bias, and is more inconsistent particularly when individual perspectives are used to predict without reference to a structured method (Mathis et al., 2017).

Restricted - External

Specifically, big enterprises and multinational organizations depend on stable, measurable indicators which may reduce the efficiency of qualitative forecasting.

Under specific conditions, like the lack of historical information or the need to use other methods, the qualitative forecasting is of great value. In cases such as mergers and market expansions, the expert opinions that are collected through qualitative measures can provide valuable foresight that is often neglected in pure numerical predictions (Ulrich et al., 2012).

2.2.3.2. Quantitative HR Forecasting

The quantitative forecasting process uses mathematical and statistical forecasts to predict the future HR needs based on the past data. Responded.

Common methods used in this discipline include trend analysis, ratio analysis, regression analysis and Markov analysis. For example, trend analysis predicts future staffing needs by examining historical growth patterns – for example a consistent 5% annual rise in sales staff. According to Ivancevich's (2007) work, ratio analysis utilizes major ratios (such as ratio of employees to production output) to estimate demand based on expected performance of business.

Remarkably, Markov analysis follows movements between employee states (promotion, transfer, or exit) and is helpful for internal labour market trends forecasting. It helps organizations to establish transition probabilities and promote strategic internal talent development (Fottler, Khatri & Savage, 2010).

Its accuracy and ability to handle large volumes of data distinguish quantitative forecasting from others. It enhances visibility and helps to develop several scenarios for workforce planning. For instance, using regression models, organizations can assess how an organization is likely to be affected by automation in terms of job roles, predict the risks involved in downsizing and plan to have employees retrained.

Restricted - External

However, the validity of quantitative methods depends on having good quality, relevant historical data to guide analysis. Even though they assume stable patterns, such methods fail to predict unexpected fluctuations and sudden shifts, especially in fast-changing or volatile environments. However, these methods lack to consider qualitative factors such as team involvement, leadership behavior, and institutional influences that play a massive role in determining workforce results (Snell, Morris & Bohlander, 2016).

Organizations overcome these constraints by combining quantitative analysis with qualitative human understandings; they create models that combine factual evidence and practical wisdom.

2.2.3.3. AI-Based HR Forecasting

The advent of AI and ML has greatly changed human resource forecasting. Using AI, companies can access vast data, supercomputing capabilities, to identify fine trends, predict employee behaviors, and make dynamic work force plans.

Machine learning algorithms analyze both structured HR datasets and unstructured information, extracted from performance reviews, emails, and social media, thus creating complex forecasting models. Machine learning applications, for instance, leverage a diverse range of data including job satisfaction, commuting distance, pay grades, and previous attrition records to forecast the employees who may leave (Davenport, Guenole & Gloor, 2020).

One of the most important use cases for AI is recruitment predictive analytics, which predicts a candidate's potential for success and retention based on historical hiring data. Such algorithms as NLP are used to analyse employee feedback and identify the early signs of low morale to avoid the risk of attrition (Meijerink, Bondarouk & Lepak, 2020).

Artificial intelligence facilitates flexible scenario planning. Instead of adopting traditional methods, AI allows simulation of several future possibilities to inform the choice of ideal staffing plans. An AI-integrated workforce planning system may choose to employ temporary

Restricted - External

staff in fluctuations with market uncertainty but permanent jobs when the job market normalizes.

Although it has its advantages, AI-based forecasting has a share of naysayers. The fears of privacy violations, data confidentiality and biased algorithms have resulted in significant discussions. A few experts fear that an overreliance on AI may reduce human judgment in HR decision-making and continue existing biases from the data used (Raghavan et al., 2020).

However, successful integration of AI requires a lot of resources to be put into the creation of data systems, hiring of expertise, and transitions. Smaller organizations, especially in developing areas, frequently encounter obstacles to the implementation of reliable AI forecasting because of not sufficient technological readiness and data governance (Marler & Boudreau, 2017).

However, AI can significantly improve the accuracy, flexibility, and alignment of HR forecasting efforts if it is used with consideration. The challenge for HR leaders is to ensure that AI complements, rather than replaces, human expertise, thereby fostering ethical and inclusive workforce planning.

2.2.3.4. Comparative Evaluation of Forecasting Methods

The choice between qualitative, quantitative, and AI-based methods depends on organizational size, industry, data maturity, and strategic priorities. Table 1 provides a comparative overview of the three approaches:

Method	**Strengths**	**Limitations**	**Best Use Cases**
Qualitative	Flexible, context-sensitive, expert-driven	Subjective, lacks scalability, prone to bias	New ventures, crisis situations, strategy formulation

Restricted - External

Quantitative	Objective, scalable, statistically robust	Requires quality data, assumes historical continuity	Stable industries, budgeting, and manpower planning
AI-Based	Dynamic, pattern-driven, predictive analytics	High cost, data and ethical concerns	Large organizations, high-turnover sectors, tech firms

Ultimately, an integrated approach—combining human judgment with data-driven models—offers the most balanced and strategic forecasting framework (Bersin, 2018). This fusion not only enhances forecast accuracy but also ensures that HR planning remains agile and human-centred.

2.3 Theoretical Framework

2.3.1 Contingency Theory

Contingency theory is a cornerstone in the studies of organizations and strategic management, which claims that every organization's context defines the most appropriate strategies for structuring and managing the organization. Rather, the best approach relies on particular internal and external circumstances (Donaldson, 2001). Contingency theory was developed in the 1950s and 1960s and was a contradiction to classical management theories that held that management should follow common, universal guidelines. Notable representatives of the initial stage of contingency theory are Burns and Stalker (1961), who investigated the flexibility of the British electronics companies, and Lawrence and Lorsch (1967), who studied the influence of the complexity of the environment on the differentiation and integration of organizations.

Contingency theory has the underlying principle that organizational efficiency is improved when the nature of an organization, its structure, management practices, and leadership are tailored to meet environmental needs. For instance, the use of mechanistic structure, which is

Restricted - External

based on the clear levels of authority and bureaucratic systems, may be appropriate for the environments that are steady but the organic structure that values the adaptability and discretion on all the levels is better for rapid or uncertain change (Burns and Stalker, 1961). This approach has since developed into several disciplines including strategic management, HRM and project management, indicating that coordinated interrelationships among strategic objectives, environmental aspects and organizational processes are key to success (Galbraith, 1973; Burns and Stalker, 1961). Ginsberg and Venkatraman, 1985).

In HRM, contingency theory has greatly enhanced the notion that HR policies should be tailored to address the specific needs of organization and the environment that surrounds it. According to Boxall and Purcell (2016), HR strategies should be implemented with reference to organizational goals, characteristics of work, work force, and external influences. In the world of human resource forecasting, strategic fit is key, as the accuracy and usefulness of forecasts depend on the ability to fit planning models to new organizational conditions.

It is both critical and effective to use contingency theory approaches to human resource forecasting in fluid project environments. In particular in banking and telecommunications, project-based entities operate in contexts of rapid technology trends, rapid changes of customer needs, and uncertain regulatory conditions that are all addressed by Söderlund in 2011. In order to address these challenges effectively, HR forecasting models need to change to be responsive, responsive to context and prepared to integrate environmental considerations into workforce planning strategies.

Methods of forecasting that are deeply embedded in historic data are, for the most part, ineffective when it comes to estimating the future workforce needs against the backdrop of dynamic market conditions. Technological development can make some skills redundant but open opportunities for new knowledge. Contingency theory recommends the use of flexible forecasting strategies by prioritizing situational modifications in environmental analysis. Thus,

Restricted - External

HR forecasting models should be flexible towards the differing levels of complexity of projects, composition of teams, and unique strategic goals they pursue (Donaldson, 2001).

The popularity of the agile project management model, which is based on short planning periods, the use of multifunctional teams, and the iterative cycles of innovation (Highsmith, 2009), indicates a need for flexible forecasting models. In this regard, forecasting strategies should be flexible enough to attend to the immediate staffing need, constant role modification and rapid employee integration. A rigid headcount-based forecasting strategy would not be appropriate. To counter the contingency approach, scenario-based forecasting that incorporates the most current project information and stakeholder views is advantageous (Dyer and Reeves, 1995). This flexibility is critical in fast-moving projects which require a continuous tweaking of workforce requirements.

Organizational structure, as outlined by contingency theory, directly influences the effectiveness of forecasts created. Centralized firms tend to leave forecasting to HR departments which use set templates to ensure consistency. For decentralized organizations – usually working within project-based or matrix structures – forecasting activities should include collaboration between project leaders, experts in different functions, and external specialists. In its turn, the best forecasting system depends on organizational design and the level of autonomy provided for project units (Galbraith, 1973).

Furthermore, contingency theory highlights the way in which leadership decisions influence the results of HR forecasting activities. Volatile and innovative leaders often support forecasting methods that not only combine innovative data and technology but also integrate them into the process. However, leaders who tend to lean towards tradition and caution tend to resist changing their forecasting procedures in search of comfort from well-established practices (Fiedler, 1967). Consequently, leadership style becomes an important contingency factor that determines the selection and implementation of HR forecasting techniques.

Restricted - External

Research has shown that contingency theory can be applied to HR forecasting situations. The results presented by Zhao et al. (2023) indicate that organizations that adjusted their forecasting methods to environmental complexity had better accuracy and a higher rate of project success. In contrast, firms that applied the same forecasting tools to all projects frequently encountered wrong staffing, which led to delays in the schedule and overspending. This evidence shows that the effective HR forecasting demands that models be flexible to environmental factors like project type, workforce size, and market instability.

With the ever-changing economic, political, and regulatory environment in Nigeria, contingency theory is particularly effective. The banking and telecommunications industries in particular are exposed to constant policy changes, volatile exchange rates and infrastructure constraints which lead to labor shortages and increased costs. Applying a contingency lens allows HR practitioners to develop forecasting models that account for these uncertainties by integrating external intelligence, stakeholder feedback, and flexible planning horizons (Adeleye and Eboagu, 2019).

However, the application of contingency theory is not without limitations. Critics argue that the theory lacks predictive power, offering post hoc explanations rather than prescriptive solutions (Van de Ven and Drazin, 1985). Additionally, the theory's emphasis on fit may lead to overly complex models that are difficult to implement in practice. For example, attempting to tailor HR forecasting models for every project may strain organizational resources and reduce standardization. To address these concerns, researchers advocate for a balanced approach that combines core forecasting frameworks with customizable elements based on contingency factors (Lawler and Boudreau, 2015).

Moreover, contingency theory has been critiqued for underemphasizing the role of power dynamics and institutional pressures that constrain organizational choice. In many developing countries, including Nigeria, HR practices are influenced not just by environmental fit but also

Restricted - External

by cultural norms, labor laws, and political considerations (Kamoche, 2000). While contingency theory provides a flexible framework for analyzing fit, it may require supplementation with other theoretical perspectives—such as institutional theory—to fully capture the complexity of forecasting practices in such settings.

Despite these limitations, contingency theory remains a valuable lens for understanding how organizations can optimize HR forecasting in project-based and volatile environments. By encouraging situational analysis and adaptive planning, the theory helps bridge the gap between strategic intent and operational execution. Its emphasis on alignment, responsiveness, and contextual intelligence aligns well with the challenges facing contemporary project-based organizations.

2.3.2 Stakeholder Theory

Stakeholder Theory Stakeholder theory is a foundational framework in both corporate governance and strategic management, emphasizing that organizations must consider the interests of all stakeholders, not just shareholders, in their decision-making processes (Freeman, 1984). The theory advocates for a more inclusive approach to organizational governance by recognizing that multiple actors—such as employees, customers, suppliers, regulators, investors, and local communities—have a legitimate stake in the outcomes and processes of organizational activities. In contrast to shareholder-centric models that prioritize profit maximization, stakeholder theory presents a more ethically grounded and socially responsive model of corporate behavior (Donaldson and Preston, 1995).

At its core, stakeholder theory rests on the principle of stakeholder salience, which refers to the prioritization of stakeholder interests based on attributes such as power, legitimacy, and urgency (Mitchell, Agle and Wood, 1997). These dimensions help organizations determine which stakeholders require more immediate or substantial attention during decision-making. For example, stakeholders with high levels of power and urgency—such as regulatory agencies

Restricted - External

or key clients—may wield more influence over organizational planning than less urgent, low-power groups. In this way, stakeholder theory provides a strategic lens through which firms can assess and manage complex relationships that influence their operations.

Another essential concept within stakeholder theory is the notion of value creation and trade. Freeman et al. (2010) argue that businesses operate within a system of cooperative and competitive relationships and that long-term success stems from creating shared value for all stakeholders rather than focusing solely on financial gains. This perspective expands the scope of organizational strategy to include ethical considerations, sustainability goals, and the well-being of employees and communities. As a result, stakeholder theory has increasingly informed best practices in areas such as corporate social responsibility (CSR), sustainability, and inclusive human resource management.

In the context of human resource forecasting and project management, stakeholder theory is particularly relevant due to the multidimensional and cross-functional nature of both practices. Project management typically involves numerous stakeholders—including clients, team members, HR professionals, suppliers, government bodies, and end-users—each with unique expectations, constraints, and definitions of success (Turner, 2019). Consequently, HR forecasting cannot be viewed as a purely technical exercise based on numerical predictions. Instead, it must be understood as a socially embedded process that requires negotiation, consensus-building, and responsiveness to stakeholder needs.

For instance, project managers may prioritize rapid staffing to meet tight deadlines, while HR professionals emphasize compliance with labor laws and internal equity. Similarly, clients may demand specific competencies or certifications from project personnel, and labor unions may advocate for job security and fair employment practices. An effective HR forecasting system must reconcile these potentially conflicting interests by involving stakeholders in the planning process, thereby enhancing transparency and trust (Friedman and Miles, 2006).

Restricted - External

Empirical evidence supports the contention that stakeholder engagement improves the quality and feasibility of HR forecasts. A study by Greenwood and Van Buren (2010) found that inclusive HR planning processes—where key stakeholders were consulted early and regularly—resulted in more accurate forecasts, greater workforce stability, and improved project outcomes. By contrast, forecasting models developed in isolation, without stakeholder input, often suffered from poor implementation due to resistance, misalignment, and a lack of contextual awareness. This underscores the importance of stakeholder theory as both a conceptual guide and a practical framework for participatory planning.

Stakeholder theory also intersects with the concept of psychological contracts in HRM. Psychological contracts refer to the unwritten expectations and obligations between employers and employees (Rousseau, 2001). Forecasting future workforce needs without considering employee aspirations, values, and concerns can erode psychological contracts and lead to disengagement or attrition. By adopting a stakeholder-oriented approach, HR forecasting can better align organizational goals with employee needs, thereby strengthening the psychological contract and enhancing retention.

In project management, the utility of stakeholder theory extends to managing expectations around resource allocation, timelines, and deliverables. Projects often operate under constraints of time, budget, and scope, which can lead to tensions among stakeholders. HR forecasting that incorporates stakeholder feedback is more likely to preempt conflicts and support balanced decision-making (Bourne, 2015). For example, involving senior management in forecasting discussions may secure the necessary budget for skill development programs, while consulting team leaders can provide granular insights into workload distribution and role suitability.

Moreover, stakeholder theory contributes to ethical and responsible decision-making in HR forecasting. Traditional forecasting models often treat labor as a cost variable to be optimized, which can lead to short-term decisions such as downsizing or outsourcing. A stakeholder

Restricted - External

perspective, however, considers the long-term social and ethical implications of such decisions. It encourages organizations to assess how workforce changes affect employee well-being, community stability, and organizational culture (Phillips, Freeman and Wicks, 2003). This is particularly important in developing economies like Nigeria, where job security and decent work are critical socioeconomic issues.

In sectors such as banking and telecommunications, which are characterized by rapid technological change and regulatory scrutiny, stakeholder-informed HR forecasting is essential. The need to reskill workers, comply with evolving labor regulations, and maintain stakeholder trust makes inclusive planning not only a moral imperative but also a strategic necessity (Okpara and Wynn, 2008). Furthermore, as these sectors increasingly adopt digital transformation initiatives, the involvement of IT departments, legal advisors, and employee representatives in HR forecasting becomes vital to ensure a smooth transition.

One emerging trend that further enhances the relevance of stakeholder theory to HR forecasting is the use of stakeholder mapping and analysis tools. These tools help identify key stakeholders, assess their interests and influence, and determine appropriate engagement strategies. When integrated into HR forecasting, stakeholder mapping can guide planners in selecting whom to consult, how frequently to involve them, and how to incorporate their feedback into decision-making. This ensures that forecasting models are contextually grounded and socially responsive (Bryson, 2004).

Despite its strengths, stakeholder theory also faces certain limitations. Critics argue that the theory lacks clear guidelines for balancing competing stakeholder interests, which can lead to ambiguity and decision paralysis (Jensen, 2002). For example, reconciling the demands of cost-conscious shareholders with those of employee unions advocating for higher wages can be challenging. To address this, scholars have proposed prioritization frameworks based on ethical principles, stakeholder salience, and organizational values (Mitchell et al., 1997; Freeman et

Restricted - External

al., 2007). Others suggest the use of deliberative processes and decision-making tools such as multi-criteria analysis to navigate trade-offs.

Another challenge is the practical implementation of stakeholder engagement in fast-paced project environments. In many cases, time constraints and budget pressures discourage extensive consultation. Moreover, power asymmetries within organizations can marginalize the voices of less powerful stakeholders, such as junior staff or minority groups. To counter this, organizations must institutionalize stakeholder engagement by embedding it into HR policies, project charters, and governance structures (Clarkson, 1995).

2.3.3 Integration of Theories

The integration of contingency theory and stakeholder theory provides a multifaceted theoretical foundation for understanding human resource (HR) forecasting in project management. Each of these theories brings unique insights into the dynamics of organizational planning, decision-making, and adaptation, particularly within volatile and multifaceted environments such as those found in the Nigerian banking and telecommunications sectors. Theoretical synthesis, in this context, is not merely the combination of two distinct perspectives but rather the development of a complementary and enriched analytical lens capable of addressing the complex challenges of HR forecasting in project-based organizations.

Contingency theory, with its central tenet of "fit" or alignment, emphasizes the importance of adapting organizational practices to specific internal and external contingencies (Donaldson, 2001). This adaptive orientation is critical for HR forecasting because labor needs and skill requirements fluctuate depending on variables such as project size, technological change, market volatility, and organizational strategy (Burns and Stalker, 1961; Galbraith, 1973). Stakeholder theory, on the other hand, emphasizes the interdependencies and ethical obligations between organizations and their multiple constituencies (Freeman, 1984). It insists

Restricted - External

that successful organizational decisions—particularly those with human impacts—must take into account the interests, expectations, and influences of various stakeholders.

Integrating these two theories offers both strategic and ethical robustness to HR forecasting. On the one hand, contingency theory provides the analytical tools necessary to tailor forecasting methods to the dynamic conditions of each project. On the other hand, stakeholder theory ensures that these methods are grounded in principles of inclusion, fairness, and mutual accountability. Together, they offer a framework that is both agile and responsible, capable of navigating the technical and moral dimensions of workforce planning.

This synthesis is particularly relevant in project management, where projects are often characterized by a high degree of uncertainty, stakeholder multiplicity, and performance pressure (Turner, 2019). Projects are temporary endeavors with specific goals, and their success is contingent upon timely access to the right talent. Forecasting human resource needs in such a context demands more than statistical extrapolation; it requires continuous environmental scanning, stakeholder engagement, and flexible planning models. The combination of contingency and stakeholder theories supports a model of HR forecasting that is both evidence-based and socially responsive.

In practical terms, contingency theory informs the technical and structural aspects of forecasting. For instance, when faced with a complex, high-risk project, the organization might adopt a more detailed forecasting model involving scenario analysis and real-time data tracking (Lawler and Boudreau, 2015). The theory encourages customization of forecasting models based on project attributes, such as urgency, team size, interdependencies, and technological complexity (Ginsberg and Venkatraman, 1985). This adaptability is essential for avoiding the pitfalls of generic forecasting templates, which often fail to reflect the realities of specific organizational contexts.

Restricted - External

Stakeholder theory complements this by ensuring that the forecasting process does not become an insular, technocratic exercise. By advocating for the inclusion of diverse stakeholder voices—such as project managers, HR professionals, employees, contractors, clients, and regulators—the theory supports a more democratic and ethically sound approach to forecasting. It facilitates the identification of stakeholder concerns and aspirations, which can significantly influence HR decisions such as recruitment, upskilling, deployment, and performance evaluation (Phillips, Freeman and Wicks, 2003).

The synergy between the two theories is particularly evident in conflict resolution and trade-off analysis. In many project environments, resource constraints, tight schedules, and competing priorities create tensions between different stakeholder groups. For example, HR departments may be concerned with regulatory compliance and budgetary limits, while project teams push for quick hiring to meet deliverables. Contingency theory can guide the technical optimization of workforce planning under constraints, while stakeholder theory can guide ethical deliberation and consensus-building (Jensen, 2002; Mitchell, Agle and Wood, 1997). When used together, these theories help decision-makers balance efficiency with equity.

From a governance perspective, integrating both theories enhances accountability in HR forecasting. Contingency theory promotes alignment with strategic goals, ensuring that HR forecasts contribute to project success and organizational competitiveness (Boxall and Purcell, 2016). Stakeholder theory, meanwhile, ensures that these forecasts are legitimate and accepted by those affected, thereby reducing resistance and enhancing implementation success (Friedman and Miles, 2006). The result is a forecasting system that is not only effective but also trusted and sustainable.

In the Nigerian context, where socio-economic volatility, regulatory unpredictability, and infrastructural limitations are prevalent, the need for such a synthesized theoretical framework is particularly acute (Okpara and Wynn, 2008). For example, forecasting models in the

Restricted - External

Nigerian telecom sector must consider unpredictable changes in licensing laws, shifts in consumer demand, currency instability, and shortages of technical talent. Contingency theory enables organizations to adapt their forecasting models quickly in response to these variables, while stakeholder theory ensures that such adaptations do not marginalize key actors such as employees, regulators, or communities.

Moreover, the cultural and institutional dimensions of stakeholder theory provide a useful corrective to some of the overly rationalistic assumptions in contingency theory. While contingency theory is strong on strategy and alignment, it often underplays the socio-political dynamics within organizations. Stakeholder theory reintroduces these dynamics by highlighting issues such as power, voice, legitimacy, and ethical obligation. It reminds HR forecasters that decisions about people are not just technical—they are inherently political and moral.

This theoretical integration also opens avenues for methodological innovation. Mixed-method forecasting approaches—combining statistical forecasting tools with participatory techniques such as focus groups, stakeholder workshops, and Delphi panels—can draw simultaneously on the strengths of both theories (Bechet, 2008; Marler and Boudreau, 2017). These methods not only improve the accuracy of forecasts but also enhance stakeholder buy-in and ethical rigor.

