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Linking HR Analytics to Organizational Performance: The Mediating Roles of HR Decision Making and Talent Management

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Abstract: *This study examines how Human Resource Analytics (HRA) influences Organizational Performance (OP) through the mediating roles of HR Decision Making (HRDM) and Talent Management (TM), drawing on the Resource-Based View (RBV) and Dynamic Capabilities Theory. Using a quantitative, deductive, cross-sectional design, data were collected from 157 HR professionals, executives, and line managers in mid- to large-sized Bangladeshi organizations through a validated self-administered questionnaire. CFA and CB-SEM (AMOS 24) were used to assess measurement validity and test structural paths. Results showed acceptable reliability and validity but indicated that HRA has no significant direct or indirect effect on OP via HRDM or TM. The insignificant mediating effects suggest that HRA alone cannot improve performance without factors such as leadership engagement, organizational readiness, analytical capability, and a data-driven culture. The study highlights the importance of contextual enablers, including technology proficiency, human capital skills, and managerial openness to analytics-based decisions. It contributes evidence from a developing country, showing how institutional and infrastructural barriers limit HRA's impact. The study refines RBV and Dynamic Capabilities Theory by positioning HRA as a conditional resource. Limitations include the cross-sectional design, sample size, and reliance on perceptual data.*

Keywords: *Human Resource Analytics, Talent Management, HR Decision Making, Organizational Performance, Resource-Based View, Dynamic Capabilities Theory.*

I. INTRODUCTION

Human Resource Analytics (HRA) has emerged as a transformative capability reshaping how organizations manage people and make strategic decisions in an increasingly data-driven world. Recent research emphasizes that HRA revolutionizes traditional human resource management (HRM) by embedding analytical rigor into decision-making and strategic planning (Andreassen et al., 2024). Through the integration of advanced statistical methods, predictive models, and business intelligence tools, HRA enables organizations to convert workforce data into actionable insights that enhance efficiency and competitiveness (Zebua et al., 2024). Empirical evidence has demonstrated that the adoption of HR analytics can lead to lower turnover, higher productivity, and improved hiring accuracy (Tessema et al., 2025). Yet, despite its recognized potential, global adoption remains inconsistent. A survey of more than 1,200 HR professionals revealed that only 20% expected analytics to become a major HR initiative, and merely 12% regarded it as a top management priority (Nair, 2020). This paradox of high potential but low implementation highlights the need to understand how HRA can be effectively utilized to enhance organizational performance, particularly in developing contexts like Bangladesh, where technological adaptation and resource limitations remain significant challenges.

HRA is defined as the systematic collection, evaluation, and interpretation of workforce data to guide evidence-based HR actions (Zebua et al., 2024). It encompasses two crucial managerial dimensions: HR decision making and talent management, which represent the internal processes through which analytics may influence organizational outcomes. HR decision making refers to data-informed choices in staffing, performance evaluation, compensation, and retention (Salehzadeh & Ziaeian, 2024), while talent management involves strategic activities aimed at attracting, developing, and retaining high-performing employees (Paul & Khan, 2024). Although prior studies have identified positive associations between HR analytics and improved organizational results (Andreassen et al., 2024), the internal mechanisms linking analytics to performance are still underexplored. To address this theoretical gap, this study conceptualizes HR analytics as the independent variable, organizational performance as the dependent variable, and HR decision making and talent management as mediators within a dual-mediation framework.

The need for this investigation arises from significant inconsistencies in both theory and practice. Despite increasing global investment in analytics capabilities, more than 60% of organizations still face data integration challenges, and only one-fourth have access to high-quality workforce data (Deloitte, 2024). Gallup (2024) also reports that employee engagement and retention remain critical HR challenges, even in analytics-driven firms. Much of the prior research remains descriptive, lacking empirical testing of causal mechanisms between analytics and performance (Álvarez-Gutiérrez et al., 2022). This study aims to fill that gap by examining how HRA affects organizational performance through its influence on HR decision making and talent management. Theoretically, it advances the Resource-Based View (Barney, 1991), Human Capital Theory (Becker, 1964), and Dynamic Capabilities Theory (Teece, 2007), framing analytics as a strategic capability that transforms HR from a reactive administrative function into a proactive, value-creating process. Practically, it offers insights for HR professionals and leaders seeking to develop evidence-based HR systems that improve decision quality, talent optimization, and performance outcomes (Mondore et al., 2011). The evolution of HR analytics has been instrumental in transforming the HR function into a strategic partner. Historically, HR departments primarily handled administrative tasks such as payroll, compliance, and employee relations, often relying on intuition rather than data (Marler & Boudreau, 2017). The introduction of analytics has shifted this paradigm by enabling predictive and prescriptive models that forecast attrition, identify high-potential employees, and anticipate workforce needs (Angrave et al., 2016). This transformation allows HR to contribute to corporate strategy through measurable, evidence-based insights that drive productivity and innovation (Davenport et al., 2010). Analytics-based HR functions now enhance both operational and strategic dimensions by reducing bias in decision making and aligning human capital investments with organizational objectives.

Empirical research supports the role of analytics in strengthening decision-making and talent management systems. van den Heuvel and Bondarouk (2016) found that the use of HR analytics positively affected perceived HR performance, which subsequently improved organizational outcomes. Similarly, Huselid (2018) reported that firms using analytics-driven HR practices achieved higher productivity and profitability. However, most studies treat HRA as a direct driver of performance, offering limited understanding of how analytics translates into tangible outcomes. As Marler and Boudreau (2017) argue, HR analytics remains a "black box," lacking clarity about the internal pathways through which its value is realized. This study addresses that theoretical ambiguity by proposing HR decision making and talent management as dual mediating mechanisms that explain how analytics influences organizational performance. The context of Bangladesh presents an important setting for this investigation. Bangladesh's economy is rapidly expanding, with sectors such as ready-made garments (RMG), banking, and telecommunications facing intense competition and labor market volatility. Yet, the use of HR analytics within Bangladeshi organizations remains at an early stage (Hossain & Mahmood, 2021). Many firms continue to rely on conventional HR practices, hindered by limited infrastructure, poor data quality, and a shortage of analytical expertise (Khokon & Hossain, 2020). While a few leading organizations have begun integrating analytics into HR processes, the overall adoption rate remains low, offering a valuable opportunity to explore how analytics-driven HR practices can enhance performance in an emerging economy. Understanding these dynamics is essential for organizations that aim to strengthen competitiveness and sustain long-term growth in a globalized environment.

Despite the growing interest in HR analytics, major research gaps persist. Previous studies have focused largely on direct effects of analytics on outcomes such as profitability and productivity (Huselid, 2018; Marler & Boudreau, 2017), neglecting the mediating processes that convert analytical insights into performance outcomes. The absence of empirical evidence on mediating mechanisms, specifically HR decision making and talent management, limits theoretical progress (Minbaeva, 2018). Moreover, the concentration of research in developed economies (Falletta & Combs, 2020) restricts its applicability to emerging contexts. Considering that Bangladesh differs in management orientation, technological readiness, and labor market structure (Hossain & Mahmood, 2021), studying these relationships in this context is both timely and necessary. Thus, this study addresses theoretical, empirical, and contextual gaps by testing a model that explores how HR analytics influences organizational performance through HR decision making and talent management within Bangladeshi firms. To achieve this aim, the study sets four specific objectives: to examine the direct effect of HR analytics on organizational performance, to investigate the mediating role of HR decision making, to assess the mediating role of talent management, and to explore the joint mediating effects of both variables. Corresponding research questions are formulated to determine how and to what extent HR analytics contributes to performance improvement. Addressing these questions will help clarify how data-driven HR practices foster competitiveness and performance in developing economies. The remainder of this article is structured as follows: the next section presents the literature review and hypothesis development, followed by the research methodology, results and discussion, and finally, the implications, limitations and future directions.