Despite the compelling case for synthesis, integrating contingency and stakeholder theories does come with challenges. One potential tension lies in reconciling the flexibility advocated by contingency theory with the sometimes conflicting interests emphasized by stakeholder theory. For instance, adapting a forecasting model to meet a project's strategic needs might involve cost-cutting measures that stakeholders perceive as unfair or exploitative. Navigating such dilemmas requires skilled leadership, transparent communication, and ethical deliberation (Freeman et al., 2010).

Restricted - External

Another limitation is the potential complexity and resource intensity of implementing an integrated model. Customizing forecasting tools while conducting thorough stakeholder engagement can be time-consuming and costly, particularly for small organizations or those in resource-constrained environments. Nevertheless, the long-term benefits—such as improved forecast accuracy, stakeholder trust, and project success—arguably outweigh these initial costs (Cascio and Boudreau, 2016).

2.4 Historical Development of Human Resource Forecasting

Human Resource Forecasting (HRF) has undergone a profound transformation from its early rudimentary practices to the advanced, data-driven, and technology-enhanced systems utilized in contemporary organizations. This evolution has been significantly influenced by broader shifts in technology, globalization, and the dynamics of the workforce. Initially driven by simple headcount planning and managerial judgment, HR forecasting has progressively integrated statistical tools, strategic planning frameworks, artificial intelligence (AI), and predictive analytics to improve accuracy and strategic alignment.

In the early 20th century, HR forecasting was largely an administrative function focused on tracking employee numbers and planning for replacements. These early approaches were simplistic and reactive, grounded in historical data and linear projections (Milkovich and Boudreau, 1994). Organizations relied on tools such as ratio analysis, trend extrapolation, and management intuition to estimate future labor needs. These techniques were limited in scope and lacked the sophistication required to respond to volatile market conditions or complex organizational strategies. Forecasts were often one-dimensional, focusing purely on quantitative metrics like headcount and turnover rates, with little attention to qualitative aspects such as skill levels, competencies, or workforce readiness.

The 1950s and 1960s saw the integration of more formalized HR planning approaches as organizations began to appreciate the strategic importance of workforce alignment. The

Restricted - External

introduction of Human Resource Planning (HRP) as a structured discipline marked a turning point. It emphasized the need to link human capital strategies with long-term organizational goals (Walker, 1980). Workforce planning tools evolved to include job analysis, manpower inventories, and succession planning matrices. However, these tools were still largely static and relied heavily on internal data, offering limited predictive power.

The 1970s and 1980s brought about a deeper understanding of organizational behavior, leading to more nuanced forecasting models that incorporated behavioral and motivational variables. Strategic Human Resource Management (SHRM) began to gain traction, emphasizing the alignment of HR strategies with business strategy (Schuler and Jackson, 1987). This period also saw the adoption of scenario planning techniques in workforce forecasting, allowing organizations to anticipate different future conditions and prepare accordingly. Yet, even with these advancements, forecasting models remained largely linear and deterministic, often failing to capture the complexities of an increasingly global and technology-driven economy.

A major shift occurred in the 1990s with the rise of enterprise resource planning (ERP) systems and the digitization of HR functions. These technologies facilitated the collection and storage of vast amounts of employee data, enabling more granular analysis and more accurate forecasts (Hendrickson, 2003). ERP systems such as SAP and Oracle began to offer integrated HR modules that could track employee movements, monitor performance, and identify skill gaps. These developments laid the groundwork for data-driven HR forecasting by enhancing the organization's capacity to analyze trends, model scenarios, and align workforce supply with projected demand.

The late 1990s and early 2000s witnessed the rise of globalization, which added new layers of complexity to HR forecasting. Multinational enterprises faced challenges in managing geographically dispersed and culturally diverse workforces. Labor market dynamics, regulatory frameworks, and talent availability varied significantly across regions, necessitating

Restricted - External

more sophisticated forecasting models that could accommodate local variations while maintaining global consistency (Brewster et al., 2005). Organizations increasingly employed labor market intelligence, benchmarking tools, and country-specific data to inform forecasting models.

In the same period, workforce transformation began to take shape as organizations shifted from manufacturing-based to knowledge-based operations. The emergence of knowledge workers—employees whose value lies in their intellectual capabilities rather than physical labor—demanded forecasting models that could assess not just headcount but also capabilities, engagement, and innovation potential (Drucker, 1999). Traditional quantitative methods proved inadequate for these tasks, leading to the incorporation of qualitative techniques such as competency modeling, workforce segmentation, and behavioral simulations.

The most significant transformation in HR forecasting emerged in the 2010s with the advent of predictive analytics and artificial intelligence (AI). These technologies offered the ability to move beyond historical analysis and toward forward-looking, dynamic forecasting. Predictive analytics leverages historical data, statistical algorithms, and machine learning techniques to identify patterns and forecast future outcomes (Bersin, 2013). For example, predictive models can now estimate attrition risks, project future skill shortages, and simulate the impact of strategic initiatives on workforce composition.

AI and machine learning further enhance HR forecasting by automating data analysis, reducing human bias, and enabling real-time decision-making. Tools such as IBM Watson and Workday's predictive analytics platform use natural language processing and advanced algorithms to deliver insights on workforce trends, training needs, and recruitment pipelines (Tambe, Cappelli and Yakubovich, 2019). These technologies support continuous forecasting, where models are regularly updated with new data inputs, ensuring that forecasts remain relevant in fast-changing environments.

Restricted - External

A growing body of literature highlights the transformative impact of AI in HR forecasting. According to Marler and Boudreau (2017), the integration of AI has enabled organizations to shift from reactive workforce planning to proactive talent management. Similarly, Boudreau and Cascio (2017) argue that AI enhances the precision of forecasting by minimizing cognitive biases and incorporating diverse data sources, including social media profiles, labor market reports, and organizational network analysis.

However, the adoption of AI in HR forecasting also raises ethical and operational concerns. Issues related to data privacy, algorithmic transparency, and decision accountability have prompted debates about the responsible use of technology in workforce planning (Bondarouk and Brewster, 2016). There is a risk that over-reliance on algorithms could marginalize human judgment and perpetuate existing biases if the underlying data are flawed. As such, scholars advocate for a hybrid approach that combines the computational power of AI with the contextual insights of HR professionals.

Another recent trend in HR forecasting is the emphasis on workforce agility and resilience. The COVID-19 pandemic highlighted the importance of flexible workforce models and the need to forecast under uncertainty. Organizations have since adopted agile forecasting methods that incorporate multiple scenarios, stress testing, and continuous updates (Deloitte, 2021). These methods enable companies to respond rapidly to disruptions, such as sudden shifts in demand, remote work requirements, and health and safety concerns.

Furthermore, HR forecasting has become increasingly integrated with strategic workforce planning (SWP), a process that aligns workforce requirements with long-term organizational strategy. SWP encompasses talent acquisition, leadership development, diversity and inclusion, and employee experience. Modern forecasting models, therefore, extend beyond staffing to include broader metrics such as employee engagement, learning agility, and cultural

Restricted - External

alignment (Ulrich and Dulebohn, 2015). This evolution reflects the recognition that workforce capabilities, not just headcount, are critical to organizational success.

In developing economies such as Nigeria, the evolution of HR forecasting has been uneven. While leading organizations in banking and telecommunications have adopted digital forecasting tools, many firms still rely on manual or semi-automated processes. Challenges such as inadequate data infrastructure, skills shortages, and regulatory uncertainty hinder the adoption of advanced forecasting models (Adeleye and Eboagu, 2019). Nonetheless, there is growing interest in leveraging mobile technology, cloud computing, and analytics platforms to improve forecasting capabilities.

2.5 HR Forecasting Techniques and Tools

2.5.1 Traditional Methods

Traditional methods of Human Resource Forecasting (HRF) have formed the bedrock of workforce planning for several decades. Although often considered less sophisticated compared to modern analytics-based approaches, these methods still provide value in numerous organizational contexts, especially where resources are limited or where historical stability allows for reasonably accurate trend extrapolations. The primary traditional methods include trend analysis, the Delphi method, and managerial judgment. Each of these approaches has its own logic, utility, and limitations, but all share a reliance on historical data, expert insight, and systematic evaluation of organizational patterns.

Trend Analysis

Trend analysis is one of the oldest and most widely used techniques in HR forecasting. It involves studying historical workforce data to identify patterns and project future staffing needs. Typically, organizations collect data on past employment levels, turnover rates, retirements, promotions, and other labor variables to determine whether these trends are likely

Restricted - External

to continue (Dessler, 2020). The fundamental assumption of trend analysis is that the future will mirror the past—at least in terms of workforce behavior.

For instance, if an organization has experienced an average annual turnover rate of 10% over the last five years, it may project a similar rate for the upcoming year. If the business plans to expand production by 20%, trend analysis can help estimate how many additional workers will be needed, assuming productivity ratios remain constant (Jackson, Schuler and Werner, 2012). This method is particularly useful for stable environments with minimal market or technological disruptions.

However, one of the key criticisms of trend analysis is its rigidity. The technique does not account for sudden changes in the business environment such as economic downturns, policy shifts, or the introduction of new technologies. It also assumes that past patterns are reliable predictors of future behavior, which may not hold true in volatile industries (Wright and McMahan, 2011). Moreover, trend analysis often overlooks qualitative factors such as employee motivation, engagement, or cultural shifts that can significantly affect workforce dynamics.

Despite these limitations, trend analysis remains valuable for routine operational forecasting, particularly when combined with other methods. According to Bechet (2008), organizations that use trend analysis as a baseline and overlay it with qualitative insights tend to achieve more accurate and actionable forecasts. In essence, the method is best suited for providing a starting point in the forecasting process rather than a definitive solution.

The Delphi Method

The Delphi method is a structured, qualitative forecasting technique that relies on the collective judgment of experts. Developed by the RAND Corporation in the 1950s, the method is designed to achieve a convergence of opinion among a panel of experts through iterative rounds of questionnaires and controlled feedback (Linstone and Turoff, 2002). In HR forecasting, the

Restricted - External

Delphi method can be used to gather insights on future workforce requirements, skills evolution, or potential risks related to talent management.

A typical Delphi process involves multiple rounds. In the first round, experts are asked open-ended questions about future HR trends or organizational needs. Their responses are then synthesized and used to create more focused questions for the next round. This process continues until a consensus is reached or until diminishing returns make further rounds unnecessary. Throughout the process, responses remain anonymous to minimize groupthink and social pressure.

The strength of the Delphi method lies in its ability to integrate diverse perspectives, especially when forecasting for uncertain or rapidly evolving situations. It allows organizations to tap into the tacit knowledge of internal and external experts, providing a broader and more nuanced understanding of potential future scenarios (Okoli and Pawlowski, 2004). For example, in preparing for digital transformation, a company may use the Delphi method to forecast the types of new skills required across departments, taking into account input from IT, HR, operations, and strategic leadership.

However, the method also has its limitations. It is time-consuming and can be resource-intensive, especially when multiple rounds are required. The quality of the outcome depends heavily on the selection of panel members and the skill of the facilitator in synthesizing and feeding back responses. Furthermore, the lack of quantitative rigor may reduce its appeal in organizations that prefer data-driven decision-making (Rowe and Wright, 1999).

Nonetheless, the Delphi method continues to be a preferred choice for forecasting in areas where historical data are sparse or where rapid environmental changes make quantitative modeling difficult. It is especially useful for long-range forecasting and scenario planning, where the focus is on exploring possibilities rather than predicting certainties (Gordon, 1994).

Restricted - External

Managerial Judgment

Managerial judgment is perhaps the most commonly used method of HR forecasting, particularly in small and medium-sized enterprises (SMEs) or in contexts where formal forecasting tools are unavailable. It involves relying on the intuition, experience, and insights of managers to estimate future workforce needs. This method can be either formal—such as structured interviews and planning sessions—or informal, involving ad hoc consultations and rule-of-thumb estimations.

The appeal of managerial judgment lies in its simplicity and flexibility. Managers are often best placed to understand the specific talent needs of their departments, considering both operational demands and team dynamics. According to Ulrich and Dulebohn (2015), the embeddedness of managers within their units gives them access to real-time information and tacit knowledge that may not be captured in centralized databases.

However, reliance on managerial judgment is fraught with risks. Forecasts based solely on intuition are susceptible to cognitive biases such as overconfidence, anchoring, and availability heuristics (Kahneman, 2011). Moreover, individual managers may have conflicting interests or may lack the strategic perspective required for effective forecasting. This can result in inconsistent and inaccurate projections, especially in large organizations with multiple layers of hierarchy.

To mitigate these risks, some organizations combine managerial judgment with structured data collection and review processes. For example, a bottom-up approach may be used, where departmental forecasts are aggregated and then reviewed by senior management to ensure strategic alignment (Armstrong and Taylor, 2020). Others use calibration sessions where managers are trained to evaluate talent needs against standardized criteria and benchmarks.

Despite its drawbacks, managerial judgment remains indispensable in situations where rapid decisions are required, or where data are incomplete or ambiguous. It is also valuable in

Restricted - External

integrating non-quantifiable information—such as team morale, interpersonal dynamics, and emerging skill needs—that may not yet be reflected in formal metrics.

Comparative Reflections

Each of the traditional methods—trend analysis, Delphi method, and managerial judgment—has unique strengths and weaknesses. Trend analysis offers a straightforward, data-driven approach but lacks adaptability. The Delphi method facilitates informed consensus but is time-consuming and qualitative. Managerial judgment provides contextual sensitivity but is vulnerable to bias. Given these limitations, many organizations adopt a hybrid approach, combining methods to compensate for the deficiencies of each.

For instance, trend analysis might be used to establish a baseline forecast, while the Delphi method adds scenario depth, and managerial judgment contextualizes the forecast to current operational realities. According to Cascio and Boudreau (2016), such triangulation enhances forecasting accuracy, particularly in dynamic environments where no single method suffices.

In developing contexts like Nigeria, the reliance on traditional methods is often a necessity due to constraints in data availability, technological infrastructure, and skilled personnel. However, as organizations in these regions increasingly digitize their HR functions, there is an opportunity to enhance traditional methods with modern tools without entirely discarding them. Traditional methods thus remain relevant, not as relics of the past but as foundational components of a comprehensive forecasting strategy.

2.5.2 Modern and Technological Approaches

The transformation of Human Resource Forecasting (HRF) over the past two decades has been largely driven by technological innovation and the increasing complexity of organizational environments. As businesses grapple with the demands of globalization, digital disruption, and agile transformation, they have increasingly turned to modern forecasting tools and methodologies to anticipate talent needs with greater accuracy and strategic alignment. This

Restricted - External

section critically explores three major pillars of modern HR forecasting: predictive analytics, artificial intelligence (AI) and machine learning (ML), and workforce analytics dashboards.

Predictive Analytics

Predictive analytics refers to the use of statistical algorithms, machine learning models, and historical data to predict future events or behaviors (Bersin, 2013). In HR forecasting, predictive analytics allows organizations to go beyond retrospective data analysis and proactively plan for future workforce scenarios. By analyzing trends in turnover, promotions, hiring cycles, employee engagement, and performance, HR professionals can estimate future labor needs, skills shortages, and potential risks to organizational capability.

For instance, by using predictive models, companies can identify patterns in employee exits and anticipate which groups are most likely to leave within a certain period. These insights enable HR teams to plan targeted retention strategies, adjust recruitment plans, and reallocate training resources. Predictive analytics has also been used to simulate workforce demand under different business scenarios, such as market expansion, digital transformation, or economic downturns (Boudreau and Ramstad, 2007).

A notable advantage of predictive analytics is its ability to combine structured and unstructured data. Organizations can use not only internal HR records but also external sources such as labor market intelligence, economic indicators, and social media activity to enrich their forecasts. This holistic view enables a more accurate and comprehensive workforce strategy (Minbaeva, 2018).

Despite its benefits, predictive analytics also poses challenges. The quality of the predictions depends heavily on the quality of the input data. Inaccurate, incomplete, or biased data can lead to misleading forecasts. Moreover, predictive models require significant expertise in data science, which may be lacking in traditional HR departments. As such, many organizations

Restricted - External

have begun to develop cross-functional teams involving HR professionals, data scientists, and IT specialists to implement these systems effectively (Marler and Boudreau, 2017).

Artificial Intelligence and Machine Learning in HR Forecasting

AI and ML have become game-changers in the field of HR forecasting by automating complex analyses and uncovering patterns that may not be apparent through traditional statistical methods. AI refers to systems that can perform tasks typically requiring human intelligence, such as decision-making and natural language processing, while ML enables systems to improve their performance over time without being explicitly programmed (Kaplan and Haenlein, 2019).

In HR forecasting, AI can be applied to automate resume screening, identify high-potential employees, match candidates to job openings based on skill and cultural fit, and forecast training needs based on job transitions. For instance, machine learning algorithms can analyze historical project data to determine the skill sets most often associated with successful outcomes and recommend optimal team compositions for future projects (Tambe, Cappelli and Yakubovich, 2019).

AI systems can also enhance the speed and scalability of forecasting. Unlike manual or semi-automated systems, AI can process vast datasets in real-time and adjust forecasts based on live inputs. This capability is particularly valuable in volatile environments where workforce needs may change quickly due to external disruptions such as pandemics, regulatory shifts, or market volatility (Deloitte, 2021).

However, the use of AI and ML in HR forecasting is not without ethical and practical concerns. The opacity of some algorithms—often described as “black box” models—makes it difficult to explain how decisions are made. This lack of transparency can undermine trust in forecasting outcomes and expose organizations to legal and reputational risks, especially in regions with strict data protection laws (Tambe et al., 2019). Furthermore, algorithmic bias—stemming from

Restricted - External

historical data that reflect past discrimination—can perpetuate inequalities in hiring and promotion decisions (Binns, 2018).

To address these issues, scholars and practitioners advocate for the development of explainable AI (XAI) and ethical AI frameworks in HR forecasting. These include designing models that provide interpretable results, auditing algorithms for bias, and ensuring that AI systems are aligned with organizational values and diversity goals (Floridi et al., 2018).

Workforce Analytics Dashboards

Workforce analytics dashboards are user-friendly, interactive platforms that consolidate and visualize key HR metrics to support real-time decision-making. These tools integrate data from various HR systems—including recruitment, performance management, learning and development, and employee engagement—and present them in a centralized interface with customizable views.

Dashboards serve as the operational interface of modern HR forecasting systems, translating complex data into actionable insights for both HR professionals and business leaders. They allow users to monitor trends such as attrition rates, skills gaps, training effectiveness, and diversity ratios, while also modeling the impact of strategic initiatives on workforce outcomes (Harris, Craig and Light, 2010).

Modern dashboards often feature embedded analytics and AI capabilities, enabling real-time alerts, what-if scenario simulations, and predictive forecasting. For example, a dashboard might alert HR leaders if a particular business unit is at risk of talent shortages based on current turnover and hiring trends. Alternatively, it might simulate the effects of hiring freezes or remote work policies on workforce productivity and morale.

The accessibility and visual clarity of dashboards make them especially valuable in fostering data-driven decision-making across the organization. Executives and line managers can use

Restricted - External

them to align workforce planning with business objectives, while HR teams can leverage them to track the effectiveness of interventions and adjust strategies accordingly (Bersin, 2013). However, the utility of dashboards depends on data quality, integration, and user training. In many organizations, HR data are siloed across multiple platforms, making integration difficult. Moreover, users may require training to interpret visualizations correctly and draw meaningful conclusions. Therefore, successful implementation requires not only technological investment but also change management and capacity-building efforts (Harris et al., 2010).

2.5.3 Comparative Analysis

A comprehensive understanding of Human Resource Forecasting (HRF) requires a critical comparison of traditional and modern forecasting techniques. While both serve the fundamental purpose of anticipating workforce needs, they differ significantly in their methodologies, data requirements, scalability, accuracy, and strategic impact. This section provides a comparative analysis of these approaches, highlighting their benefits, limitations, and suitability for various organizational contexts.

Methodological Foundations

Traditional methods such as trend analysis, the Delphi method, and managerial judgment are rooted in historical data and expert intuition. They tend to follow a linear, often deterministic, logic and are typically manual or semi-automated in execution (Dessler, 2020). These methods rely heavily on past trends and human expertise, making them relatively easy to implement but less responsive to environmental volatility.

In contrast, modern methods such as predictive analytics, artificial intelligence (AI), and workforce dashboards leverage advanced statistical models, real-time data, and machine learning algorithms to provide dynamic and forward-looking insights (Tambe, Cappelli and Yakubovich, 2019). These tools allow for iterative updates and can incorporate a wide array of structured and unstructured data sources.

Restricted - External

Data Requirements and Integration

Traditional forecasting methods are typically based on readily available internal HR data, such as headcount, turnover rates, and historical hiring patterns. This makes them accessible for organizations with limited technological infrastructure. However, their reliance on internal data can lead to narrow and sometimes misleading forecasts, especially in fast-changing environments (Jackson, Schuler and Werner, 2012).

Modern approaches demand more comprehensive data sets, including external labor market trends, performance metrics, and behavioral data. Integration across different HR systems and functions is often necessary. While this makes modern methods more data-intensive and technically demanding, it also enhances the depth and breadth of the forecasts (Minbaeva, 2018).

Accuracy and Predictive Power

Modern HR forecasting tools generally offer superior accuracy due to their ability to identify complex patterns, update forecasts in real time, and simulate multiple scenarios. Predictive analytics and AI can detect early warning signs of attrition, model the impact of training programs, and align workforce capabilities with strategic objectives (Marler and Boudreau, 2017).

Traditional methods, though less accurate, still have value in stable or low-variance environments. They can provide a reliable baseline or complement modern tools with qualitative insights, especially where historical stability allows for dependable extrapolation (Bechet, 2008).

Scalability and Speed

Traditional methods are often limited in scalability. The manual nature of trend analysis or Delphi studies means they are time-consuming and may not scale well in large, complex

Restricted - External

organizations. Managerial judgment, while context-sensitive, is inherently limited by individual cognitive capacity and subjective biases (Kahneman, 2011).

Modern methods, by contrast, excel in scalability and speed. AI-driven platforms can process vast amounts of data within seconds and generate actionable forecasts across departments or geographic regions. This makes them ideal for large enterprises or project-based organizations where resource allocation must be agile and responsive (Deloitte, 2021).

Cost and Accessibility

Traditional forecasting techniques are relatively low-cost and do not require sophisticated technology or specialized personnel. This makes them attractive for small and medium enterprises (SMEs) and organizations in developing economies where budget constraints are significant (Okpara and Wynn, 2008).

Modern forecasting tools, while more expensive to implement initially, often provide a higher return on investment (ROI) through improved planning, reduced turnover, and optimized talent deployment. However, the need for data scientists, IT integration, and ongoing system maintenance can be prohibitive for some organizations (Marler and Boudreau, 2017).

Flexibility and Adaptability

Traditional methods are generally rigid and may not adapt quickly to sudden changes in market conditions or internal dynamics. For instance, trend analysis assumes continuity, which can be a flaw in highly dynamic industries like technology or finance.

Modern methods, especially those incorporating AI and machine learning, are inherently adaptable. They can adjust to new data inputs, incorporate external shocks (e.g., pandemics or regulatory changes), and re-forecast based on real-time developments (Tambe et al., 2019).

Transparency and Interpretability

One area where traditional methods hold an advantage is in interpretability. The logic behind trend analysis or managerial judgment is straightforward and easy for stakeholders to

Restricted - External

understand. This transparency can foster greater trust and buy-in among decision-makers (Ulrich and Dulebohn, 2015).

Modern methods, particularly those involving complex algorithms, often operate as "black boxes," making it difficult to explain how conclusions were reached. This lack of transparency can be problematic, particularly in regulated industries or regions with strong data governance requirements (Binns, 2018).

Strategic Alignment

Modern forecasting tools are more aligned with strategic workforce planning. They facilitate long-term talent strategy, scenario planning, and alignment with organizational goals. Dashboards and predictive models allow HR to engage in strategic discussions and provide evidence-based recommendations to senior leadership (Bersin, 2013).

Traditional methods, though useful for operational planning, often fail to capture the strategic nuances required for long-term competitiveness. They are less effective in supporting innovation, digital transformation, or cross-functional integration.

Contextual Suitability

In emerging markets like Nigeria, where technological adoption varies significantly across sectors and organizations, the choice between traditional and modern methods often depends on contextual factors such as infrastructure, workforce education levels, and data availability (Adeleye and Eboagu, 2019). In such settings, a hybrid model that combines the accessibility of traditional methods with the precision of modern tools may be most effective.

For example, in the Nigerian telecom sector, modern tools may be deployed for demand forecasting in urban centers with high data connectivity, while traditional methods remain in use for rural branches with limited digital infrastructure. This context-sensitive approach ensures both feasibility and effectiveness.

Restricted - External

Integration Possibilities

The future of HR forecasting lies in the integration of traditional and modern techniques. Hybrid models that combine trend analysis with predictive analytics or use Delphi insights to fine-tune AI algorithms can deliver both robustness and flexibility. According to Cascio and Boudreau (2016), integrated forecasting frameworks that leverage multiple data sources and analytical methods provide the highest reliability and organizational relevance.

Organizations are increasingly recognizing the value of a layered approach. For instance, predictive tools might identify emerging skills gaps, while focus groups and expert panels validate these findings and provide qualitative context. Similarly, dashboards can visualize trend data, while managerial insights help interpret anomalies and suggest interventions.

2.6 HR Forecasting and Project Management Integration

The integration of Human Resource Forecasting (HRF) into project management planning is no longer a discretionary strategy but an operational imperative for contemporary organizations. The volatile, uncertain, complex, and ambiguous (VUCA) nature of today's business environment underscores the necessity for predictive foresight in aligning workforce capabilities with project requirements. Despite a growing body of literature emphasizing this integration, the practice remains underdeveloped in many contexts, particularly in emerging markets where organizational agility is often constrained by rigid hierarchies, inadequate data systems, and ad hoc planning.

At its core, project management is about orchestrating resources—time, money, technology, and people—to achieve specific objectives within defined constraints (PMI, 2021). However, people, as a resource, are not fungible like capital or tools. Human resources possess agency, emotions, competencies, and limitations that must be strategically aligned with project scopes and deliverables. HR forecasting, when effectively aligned with project planning, transforms

Restricted - External

the workforce from a cost center to a strategic asset, ensuring that the right talent is available at the right time, in the right quantity, and with the right skills.

2.6.1. Strategic Alignment of HR Forecasting and Project Planning

The first dimension of HRF integration concerns strategic alignment. Projects fail not necessarily due to technological or financial constraints but often because of misalignment between workforce capabilities and project demands (Pinto, 2020). HR forecasting enables organizations to anticipate talent needs based on project pipelines, enabling proactive recruitment, training, or internal mobility. This alignment becomes even more critical in knowledge-intensive sectors such as telecommunications, banking, or IT, where talent scarcity and skills obsolescence are ongoing risks.

Critically, strategic alignment also necessitates a shift from transactional to transformational HR roles within project teams. Traditional HR functions such as payroll and compliance must evolve to include workforce analytics, capability building, and organizational development as integral components of project planning (Ulrich et al., 2012). Yet, in many organizations, HR remains a peripheral player in project design, consulted only when recruitment becomes urgent. This reactive stance undermines project timelines and quality, as project managers scramble to fill roles without sufficient lead time or clarity on role expectations (Turner, 2019).

Furthermore, strategic alignment requires cross-functional collaboration. Effective HRF integration demands the involvement of HR professionals, project managers, finance officers, and line managers in joint planning sessions. Such collaboration ensures that workforce forecasts reflect operational realities, financial constraints, and strategic aspirations. The absence of such integrative mechanisms often leads to siloed decision-making, resulting in workforce gaps, duplication of efforts, and misallocation of talent (Wright and McMahan, 2011).

Restricted - External

2.6.2. Influence on Project Cost, Timelines, and Deliverables

The second critical area where HR forecasting directly impacts project management is cost control. Labor typically constitutes one of the largest components of project budgets. Inaccurate forecasting can lead to either under-resourcing, which delays project execution, or over-resourcing, which inflates costs. Both scenarios compromise project success (Kerzner, 2017). A well-structured HRF model allows for resource leveling and smoothing, ensuring that staffing levels match project phases—intensifying during peak workload and tapering during low-intensity periods.

Equally important is the influence on timelines. The availability of appropriately skilled personnel at project initiation is essential for momentum and stakeholder confidence. Delays in staffing, particularly for critical path roles, can cascade into project delays and reputational damage. HR forecasting mitigates this risk by identifying staffing bottlenecks in advance and providing lead time for recruitment or internal mobility. Predictive tools can simulate various staffing scenarios and their impact on timelines, allowing project managers to make data-informed decisions (Bersin, 2013).

Deliverables are also contingent on workforce capability. A project staffed with mismatched skills or inexperienced personnel is likely to experience quality issues, rework, and reduced client satisfaction. HR forecasting supports deliverable quality by enabling skill-based resource allocation and gap analysis. Organizations can align competency frameworks with project work breakdown structures (WBS), ensuring that team members have the requisite technical and behavioral competencies (PMI, 2021). Moreover, forecasting supports performance benchmarking, allowing project leads to monitor productivity and adjust resource plans dynamically.

Restricted - External

2.6.3. Resource Allocation, Skills Mapping, and Succession Planning

From an operational standpoint, HR forecasting informs three interlinked processes: resource allocation, skills mapping, and succession planning. Resource allocation is often considered a logistical task, but in strategic HRF, it becomes a dynamic, real-time optimization problem. Forecasting tools enable organizations to allocate resources not just based on availability but on suitability, factoring in experience, learning agility, and performance history (Ulrich and Dulebohn, 2015).

Skills mapping takes this further by creating a visual and data-driven representation of organizational competencies. HRF allows firms to map existing skills against projected project requirements, identifying surpluses, deficits, and opportunities for development. This process is crucial in agile or matrix organizations, where employees frequently shift between projects and roles (Serrador and Pinto, 2015). Accurate skills mapping also supports just-in-time learning strategies, where training interventions are timed to coincide with project demands, maximizing ROI.

Succession planning is often overlooked in project contexts, assumed to be relevant only for permanent roles. However, project-based organizations face significant risks from knowledge attrition and leadership vacuums when project leads or subject matter experts exit. HR forecasting identifies critical roles and high-potential individuals, enabling the development of succession pipelines. This proactive approach not only mitigates continuity risks but also enhances employee engagement by signaling career growth opportunities (Boxall and Purcell, 2016).

2.7 Industry-Specific Insights: Nigeria's Banking and Telecom Sectors

The Nigerian banking and telecommunications sectors represent two of the most dynamic and economically significant industries in West Africa. Both are characterized by rapid technological change, regulatory flux, and growing competitive pressures, all of which

Restricted - External

underscore the strategic importance of effective human resource forecasting (HRF). However, the contextual realities of these sectors—ranging from skill shortages and infrastructural gaps to institutional rigidity—demand a critical and contextualized analysis of how HR forecasting operates in practice.

The banking sector in Nigeria has undergone dramatic changes in recent decades. Following the consolidation policy implemented by the Central Bank of Nigeria in 2005, the sector has experienced increasing automation, stricter compliance requirements, and heightened competition from fintech startups (Sanusi, 2011). These developments have significantly altered HR demands, requiring a shift from generalist banking skills to specialized knowledge in areas such as cybersecurity, digital finance, and regulatory compliance.

Despite this shift, many banks continue to rely on traditional HR planning models that fail to account for future-oriented talent needs. According to Akinyemi and Adejumo (2018), HR forecasting in Nigerian banks is often reactive, relying on immediate vacancy rates and anecdotal managerial input rather than systematic data analysis or strategic alignment. This approach results in frequent mismatches between employee competencies and job demands, leading to underperformance, low morale, and high turnover rates.

The telecommunications sector has similarly evolved, driven by the explosive growth in mobile and internet penetration. Operators like MTN, Airtel, and Glo have invested heavily in infrastructure and digital services, transitioning from voice-based to data-centric business models. However, these strategic shifts have outpaced workforce planning practices. The sector faces acute shortages in technical roles such as software development, data analytics, and network engineering, while over-recruitment persists in administrative and customer service functions (Osibanjo et al., 2014).

Moreover, both sectors suffer from a dual burden of talent scarcity and brain drain. Nigeria's higher education system has not kept pace with industry demands, resulting in a disconnect

Restricted - External

between academic output and employability. At the same time, highly skilled professionals frequently emigrate in search of better opportunities, leaving organizations with a shallow talent pool and high replacement costs (Oyelere and Adeyemi, 2020). These trends highlight the urgent need for predictive HR forecasting mechanisms that can anticipate future skill requirements, monitor talent supply chains, and inform proactive development strategies.

2.7.1. Workforce Dynamics and Talent Availability

The workforce dynamics in Nigeria's banking and telecom sectors are shaped by demographic trends, labor market structures, and organizational cultures. Nigeria's youthful population—estimated at a median age of 18.1 years—presents both an opportunity and a challenge for workforce planning. On one hand, it offers a large labor supply; on the other, it demands significant investment in training and orientation due to limited work experience and soft skill deficiencies (Adeleye et al., 2019).

In the banking sector, workforce demographics are becoming increasingly polarized. Entry-level recruitment is robust, often sourced from graduate trainee programs. However, the middle management tier is relatively thin due to poor retention and limited internal mobility. This creates a succession bottleneck and exacerbates the risk of leadership vacuums in critical roles (Okpara and Wynn, 2008). The reliance on poaching talent from competitors also fuels wage inflation and reduces organizational loyalty.

In contrast, the telecom sector is characterized by a high degree of workforce fragmentation. Large operators often outsource technical services to third-party vendors, resulting in a layered labor structure with varying degrees of engagement, accountability, and alignment with organizational goals (Osibanjo et al., 2014). This fragmentation complicates HR forecasting by obscuring visibility into actual workforce capacity and skill availability. Additionally, contractual workers tend to be excluded from strategic planning discussions, despite being integral to service delivery.

Restricted - External

Another critical dynamic is the rise of digital labor. Remote work, gig contracts, and platform-based employment models are becoming increasingly common, particularly in telecoms. While these models offer flexibility and cost advantages, they also introduce complexity into HR forecasting, particularly in tracking workforce utilization, performance, and availability across non-traditional employment categories (Tambe et al., 2019).

2.7.2. Case studies of previous findings on forecasting in Nigerian organizations.

Several studies and institutional reports shed light on the limitations and opportunities of HR forecasting in Nigerian organizations. For instance, the 2021 PwC Nigeria Workforce of the Future Survey revealed that less than 40% of surveyed organizations had formalized HR forecasting processes, and only 18% used data analytics for workforce planning. The report emphasized the lack of integration between business strategy and HR practices, with most forecasting still driven by short-term operational needs rather than long-term strategic goals (PwC, 2021).

In the banking sector, a case study of Zenith Bank conducted by Onasanya and Ogunlade (2016) demonstrated how inadequate forecasting resulted in talent shortfalls during a major digital transformation project. The bank's HR department underestimated the number of cybersecurity professionals required, leading to delays in project execution and increased reliance on expensive expatriate consultants. The authors recommended a shift toward predictive modeling using both internal metrics and external labor market data.

Similarly, in the telecom sector, a study by Uche and Eze (2020) analyzed HR planning practices at Airtel Nigeria. The research highlighted how manual forecasting methods, based on quarterly manager inputs, were unable to cope with the volatility of project requirements. The company subsequently piloted a workforce analytics dashboard that integrated project management timelines with recruitment planning. This integration resulted in a 15% reduction in project delays and improved workforce deployment efficiency.

Restricted - External

These cases demonstrate that while Nigerian organizations are beginning to recognize the value of HR forecasting, practical implementation remains uneven. Barriers include limited data literacy among HR professionals, fragmented HR information systems, and organizational resistance to change. To address these issues, scholars advocate for capacity-building programs, HR-IT collaboration, and regulatory incentives for data-driven workforce planning (Akinyemi and Adejumo, 2018). The state of HR forecasting in Nigeria's banking and telecom sectors reflects broader institutional weaknesses in planning, governance, and knowledge management. The absence of robust forecasting practices is symptomatic of a reactive organizational culture where short-term problem-solving takes precedence over long-term capability building. This short-termism is reinforced by external pressures such as shareholder expectations, regulatory audits, and quarterly performance targets.

Moreover, the prevailing view of HR as an administrative function limits its strategic potential. Until HR is fully embedded in corporate planning processes—with a seat at the table in strategic decision-making—forecasting will remain peripheral. There is a need for a paradigm shift toward strategic human capital management, where talent planning is aligned with innovation, competitiveness, and sustainability goals (Boxall and Purcell, 2016).

Another critical issue is equity and inclusion. Forecasting models that ignore workforce diversity and socioeconomic barriers risk perpetuating systemic biases. For instance, reliance on elite universities for talent pipelines may exclude qualified candidates from underprivileged backgrounds. Similarly, the exclusion of non-permanent workers from HR databases distorts workforce analytics and marginalizes significant labor segments. Inclusive forecasting must account for these disparities and design interventions that promote equitable access to opportunities.

Finally, global trends offer valuable lessons. Countries such as India, South Africa, and Brazil have implemented national skills forecasting initiatives that integrate industry data, academic

Restricted - External

research, and policy planning. Nigeria could benefit from a similar multi-stakeholder framework that aligns educational curricula with labor market needs, incentivizes organizational forecasting practices, and fosters public-private partnerships for workforce development (ILO, 2020).

2.8 Barriers to Effective HR Forecasting

2.8.1 Organizational Barriers

A critical examination of organizational barriers to effective human resource forecasting (HRF) reveals deep-rooted structural and cultural impediments that undermine the precision and strategic value of forecasting practices. While technological and external factors also play significant roles, the organizational context—comprising leadership commitment, data infrastructure, and cultural readiness—often serves as the primary determinant of forecasting success or failure. Three central organizational barriers are particularly prevalent: lack of leadership support, inadequate HR data, and resistance to change.

Lack of Leadership Support

Leadership support is indispensable for embedding HR forecasting into strategic decision-making processes. However, in many organizations, top management regards HRF as a peripheral activity rather than a strategic imperative. This marginalization is often reflected in minimal budget allocations, absence of HR representation in project governance forums, and limited accountability for workforce planning outcomes (Ulrich and Dulebohn, 2015). Without executive sponsorship, HR forecasting initiatives struggle to secure the necessary resources and visibility to influence organizational planning at the highest levels.

Evidence indicates that when leaders fail to champion forecasting initiatives, the discipline is perceived as a compliance exercise rather than a value-adding activity. For instance, Okpara and Wynn (2008) observed in Nigerian firms that executives frequently prioritize short-term financial metrics over long-term human capital planning, resulting in reactive staffing

Restricted - External

practices. This short-sighted approach invariably leads to talent shortages during critical project phases, triggering emergency hiring and inflated costs.

Moreover, the absence of leadership support exacerbates silos between HR and other business functions. In complex, project-driven environments, forecasting requires cross-functional collaboration; HR must work alongside finance, operations, and IT to integrate workforce projections with budgetary and technological plans (Boxall and Purcell, 2016). However, when senior leaders fail to enforce collaborative norms, departments revert to isolated planning, producing disjointed forecasts that lack coherence and strategic alignment.

Resolving this barrier requires leaders to demonstrate a visible commitment to HR forecasting. Studies show that organizations where CEOs and C-suite executives actively participate in workforce strategy sessions are more likely to achieve accurate and actionable forecasts (Lawler and Boudreau, 2015). These leaders set the tone by embedding forecasting metrics into performance dashboards, linking them to organizational KPIs, and holding functional heads accountable for forecast variance.

Inadequate HR Data

The second organizational barrier is the inadequacy of HR data. Effective forecasting depends on high-quality data encompassing employee demographics, performance metrics, turnover trends, and skill inventories. Yet, many organizations maintain fragmented HR information systems (HRIS) that fail to capture the full spectrum of workforce-related data (Hendrickson, 2003). Data silos often arise from decentralized record-keeping, disparate software platforms, and lack of integration between HR, payroll, and talent management modules.

In the context of Nigeria's banking and telecommunications sectors, data fragmentation is aggravated by legacy systems that cannot support advanced analytics. Osibanjo et al. (2014) highlighted that many Nigerian telecom operators rely on basic payroll systems that record only headcount and attendance, omitting critical variables such as skill proficiency, learning

Restricted - External

trajectories, and performance evaluations. Consequently, forecasting models built on such incomplete data are inherently flawed, producing projections that are neither reliable nor strategic.

Furthermore, data quality issues such as inaccuracy, incompleteness, and inconsistency further degrade forecasting outcomes. Erroneous or outdated personnel records, coupled with lack of standardized data entry protocols, lead to miscalculations in attrition rates, skills gaps, and workforce supply estimates (Minbaeva, 2018). Without robust data governance frameworks, organizations cannot ensure the integrity of their forecasting inputs, undermining confidence in the entire process.

Addressing data inadequacies necessitates a strategic investment in integrated HRIS platforms and data governance practices. Organizations must establish clear data stewardship roles, standardized data collection procedures, and regular data audits to maintain completeness and accuracy (Marler and Boudreau, 2017). Additionally, collaboration with IT departments is crucial to design scalable data architectures that facilitate seamless integration of HR, finance, and project management data sources.

Resistance to Change

Resistance to change represents a formidable cultural barrier to effective HR forecasting. Forecasting initiatives often entail new processes, technologies, and roles, which can be perceived as threats by employees and managers alike. Resistance manifests in various forms: skepticism about the accuracy of forecasts, reluctance to adopt new software tools, and unwillingness to share information across departmental boundaries (Kotter and Schlesinger, 2008).

In the Nigerian context, cultural factors exacerbate resistance. A hierarchical organizational culture, prevalent in many domestic firms, discourages upward feedback and cross-functional transparency. Middle managers may view forecasting as an external critique of their decision-

Restricted - External

making, leading to non-cooperation or superficial compliance (Akinyemi and Adejumo, 2018). Frontline employees, fearing that accurate forecasts may highlight redundancies, might withhold information or downplay intentions to leave, skewing supply projections.

Moreover, the introduction of advanced forecasting tools often triggers fear of job displacement. Employees may perceive AI-driven analytics and dashboards as instruments for surveillance or downsizing, rather than enablers of strategic insight (Bondarouk and Brewster, 2016). This fear can generate active sabotage of forecasting efforts or passive disengagement from training programs.

Overcoming resistance requires a multifaceted change management strategy. Leaders must articulate a compelling vision for HR forecasting that emphasizes transparency, employee development, and strategic empowerment. Effective communication campaigns should highlight success stories where forecasting improved career pathways, reduced workload stress, or enabled skill enrichment. Additionally, involving stakeholders in the design and rollout of forecasting tools fosters ownership and reduces apprehension (Kotter, 1996).

Training and capability-building are equally critical. Organizations need to invest in upskilling HR and managerial staff, not only in technical competencies but also in data literacy and collaborative practices. Establishing forecasting champions within business units can facilitate peer-to-peer learning and serve as conduits for feedback and adaptation (Ulrich et al., 2012).

Interplay of Barriers and Implications

These organizational barriers do not operate in isolation; they are interdependent and often mutually reinforcing. For example, lack of leadership support can perpetuate inadequate data investments, which in turn fuels resistance to change when forecasting tools appear disconnected from operational realities. Similarly, data inadequacies can erode managerial confidence in forecasting, reducing willingness to collaborate and champion new processes.

Restricted - External

The implications of unchecked barriers are profound. Projects suffer from talent shortages, cost overruns, and schedule delays. Strategic initiatives, such as digital transformation or market expansion, falter due to misaligned workforce capabilities. Organizations become trapped in a reactive loop, continuously firefighting staffing crises rather than proactively optimizing talent deployment.

2.8.2 Technological Barriers

Technological limitations are among the most significant impediments to the effective application of human resource forecasting in project-oriented organizations. While the evolution of forecasting tools—such as predictive analytics, machine learning (ML), and artificial intelligence (AI)—has theoretically enhanced the precision and responsiveness of workforce planning (Marler & Boudreau, 2017), the practical adoption of these innovations remains uneven, particularly in emerging economies. Two core dimensions of technological barriers include (a) limited access to forecasting tools and (b) insufficient capacity in data interpretation.

Limited Access to Forecasting Tools

Despite the recognized value of advanced forecasting technologies, many organizations—especially in the Global South—struggle to adopt them due to infrastructural deficits, high implementation costs, and misalignment with existing HR systems. In Nigeria's banking and telecommunications sectors, for instance, organizations often lack real-time data integration systems that are prerequisites for the effective deployment of AI or analytics-based forecasting tools (Adeleye et al., 2020). These tools typically require not only substantial investment in software and hardware but also a supporting digital architecture that includes centralized HR information systems (HRIS), high-quality relational databases, and scalable cloud-based platforms (Davenport, Guenole & Harris, 2018).

Restricted - External

One of the major contributing factors is financial constraint. Unlike multinational corporations with global capital support, many Nigerian enterprises operate within tight budgetary frameworks, making it difficult to justify expenditures on AI-enabled forecasting tools whose return on investment may not be immediately visible (Bondarouk & Brewster, 2016). Moreover, the technology market in many African countries is still nascent. Local vendors of HR analytics solutions are few, and international providers often design products for Western organizational environments, leading to compatibility issues in implementation (Harzing & Pinnington, 2011). As such, even where tools are acquired, they may be underutilized or poorly configured.

Compounding these issues is a lack of policy support for technology adoption. While national development strategies may mention digital transformation in broad terms, they often lack detailed frameworks for HR digitalization. This leads to inconsistent technological adoption across sectors and organizations. In some cases, regulatory uncertainty discourages investment in HR analytics due to concerns about data privacy, algorithmic accountability, or compliance burdens (Tambe, Cappelli & Yakubovich, 2019). The result is a fragmented technological landscape that prevents the integration of sophisticated forecasting tools into mainstream HR operations.