II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Human Resource Analytics

Human Resource Analytics (HRA) represents a major transformation in human resource management, moving from intuition-based practices to evidence-driven decision-making. Marler and Boudreau (2017) define it as "a practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to human resources processes, human capital, organizational performance, and external benchmarks to establish business impact and enable data-driven decision-making." HRA collects and interprets workforce data to enhance recruitment, training, and retention strategies. It operationalizes the Resource-Based View (RBV) by maximizing the value of human capital while aligning with Human Capital Theory through data-driven workforce investments (Andreassen et al., 2024). HRA has evolved from descriptive reporting to advanced predictive and prescriptive analytics that forecast talent needs and organizational outcomes (Angrave et al., 2016). Empirical research shows that analytics adoption reduces turnover, improves productivity, and strengthens HR's strategic role (Tessema et al., 2025). McCartney and Fu (2022) established that analytics promotes evidence-based management, linking HR technology and performance improvement. Moreover, HR analytics enhances the strategic contribution of HR by identifying skill gaps, optimizing workforce planning, and aligning HR initiatives with business goals (Nair, 2020). Modern organizations use HRA to address complex workforce challenges through quantitative insights rather than subjective intuition. Analytics allows HR professionals to design predictive models of attrition, analyze engagement trends, and support fair compensation planning (Rasmussen & Ulrich, 2015). In this way, HR analytics serves as a strategic capability that enhances agility, innovation, and sustained competitiveness in dynamic business environments.

Talent Management

Talent Management (TM) refers to a structured and strategic process for attracting, developing, and retaining high-potential employees who drive business performance. It integrates all HR activities such as recruitment, training, succession planning, and retention to ensure that organizational objectives are achieved efficiently (Andreassen et al., 2024). As competition intensifies globally, TM has become vital for workforce sustainability. Marler and Boudreau (2017) observed that only a small number of firms have formalized TM strategies, while Suharso and Rahman (2025) highlighted that merely 3–5 percent of employees qualify as high-potential talent, indicating critical shortages. TM enhances firm performance by ensuring the right people occupy the right roles at the right time. Collings et al. (2019) argue that effective TM practices help organizations retain key talent and develop leaders to meet future demands. Since the "War for Talent" identified human capital as the primary source of competitive advantage, firms have recognized TM as essential to innovation and resilience. Subramaniam (2018) found that well-implemented TM improves job satisfaction, commitment, and productivity. Analytics complements TM by providing data that identifies high performers, predicts turnover, and aligns training with strategic goals. By combining data-driven insights with employee development programs, analytics transforms TM into a capability that satisfies the VRIN criteria of RBV (Barney, 1991). Consequently, effective TM systems create long-term value through enhanced engagement, retention, and adaptability.

HR Decision Making

HR Decision Making (HRDM) involves the systematic use of information to determine HR policies and actions. Salehzadeh et al. (2024) define it as a multifaceted process encompassing staffing, compensation, and retention decisions that influence overall performance. With increasing organizational complexity, HRDM has evolved from experience-based judgment to evidence-based decision frameworks supported by analytics. HR leaders are now regarded among the most influential decision-makers, second only to top executives (AIHR, 2024). Effective HRDM contributes directly to profitability, productivity, and employee satisfaction. Dubey (2023) reported that organizations using structured decision frameworks achieved 21 percent higher profitability and 17 percent productivity gains. Analytics enhances HRDM by ensuring transparency and reducing bias through data-informed evaluations of training, recruitment, and performance. Abubakar et al. (2019) found that HRDM mediates the relationship between analytics and performance, translating insights into organizational outcomes. Analytical tools such as the Analytic Hierarchy Process (AHP) and Fuzzy Analytic

Hierarchy Process (FAHP) improve objectivity in employee selection and evaluation (Kure, 2025). HRDM therefore represents the mechanism through which analytics capabilities are converted into strategic and measurable results, driving operational excellence and continuous improvement.

Organizational Performance

Organizational Performance (OP) represents the extent to which a firm achieves its strategic and operational goals. Richard et al. (2009) defines it as the actual output compared with intended objectives, including financial measures like ROI and non-financial indicators such as customer satisfaction and innovation. Akal (1992) explains that performance reflects how effectively activities serve their purpose, linking efficiency with strategic alignment. HR analytics enhances OP by improving decision-making quality, optimizing talent deployment, and ensuring the alignment of human capital with strategic goals (Abubakar et al., 2019). Nitzl et al. (2019) demonstrated that analytics-driven TM improves employee engagement, retention, and innovation. Firms adopting analytics report higher adaptability and profitability, while Wood and Ogbonnaya (2018) confirmed that high-performance work systems enhance value for both employees and employers. Performance management supported by analytics leads to better measurement, stronger accountability, and higher ROI. Paul and Khan (2024) emphasized that integrated systems linking HR analytics, TM, and decision-making foster organizational resilience, allowing firms to sustain competitive advantage in dynamic markets.