Critically, the mere availability of technology does not ensure its use. Technology adoption in HR forecasting is not a plug-and-play solution—it requires a shift in operational logic from reactive personnel tracking to proactive talent modeling (Boudreau & Ramstad, 2007). Organizations must go beyond automating basic tasks (e.g., payroll processing or leave tracking) and instead leverage technology for scenario planning, attrition risk assessment, and skill forecasting. Unfortunately, without proper change management and technological maturity, many firms remain stuck in legacy systems that cannot support such analytical functions (Ulrich & Dulebohn, 2015).

Restricted - External

Skills Gap in Data Interpretation

Equally consequential is the skills gap in interpreting HR data and transforming it into actionable forecasting insights. The efficacy of even the most advanced forecasting tool is contingent upon the analytical acumen of its users. However, most HR departments, especially in developing economies, lack personnel with sufficient training in statistical reasoning, data science, or predictive modeling (Marler & Boudreau, 2017). The traditional skill set of HR professionals—rooted in administrative efficiency and compliance—has not evolved at pace with the increasing datafication of HR functions.

This misalignment leads to several issues. First, forecasting models are often oversimplified or misapplied. For instance, rather than using regression analysis or machine learning for nuanced workforce predictions, some HR teams continue to rely on linear extrapolations from outdated manpower ratios (Aguinis, Edwards & Bradley, 2017). These methods fail to account for the volatility and non-linearity of modern project environments. Second, when tools are used, they are often treated as "black boxes," with HR professionals relying on default outputs without fully understanding underlying assumptions, limitations, or data quality dependencies (Van den Broek, Bos-Nehles & Janssen, 2021). This practice introduces both epistemological and ethical risks.

Moreover, the absence of interdisciplinary collaboration between HR, IT, and data science departments further exacerbates the challenge. In many Nigerian firms, HR functions operate in silos, with minimal interface with analytics experts who could provide technical guidance (Ogunyemi & Akinlabi, 2020). The disconnect prevents HR professionals from developing data literacy or embedding analytics into their strategic workflows. Even where dashboards are implemented, users often lack the capacity to move from descriptive statistics (e.g., employee turnover rates) to predictive and prescriptive insights (e.g., forecasting which roles will face skill shortages in six months).

Restricted - External

Another critical factor is the lack of investment in training and professional development. While some global organizations have created “HR analytics academies” or data science upskilling programs, these initiatives are rare in the African context. Research shows that few Nigerian universities offer specialized courses in HR analytics or data-driven workforce planning, resulting in a skills vacuum among new entrants into the profession (Nwankwo, 2022). Consequently, organizations are left with two unsatisfactory options: either outsource forecasting to external consultants—thus losing internal capability and continuity—or rely on suboptimal internal processes that undermine project outcomes.

Importantly, this skills gap has strategic implications. HR forecasting is not just a technical activity; it is a form of strategic foresight that influences decisions about recruitment, training, budgeting, and project risk mitigation. When forecasting is weak or misinformed, organizations either overhire, leading to budgetary waste, or underhire, resulting in project delays and client dissatisfaction (Pfeffer & Sutton, 2006). In project-intensive sectors such as telecommunications and banking, where delivery timelines are critical, such inefficiencies are particularly costly.

From a theoretical lens, the skills gap also weakens the practical applicability of contingency theory in HR forecasting. The theory posits that HR systems must adapt to organizational complexity and environmental uncertainty (Donaldson, 2001). However, without the analytical competence to interpret data and simulate future scenarios, HR departments cannot develop truly adaptive forecasting models. Similarly, stakeholder theory—which demands responsiveness to employee, customer, and regulatory expectations—loses traction when HR lacks the analytical tools to identify and prioritize stakeholder needs within forecasting frameworks (Freeman, 2010).

Addressing the skills gap requires a multi-pronged approach. At the organizational level, HR functions need to rebrand themselves as data-informed strategic partners rather than

Restricted - External

compliance-driven cost centers. This shift necessitates not only new hiring strategies—targeting professionals with hybrid skills in HR and analytics—but also substantial investment in continuous learning (Bersin, 2017). At the institutional level, academia must revise HRM curricula to include modules on statistics, coding, and data visualization, while governments and professional bodies should incentivize certification programs in HR analytics.

2.9 HR Forecasting Post-COVID-19

The COVID-19 pandemic served as a powerful disruptor to established business processes globally, with human resource forecasting (HRF) being no exception. In Nigeria, where organizational structures in banking and telecommunications had remained largely hierarchical and rigid, the pandemic prompted an urgent and at times chaotic reimagining of how the workforce was managed. Forecasting models based on traditional metrics and pre-pandemic assumptions became obsolete virtually overnight. This section critically explores how Nigerian organizations—particularly in the banking and telecom sectors—experienced disruptions, transitioned to flexible and hybrid work models, and responded with varying success in adapting HR forecasting models to prolonged uncertainty.

2.9.1 Disruptions Caused by the Pandemic

COVID-19 caused severe disruptions to employment patterns, demand cycles, and operational continuity. In Nigeria, a country where informal work accounts for over 80% of the labor force (ILO, 2021), even formal sectors like banking and telecommunications had not robustly developed contingency models to account for systemic shocks. Consequently, the pandemic destabilized workforce planning structures, creating immediate gaps between workforce supply and operational demand.

In the **banking sector**, lockdown measures and restrictions on physical contact led to the closure of many branches and a sharp decline in over-the-counter transactions. For example, Zenith Bank and First Bank of Nigeria had to temporarily shutter up to 50% of their physical

Restricted - External

locations during the peak of the pandemic (Vincent, 2021). This sudden drop in physical banking led to an unanticipated spike in digital transactions, straining the capacity of call centers, back-end support, and cybersecurity personnel. Yet, existing HR forecasts had focused primarily on branch-based service delivery, with little allocation for digital channels. This mismatch highlighted how vulnerable traditional, linear forecasting models were to sudden operational shifts (Kenku and Ogunkuade, 2024).

The **telecommunications sector**, in contrast, saw a surge in demand for internet and voice services as companies, schools, and households pivoted to remote platforms. MTN Nigeria reported a 22% increase in internet usage in Q2 2020 alone (KPMG, 2020). The sudden boom in digital communication placed pressure on customer service, network support, and field maintenance teams. Yet, due to the pandemic, many technical teams could not access transmission sites owing to inter-state movement restrictions, leading to service lags and congestion. Forecasting models that had projected slow, linear growth in service demand were inadequate in anticipating this scale and speed of transformation (Adeleye et al., 2020).

Moreover, **human resource departments were unprepared for the rate of employee absenteeism**, whether due to illness, caregiving duties, or psychological stress. Absenteeism rates climbed to over 15% in some banks and telcos during the second quarter of 2020 (Deloitte, 2021), causing unanticipated workflow bottlenecks. Yet, these fluctuations were not accounted for in traditional workforce plans that assumed stable attendance and low volatility.

The combined effects of health risks, operational halts, and technology dependencies created a scenario where **forecasting had to move from prediction to adaptability**—a radical departure from the established HRM paradigms in Nigerian corporate settings.

2.9.2 Emergence of Flexible and Hybrid Workforce Models

Perhaps the most enduring transformation instigated by the pandemic has been the normalization of flexible and hybrid work arrangements. Nigerian firms that had long resisted

Restricted - External

remote work due to trust issues, infrastructural constraints, and cultural expectations were forced to revise their assumptions. In sectors like banking and telecoms, this transition represented both a logistical challenge and an opportunity to modernize HR planning.

In banking, remote work was initially limited to non-customer-facing staff—e.g., compliance officers, financial analysts, and human resource personnel. Guaranty Trust Bank, Access Bank, and UBA all implemented hybrid work policies by mid-2020, rotating staff between in-office and remote assignments (Onyemere et al., 2024). However, issues such as lack of stable electricity, poor internet access, and digital illiteracy among certain segments of staff hampered the implementation. HR forecasts did not include metrics for remote productivity or technology readiness, complicating workforce planning efforts (Igomu et al., 2023).

The telecommunications sector demonstrated comparatively stronger adaptability. MTN Nigeria, in particular, swiftly deployed collaboration tools, virtual project management platforms, and internal guidelines for telecommuting (MTN Nigeria, 2020). A structured hybrid model was adopted for administrative and corporate functions, while technical teams were placed on standby rotations or dispatched with strict compliance to health protocols. The sector benefitted from its pre-existing digital orientation and was better equipped to support a geographically dispersed workforce.

Critically, the emergence of hybrid models **challenged existing notions of visibility, productivity, and control**. Many Nigerian managers were conditioned to associate physical presence with accountability, leading to micromanagement tendencies even in remote setups. A survey by SHRM Nigeria (2022) revealed that 37% of supervisors continued to conduct multiple daily check-ins with remote employees, undermining autonomy and trust.

This evolution necessitated **a redefinition of performance indicators**, job roles, and even employment contracts. Prior HRF models, which linked headcount to office space or branch-specific targets, were now insufficient. Workforce planning had to consider employee

Restricted - External

preference, location-based resource availability, and the digital maturity of roles (Jobberman, 2021).

However, not all organizations adapted effectively. Many SMEs and even mid-sized banks reverted to rigid attendance policies once lockdowns eased, fearing a loss of organizational cohesion. Such regression signals a cultural resistance that could stall the long-term benefits of flexible workforce models if not addressed systemically through training, policy reform, and trust-building.

2.9.3 Adaptation of Forecasting Models for Uncertainty

One of the most significant HR lessons from the pandemic was the inadequacy of traditional forecasting techniques—particularly in volatile, uncertain, complex, and ambiguous (VUCA) environments. Nigerian organizations had, for years, relied on linear models rooted in historical data, assuming predictable attrition rates, growth patterns, and project cycles. COVID-19 shattered this illusion of stability.

In response, some forward-looking organizations began experimenting with **scenario-based forecasting**. For example, Deloitte (2021) reports that several Tier-1 banks in Nigeria began modeling multiple recovery pathways—e.g., V-shaped, W-shaped, or prolonged stagnation—and linked each to different staffing assumptions. Under each scenario, HR departments could simulate hiring freezes, recruitment drives, or reskilling initiatives.

Similarly, **telecom companies began integrating customer usage data into workforce forecasting**. For instance, real-time analytics on network congestion were used to predict where field technicians would be needed in coming weeks, allowing for proactive scheduling and training (KPMG, 2020). This move from descriptive to predictive analytics marked a shift toward more dynamic, data-driven HR planning.

Nevertheless, such innovations were limited by several systemic constraints:

Restricted - External

- **Lack of technical capacity in HR departments:** Many HR professionals in Nigeria lack formal training in data analytics, rendering advanced forecasting models underutilized or misunderstood (Marler and Boudreau, 2017).
- **Fragmented HR information systems (HRIS):** Without centralized and integrated data platforms, real-time forecasting becomes unfeasible. Many firms still rely on manual Excel spreadsheets that are prone to error and incapable of real-time adjustments (Adeleye et al., 2020).
- **Resistance from leadership:** Top management in some firms were reluctant to abandon familiar, long-standing methods, citing the unpredictability of the models as justification for reverting to traditional planning.

Additionally, while some organizations began cross-training employees or creating agile talent pools, these practices were more reactive than strategic. Very few firms formalized **talent buffers** or created **redundancy mapping frameworks** to anticipate future uncertainties. This underscores a lingering "firefighting" approach, where forecasting remains a response mechanism rather than a proactive strategic function.

There is also a critical need for **legislative and regulatory adaptation**. Labor laws in Nigeria do not currently address remote work, telecommuting entitlements, or hybrid workplace liabilities, leaving organizations in a grey area. The lack of formal regulation complicates long-term workforce modeling, especially for roles that remain partly remote or contingent (Umezinwa, 2022).

2.10 Review of Empirical Studies

A rigorous review of empirical studies provides the foundation for understanding the landscape of human resource forecasting (HRF), particularly within project-driven industries. This section explores key scholarly contributions and industry insights—both globally and in

Restricted - External

Nigeria—highlighting methodologies, findings, strengths, limitations, and their relevance to the present study on HR forecasting in project-based environments.

2.10.1. Empirical Studies on HR Forecasting in Developed Contexts

Several landmark studies from developed economies have emphasized the strategic role of HR forecasting in improving organizational agility and workforce alignment. One of the most influential contributions comes from Boudreau and Ramstad (2007), who introduced the "talentship" model, linking HR forecasting directly to business outcomes. Their empirical observations, based on interviews and comparative case analyses across U.S.-based Fortune 500 companies, demonstrate that effective HR forecasting correlates strongly with improved talent management and resource optimization. However, their focus on mature markets with high analytical capacity limits the applicability of their findings to contexts like Nigeria, where infrastructure and HR analytics maturity remain nascent.

Marler and Boudreau (2017) furthered this discourse with a comprehensive meta-analysis of HR analytics in forecasting. Reviewing 56 studies across diverse industries, they found that predictive models—particularly those using AI and statistical algorithms—improved forecasting accuracy and project delivery timelines. Yet, a key limitation of their analysis is the implicit assumption that organizations possess the technical and human capability to implement such systems. This assumption is problematic in environments like Nigeria where many firms rely on manual HR processes.

A similar study by Tambe, Cappelli, and Yakubovich (2019) used a cross-sectional survey method to examine 92 organizations in Europe and North America that had adopted AI-driven HR forecasting tools. Their findings underscore that organizations using machine learning models for workforce planning reported higher levels of retention and more efficient recruitment processes. However, their narrow sectoral focus—predominantly on technology

Restricted - External

firms—means that the conclusions may not generalize to more traditional sectors such as banking or telecommunications, especially in emerging markets.

In summary, while studies from developed economies confirm the effectiveness of advanced forecasting tools, they often assume high levels of data availability, digital infrastructure, and analytical proficiency. These preconditions may not align with the operational realities in Nigeria, necessitating a closer look at context-specific empirical work.

2.10.2. Empirical Studies on HR Forecasting in Nigeria

In recent years, Nigerian researchers have begun to explore the application of HR forecasting within local organizational contexts. A significant contribution is the study by Kenku and Ogunkuade (2024), which used a mixed-method approach involving surveys and executive interviews across Nigeria’s banking sector. The authors found that only a third of banks employed structured HR forecasting models, and less than 15% integrated any form of analytics into workforce planning. Their study is particularly useful for its dual focus on quantitative data and narrative insights, but the sampling frame was largely limited to urban areas, which may skew generalizability.

Another notable empirical work is the study by Onyemere et al. (2024), which investigated the readiness of Nigerian banks to adopt remote working models and their implications for workforce planning. Using qualitative interviews across six commercial banks, the authors found that while digitalization had accelerated due to COVID-19, HR forecasting remained primarily reactive. Their study provides rich insights into the shift in workforce configurations post-pandemic but stops short of offering a quantitative measure of forecasting effectiveness.

In the telecommunications sector, Osibanjo et al. (2014) employed a survey design targeting 350 employees from three major telecom operators: MTN, Airtel, and Globacom. Their findings suggested that effective workforce forecasting contributed to lower turnover and improved job satisfaction. However, their reliance on static forecasting techniques such as

Restricted - External

managerial judgment and trend analysis—without integrating technology or real-time data—limits the applicability of their findings in today's fast-evolving digital landscape.

A broader study by Adeleye et al. (2020) explored digital HRM adoption across African firms, with Nigeria as a key case. Through semi-structured interviews with HR executives from 15 telecom firms, the study revealed that while there was growing interest in analytics-driven forecasting, implementation was superficial. Forecasting efforts were often reactive, and most firms lacked the data infrastructure or trained personnel to fully benefit from digital tools.

These studies, while valuable, reveal a significant gap: few focus specifically on HR forecasting in the context of **project management**, where workforce needs can fluctuate rapidly and are tightly tied to project cycles. Moreover, most Nigerian studies do not adequately incorporate the influence of external shocks (such as the COVID-19 pandemic) on workforce planning dynamics.

2.10.3. Methodological Comparisons and Critical Appraisal

When comparing methodologies, it becomes clear that international studies tend to adopt longitudinal designs or meta-analytic frameworks, allowing for broader generalizability and the detection of causal patterns. For instance, Marler and Boudreau (2017) used a meta-analytical framework that could consolidate findings across dozens of contexts, thereby enhancing robustness. Nigerian studies, in contrast, often rely on case studies or cross-sectional surveys, which provide contextual depth but may lack statistical power and replicability.

The study by Kenku and Ogunkuade (2024) is exemplary in applying a mixed-method design, combining survey data from 180 HR professionals with qualitative interviews. This allows for triangulation of results and strengthens the internal validity of the findings. However, their overrepresentation of firms in Lagos and Abuja introduces geographic bias, limiting insight into regional HR forecasting variations.

Restricted - External

Onyemere et al. (2024) provide strong narrative depth in exploring remote workforce adoption but fall short methodologically by not including a control group or a comparative analysis across different sectors. Similarly, while Adeleye et al. (2020) offer rich qualitative data, the lack of a longitudinal component makes it difficult to assess how HR forecasting capabilities have evolved over time, particularly during or after crises like the pandemic.

In contrast, international studies often incorporate data triangulation, rigorous statistical controls, and theoretically grounded models. For example, Tambe et al. (2019) integrated organizational behavior theory to explain adoption barriers for AI-based forecasting tools. Such theoretical depth is frequently missing in local studies, limiting their conceptual contributions.

2.10.4. Key Findings and Their Implications

Despite methodological differences, the reviewed studies converge on several key findings. First, effective HR forecasting contributes significantly to organizational resilience, especially during crises. Boudreau and Ramstad (2007) and Tambe et al. (2019) demonstrate that predictive models can reduce employee attrition and improve resource allocation. These findings are echoed, albeit more cautiously, in the Nigerian context by Osibanjo et al. (2014), who observed that even basic forecasting methods were associated with lower staff turnover.

Second, the use of data-driven forecasting tools is still limited in Nigerian firms. Adeleye et al. (2020) and Kenku and Ogunkuade (2024) both highlight the low level of analytics integration in HR processes. This has profound implications for project-based industries, where the inability to anticipate talent needs can lead to project delays, cost overruns, and workforce burnout.

Third, there is a general consensus that cultural, infrastructural, and institutional constraints shape the adoption and success of HR forecasting. For instance, Onyemere et al. (2024) note that managerial resistance to remote work—and by extension, to flexible forecasting models—undermines the potential benefits of workforce agility. This is further complicated by legal and

Restricted - External

regulatory gaps, such as Nigeria's lack of formal provisions for telecommuting and hybrid employment contracts.

These findings support the argument that HR forecasting in Nigeria must be redefined through a lens of contingency and stakeholder engagement. The one-size-fits-all models prevalent in international literature are ill-suited to the local context unless they are adapted to account for resource limitations, organizational culture, and fluctuating political-economic conditions.

2.11 Identified Research Gaps

A careful review of the existing literature on human resource forecasting (HRF) reveals several conceptual, methodological, contextual, and practical gaps that limit both theoretical advancement and applied effectiveness—particularly in project-based environments such as banking and telecommunications in Nigeria. Although considerable progress has been made globally in linking HR forecasting with strategic workforce planning, digital transformation, and performance outcomes, this body of knowledge remains fragmented and under-contextualized in many developing economies.

One of the most salient gaps in the literature is the limited attention to sector-specific HR forecasting practices in Nigeria, especially within project-intensive industries like banking and telecommunications. Existing studies often examine HR forecasting as a component of broader HRM strategies (e.g., Adeleye et al., 2020; Kenku and Ogunkuade, 2024), but rarely do they investigate how forecasting functions within sectors where workforce needs are closely tied to project timelines, client deliverables, and evolving technical requirements.

Moreover, where banking or telecom organizations are mentioned, they are frequently generalized under the umbrella of corporate or private sector studies, which fails to acknowledge the unique forecasting challenges these industries face—such as fluctuating demand for digital talent, real-time operational scaling, and compliance with fast-changing regulatory frameworks. The result is a knowledge vacuum on how HR forecasting models are

Restricted - External

designed, implemented, or evaluated in Nigerian project-based contexts, leading to a mismatch between academic frameworks and workplace realities.

A broader and more global gap in the literature is the under-theorization of HR forecasting within project-based work environments. Most extant research treats workforce forecasting through the lens of routine business operations, assuming relatively stable demand, cyclical hiring patterns, and clear-cut departmental structures. However, project management environments are fundamentally different. Projects are typically temporary, cross-functional, and prone to rapid scope changes—all of which necessitate agile and dynamic HR forecasting tools.

This is especially relevant in Nigeria's banking and telecom sectors, where large-scale digital transformation initiatives, infrastructure upgrades, and regulatory compliance projects frequently create bursts of temporary workforce demand (Onyemere et al., 2024; Osibanjo et al., 2014). Yet, very few empirical or theoretical models in the literature explicitly address how HR forecasting should operate under these dynamic, short-cycle conditions. This oversight limits the utility of existing models and leaves project managers and HR professionals without a validated framework for aligning human resources with fluctuating project demands.

A recurring theme in international literature is the increasing role of technology—especially artificial intelligence (AI), machine learning (ML), and predictive analytics—in refining HR forecasting accuracy (Tambe et al., 2019; Davenport et al., 2018). These tools allow for real-time data collection, scenario modeling, and predictive simulations that can greatly enhance decision-making.

However, Nigerian empirical studies rarely investigate the use or effectiveness of these technologies. Many continue to document reliance on traditional methods such as managerial judgment, basic ratio analysis, or retrospective trend projections (Adeleye et al., 2020). The limited presence of studies examining how Nigerian organizations might adopt, localize, or

Restricted - External

even resist these advanced tools presents a major gap in understanding the technological readiness and practical feasibility of modern HR forecasting techniques in this context.

Even when tools like HRIS are mentioned, few studies delve into the analytical capacity of those systems or the digital literacy of HR professionals using them. This disconnect highlights the need for research that examines not just the availability of technological forecasting tools but also their functionality, contextual fit, and operational impact in Nigerian organizations.

Another overlooked dimension in the HR forecasting literature is the role of stakeholders—particularly employees, unions, regulators, and even customers—in shaping forecasting decisions. Theoretical frameworks such as stakeholder theory emphasize the importance of engaging multiple interest groups in organizational planning (Freeman, 2010), yet most HR forecasting models remain top-down and executive-led, with minimal reference to collaborative forecasting practices.

This omission is particularly critical in Nigerian project-based sectors where employee input, regulatory requirements, and client expectations can significantly influence workforce planning outcomes. For instance, in telecommunications, client-driven service-level agreements (SLAs) and regulator-imposed quality standards often dictate project schedules, which in turn should shape HR forecasting parameters. However, few studies explore how these external forces are incorporated into forecasting systems.

In banking, union negotiations over working hours or health and safety during COVID-19 disruptions had direct implications for workforce deployment. Still, stakeholder perspectives on forecasting decisions remain virtually absent from the academic discourse. Addressing this gap could enhance the inclusivity, ethical legitimacy, and practical responsiveness of HR forecasting frameworks.

While there is growing international recognition that COVID-19 has transformed workforce structures and forecasting paradigms (Marler and Boudreau, 2017; Deloitte, 2021), local

Restricted - External

Nigerian research is only beginning to address these changes. The pandemic accelerated the adoption of flexible and hybrid work models, exposed the fragility of static forecasting methods, and emphasized the need for scenario-based and real-time planning.

Despite this, few Nigerian studies have critically examined how organizations recalibrated their HR forecasting models in response to these systemic disruptions (Kenku and Ogunkuade, 2024; Onyemere et al., 2024). As a result, there is little empirical evidence on whether and how Nigerian organizations have institutionalized agile forecasting practices post-COVID. This is a significant oversight given that project-based environments—where time, skill specificity, and resource allocation are especially volatile—are among the most vulnerable to forecasting failures during crises.

There is also limited discussion on the barriers to adaptation, such as inadequate HR information systems, cultural resistance to remote management, or limited access to real-time workforce data. Thus, an updated empirical investigation that accounts for the post-COVID realities of HR forecasting in Nigeria is urgently needed.

Lastly, there is a general lack of theoretical anchoring in many Nigerian HR forecasting studies. While international studies often apply models like contingency theory or resource-based views to explain organizational behaviour, local studies frequently adopt a descriptive tone without embedding their analysis within a coherent theoretical framework.

This not only reduces analytical rigour but also limits the capacity of these studies to generate transferable insights or to challenge and refine existing theory. For example, the strategic misalignment between HR functions and project delivery objectives in Nigerian banks could be better explained through the lens of contingency theory, while stakeholder theory could elucidate why inclusive forecasting leads to better employee buy-in and planning accuracy.

The absence of such theoretical engagement suggests a need for studies that do more than describe forecasting practices—they must also interrogate them using established or emerging

Restricted - External

theoretical frameworks. Doing so would strengthen the academic legitimacy and practical applicability of research findings, particularly in policy-making and strategic HR planning.

2.12 Summary

This chapter has critically examined the theoretical and empirical foundations of human resource forecasting (HRF), with a deliberate emphasis on its application within project-based environments—particularly in Nigeria's banking and telecommunications sectors. Through a structured and thematic review, the chapter laid the groundwork for understanding the conceptual, practical, and contextual dynamics of HR forecasting as a strategic tool for enhancing project performance and organizational agility.

The chapter began by outlining the purpose and scope of the literature review, emphasizing the importance of reviewing prior scholarship to establish a solid foundation for the current investigation. It then proceeded to define key concepts such as human resource forecasting and project management, drawing attention to their interdependence. The discussion illustrated that HR forecasting, when done effectively, supports the strategic allocation of human capital resources, which is essential for timely and cost-efficient project execution.

The theoretical framework section introduced two key perspectives: contingency theory and stakeholder theory. These lenses provided a dual-level explanation for the conditions under which HR forecasting models succeed or fail. Contingency theory highlighted the importance of aligning forecasting practices with environmental volatility and organizational complexity, while stakeholder theory emphasized inclusive, participatory approaches to planning that incorporate diverse interests and expectations. Together, these theories offer a robust framework for examining forecasting practices in dynamic, project-intensive sectors.

The chapter also provided a historical overview of HR forecasting, tracing its evolution from manual, intuition-based methods to advanced analytics and AI-driven systems. This section was particularly relevant in contextualizing the shift from traditional to modern forecasting

Restricted - External

techniques and highlighting how these shifts have redefined the forecasting function within human resource management.

Following this, the chapter delved into specific forecasting tools and techniques, categorizing them into traditional, technological, and hybrid approaches. Traditional models, such as ratio analysis and managerial judgment, were found to be useful but increasingly inadequate in the face of rapid technological and organizational change. Modern methods—such as predictive analytics, AI algorithms, and workforce dashboards—offered greater precision and agility, although their adoption remains uneven across Nigerian organizations due to infrastructural and capacity limitations.

One of the most critical sections of the review addressed the integration of HR forecasting with project management. It was observed that in project-based environments, HRF cannot be treated as a periodic or isolated function. Instead, it must be dynamic, iterative, and closely aligned with project timelines, resource demands, and deliverables. Empirical and industry evidence suggested that misalignment between forecasting and project planning often leads to inefficiencies, such as skills mismatches, resource gaps, and cost overruns.

The literature also revealed valuable sector-specific insights into Nigeria’s banking and telecommunications industries. These sectors face unique forecasting challenges, including regulatory volatility, digital disruption, talent scarcity, and uneven workforce distribution. Case examples and industry data illustrated how these challenges have been exacerbated by recent socio-economic shifts, especially the COVID-19 pandemic, which forced organizations to reconfigure work models and revise forecasting assumptions.

The chapter further explored barriers to effective forecasting, categorizing them into organizational, technological, and environmental constraints. Key issues included a lack of leadership support, inadequate HR data systems, resistance to change, limited access to forecasting technologies, and external uncertainties such as economic instability and weak

Restricted - External

regulatory frameworks. These barriers collectively underscore the complexity of implementing accurate and actionable HR forecasts in Nigeria's evolving business landscape.

The review of empirical studies confirmed the strategic value of HR forecasting but also exposed several limitations in the existing literature, including an over-reliance on traditional methods, limited local research on forecasting within project contexts, and a lack of technological integration in HR functions. It also highlighted the methodological shortcomings of many Nigerian studies, such as narrow geographic focus, weak theoretical grounding, and limited cross-sector comparisons.

These critical reflections led to the identification of key research gaps. Notably, the literature lacks in-depth, sector-specific investigations into HR forecasting within project-based environments in Nigeria. There is also insufficient attention to post-pandemic workforce configurations, the role of stakeholder engagement in forecasting, and the use of modern digital forecasting tools. Moreover, the absence of rigorous theoretical frameworks in many local studies diminishes the explanatory and predictive power of their findings.

Collectively, the themes reviewed in this chapter point to a clear and compelling need for a focused empirical investigation into HR forecasting in Nigerian banking and telecom projects. This study aims to address these gaps by applying a theoretically grounded and contextually nuanced approach that explores how forecasting models are conceived, implemented, and evaluated within real-world project environments.

By critically synthesizing both global and local insights, this literature review not only establishes the intellectual foundations of the study but also situates it within a broader discourse on workforce agility, digital transformation, and project success. It sets the stage for the next chapter, which outlines the methodological design for investigating the practices, tools, challenges, and strategic impacts of HR forecasting in Nigerian organizations operating under project-based models.

Restricted - External

CHAPTER THREE

METHODOLOGY

3.1 Introduction

The methodology chapter functions as an operational plan for research by presenting the step-by-step procedures used to handle study objectives and research questions and hypotheses (Saunders et al., 2019). The research design and population selection method along with sampling approach and data collection tools and analysis methods and ethical constraints are described in this chapter. A mixed-methods approach was selected to analyze human resource forecasting in project management because it combines quantitative accuracy measurements with qualitative stakeholder experiences according to Creswell & Creswell (2023).

The research questions guiding this investigation include:

1. What is the correlation between technological adoption in HR forecasting and project success?
2. How does forecasting accuracy impact workforce efficiency?
3. What differences exist in stakeholder satisfaction across forecasting methods?
4. What organizational barriers limit forecasting effectiveness?

The hypotheses tested are:

H1: AI-enhanced forecasting improves project success rates.

H2: Higher forecasting accuracy correlates with better workforce utilization.

H3: Integrated forecasting approaches increase stakeholder satisfaction.

H4: Data quality and resistance to change hinder forecasting effectiveness.

By detailing the methodological framework, this chapter ensures **replicability, reliability, and validity**, enabling future researchers to assess the study's rigor (Yin, 2018).

Restricted - External

3.2 Research Design

This study employs a research design which serves as its methodological foundation to examine human resource forecasting in project management through quantitative methods under positivist philosophical principles. The selected design approach addresses both objective analysis of HR forecasting method-project outcome correlations and statistical reliability and practical relevance for Nigeria's banking and telecommunications industries. Standardized instruments serve quantitative methods well since they help precisely assess variables such as forecasting accuracy and stakeholder satisfaction alongside workforce utilization rates using objective measurement methods which minimize human interpretation and maximize replication potential. This study adopts the positivist paradigm because it supports empirical data collection and deductive testing methods which match the research goals of assessing HR technological adoption effects on organizational performance.

The research questions require statistical hypothesis testing through quantitative methods so the study uses a single quantitative approach instead of mixed methods. The collection of numerical data from 300 HR and project management respondents provides enough statistical strength to identify significant connections while making the study results applicable to similar organizational environments. The research method relies on structured surveys with Likert scales and closed-ended questions because these tools enable standardized evaluation of core constructs yet reduce possible researcher bias present in qualitative analysis. The chosen methodology represents today's business standards because data-driven approaches lead human resource forecasting in sectors with fast-moving technologies and workforce dynamics.

The survey design collects data at one point in time to efficiently measure current HR forecasting practices and analyze differences between banking and telecommunications organizations. This practical method provides efficient research benefits yet restricts the study from analyzing long-term developments or proving direct cause-effect links which upcoming

Restricted - External

research approaches through repeated measurement designs. The study follows a positivist framework that focuses on quantifiable results between variables yet excludes characteristics of human resources forecasting linked to organizational culture and individual decision making which would better emerge from qualitative research.

Multiple factors led to the dismissal of alternative research approaches which could have delivered more detailed contextual information. The study's main requirements for hypothesis testing together with resource limitations made qualitative research methods unneeded to fulfill its essential goals. Quantitative data collection methods match the positivist approach because they produce standardized measurements through objective methods and controlled analysis. The singular research method limits comprehension about the factors that influence forecasting success or failure across different situations which future research needs to explore through qualitative methods.

The research design receives substantial impact from the fundamental principles of positivism. The research bases its decision-making on measurable indicators of forecasting effectiveness while ignoring human perception of reality. Empirical testing of forecasting sophistication and project success metrics relationships depends on statistical tools which employ regression analysis and ANOVA and correlation coefficients. Standardized measurement devices eliminate researcher bias and create consistent measurement results between various organizational environments. The researchers applied these methodological techniques as a part of their positivist approach to generate generalizable findings through quantitative and systematic observation methods.

The research design received guidance from practical needs because of its deployment within Nigeria's banking and telecom sectors. The quantitative survey method enables quick data collection across various organizations because it works efficiently with busy professionals' scheduling needs. The digital distribution methods enable quick response gathering and the

Restricted - External

closed-ended format makes data analysis simpler than alternative qualitative methods. These targeted sectors deliver appropriate results for organizations with serious workforce planning difficulties but restrict the transferability of findings to organizations operating in diverse industrial environments.

The positivist quantitative research design provides strong benefits for hypothesis testing and statistical analysis yet it has important constraints to consider. The cross-sectional design method lacks the ability to demonstrate either the order of events or the direct cause-and-effect relationships between research variables. Self-report surveys used in the research create common method bias although procedural steps such as anonymous responses and random question ordering help minimize this effect. The positivist paradigm's conception of objective reality creates a simplified view of complex organizational phenomena which include human assessments and social interactive elements. The research limitations receive partial mitigation by employing proper sampling techniques and statistical control methods for external variables and clear documentation of methodological boundaries.

The research design requires multiple essential steps for practical execution starting with survey instrument testing to determine reliability and validity which leads to full-scale survey distribution. The use of probability sampling enables representative organization participation alongside statistical power analysis for determining sample size based on expected effects. The research design incorporates data cleaning procedures to handle missing data and outliers and selects statistical tests according to variable types and research questions. The structured methodology strengthens both the research quality and replicability of results for future investigations.

3.3 Population and Sample

The choice of suitable population with precise sampling methods represents a fundamental methodological decision which determines both the research findings' validity and their ability

Restricted - External

to generalize (Saunders et al., 2019). The research centers its analysis on Nigerian banking and telecommunications organizations with more than 250 employees which requires examination from practical and theoretical standpoints. This specific research population selection bases its foundation on multiple essential factors that combine the study goals with industry-specific characteristics.

Project-based workforces along with rapid technological changes make the Nigerian banking and telecommunications sectors suitable research environments (Kerzner, 2022). The constant pressure these industries experience requires them to modify their human resource forecasting systems for adjusting to changing project requirements and digital transformation needs and regulatory changes (Pinto, 2023). The research focuses on these industries to gain access to organizations that require complex HR forecasting systems and possess the capabilities to execute them successfully. The research design should explicitly address the limited ability to generalize findings outside the specific sectors because of its focused approach according to Bryman (2016).

The study population does not include small and medium-sized enterprises because their HR practices lack the maturity required for this research. Boudreau and Ramstad (2023) establish that smaller organizations generally do not have established HR structures or technical infrastructure along with dedicated workforce planning functions needed for advanced forecasting methods. The restriction of study participants to large organizations strengthens research validity for this population but leaves a critical knowledge gap regarding how forecasting principles would evolve during business growth stages for smaller companies (Marler & Boudreau, 2023). Research on HR departments and Nigerian industrial classification standards led to the selection of 250 employees as the threshold for organizations to establish formal HR departments (Easterby-Smith et al., 2021).

Restricted - External

The research strategy uses stratified random sampling to obtain balanced representation in banking and telecommunications sectors by selecting 200 HR and project managers from each sector. The research design provides multiple methodological benefits yet includes some restrictions which require evaluation. The sector-based stratification method allows researchers to control for different forecasting practices while preserving sample homogeneity according to Field (2022). The method of equal sector allocation provides enough statistical power for individual sector analysis but produces a minor distortion in national forecasting practice data (Creswell & Creswell, 2023).

The selection of 400 respondents followed Taro Yamane's (1967) finite population calculation method which needs detailed evaluation. The formula lacks accuracy when used for sample size calculation because it makes assumptions about simple random sampling even though the study employs stratified design (Bartlett et al., 2001). The study design using population size and desired precision level in its formula requires clarification about operationalization within the study context. Power analysis which uses anticipated effect sizes would have provided a better approach to determining sample size because the study focused on detecting variable relationships instead of population parameter estimation (Faul et al., 2009).

Special attention needs to be directed at the way the sampling frame was constructed. The study benefits from knowledgeable insights about forecasting practices by including HR and project managers but fails to capture the perspectives of team members and external partners and finance professionals. The study's focus on manager perspectives might create biases because managers could enhance their reports on forecasting systems effectiveness while hiding implementation difficulties because of professional pride or loyalty to their organizations as shown in Podsakoff et al. (2012). Future research needs to include multi-level sampling techniques which allow researchers to capture the views of different organizational stakeholders.

Restricted - External

The sampling process within Nigeria faces practical issues which need to be recognized. The banking sector shows high market concentration because large dominant players position against the industry characteristic of telecommunications which creates an unbalanced distribution of organizations per stratum (Yin, 2018). The researcher faces access limitations due to organizational restrictions and concerns about disclosing sensitive HR information so proper ethical procedures and participant confidentiality agreements must be established (Saunders et al., 2019). Professional network-driven survey distribution in this study introduces unintended sampling biases since some types of organizations or managerial levels could be disproportionately represented (Dillman et al., 2014).

The researcher needs to examine the effects that sampling techniques have on research analysis. The stratified design provides valuable sector comparisons but researchers need to use appropriate statistical methods to handle possible differences between groups (Field 2022). The study's sufficient overall sample count remains challenging for performing detailed assessments on particular forecasting strategies and organizational categories. The study limitations should direct both analytical methods and interpretation procedures while researchers should express measurement precision limitations for subgroup results (Creswell & Creswell, 2023).

3.4 Data Collection and Instrumentation

Research data collection methods and measurement tools serve as essential points where theoretical concepts transform into quantifiable variables requiring thorough evaluation of conceptual accuracy and methodological validity (Saunders et al., 2019). The main quantitative instrument of this study features a structured survey questionnaire which draws from Marler and Boudreau's (2023) HR Forecasting Effectiveness Scale but requires detailed evaluation from different points of view. This adaptation establishes strong theoretical roots yet raises important questions about how well the model matches Nigerian organizations which operate

Restricted - External

under different HR practices than Western standards (Jackson et al., 2022). The survey divides its content into three sections to provide extensive construct coverage while addressing participant fatigue but this structure reduces the depth of investigation which could be enhanced by additional qualitative research methods (Creswell & Creswell, 2023).

The 5-point Likert scale employed in the first section to measure forecasting method adoption aligns with psychometric conventions yet requires assessment of its effectiveness to depict organizational implementation complexities (DeVellis, 2017). The standardized quantitative data provided by Likert scales can undergo statistical analysis yet their use to categorize continuous organizational behaviors may reduce their accuracy (Norman, 2010). The researchers selected five points instead of seven or nine points to strike a balance between scale discrimination and respondent comprehension although subtle implementation intensity variations might be concealed (Dawes 2008). The unidirectional nature of the usage frequency scale fails to capture essential qualitative aspects which influence forecasting results according to Schwarz (1999).

The second section emphasizes project success metrics through deadline adherence percentages according to Kerzner (2022) yet challenges the sole reliance on quantitative measures in project management research (Kerzner, 2022). The objective metrics provide clear measurement but they do not capture all important aspects of project success including team morale and stakeholder satisfaction and long-term strategic alignment (Pinto, 2023). The use of limited success metrics poses a risk of enforcing the "tyranny of measurable outcomes" which Tourish (2019) identifies as a problem in organizational research. Future versions of the instrument should consider adding qualitative assessment methods and multiple success scale measurements to achieve better comprehensive evaluations (Jugdev & Müller, 2005).

The third section includes open-ended barrier questions which serve as a partial acknowledgment of quantitative limitations by enabling new themes that go beyond fixed

Restricted - External

response options (Braun & Clarke, 2022). The small amount of qualitative data in this survey design presents analytical hurdles because brief survey responses typically lack sufficient depth for proper thematic analysis and produce non-standardized data processing issues (Sandelowski, 2010). Survey respondents may experience fatigue toward the end of the survey which could reduce their response quality because open-ended items are positioned at this point (Podsakoff et al., 2012). The study would have benefited from a more complex mixed-methods design that included qualitative components yet it would need substantial additional funding and longer research duration (Creswell & Plano Clark, 2018).

The validation process that includes a pilot test with 30 respondents and confirmatory factor analysis (CFA) adheres to psychometric standards yet requires assessment for its suitability within the study environment. The reported Cronbach's α value above 0.80 indicates acceptable internal reliability but provides minimal understanding about the instrument's overall performance (Tavakol and Dennick 2011). A sample size of 30 respondents which is typical in practice might not produce stable reliability estimates for multi-dimensional scales according to Hair et al. (2019). The validation context of the original scale in Western organizations creates potential issues with measurement properties because Nigerian organizational practices and response styles may differ significantly (Harzing, 2006). The planned confirmatory factor analysis will demonstrate construct validity but cannot confirm that the instrument measures Nigerian-specific HR forecasting aspects effectively (Brown, 2015).

The adaptation process includes various opportunities together with challenges that need thorough examination. The use of an established scale improves research comparability yet it might unintentionally bring conceptual biases from the original instrument (Van de Vijver & Leung, 2021). The item selection process for retention or modification or exclusion remains unclear thus raising questions about the proper inclusion of relevant Nigerian organizational factors (Harkness et al., 2010). The instrument's emphasis on formal forecasting methods fails

Restricted - External

to recognize informal or hybrid approaches which might prevail in the study context yet remain outside traditional HR metrics (Pauuwe & Farndale, 2017). The measurement tool shows practical utility yet its conceptual basis requires additional localization steps to fully detect the investigated phenomena.

The data collection process becomes more complicated because of practical implementation factors. Digital distribution presents operational efficiency through its method yet it creates sampling bias because it shuts out organizations and individuals missing access to technology or lacking digital literacy abilities (Dillman et al., 2014). Survey responses based on self-reporting create concerns about common method variance because the study investigates relationships between reported practices and outcomes according to Podsakoff et al. (2012). Procedural remedies consisting of item randomization and anonymity assurance were utilized although they are insufficient to eliminate completely response biases originating from social desirability and recall accuracy concerns (Tourangeau et al., 2000). The study faces a major drawback because it depends on potentially unreliable subjective measurements when no objective performance data (e.g., actual project completion rates) is available (Marchington, 2015).

Data collection techniques generate significant implications that affect the interpretation along with analysis of results. The widespread statistical practice of analyzing ordinal Likert scales with interval-level techniques requires evaluation of the assumptions about data nature (Carifio & Perla, 2007). The planned CFA depends on multivariate normality which does not necessarily apply to Likert-type items therefore alternative estimation approaches or robustness checks may be needed (Finney & DiStefano, 2013). Systematic qualitative coding methods should be implemented to analyze open-ended barrier responses because these responses will be brief and variable in nature (Saldana, 2021). This analysis will require careful procedures to maintain both systematic analysis and preserve nuanced meanings.

Restricted - External

3.5 Procedures

The quantitative procedural framework of this study was developed to maintain methodological rigor as researchers worked through practical limitations of studying Nigerian banking and telecommunications organizations. The research foundation begins with SSBM Geneva ethical approval and organizational consent but requires evaluation of its dual purpose for protecting participants and enabling data collection. The bureaucratic approval methods of formal ethics oversight mechanisms in cross-cultural studies might accidentally privilege Western research paradigms above local ethnic values according to Marshall and Batten (2004). Importantly institutional review boards offer important oversight according to Sieber and Tolich (2013). According to Clark (2019) organizational consent requirements create new gatekeeping problems because corporate policies sometimes block specific viewpoints and sensitive data from reaching researchers before participant access occurs which could result in biased samples toward organizations with advanced human resource policies or those seeking to present a positive image.

Contemporary research practices included distributing online surveys through Google Forms by utilizing professional networks (LinkedIn and Nigerian Institute of Management [NIM] and Chartered Institute of Personnel Management [CIPM]) but these approaches introduce concerns about digital divisions in the study's participant representation. The use of digital distribution for data collection provides cost-effective and efficient data collection (Wright, 2017) but it creates a substantial limitation by excluding professionals who are not active on these platforms or work in organizations with restricted internet policies (Adeleke & Oyenuga, 2022) in the Nigerian context where digital participation varies by organization size and sector. The distribution method through professional associations could introduce a bias that limits inclusion of project managers who do workforce planning tasks although lacking formal HR credentials (Ulrich & Dulebohn, 2023). The chosen sampling technique remains practical but

Restricted - External

creates systematic underrepresentation of specific organizational types and hierarchical levels which reduces the overall applicability of discovered results.

The follow-up plan with two reminder attempts during four weeks reflects Dillman et al.'s (2014) tailored design method yet it might not adjust sufficiently for cultural survey participation standards between countries. Harzing (2006) shows that African participants need customized interaction methods beyond Western survey standards because they differ substantially from Western response tendencies. The four-week strict deadline poses problems for Nigerian banking sector employees because it does not match local work schedules or seasonal work availability peaks that occur during month-end and quarter-end periods (Adeyemi & Ojo, 2021). The practice of sending reminder messages poses a greater concern because participants in hierarchical organizational environments tend to view these communications negatively instead of perceiving them as beneficial (Hofstede et al., 2010). Methodological standardization faces challenges with contextual adaptation in cross-cultural research because of these procedural issues.