Theoretical Foundation

This study builds upon two interrelated theories: the Resource-Based View (RBV) and Dynamic Capabilities Theory (DCT). The RBV asserts that sustainable competitive advantage arises from resources that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). Human capital represents a strategic resource that meets these criteria when effectively managed. HR analytics enhances this capability by converting workforce data into insights that improve recruitment, retention, and development. Talent management and HR decision making are the key processes through which analytics translates human capital into organizational value (Wright et al., 2014). Dynamic Capabilities Theory expands the RBV by explaining how firms adapt and reconfigure resources to respond to rapid environmental changes (Teece, 2018). It identifies sensing, seizing, and transforming as the mechanisms of renewal. HR analytics functions as a sensing tool that identifies workforce trends, HR decision making represents seizing through data-informed choices, and talent management reflects transforming by aligning the workforce with evolving business needs. Together, these theories explain how analytics-driven HR functions generate sustained organizational performance.

Conceptual Framework

Based on the theoretical foundation, the proposed framework suggests that HR analytics influences organizational performance both directly and indirectly through HR decision making and talent management. These mediators represent the mechanisms that operationalize the value of analytics in organizational contexts.

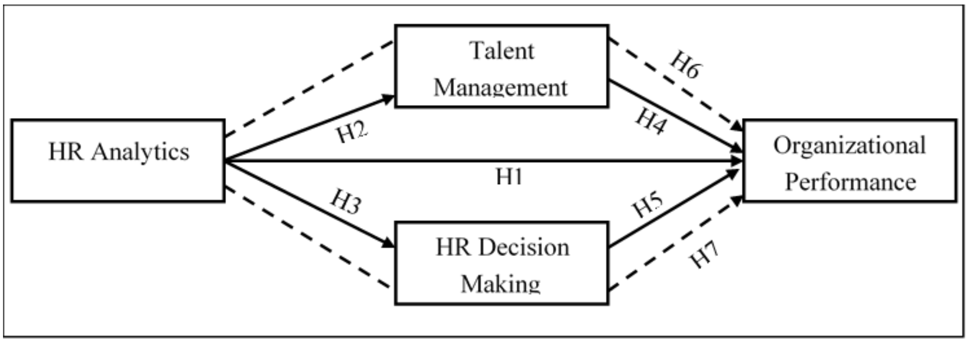

Fig 1: Conceptual Framework

Hypothesis Development

Drawing upon RBV and DCT, the following hypotheses are proposed. HR analytics strengthens performance by improving decision quality, optimizing resource allocation, and enhancing productivity. Through data analysis on employee engagement and capability gaps, organizations can align HR strategies with corporate goals, leading to improved efficiency and profitability (Marler & Boudreau, 2017; Huselid, 2018). Based on this evidence, the following hypothesis is proposed:

H1: HR Analytics has a positive and significant direct effect on Organizational Performance.

Analytics supports talent acquisition, development, and retention by providing data that identifies potential, forecasts attrition, and tailors' development programs (King, 2016; Collings & Mellahi, 2013). By aligning human capital initiatives with business needs, HR analytics ensures an effective and competitive workforce. Therefore, the following hypothesis is proposed:
H2: HR Analytics has a positive and significant direct effect on Talent Management.

Integrating analytics into HRDM replaces intuition with objective evidence. Data enables managers to assess training ROI, forecast hiring success, and optimize workforce allocation (Boudreau & Cascio, 2017). Analytics-driven HR decisions foster fairness, transparency, and strategic consistency across HR functions. Based on this evidence, the following hypothesis is proposed:
H3: HR Analytics has a positive and significant direct effect on HR Decision Making.

Effective TM enhances organizational success by cultivating a motivated and capable workforce. Drawing from RBV, superior TM practices create human capital that is valuable and inimitable, leading to sustained advantage (Barney, 1991; Huselid, 2018). Therefore, the following hypothesis is proposed:
H4: Talent Management has a positive and significant direct effect on Organizational Performance.

Evidence-based decisions regarding staffing, rewards, and development improve workforce alignment and engagement, which directly boost productivity and profitability (Pfeffer & Sutton, 2006). High-quality HR decisions ensure efficient use of human resources and strengthen strategic execution. Based on this evidence, the following hypothesis is proposed:
H5: HR Decision Making has a positive and significant direct effect on Organizational Performance.