3.6 Data Analysis

The quantitative data analysis methodology used for this research provides maximum methodological strength but also creates the most substantial challenge by potentially reducing complex organizational phenomena to simple categories. The statistical strength of planned analytical methods requires evaluation to determine their effectiveness in representing the complex human resource forecasting requirements of changing project settings. The three-tiered analytical method utilizing descriptive statistics along with inferential analyses and software implementation matches traditional quantitative research standards yet risks hiding essential factors that shape HR forecasting success (Silverman, 2020).

The descriptive statistical analysis of means and standard deviations for forecasting adoption rates creates a base understanding of current practices yet fails to demonstrate what these

Restricted - External

numbers show about organizational conduct. According to Wainer (2016) descriptive statistics tend to hide more information than they display during complex organizational procedure analysis by obscuring important differences between organizational groups or sectors. The application of mean adoption rates depends on treating ordinal Likert scales as interval data which research methodology experts including Carifio and Perla (2007) have thoroughly questioned. The emphasis on mean and standard deviation statistics prevents researchers from detecting distribution shapes as well as identifying outliers or bimodal patterns which could reveal different approaches to forecasting implementation (Tukey, 1977). The limitations indicate that descriptive statistics should serve as an initial foundation but researchers need to integrate advanced exploratory data analysis methods to extract complete understanding from their dataset.

The proposed inferential statistical tests for hypothesis testing offer valuable opportunities alongside demanding requirements which researchers must handle carefully. The application of regression analysis to investigate forecasting methods' impact on project success (H1, H2) follows common practice yet requires several assumptions that typically fail to hold true in organizational research settings. The analysis of interrelated HR practices using regression models in management studies reveals problems with multicollinearity and non-normal error distributions in conjunction with heteroscedasticity that affects significance test validity according to Osborne (2017). The planned ANOVA for evaluating stakeholder satisfaction across forecasting methods (H3) requires both homogeneous variance and normal distribution of residuals that could potentially be violated when analyzing actual organizational data (Field, 2022). These parametric techniques rely on linear variable relationships but the actual phenomena could show threshold effects or diminishing returns which demand alternative modeling methods according to Wooldridge (2019).

Restricted - External

SPSS v28 functions as the primary analytical software because it is widely used in business research yet requires assessment based on modern statistical computing advancements. The user-friendly interface of SPSS v28 for standard analyses does not match the capabilities of open-source R software which proves essential for this research project. SPSS v28 has restricted functions for treating missing data using modern methods and insufficient bootstrapping capabilities for small sample inference and provides insufficient visualization tools for complex data relationships according to Muenchen (2021). The analytical limitations create major problems during data analysis of organizational information that regularly includes missing values alongside non-normal distributions and complex interaction effects (Hair et al., 2019). The proprietary nature of the software creates transparency and reproducibility barriers that oppose growing open science practices in management research (Nosek et al., 2015).

The analytical approach needs careful examination regarding its control variable management and treatment of confounding elements because of the research context's organizational setting. The research design properly addresses sector and organizational size as controls yet fails to incorporate essential covariates which include technology infrastructure maturity, leadership support for HR analytics and workforce demographic characteristics that strongly impact forecasting effectiveness (Boudreau & Ramstad, 2023). A major drawback of this study is its failure to employ multilevel modeling which would address the hierarchical data structure of employees within teams and organizations according to the HR analytics literature (Snijders & Bosker, 2012). The analytical weaknesses result in basic findings which do not properly represent the sophisticated multilevel factors that determine project environment forecasting success.

The proposed analysis seems to disregard vital possibilities for data-driven exploratory methods which would strengthen the confirmatory hypothesis testing. The combination of

Restricted - External

cluster analysis with structural equation modeling has potential to uncover organizational forecasting patterns and establish better outcomes-based forecasting mediations according to Kline (2015). Variable-centered analysis limitations exist because person-centered methods hold promise to detect different organizational patterns in forecasting implementation (Bergman & Lundh, 2015). The proposed analysis framework tests the study hypotheses yet fails to uncover vital patterns in the data which could enhance research on HR forecasting practices.

The analysis plan shows limited development regarding the handling of possible interaction effects and non-linear relationships despite the intricate nature of the studied phenomena. According to Edwards and Berry (2010) organizational practices function independently very rarely and their joint effects tend to produce outcomes that differ significantly from their standalone effects. The study would have achieved more specific context-sensitive findings by explicitly testing how forecasting methods interact with organizational characteristics such as AI forecasting performance between banks and telecom companies (Aguinis et al., 2017). The model's linear forecasting sophistication-outcome relationship fails to detect essential thresholds which determine when capabilities become mandatory and when additional investment stops producing returns (Haans et al., 2016).

3.7 Limitations

The structured methodology employed in this study includes major limitations which need thorough assessment to establish both the research findings' validity and possible end uses. The study examined the banking and telecommunications industries exclusively in Nigeria which limits the ability to generalize this research to other essential economic sectors like manufacturing and agriculture because workforce forecasting obstacles differ in those sectors due to seasonal staff changes and distinct skills and project management characteristics (Adeleye, 2021). The study faces significant challenges because manufacturing generates 10%

Restricted - External

of Nigeria's GDP yet its workforce structure differs substantially from banking and telecoms service sectors (World Bank, 2022) which means the presented findings may not capture essential HR forecasting variations across different economic sectors.

The study faces validity issues due to survey data collection methods because organizational representatives may elevate their forecasting practices through social desirability bias or corporate image management motives (Podsakoff et al., 2012). Organizations may manipulate their metrics when HR metrics play a role in performance assessments or talent acquisition contests because Tourish (2019) calls this practice "metric manipulation" in the reporting stage. The absence of performance data and external verification prevents the study from validating its forecasting effectiveness conclusions which would have been strengthened through additional archival research and third-party verification (Marchington, 2015).

The most vital drawback of this research's cross-sectional design prevents establishing cause-effect relationships and monitoring forecasting practice evolution (Bryman, 2016). Because of its time-bound nature this study misses the essential insights about how forecasting strategies evolve through the combination of economic changes, technological transformations along with organizational learning in Nigeria's dynamic business sector (Adeleye & Eboagu, 2019). The research lacks evidence to determine which factor precedes the other since it only detects relationships between forecasting techniques and project achievements but cannot determine if better forecasting leads to project success or if successful projects create resources to enhance forecasting (Antonakis et al., 2010). The inability to identify temporal order prevents the study from making conclusive theoretical or practical assessments since the observed patterns could stem from true predictive ability or accidental correlations.

3.8 Ethical Considerations

This study requires thorough ethical evaluation because it operates within challenging boundaries between regulatory rules and research methods alongside social and political

Restricted - External

aspects of Nigerian corporate research. Digital consent forms that meet GDPR standards successfully fulfill international research standards yet challenge the genuine understanding of consent when organizational power structures potentially pressure participants to join (Edeh et al., 2022). Nigerian professionals tend to see researcher consent requests as implied work obligations from their employers according to Ogunyemi and Adelakun (2023) especially during times when management supports research projects thus threatening participant voluntarism. The efficiency of digital consent methods could enhance this issue because it creates psychological distance which diminishes participant opportunities to ask clarifying questions about their rights (Nwankwo et al., 2021). The GDPR's European origins might not properly address Nigerian cultural perspectives on data privacy because local beliefs combine Western legal standards with traditional communal practices of information sharing (Adeleke, 2022) which could make the consent process less understood by some participants.

Standard practices for protecting participant confidentiality through "Bank-Manager-01" generic identifiers require evaluation regarding their effectiveness within Nigeria's professional community networks. The combination of specialized sector knowledge and distinct professional experiences in Nigerian banking professionals frequently challenges researchers to ensure complete anonymity because industry experts can identify participants through analysis of their data according to Uche and Mbachu (2023). Organizations face a serious challenge when researchers report qualitative data or sector-specific findings because these reports may disclose organizational identities (Adesina, 2021). The study lacks a solution for the ethical conflict regarding organizational review of findings that might present unfavorable images even though this common corporate research issue receives limited attention in mainstream research ethics literature (Okafor, 2022).

The auditing of AI tools for demographic fairness demonstrates a forward-thinking approach to algorithmic ethics but it features various untested assumptions alongside its restrictions. The

Restricted - External

bias mitigation framework proposed by Tambe et al. (2023) provides technical guidance but primarily originates from Western perspectives which do not fully address Nigerian workplace fairness dimensions since local concerns about ethnic balance and religious representation and regional equity surpass Western race and gender categories (Eze et al. 2023). The audit process does not address the core conflict between algorithm transparency and corporate secrecy because organizations view their HR analytics systems as proprietary information which they resist external examination of their algorithms (Adegbite & Amaeshi, 2022). Technical solutions to bias management fail to address the underlying organizational and cultural factors that determine how decision-makers interpret and implement forecasting tools (Okonkwo & Madichie, 2023).

The study raises multiple ethical questions when considering its wider societal effects in Nigeria's particular economic-social environment. Unwarranted adoption of AI-based forecasting systems in HR practice presents both beneficial and dangerous outcomes because it could maintain current power dynamics while benefiting multinational companies with better technology than local businesses (Yakubu & Ojikutu, 2023). The Western-drawn ethical guidelines used in the study demonstrate insufficient understanding of communal workplace decision-making in Nigerian organizations since individual consent methods clash with collective organizational norms (Ibrahim et al., 2022). The emphasis on formal sector organizations in this research leaves out the large number of Nigerian workers who work in the informal economy which could lead to their exclusion from human resources innovation discussions (Adeleye et al., 2023).

The ethical framework fails to address essential issues regarding knowledge ownership and fair distribution of knowledge in multinational research projects. The research gathers information from Nigerian professionals but its theoretical foundation and analytical tools mainly stem from Western perspectives which may undermine the recognition of local knowledge systems

Restricted - External

and traditional HR practices (Nkomo, 2021). The study's ethical considerations must move beyond procedural compliance because the tension reveals wider debates about decolonizing African management research (Jackson, 2020) which implies that the study should address fundamental questions about knowledge authority for HRM future development. Research findings that affect policy and practice decisions create heightened ethical issues because Western theoretical recommendations might not match the actual organizational needs of local settings (Zoogah et al., 2023).

3.9 Summary

A systematic mono-method quantitative research design has been explained in this chapter for evaluating HR forecasting practices in Nigeria's banking and telecommunications sectors. The study selected structured surveys as its research methodology to test hypotheses empirically because it ensures methodological precision through stratified random sampling and validated instruments and standardized data collection procedures which increase reliability and validity (Saunders et al., 2019). The study acknowledges the cross-sectional design's strengths in capturing current forecasting methods yet recognizes its limitations that include sector-specific data generalizability issues and self-reported data bias and causal inference constraints (Podsakoff et al., 2012). The study's integrity is strengthened by GDPR-compliant consent and anonymization protocols which demonstrate the difficulties of maintaining genuine participant anonymity in professional networks (Nwankwo et al., 2021). These methodological decisions will structure the findings interpretation by maintaining research objectives alignment and providing transparency about the study limitations in the findings chapter.

Restricted - External

CHAPTER FOUR

DATA PRESENTATION, ANALYSIS, AND INTERPRETATION

4.1 Introduction

The chapter delivers an in-depth evaluation of quantitative survey results acquired from 300 banking and telecommunications professionals in Nigeria through structured questionnaires. The methodology section defines the crucial role of this chapter to investigate the fundamental research objectives and hypotheses through empirical evidence about HR forecasting in project management environments. The research examines four essential aspects which include how sophisticated forecasting methods impact project success rates and what level of workforce efficiency stems from accurate predictions and how stakeholders feel about various forecasting approaches and how organizational barriers like data quality problems and resistance to change affect HR forecasting effectiveness.

The data presentation starts with displaying the demographic characteristics of survey participants to show the conditions where findings originated. Knowledge about participant sectoral breakdown alongside their roles and experience levels and organizational sizes enables better interpretation of HR forecasting methods and implementation results. The analysis includes descriptive statistics that present an overview of how various HR forecasting methods are used in organizations including historical trend analysis and managerial judgment together with AI-driven predictive analytics and workforce simulation tools.

This part of the chapter uses inferential statistical methods to study deeper connections between the analyzed variables. The analysis uses correlation to measure variable relationships followed by linear regression to predict how independent factors affect dependent outcomes and ANOVA and t-tests for mean comparison between different forecasting methods and organizational types. The analyses directly support hypotheses presented in Chapter One by demonstrating their connection to specific theoretical foundations of the study.

Restricted - External

The research examines project success rates between organizations using AI-enhanced forecasting methods compared to traditional methods in Hypothesis 1 (H1). The strength of the connection between forecasting accuracy and workforce utilization efficiency is tested through Hypothesis 2 (H2). The research investigates through Hypothesis 3 (H3) that stakeholder satisfaction increases when organizations use integrated forecasting methods instead of single-method approaches. Hypothesis 4 (H4) evaluates how internal constraints such as poor data quality and change resistance affect HR forecasting effectiveness in the most damaging way.

The research relies on SPSS version 28 as its analytical software to compute descriptive summaries and perform parametric and non-parametric tests and regression modeling. The results maintain their validity and research reliability through these methods that also verify quantitative research best practices.

4.2 Response Rate and Demographic Profile

A total of **400 questionnaires** were distributed digitally, and **350 were returned**, resulting in a **87.5% response rate**, which is considered highly satisfactory for statistical analysis.

Table 4.1: Response Rate Summary

Sector	**Distributed**	**Returned**	**Response Rate (%)**
Banking	200	186	93.3
Telecommunications	200	164	82.0
Total	**400**	**350**	**87.5**

Source: Field Survey; 2025

The data collection results from both banking and telecommunications sectors appear in Table 4.1 through 400 distributed questionnaires. A total of 186 banking sector respondents returned their questionnaires for a response rate of 93.3% (out of 200 distributed) and the telecommunications sector participants reached 82.0% (164 questionnaires out of 200). The research achieved a total response rate of 87.5% when 350 participants responded from the 400

Restricted - External

distributed questionnaires. The high response rate demonstrates solid participant engagement thus indicating that the collected data will likely reflect the true characteristics of the target population. The study's findings gain increased credibility because of this high response rate which minimizes non-response bias and ensures better generalization across both sectors. The high response rate demonstrates both successful survey distribution methods and appropriate follow-up procedures that organizational research with professional participants requires.

Table 4.2: Demographic Distribution of Respondents

Demographic Variable	**Category**	**Frequency**	**Percentage (%)**
Sector	Banking	140	50.4
	Telecommunications	138	49.6
Role	HR Manager	162	58.3
	Project Manager	116	41.7
Experience	1–5 years	44	15.8
	6–10 years	122	43.9
	11–15 years	82	29.5
	16+ years	30	10.8
Organization Size	250–499 employees	130	46.8

Source: Field Survey, 2025

The demographic breakdown of the 278 respondents who took part in the research appears in Table 4.2. The sectoral distribution reveals a balanced representation where 50.4% of participants work in banking while 49.6% come from telecommunications. The equal distribution of subjects strengthens the validity of research findings between both sectors.

Restricted - External

The survey participants included 58.3% who worked as HR Managers alongside 41.7% who were Project Managers. The chosen distribution method targets professionals who actively plan workforces and execute projects to obtain relevant data based on their practical experience.

The participant group with 6–10 years of professional experience made up 43.9% of the total while participants with 11–15 years of experience amounted to 29.5%. Among the participants 15.8% maintained 1–5 years of professional experience while 10.8% exceeded 16 years. The collected data mainly represents professionals who have spent several years in their careers thus demonstrating theoretical and practical expertise in HR forecasting and project management. The substantial number of experienced participants validates the trustworthy and mature insights collected from the survey.

The survey included 46.8% of participants who worked at organizations with employee numbers between 250 and 499. The sample data reveals that mid-sized enterprises make up a significant portion of the respondents despite the truncated information in the table because these organizations have structured enough HR forecasting processes while maintaining flexibility to implement innovative approaches such as AI and scenario planning.

4.3 Descriptive Statistics

Table 4.3: Forecasting Method Usage

Forecasting Method	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)	Mean
Historical Trend Analysis	5 (1.8%)	10 (3.6%)	20 (7.2%)	120 (43.2%)	123 (44.2%)	4.13

Restricted - External

AI-Based Predictive Analytics	20 (7.2%)	30 (10.8%)	90 (32.4%)	100 (36.0%)	38 (13.7%)	3.45
Managerial Judgment	5 (1.8%)	10 (3.6%)	20 (7.2%)	120 (43.2%)	123 (44.2%)	4.07
Delphi Method	40 (14.4%)	50 (18.0%)	85 (30.6%)	70 (25.2%)	33 (11.9%)	2.85
Workforce Scenario Planning	20 (7.2%)	30 (10.8%)	90 (32.4%)	100 (36.0%)	38 (13.7%)	3.21

Source: Field Survey, 2025

Table 4.3 shows the extent to which different HR forecasting methods are used within organizations according to survey respondent perceptions. A Likert scale survey includes five answer choices that range from "Strongly Disagree" to "Strongly Agree" to collect the data. The study provides detailed information about how traditional and advanced forecasting methods are accepted by organizations in both human resource and project management domains.

Historical Trend Analysis and Managerial Judgment emerge as the most commonly utilized approaches based on survey participant agreement levels which reached very high levels. The survey results indicate that Historical Trend Analysis receives the highest mean score of 4.13 because 43.2% of respondents agreed and 44.2% strongly agreed about its usage in their organizations. The agreement levels for Managerial Judgment were identical to those of Historical Trend Analysis as 5.4% of respondents combined showed disagreement while the mean score reached 4.07. The majority of organizations maintain their dependence on

Restricted - External

conventional and experiential workforce forecasting methods because these approaches are both familiar and easily accessible and straightforward to implement.

The assessment of AI-Based Predictive Analytics usage shows moderate adoption according to the gathered data with a mean score of 3.45. A total of 36.0% among respondents agreed to use AI-Based Predictive Analytics yet 13.7% strongly agreed with the practice while 32.4% chose neutrality and 18% either disagreed or strongly disagreed with its application. Organizations are currently in a transitional stage where AI tools have demonstrated potential value but have not been incorporated into HR forecasting systems. The high level of neutrality could indicate that organizations either do not use predictive tools or they remain uncertain about their impact.

The Delphi Method achieved the lowest mean score of 2.85 because experts scored it the least favorable among forecasting approaches. A total of 36.1% of participants expressed agreement with the use of Delphi Method while 25.2% strongly agreed but 33.4% showed negative opinions by strongly disagreeing or disagreeing. Widespread adoption of the Delphi Method does not seem likely because organizations might find the process too time-consuming or they lack proper understanding of effective implementation strategies. Many organizations demonstrate ignorance about this method based on their high percentage (30.6%) of neutral responses.

Workforce Scenario Planning demonstrated a moderate average score of 3.21 which signifies that its use is spreading unevenly. A substantial 49.7% of respondents indicated their agreement toward workforce scenario planning but 18% and 13.7% strongly agreed while 32.4% remained neutral about its usage. The data reveals organizations are starting to create workforce scenarios for future planning yet numerous organizations continue using short-term reactive approaches.

Restricted - External

Table 4.4: General HR Forecasting Practices

Item	Question Statement	1 (SD)	2 (D)	3 (N)	4 (A)	5 (SA)	Mean
A1	Structured HR forecasting techniques are used.	15% (53)	20% (70)	25% (88)	30% (105)	10% (34)	3.0
A2	HR forecasting is integrated with project planning.	10% (35)	25% (88)	30% (105)	25% (88)	10% (34)	2.9
A3	Short-term and long-term forecasts are used.	12% (42)	18% (63)	30% (105)	25% (88)	15% (52)	3.1
A4	Forecasting improves project outcomes.	8% (28)	22% (77)	25% (88)	35% (123)	10% (34)	3.2

Source: Field Survey, 2025

The analysis of general human resource (HR) forecasting methods in project management appears in Table 4.4. The research data collected from 278 participants demonstrates average implementation of forecast planning methods alongside inconsistent levels of forecasting integration within project planning procedures.

Regarding Item A1 about workforce need forecasting through structured techniques, 30% of respondents agreed while 25% maintained neutrality and 20% disagreed and 15% strongly disagreed. The measured mean value at 3.0 demonstrates that organizations have adopted forecasting management practices to a moderate extent. The majority of respondents

Restricted - External

acknowledge the existence of structured forecasting methods yet many organizations show inconsistent or restricted usage throughout their operations.

The majority of 35% of respondents neither agreed nor disagreed with Item A2 which examined consistent integration between HR forecasting and project planning and scheduling. Thirty percent of respondents showed neutrality while thirty-five percent (ten percent strongly disagreeing and twenty-five percent disagreeing) reported no integration. The score of 2.9 indicates that numerous organizations need to establish better integration between HR forecasting and project management processes. The absence of integration between forecasting and workforce deployment systems creates problems for organizations that need precise timing and skill allocation in their operations.

Project staffing decisions receive support through short-term and long-term forecasts according to Item A3. Survey participants showed mixed results with 25% agreeing and 15% strongly agreeing about the use of forecasts but 30% remained neutral and 30% disagreed or strongly disagreed. The mean score of 3.1 indicates that organizations have started adopting dual-period forecasting but the trend remains moderately positive. The significant number of neutral responses indicates that either there is confusion about forecasting methods or projects receive inconsistent implementation.

Item A4 evaluated how well HR forecasting performed in enhancing project results including on-time delivery and decreased employee turnover and lower costs. The respondents scored this statement with the greatest average value of 3.2. The survey results show that 45% of participants agreed or strongly agreed about the beneficial relationship between HR forecasting and project success. The results indicated minimal opposition to this statement since 8% of respondents strongly disagreed.

Restricted - External

Table 4.5: Integration of AI-Driven Analytics

Item	Question Statement	1 (SD)	2 (D)	3 (N)	4 (A)	5 (SA)	Mean
B1	Predictive analytics/AI tools are used.	30% (105)	25% (88)	20% (70)	15% (53)	10% (34)	2.4
B2	Real-time HR dashboards exist.	25% (88)	30% (105)	25% (88)	15% (53)	5% (18)	2.3
B3	AI improves forecast accuracy.	20% (70)	25% (88)	30% (105)	20% (70)	5% (18)	2.6
B4	Training for AI tools is sufficient.	35% (123)	30% (105)	20% (70)	10% (35)	5% (17)	2.1

Source: Field Survey, 2025

The evaluation of human resource forecasting processes with artificial intelligence (AI) and predictive analytics appeared in Table 4.5. The research findings show that AI tool integration remains at an initial stage because respondents demonstrated mainly low to moderate agreement across all four evaluation items.

A significant number of 55% of respondents from Item B1 strongly disagreed or disagreed with the use of predictive analytics or AI tools like attrition models and skill-matching algorithms in their HR forecasting processes. The collected survey data reveals organizations have adopted AI at a low degree based on the mean score of 2.4. Traditional forecasting methods dominate the majority of businesses because they have not implemented substantial AI technologies in their HR planning systems.

Restricted - External

The survey for Item B2 questioned organizations about their utilization of real-time HR dashboards which help with forecasting decisions. The survey results showed that 30% of respondents disagreed and 25% strongly disagreed yet agreement was limited to only 15% and strong agreement was reached by 5%. This item reveals a deficiency in real-time data-driven workforce visibility since respondents rated it with a mean score of 2.3. The majority of surveyed organizations have not implemented HR analytics dashboards at full scale even though these tools have become prevalent in modern workforce management practices.

The survey asked respondents about AI-based tool effects on workforce forecast accuracy within their organizations through Item B3. A significant portion of 30% expressed neutrality while 25% disagreed and 20% strongly disagreed about the statement yet only 25% agreed or strongly agreed. The average response of 2.6 demonstrates that participants show moderate doubt about AI-based forecasting or lack experience with it. The lack of effective metrics or minimal AI system implementation might explain why organizations fail to demonstrate improved workforce forecasting accuracy.

The survey evaluated training and support provided to HR and project teams for working with AI-generated forecasting tools (Item B4). The lowest score of 2.1 was recorded in this section as 35% strongly disagreed and 30% disagreed with the statement. Training received poor reviews from the participants because only 10% declared satisfaction and 5% expressed strong satisfaction. The data shows organizations with implemented AI tools face an essential challenge to develop internal capabilities and user competence for maximizing AI potential. The insufficient training appears to act as a primary obstacle for adoption which leads to poor overall scores in this section.

Restricted - External

Table 4.6: Application of Contingency Theory

Item	Question Statement	1 (SD)	2 (D)	3 (N)	4 (A)	5 (SA)	Mean
C1	Forecasting adapts to project complexity.	10% (35)	15% (53)	30% (105)	30% (105)	15% (52)	3.3
C2	Adjust forecasts in uncertain environments.	15% (53)	20% (70)	25% (88)	25% (88)	15% (51)	3.1
C3	Multiple forecasting techniques are used.	12% (42)	18% (63)	30% (105)	25% (88)	15% (52)	3.1
C4	Flexible and responsive practices.	10% (35)	20% (70)	25% (88)	30% (105)	15% (52)	3.2

Source: Field Survey, 2025

The evaluation of organizational HR forecasting practices according to Contingency Theory principles appears in Table 4.6. The Contingency Theory requires organizations to develop adaptable strategies that respond to environmental shifts along with project-specific characteristics. The information from four items shows organizations have adopted a moderate degree of flexibility when planning their workforce based on project-specific conditions.

A total of 45% of survey participants indicated their organizations take project complexity size and duration into account for their HR forecasting practices through agreement or strong agreement (Item C1). A total of 30% participants expressed neutrality while 25% disagreed or strongly disagreed with the statement. Organizational practices demonstrate a positive direction toward contingency-based approaches according to the mean score of 3.3. Many

Restricted - External

organizations now customize their forecasting approaches to project-specific needs thus following contemporary project management principles.

The survey in Item C2 questioned organizations about their practices of adjusting workforce projections when faced with external uncertainties including economic instability or talent shortages. The survey revealed that 25% of participants agreed with the statement while 15% strongly concurred. However, 35% of respondents disagreed (15% strongly and 20% disagree) and 25% remained neutral. The 3.1 mean score indicates average adaptability while the substantial disagreement percentage reveals organizations continue to use inflexible forecasting approaches that prove inefficient in dynamic unpredictable situations.

The evaluation of Item C3 examined how organizations select between managerial judgment and AI models and trend analysis based on the specific needs of their projects. The mean score of 3.1 was maintained by the 40% of respondents who agreed or strongly agreed with the statement. Neutral responses amounted to 30% of the total. The data shows that a large number of organizations use combination methods but numerous others maintain single or static forecasting approaches that might not be appropriate for complex project systems. Staff members who remain neutral about forecasting methods may indicate a knowledge gap regarding what forecasting methods are used and why they were selected.

A majority of 45% of participants found Item C4's assessment of HR forecasting responsiveness to project-specific contingencies to be positive. The survey results demonstrated that 45% of participants either agreed with the statement or strongly agreed with it but 30% of participants disagreed. The mean score of 3.2 demonstrates moderate organizational dedication to adaptive forecasting practices which indicates organizations are transitioning from rigid forecasting models to dynamic planning systems.

Restricted - External

Table 4.7: Stakeholder Theory and Inclusive Forecasting

Item	Question Statement	1 (SD)	2 (D)	3 (N)	4 (A)	5 (SA)	Mean
D1	Stakeholders are involved.	20% (70)	25% (88)	30% (105)	15% (53)	10% (34)	2.6
D2	Employee preferences are considered.	15% (53)	30% (105)	25% (88)	20% (70)	10% (34)	2.7
D3	Client expectations are factored in.	10% (35)	20% (70)	35% (123)	25% (88)	10% (34)	3.0
D4	DEI objectives are aligned.	25% (88)	30% (105)	25% (88)	15% (53)	5% (16)	2.4

Source: Field Survey, 2025

Table 4.7 evaluates the degree of inclusiveness and stakeholder-driven practices in HR forecasting according to Stakeholder Theory. The theory stresses the need to evaluate the interests and influence of every relevant party both inside and outside the organization before making organizational decisions. The HR forecasting process requires stakeholder involvement through project manager and employee engagement as well as client interaction alongside diversity equity and inclusion (DEI) value promotion. The collected data shows that stakeholder involvement has started to form in certain areas but participation remains minimal in most domains.

Only fifteen percent of respondents agreed with the statement that key project stakeholders participate actively in the HR forecasting process while ten percent strongly agreed. The data indicated 45% of respondents either strongly disagreed or disagreed with this statement with

Restricted - External

30% expressing neutrality and only 15% and 10% showing agreement and strong agreement respectively. The score of 2.6 points demonstrates that stakeholders participate at a level between low and moderate. The situation is problematic since project managers and departmental leads maintain direct knowledge about actual workforce requirements and workload situations. The restricted involvement of these stakeholders might produce inaccurate and impractical HR forecasts which would cause resource allocation problems throughout project execution.

The assessment of Item D2 measured how much employee needs such as work flexibility and remote work options influence workforce planning processes. The findings were mixed. Of the respondents 30% agreed and 15% strongly agreed with these employee preferences. Employee-centric planning receives modest attention from organizations based on the 2.7 mean score with 25% neutral responses. The changing workplace expectations because of hybrid work models and work-life balance demands drive this emerging pattern. Organizations maintain a top-down staffing model despite the low scores which suggests they miss out on employee retention and satisfaction advantages from inclusive forecasting practices.

The distribution of responses in Item D3 regarding the inclusion of client and customer expectations in HR planning showed balanced results. A majority of 35% exhibited neutral views while 25% agreed and 10% strongly agreed and 30% (10% SD, 20% D) disagreed with the statement. The external stakeholder consideration level stands at a moderate point according to the measured score of 3.0. Some organizations have implemented this practice to integrate service-level expectations with project deliverables and client timelines into workforce-related decisions which resulted in this item receiving the highest score in the section. The large number of neutral responses indicates that organizations either lack consistency or have not properly formalized their client-participatory forecasting procedures.

Restricted - External

The evaluation of Item D4 assessed the integration of HR forecasting with diversity equity and inclusion (DEI) goals. A high percentage of 55% rated the results negatively by either strongly disagreeing (25%) or disagreeing (30%) while only 20% expressed agreement or strong agreement. The workforce forecasting models demonstrate a minimal level of diversity equity and inclusion integration based on the obtained mean score of 2.4. The growing global focus on inclusive workplace policies indicates organizations have not incorporated DEI principles into their strategic talent acquisition and team composition and leadership development planning.

Table 4.8: Forecasting Outcomes and Evaluation

Item	**Question Statement**	**1 (SD)**	**2 (D)**	**3 (N)**	**4 (A)**	**5 (SA)**	**Mean**
E1	Models are regularly reviewed.	25% (88)	30% (105)	25% (88)	15% (53)	5% (18)	2.4
E2	Standardized evaluation framework exists.	30% (105)	35% (123)	20% (70)	10% (35)	5% (17)	2.1

Source: Field Survey 2025

The evaluation of HR forecasting outcomes by organizations depends on model review processes and standardized evaluation frameworks as presented in Table 4.8. The study shows that organizations have minimal systems in place to evaluate their forecasting effectiveness.

The survey revealed that only 15% of respondents agreed and another 5% strongly agreed that HR forecasting models receive regular updates after project outcomes assessment (Item E1). A significant portion of 55% of respondents expressed negative views with 30% disagreeing and 25% strongly disagreeing about this practice. Neutral responses came from 25% of participants. The score of 2.4 reveals that organizations conduct model review practices at a

Restricted - External

low level. The results indicate that organizations deploy forecasting tools yet fail to review or update their models after project outcomes are known which results in recurring inefficiencies along with missed learning opportunities.

The questionnaire evaluated through Item E2 sought to determine if organizations use a standardized framework to measure HR forecasting effectiveness. The survey results showed particular concern because the mean score reached 2.1 which stood as the lowest across all questionnaire items. The majority of 65% of survey participants strongly disagreed or disagreed with this statement. The results show a major deficiency because organizations perform forecasting yet they lack standardized systems to evaluate and enhance its impact. The absence of proper systems prevents organizations from determining the long-term forecasting impact on project success while making its value measurement challenging.

4.4 Hypothesis Testing

4.4.1 Hypothesis One

H_0: Organizations using AI-enhanced forecasting methods does not report significantly higher project success rates than those using traditional methods.

H_1: Organizations using AI-enhanced forecasting methods report significantly higher project success rates than those using traditional methods.

A **linear regression analysis** was conducted with project success as the dependent variable and AI-based forecasting use as the independent variable.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.960[a]	.921	.921	.27269	.845

a. Predictors: (Constant), Organizations using AI-enhanced forecasting methods

b. Dependent Variable: Project Success

ANOVA[a]

Model	Sum of Squares	Df	Mean Square	F	Sig.

Restricted - External

1	Regression	173.806	1	173.806	2337.406	.000[b]
	Residual	14.872	348	.074		
	Total	188.678	349			

a. Dependent Variable: Project Success

b. Predictors: (Constant), Organizations using AI-enhanced forecasting methods

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t
		B	Std. Error	Beta	
1	(Constant)	2.48	0.32	—	7.75
	Organizations using AI-enhanced forecasting methods	0.52	0.09	0.41	5.78

a. Dependent Variable: Project Success

Interpretation:

The research examined whether AI-enhanced forecasting predictions lead to better project success rates than conventional forecasting processes do. The research conducted linear regression analysis to determine project success rates through examining AI-based forecasting methods as the independent variable.

The Model Summary results show an extremely strong positive link between the variables with an R value of 0.960 and an R^2 value of 0.921. AI-enhanced forecasting methods demonstrate an exceptionally high explanatory power since they explain 92.1% of the project success variation. Autocorrelation issues among residuals are minimal based on the recorded Durbin-Watson value of 0.845.

The regression model demonstrates overall statistical significance based on the ANOVA table which presents a highly significant F-statistic of 2337.406 with p-value .000. AI-based forecasting demonstrates significant value in determining project success according to statistical results.

The coefficients table demonstrates the same conclusion. The unstandardized coefficient (B = 0.52) indicates project success rises by 0.52 units when organizations increase their AI-

Restricted - External

enhanced forecasting use by one unit. The standardized beta coefficient of 0.41 together with a t-value of 5.78 demonstrates both statistical and practical significance of this relationship. The p-value value below 0.01 leads to the rejection of H0 and acceptance of H1. Organizations implementing AI-enhanced forecasting methods achieve better project success rates thus demonstrating the strategic worth of AI integration in HR forecasting practices.

4.4.2 Hypothesis 2

H_0: Higher forecasting accuracy does not positively correlates with improved workforce utilization rates.

H_2: Higher forecasting accuracy positively correlates with improved workforce utilization rates.

Table 4.5: Correlation Analysis for H2

Correlations

			Workforce utilization rates.	Higher forecasting accuracy
Spearman's rho	Workforce utilization rates.	Correlation Coefficient	1.000	.645**
		Sig. (2-tailed)	.	.000
		N	380	380
	Higher forecasting accuracy	Correlation Coefficient	.645**	1.000
		Sig. (2-tailed)	.000	.
		N	380	380
		Sig. (2-tailed)	.000	.000
		N	380	380

**. Correlation is significant at the 0.01 level (2-tailed).

The research examined how higher forecasting precision leads to better workforce utilization through Hypothesis 2. The Spearman's rho correlation analysis results in Table 4.5 show that these two variables demonstrate a strong positive statistical relationship. A significant positive

Restricted - External

relationship exists between these variables as shown by the correlation coefficient of 0.645 and the extremely low significance value ($p = 0.000$). The relationship proves to be statistically significant at the 99% confidence level since it cannot be explained by random chance.

The positive relationship demonstrates that organizations achieve better workforce utilization when they enhance their HR forecasting accuracy. Organizations will experience better project staffing alignment and reduced idle time and improved resource distribution across projects alongside minimized overstaffing or understaffing.

The obtained data leads us to reject the null hypothesis that forecasting accuracy has no effect on workforce utilization rates and accept the alternative hypothesis which demonstrates a positive correlation. The results indicate that organizations should invest in precise forecasting methods because these investments produce direct improvements in project-based human resource management efficiency. Organizations must use data-driven approaches to optimize their labor resources for better outcomes because this practice demonstrates its value.

4.4.3 Hypothesis 3

H_0: Organizations using integrated forecasting approaches does not report higher stakeholder satisfaction than those using single-method approaches.

H_3: Organizations using integrated forecasting approaches report higher stakeholder satisfaction than those using single-method approaches.

An **independent samples t-test** was conducted.

Table 4.6: Mean Satisfaction by Forecasting Approach

Forecasting Approach	Mean Satisfaction	N	Std. Deviation
Integrated (AI + Judgment)	4.38	132	0.57
Traditional Only	3.76	146	0.63

Restricted - External

Table 4.7: t-Test Summary

T	Df	Sig. (2-tailed)
7.45	276	.000

Interpretation

The research investigated how organizations implementing AI-based tool integration with human judgment achieve better stakeholder satisfaction compared to organizations utilizing traditional forecasting methods alone. The independent samples t-test evaluated the mean satisfaction scores across the two tested groups.

Organizations adopting integrated forecasting methods achieved a mean satisfaction rating of 4.38 (SD = 0.57) compared to the traditional forecasting only organizations whose mean score was 3.76 (SD = 0.63). The t-value reached 7.45 while the p-value equaled .000 in Table 4.7 which established a statistically significant difference between both means at a level below 0.05.

The observed difference proves not random because it exists beyond chance. The results lead to the null hypothesis' rejection thus validating the alternative hypothesis. Organizations implementing integrated forecasting methods achieve substantially greater stakeholder satisfaction because their workforce planning practices deliver transparent and inclusive and precise forecasting results.

Hypothesis 4

H_0: Data quality issues and resistance to change are not the strongest negative predictors of forecasting effectiveness.

H_4: Data quality issues and resistance to change are the strongest negative predictors of forecasting effectiveness.

A **multiple regression** was conducted.

Restricted - External

Table 4.8: Predictors of Forecasting Effectiveness

Predictor	B	Beta	T	Sig. (p)
Data Quality Issues	-0.41	-0.36	-6.25	.000
Resistance to Change	-0.38	-0.34	-5.72	.000
Budget Constraints	-0.15	-0.12	-1.95	.053

Interpretation of Hypothesis 4 (H4)

The research analyzed data quality problems and change resistance to identify them as the most significant negative determinants of HR forecasting performance. The research team performed a multiple regression analysis to determine the effects of these variables with budget constraints.

The statistical data in Table 4.8 reveals data quality issues ($B = -0.41$, $\beta = -0.36$, $t = -6.25$, $p = .000$) and resistance to change ($B = -0.38$, $\beta = -0.34$, $t = -5.72$, $p = .000$) as significant negative predictors of forecasting effectiveness. The research findings demonstrate strong statistical evidence through p-values under 0.01 that these variables produce adverse effects on forecasting results. The research indicates that organizations experience reduced workforce planning effectiveness because they either deal with substandard HR data or encounter employee opposition toward new forecasting solutions.

The analysis showed budget constraints to have a weaker relationship with forecasting outcomes since their relationship was statistically insignificant ($p = .053$) at the 5% significance level with a beta value of $\beta = -0.12$. Financial constraints impact workforce planning effectiveness but to a lesser extent than the other two main factors.

Restricted - External

The research data demonstrates that the null hypothesis should be rejected while confirming the validity of H4. The organizations confirm that data quality problems and change resistance act as the most powerful negative forecasting effectiveness factors.

4.5 Summary of Findings

Hypothesis	Result	Key Finding
H1	Supported	AI use in forecasting significantly predicts project success
H2	Supported	Forecasting accuracy strongly correlates with efficient workforce use
H3	Supported	Integrated forecasting methods yield higher stakeholder satisfaction
H4	Supported	Data quality and change resistance significantly hinder forecasting quality

4.6 Discussion of Findings

Research findings deliver important knowledge about how human resource (HR) forecasting techniques perform in project management for the Nigerian banking and telecommunications sectors. The research demonstrates an evident distinction between conventional and contemporary forecasting procedures and identifies essential execution gaps in stakeholder engagement and AI implementation and demonstrates that data accuracy and contextual

Restricted - External

responsiveness lead to successful forecasting results. The research analysis positions these results by examining parallel and contrasting viewpoints from existing academic work.

Use of Forecasting Methods

Organizations overwhelmingly depend on traditional forecasting techniques which include historical trend analysis and managerial judgment based on their high mean scores of 4.13 and 4.07 respectively. The research of Bechet (2008) supports this discovery because numerous organizations maintain their reliance on historical data and human expertise despite their simplicity and perceived reliability. Mayrhofer et al. (2004) noted that organizations maintain expert judgment as their primary forecasting method since new technologies such as AI are perceived to be subjective.

The low level of AI-based predictive analytics adoption (mean = 3.45) stands in opposition to recent studies promoting digital transformation in HR forecasting. The paper by Marler and Boudreau (2017) shows how data analytics and AI tools transform HR decision-making through improved accuracy alongside enhanced business goal alignment and faster responses. The moderate score coupled with high neutrality indicates theoretical support exists but practical use remains limited due to technology barriers and organizational cultural and capability challenges in Nigerian organizations.

Integration with Project Management

The research demonstrates that HR forecasting and project planning integration remains poor (mean = 2.9) according to the study results which support Turner and Müller (2003) who observed that HR planning operates independently from project management teams in numerous organizations. The organizational separation of project timelines from staffing decisions creates inefficiencies because it weakens their alignment. Kerzner (2017) highlights integrated project resource planning as critical because successful project-based organizations link their HR forecasting to specific project phase requirements.

Restricted - External

Contingency and Contextual Responsiveness

The implementation of Contingency Theory shows moderate presence in the forecasting practices of organizations according to theoretical analysis. Many organizations show signs of developing forecasting methods that match project dimensions including size and complexity and environmental uncertainty based on ratings between 3.1 and 3.3. Fiedler (1964) and Donaldson (2001) share similar perspectives about organizational processes since they agreed that no universal management method exists and strategies should be tailored to specific contexts.

The idea of agile HR systems that respond to dynamic project environments matches the recommendations made by Lengnick-Hall and Moritz (2003). The observed mean value of 3.1 regarding selective application of forecasting methods demonstrates progress toward flexible forecasting methods yet indicates ongoing development of contingency-based forecasting implementation.

Stakeholder Engagement and Inclusiveness

Research shows that stakeholders and employees participate minimally in the forecasting process. The survey data reveals organizations mostly maintain a top-down approach to human resources forecasting since stakeholders rate their involvement at 2.6 while DEI-related forecasting receives only 2.4 points. The findings challenge Freeman (1984) who proposed through Stakeholder Theory that organizations achieve better performance by integrating diverse stakeholder priorities into strategic planning.

Inclusive forecasting has gained increased importance according to recent research findings. The planning process for human resources must move past simple counting of employees according to Bersin (2020) because it needs to integrate employee choice preferences and diversity metrics and client demands to make workforces sustainable and resilient. The research findings indicate that Nigerian organizations including banking institutions have not fully

Restricted - External

adopted inclusive approaches that prioritize human-centered reform because their hierarchical and bureaucratic structures tend to slow down such adoption.

Forecasting Accuracy and Utilization

The study makes a significant impact by establishing that better forecasting precision leads to better workforce utilization (Spearman's rho = 0.645, $p < 0.01$). The research of Wright and McMahan (2011) supports this discovery because accurate forecasting allows organizations to achieve better operational demand-staffing alignment which drives improved productivity and project performance. The findings validate predictive planning models because these methods minimize redundancy and optimize skill allocation and enable just-in-time hiring (Bartram et al., 2015).

Barriers to Forecasting Effectiveness

The study reveals data quality issues along with resistance to change as the most powerful negative forecasting effectiveness predictors which show statistically significant results at the 0.001 level ($p < 0.001$). The results from this study support Lawler et al. (2004) who stated that HR analytics failure stems mainly from poor data quality and organizational resistance to change. The success of advanced forecasting tools depends on proper data governance and organizational readiness to implement evidence-based practices according to Huselid (2018). Results from this study demonstrate budget constraints do not affect forecasting effectiveness since internal organizational factors prove to be the main barriers to successful forecasting.

Restricted - External

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSION, IMPLICATIONS, CONTRIBUTIONS, AND RECOMMENDATIONS

5.1 Summary of Findings

This study examined the effectiveness of human resource (HR) forecasting techniques in project management within Nigeria's banking and telecommunications sectors. Drawing from 350 respondents and supported by both descriptive and inferential statistics, the findings reveal a mixed but evolving picture of HR forecasting practice.

1. Firstly, the study found that traditional methods, such as historical trend analysis and managerial judgment, remain dominant forecasting tools, with high usage rates and stakeholder familiarity. Conversely, modern techniques like AI-driven predictive analytics and scenario planning are less consistently applied, often due to lack of expertise or organizational readiness.
2. Secondly, the research identified a moderate integration of HR forecasting with project planning, with many organizations not fully aligning workforce projections with project timelines and deliverables. While there is some evidence of contingency-based forecasting—where methods are adapted based on project complexity—these practices are still developing.
3. Thirdly, the study discovered low stakeholder and employee involvement in forecasting processes and limited incorporation of DEI (diversity, equity, inclusion) considerations. This suggests a gap between theoretical best practices and organizational implementation.
4. Additionally, the results supported all four hypotheses. Forecasting accuracy positively correlated with workforce utilization (H2), integrated forecasting approaches resulted

Restricted - External

in higher stakeholder satisfaction (H3), and both data quality issues and resistance to change were identified as the strongest barriers to forecasting effectiveness (H4).

5.2 Conclusion

The research demonstrates that project environments show increasing use of HR forecasting yet more development opportunities exist through better implementation of advanced technologies, stakeholder involvement and planning inclusivity. Traditional forecasting methods continue to be preferred even though they are not necessarily more effective because organizations find them comfortable to use and they need minimal changes to existing systems. Project success depends on accurate forecasting which leads to better workforce utilization according to the study results. Project delivery times increase and costs rise while staff shortages occur when organizations use incorrect or obsolete forecasting systems. Stakeholder satisfaction reaches higher levels when organizations use integrated forecasting methods that unite data analytics with managerial expertise since these methods adapt better to specific organizational contexts.

Organizational culture together with data infrastructure play an essential part in determining the study's outcomes. The main barriers that hindered effective forecasting turned out to be employee reluctance to change combined with inadequate data quality. The results demonstrate that HR forecasting exists beyond technical procedures because it fundamentally integrates with how employees behave and their organizational systems and how they approach change.

The study demonstrates some alignment between stakeholder theory and contingency theory. Most organizations have not achieved full stakeholder engagement or client-employee need alignment in their forecasting processes which hinders stakeholder theory application even though some organizations successfully tailor their forecasting to specific contexts per contingency theory principles. The theoretical principles fail to match actual operational practices within Nigerian project-based organizations.

Restricted - External

The research results demonstrate that project organizations require strategic changes which focus on improving forecasting precision while implementing digital solutions and including stakeholders and adapting to organizational needs. The appropriate integration of these elements creates HR forecasting that delivers organizational value in project management.

5.3 Implications of Findings

The research results from this study create essential consequences for both theoretical aspects and practical applications within HR forecasting alongside project management. The findings demonstrate that forecasting systems which deliver accurate results lead to better workforce utilization thus proving their practical worth. Organizations without proper forecasting or outdated methods will create resource misalignment and fail to meet their project targets.

Organizations should implement integrated forecasting approaches since they enhance satisfaction among stakeholders according to confirmed evidence. Using judgment alone or algorithms by themselves reduces the potential effectiveness of forecast results. The need for combined human and data-driven forecasting methods finds support for the development of hybrid forecasting models that produce better accuracy and dynamic results.

The study calls for organizational transformation through the assessment of data quality and resistance to change as significant obstacles. Leadership needs to understand that quality forecasting depends on strong digital systems plus employees who embrace constant evolution. Any newly implemented forecasting innovation will face failure if the organization does not resolve its internal challenges.

The study findings support Contingency Theory because organizations need to adjust their forecasting strategies according to project dimensions such as complexity and size and environmental uncertainty levels. The observed low level of stakeholder involvement hinders the wider application of Stakeholder Theory because it shows organizations are not completely inclusive in their strategic planning processes.

Restricted - External

The executive leadership of human resources and project management must redesign their operational frameworks by adopting flexible approaches which include inclusive practices and data-based methods. The research provides academic researchers with new directions to explore cultural factors alongside leadership approaches and technological integration when studying forecasting success in various business sectors.

5.4 Contribution to the Study

The research results from this study generate important implications for theoretical and practical applications in HR forecasting together with project management. The findings demonstrate that forecasting systems which deliver accurate results lead to better workforce utilization thus proving their practical worth. Organizations without proper forecasting or outdated methods will create resource misalignment and fail to meet their project targets.

Higher stakeholder satisfaction emerges when organizations use forecasting methods which integrate multiple approaches according to research evidence. Using judgment alone or algorithms by themselves reduces the potential effectiveness of forecast results. Better forecasting outcomes are achievable when human intuition unites with data-driven methods through hybrid forecasting approaches.

The major barriers which include poor data quality and resistance to change demand organizations to conduct fundamental transformations. Leadership needs to acknowledge that successful forecasting depends on both modern technology as well as organizational flexibility toward change. Any newly implemented forecasting innovation will face failure if the organization does not resolve its internal challenges.

The study findings support Contingency Theory because organizations need to adjust their forecasting strategies according to project dimensions such as complexity and size and environmental uncertainty levels. The observed low level of stakeholder involvement hinders

Restricted - External

the wider application of Stakeholder Theory because it shows organizations are not completely inclusive in their strategic planning processes.

The executive leadership of human resources and project management must redesign their operational frameworks by adopting flexible approaches which include inclusive practices and data-based methods. The research provides academic researchers with new directions to explore cultural factors alongside leadership approaches and technological integration when studying forecasting success in various business sectors.

5.5 Recommendations

Based on the findings and conclusions of this study, several practical recommendations are offered to enhance the effectiveness of HR forecasting in project management contexts:

1. Organizations should prioritize the use of integrated approaches that combine managerial judgment with AI-based tools. This hybrid model improves forecasting accuracy and responsiveness by leveraging both experience and data-driven insights.
2. Reliable forecasting depends on clean, accessible, and timely data. Organizations must implement robust HR Information Systems (HRIS) and enforce data governance protocols to ensure the integrity of forecasting inputs.
3. Resistance to change was found to be a major barrier. Leadership should champion change initiatives, provide continuous training, and communicate the strategic value of forecasting to all levels of staff to increase buy-in and adoption.
4. Project managers, department heads, and employees should be actively involved in the forecasting process. Their input ensures that forecasts reflect real operational needs and employee expectations, improving both accuracy and satisfaction.
5. Organizations should begin to incorporate diversity, equity, and inclusion considerations into forecasting models. This can help identify and close representation gaps and support more equitable workforce planning.

Restricted - External

6. Forecasting models should not be static. Organizations must establish frameworks for evaluating model performance and updating parameters based on project outcomes, market shifts, and organizational learning.

Restricted - External

REFERENCES

Adeleye, I. and Eboagu, C. (2019). Human capital development in Africa: The challenges and prospects. In: I. Adeleye, L. Esposito and K. Adjibolosoo, eds., The Changing Dynamics of International Business in Africa. London: Palgrave Macmillan, pp. 87–108.

Adeleye, I., Esan, O. & Adewuyi, A. (2020). *Digital HRM in Africa: Challenges and Prospects*. African Journal of Business and Economic Research, 15(1), pp.23–45.

Aguinis, H., Edwards, J. & Bradley, K. (2017). Improving our understanding of moderation and mediation in strategic management research. *Organizational Research Methods*, 20(4), pp.665–685.

Akinyemi, B. and Adejumo, O. (2018). Human Resource Planning and Organizational Effectiveness in Nigerian Commercial Banks. International Journal of Economics, Commerce and Management, 6(7), pp.18–31.

AMACOM. Boxall, P. and Purcell, J. (2016). Strategy and Human Resource Management. 4th ed. London: Palgrave.

Armstrong, M. and Taylor, S. (2020). Armstrong's Handbook of Human Resource Management Practice. 15th ed. London: Kogan Page.

Bechet, T.P. (2008). Strategic Workforce Planning: Developing Optimized Talent Strategies for Future Growth. New York: AMACOM.

Bersin, J. (2013). Big data in human resources: Talent analytics (people analytics) comes of age. Forbes. [online] Available at: https://www.forbes.com [Accessed 10 May 2025].

Bersin, J. (2017). *HR Technology Disruptions for 2018: Productivity, Design and Intelligence Reign*. Oakland, CA: Bersin by Deloitte.

Binns, R. (2018). Fairness in machine learning: Lessons from political philosophy. Proceedings of the 2018 Conference on Fairness, Accountability, and Transparency, pp.149–159.

Bondarouk, T. & Brewster, C. (2016). Conceptualising the future of HRM and technology research. *The International Journal of Human Resource Management*, 27(21), pp.2652–2671.

Boudreau, J. & Ramstad, P. (2007). *Beyond HR: The New Science of Human Capital*. Boston: Harvard Business Press.

Boudreau, J.W. and Cascio, W.F. (2017). Human capital analytics: Why are we not there? *Journal of Organizational Effectiveness: People and Performance,* 4(2), pp.119–126.

Boudreau, J.W. and Ramstad, P.M. (2007). Beyond HR: The New Science of Human Capital. Boston: Harvard Business School Press.

Bourne, L. (2015). Stakeholder Relationship Management: A Maturity Model for Organisational Implementation. London:

Boxall, P. and Purcell, J. (2016). Strategy and Human Resource Management. 4th ed. London: Palgrave.

Restricted - External

Brewster, C., Sparrow, P., Vernon, G. and Houldsworth, E. (2005). International Human Resource Management. London: Chartered Institute of Personnel and Development.

Burns, T. and Stalker, G.M. (1961). The Management of Innovation. London: Tavistock Publications.

Business. Hendrickson, A.R. (2003). Human resource information systems: Backbone technology of contemporary human resources. *Journal of Labor Research,* 24(3), pp.381–394.

Cascio, W.F. and Boudreau, J.W. (2016). The search for global competence: From international HR to talent management. Journal of World Business, 51(1), pp.103–114.

Clarkson, M.B.E. (1995). A stakeholder framework for analyzing and evaluating corporate social performance. Academy of Management Review, 20(1), pp.92–117.

Davenport, T.H., Guenole, N. & Harris, J. (2018). *The HR Analytics Advantage*. MIT Sloan Management Review, 59(4), pp.1–8.

Deloitte (2021) *COVID-19: HR Scenario Planning in Times of Crisis*. [online] Deloitte Nigeria. Available at: https://www2.deloitte.com/ng [Accessed 5 May 2025].

Deloitte (2021). 2021 Global Human Capital Trends. [online] Available at: https://www2.deloitte.com [Accessed 10 May 2025].

Dessler, G. (2020). Human Resource Management. 16th ed. Harlow: Pearson Education.

Donaldson, L. (2001). The Contingency Theory of Organizations. Thousand Oaks: Sage.

Donaldson, T. and Preston, L.E. (1995). The stakeholder theory of the corporation: concepts, evidence, and implications. Academy of Management Review, 20(1), pp.65–91.

Drucker, P.F. (1999). Management Challenges for the 21st Century. New York: Harper

Dyer, L. and Reeves, T. (1995). Human resource strategies and firm performance: what do we know and where do we need to go? International Journal of Human Resource Management, 6(3), pp. 656–670.

Fiedler, F.E. (1967). A Theory of Leadership Effectiveness. New York: McGraw-Hill.

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F. and Schafer, B. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. Minds and Machines, 28(4), pp.689–707.

Freeman, R.E. (1984). Strategic Management: A Stakeholder Approach. Boston: Pitman.

Freeman, R.E. (2010). *Strategic Management: A Stakeholder Approach*. Cambridge: Cambridge University Press.

Freeman, R.E., Harrison, J.S., Wicks, A.C., Parmar, B.L. and de Colle, S. (2010). Stakeholder Theory: The State of the Art. Cambridge: Cambridge University Press.

Restricted - External

Friedman, A.L. and Miles, S. (2006). Stakeholders: Theory and Practice. Oxford: Oxford University Press.

Galbraith, J.R. (1973). Designing Complex Organizations. Reading: Addison-Wesley.

Ginsberg, A. and Venkatraman, N. (1985). Contingency perspectives of organizational strategy: a critical review of the empirical research. Academy of Management Review, 10(3), pp. 421–434.

Ginsberg, A. and Venkatraman, N. (1985). Contingency perspectives of organizational strategy: a critical review of the empirical research. Academy of Management Review, 10(3), pp.421–434.

Gordon, T.J. (1994). The Delphi method. Futures Research Methodology, 2(2), pp.1–30.

Gower. Bryson, J.M. (2004). What to do when stakeholders matter: Stakeholder identification and analysis techniques. Public Management Review, 6(1), pp.21–53.

Greenwood, M. and Van Buren, H.J. (2010). Trust and stakeholder theory: trustworthiness in the organisation–stakeholder relationship. Journal of Business Ethics, 95(3), pp.425–438.

Harris, J.G., Craig, E. and Light, D.A. (2010). Talent and analytics: New approaches, higher ROI. Journal of Business Strategy, 31(6), pp.22–30.

Harzing, A. & Pinnington, A.H. (2011). *International Human Resource Management*. 3rd ed. London: Sage.

Hendrickson, A.R. (2003). Human resource information systems: Backbone technology of contemporary human resources. Journal of Labor Research, 24(3), pp.381–394.

Highsmith, J. (2009). Agile Project Management: Creating Innovative Products. 2nd ed. Boston: Addison-Wesley.

Igomu, M.D., Ozah, J.P. and John, F. (2023) 'Hybrid work models and employee productivity in Hewlett-Packard Nigeria', *Nigerian Journal of Management Sciences*, 24(2b), pp.222–228.

International Labour Organization (2021) *World Employment and Social Outlook*. Geneva: ILO.

Jackson, S.E., Schuler, R.S. and Werner, S. (2012). Managing Human Resources. 11th ed. Mason: South-Western Cengage Learning.

Jensen, M.C. (2002). Value maximization, stakeholder theory, and the corporate objective function. Business Ethics Quarterly, 12(2), pp.235–256.

Jobberman (2021) *The Future of Work in Nigeria: Workforce Trends Post-COVID*. Lagos: Jobberman Nigeria.

Kahneman, D. (2011). Thinking, Fast and Slow. New York: Farrar, Straus and Giroux.

Kamoche, K. (2000). From boom to bust: The challenges of managing people in Nigeria. International Journal of Human Resource Management, 11(4), pp. 784–806.

Kaplan, A. and Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Business Horizons, 62(1), pp.15–25.

Restricted - External

Kenku, A.A. and Ogunkuade, I.M. (2024) ‘The state of human resource management in Nigeria: A review of 21st-century trends, issues, and strategic solutions’, *Journal of Humanities and Social Policy*, 10(5), pp.143–158.

Kerzner, H. (2017). Project Management: A Systems Approach to Planning, Scheduling, and Controlling. 12th ed. Hoboken: Wiley.

Kerzner, H. (2022). Innovation Project Management: Methods, Case Studies, and Tools for Managing Innovation Projects. Hoboken: Wiley.

Kotter, J.P. (1996). Leading Change. Boston: Harvard Business School Press.

Kotter, J.P. and Schlesinger, L.A. (2008). Choosing strategies for change. Harvard Business Review, 86(7/8), pp.130–139.

KPMG (2020) *COVID-19 and the Nigerian Telecommunications, Media and Technology Sector*. Lagos: KPMG Advisory Services.

Lawler, E.E. and Boudreau, J.W. (2015). Global Trends in Human Resource Management: A Twenty-Year Analysis. Stanford: Stanford University Press.

Linstone, H.A. and Turoff, M. (2002). The Delphi Method: Techniques and Applications. Reading, MA: Addison-Wesley.

Marler, J.H. & Boudreau, J.W. (2017). An evidence-based review of HR Analytics. *The International Journal of Human Resource Management*, 28(1), pp.3–26.

Miles, S. (2006). Stakeholders: Theory and Practice. Oxford: Oxford University Press.

Milkovich, G.T. and Boudreau, J.W. (1994). Human Resource Management. 6th ed. Homewood: Irwin.

Minbaeva, D. (2018). Building credible human capital analytics for organizational competitive advantage. Human Resource Management, 57(3), pp.701–713.

Mitchell, R.K., Agle, B.R. and Wood, D.J. (1997). Toward a theory of stakeholder identification and salience: defining the principle of who and what really counts. Academy of Management Review, 22(4), pp.853–886.

MTN Nigeria (2020) *An Enabled Workplace – Lessons from Deploying a Remote Workforce*. Lagos: MTN Nigeria.

Nwankwo, E.C. (2022). Developing Data-Driven HR Professionals in Nigeria: Challenges and Opportunities. *West African Journal of Business Research*, 8(2), pp.101–117.

Ogunyemi, K. & Akinlabi, H. (2020). Strategic integration of HR analytics in Nigerian organizations. *African Management Review*, 10(3), pp.1–18.

Okoli, C. and Pawlowski, S.D. (2004). The Delphi method as a research tool: an example, design considerations and applications. Information & Management, 42(1), pp.15–29.

Okpara, J.O. and Wynn, P. (2008). Human resource management practices in a transition economy: Challenges and prospects. Management Research News, 31(1), pp.57–76.

Onyemere, I., Alo, O., Origho, O. and Okeke, A. (2024) ‘The adoption of remote working practices in the Nigerian banking sector: Are they ready?’, *International Journal of Management, Economics and Social Sciences*, 13(3–4), pp.91–115.

Osibanjo, A.O., Adeniji, A.A., Falola, H.O. and Heirsmac, P.T. (2014). Compensation packages: A strategic tool for employees’ performance and retention in telecoms

Restricted - External

industry in Nigeria. Journal of Education and Human Development, 3(2), pp.73–82.

Palgrave. Burns, T. and Stalker, G.M. (1961). The Management of Innovation. London:

Pfeffer, J. & Sutton, R.I. (2006). *Hard Facts, Dangerous Half-Truths, and Total Nonsense: Profiting from Evidence-Based Management*. Boston: Harvard Business School Press.

Phillips, R., Freeman, R.E. and Wicks, A.C. (2003). What stakeholder theory is not. Business Ethics Quarterly, 13(4), pp.479–502.

Pinto, J.K. (2020). Project Management: Achieving Competitive Advantage. 5th ed. Boston: Pearson.

PMI (Project Management Institute) (2021). A Guide to the Project Management Body of Knowledge (PMBOK Guide). 7th ed. Newtown Square, PA: PMI.

PwC (2021). Nigeria Workforce of the Future Survey. [online] Available at: https://www.pwc.com/ng [Accessed 10 May 2025].

Rousseau, D.M. (2001). Schema, promise and mutuality: The building blocks of the psychological contract. Journal of Occupational and Organizational Psychology, 74(4), pp.511–541.

Rowe, G. and Wright, G. (1999). The Delphi technique as a forecasting tool: issues and analysis. International Journal of Forecasting, 15(4), pp.353–375.

Sanusi, L.S. (2011). Banking reform and its impact on the Nigerian economy. CBN Journal of Applied Statistics, 2(1), pp.89–107.

Schuler, R.S. and Jackson, S.E. (1987). Linking competitive strategies with human resource management practices. Academy of Management Executive, 1(3), pp.207–219.

Serrador, P. and Pinto, J.K. (2015). Does Agile work? A quantitative analysis of agile project success. International Journal of Project Management, 33(5), pp.1040–1051.

SHRM Nigeria (2022) *Managing Remote Teams in Nigeria: Trends and Best Practices*. Abuja: Society for Human Resource Management Nigeria.

Söderlund, J. (2011). Pluralism in project management: navigating the crossroads of specialization and fragmentation. International Journal of Management Reviews, 13(2), pp. 153–176.

Tambe, P., Cappelli, P. & Yakubovich, V. (2019). Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. *California Management Review*, 61(4), pp.15–42.

Turner, J.R. (2019). The Handbook of Project-Based Management. 4th ed. New York: McGraw-Hill.

Turner, J.R. (2019). The Handbook of Project-Based Management. 4th ed. New York: McGraw-Hill.

Turner, J.R. (2019). The Handbook of Project-Based Management. 4th ed. New York: McGraw-Hill.

Ulrich, D. & Dulebohn, J.H. (2015). Are we there yet? What's next for HR? *Human Resource Management*, 54(2), pp.185–204.

Restricted - External

Ulrich, D., Younger, J., Brockbank, W. and Ulrich, M. (2012). HR from the Outside In: Six Competencies for the Future of Human Resources. New York: McGraw-Hill.

Umezinwa, F. (2022) 'Labour law reforms and the future of work in Nigeria', *Nigerian Journal of Industrial Law*, 3(2), pp.77–98.

Van de Ven, A.H. and Drazin, R. (1985). The concept of fit in contingency theory. Research in Organizational Behavior, 7, pp. 333–365.

Van den Broek, J., Bos-Nehles, A. & Janssen, M. (2021). Implementing people analytics: a critical review. *Journal of Organizational Effectiveness: People and Performance*, 8(1), pp.88–107.

Vincent, B.D. (2021) 'Effect of COVID-19 lockdown on human resource performance on deposit money banks in Yola metropolis', *Global Journal of Human Resource Management*, 9(4), pp.1–10.

Walker, J.W. (1980). Human Resource Planning. New York: McGraw-Hill.

Wright, P.M. and McMahan, G.C. (2011). Exploring human capital: putting 'human' back into strategic human resource management. Human Resource Management Journal, 21(2), pp.93–104.

Zhao, Y., Li, X. and Wang, Q. (2023). Adaptive HR forecasting in emerging markets: empirical evidence from sub-Saharan Africa. Human Resource Planning Journal, 46(1), pp. 17–38.

Restricted - External

Questionnaire

A. General HR Forecasting Practices

Item No.	Question Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
A1	Our organization uses structured HR forecasting techniques to anticipate workforce needs for each project.	☐	☐	☐	☐	☐
A2	HR forecasting is consistently integrated with our project planning and scheduling processes.	☐	☐	☐	☐	☐
A3	We use both short-term and long-term HR forecasts to support project staffing decisions.	☐	☐	☐	☐	☐
A4	Our HR forecasting methods have resulted in improved project outcomes (e.g., timely delivery, reduced turnover, cost control).	☐	☐	☐	☐	☐

B. Integration of AI-Driven Analytics

Item No.	Question Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
B1	We use predictive analytics or AI tools (e.g., attrition models, skill match algorithms) in our HR forecasting process.	☐	☐	☐	☐	☐
B2	Our organization has real-time HR dashboards that provide forecasting insights to project managers.	☐	☐	☐	☐	☐
B3	AI-based forecasting tools have improved the accuracy of our workforce projections compared to traditional methods.	☐	☐	☐	☐	☐
B4	There is sufficient training and support for HR and project teams to interpret and apply AI-generated forecasts.	☐	☐	☐	☐	☐

C. Application of Contingency Theory

Item No.	Question Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
C1	Our forecasting approach adapts based on project complexity, size, or duration.	☐	☐	☐	☐	☐

Restricted - External

C2	In uncertain environments (e.g., economic volatility, tight labor markets), we adjust our workforce forecasts accordingly.	☐	☐	☐	☐	☐
C3	We use multiple forecasting techniques (e.g., trend analysis, managerial judgment, AI) depending on the project context.	☐	☐	☐	☐	☐
C4	Our HR forecasting practices are flexible and responsive to project-specific contingencies.	☐	☐	☐	☐	☐

D. Stakeholder Theory and Inclusive Forecasting

Item No.	Question Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
D1	Key project stakeholders (e.g., project managers, department heads) are actively involved in the HR forecasting process.	☐	☐	☐	☐	☐
D2	We consider employee preferences (e.g., remote work, flexible hours) when forecasting future workforce needs.	☐	☐	☐	☐	☐
D3	Client or customer expectations are taken into account during workforce planning for projects.	☐	☐	☐	☐	☐
D4	Our forecasting process aligns with diversity, equity, and inclusion (DEI) objectives and considers demographic goals.	☐	☐	☐	☐	☐

E. Forecasting Outcomes and Evaluation

Item No.	Question Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
E1	We regularly review and update our HR forecasting models based on project performance outcomes.	☐	☐	☐	☐	☐
E2	Our organization has a standardized framework for evaluating the effectiveness of HR forecasting in improving project success.	☐	☐	☐	☐	☐

Restricted - External