Analytics contributes to performance through its enhancement of TM processes. Insights gained from analytics improve recruitment precision, succession planning, and employee retention, leading to higher overall performance (Minbaeva, 2018). TM thus serves as a channel through which analytics translates into competitive advantage. Therefore, the following hypothesis is proposed:
H6: Talent Management mediates the relationship between HR Analytics and Organizational Performance.

From a DCT perspective, HRDM operationalizes analytics by transforming insights into actionable strategies (Teece et al., 1997). Analytics-based decision systems improve agility and responsiveness, enabling organizations to achieve performance excellence through effective human capital management. Based on this evidence, the following hypothesis is proposed:
H7: HR Decision Making mediates the relationship between HR Analytics and Organizational Performance.

Collectively, these hypotheses explain the direct and indirect effects of HR analytics on organizational performance. They aim to unpack the "black box" of analytics by demonstrating how HRDM and TM function as critical mediators. Testing this model contributes both theoretically, by clarifying causal pathways, and practically, by guiding organizations in leveraging analytics for improved performance in developing contexts such as Bangladesh.

III. METHODOLOGY

This study employed a quantitative, cross-sectional survey design to examine the relationships among Human Resource Analytics (HRA), Talent Management (TM), HR Decision Making (HRDM), and Organizational Performance (OP). The positivist paradigm guided this research, focusing on objectivity, numerical data, and hypothesis testing (Creswell, 2014). The quantitative approach was appropriate for testing the causal and mediating relationships proposed in the conceptual framework. Data were collected from HR professional, line managers across different organizations in Bangladesh, including manufacturing, telecommunications, and service sectors. The study used a structured questionnaire to gather responses from individuals directly involved in HR and operational decision-making. A total of 170 questionnaires were distributed both physically and online, and 157 valid responses were retained after data screening, representing a 92.4% response rate. Purposive sampling was employed to ensure participation by respondents knowledgeable about HR policies and analytics practices. The sample size met the statistical adequacy criteria for structural equation modeling, which requires at least 5 to 10 responses per indicator variable (Hair et al., 2019). Data were collected over a three-month period, ensuring diversity in respondent demographics and organizational backgrounds. Participation was voluntary, and respondents were informed about the academic purpose of the study, which helped minimize response bias and ensure reliability.

The survey instrument comprised two parts: demographic details and measures of the study constructs. The constructs included HR Analytics, Talent Management, HR Decision Making, and Organizational Performance. All items were adapted from established scales used in previous research to ensure content validity and alignment with theoretical definitions. HR Analytics was measured using items from Angrave et al. (2016) and Rasmussen and Ulrich (2015), capturing the extent of analytical integration in HR decisions, performance tracking, and predictive planning. Talent Management items were adapted from Collings et al. (2019) and Subramaniam (2018), focusing on attracting, developing, and retaining high-potential employees. HR Decision Making was measured using scales from Salehzadeh et al. (2024) and Abubakar et al. (2019), reflecting evidence-based decisions in staffing, compensation, and development. Organizational Performance was assessed using items adapted from Richard et al. (2009) and Huselid (2018), covering both financial and non-financial indicators such as productivity, employee engagement, and overall effectiveness. All constructs were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The reliability and validity of the measurement scales were examined using Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). Cronbach's alpha values for all constructs exceeded 0.70 (Nunnally & Bernstein, 1994), confirming internal consistency. Factor loadings were above 0.60, and AVE values exceeded the 0.50 benchmark (Fornell & Larcker, 1981), establishing convergent validity. Discriminant validity was confirmed as the square root of AVE for each construct was higher than its inter-construct correlations. Multicollinearity was assessed through variance inflation factors (VIF), which were below 3.0, indicating acceptable independence among variables. These results validated the reliability and validity of the constructs for further analysis.

Data were analyzed using SPSS (Version 26) for preliminary tests and AMOS (Version 24) for covariance-based structural equation modeling (CB-SEM). SPSS was used for descriptive analysis, data screening, and correlation testing. AMOS was employed to perform confirmatory factor analysis (CFA) and to test the structural model. Model fit was assessed using established indices such as Chi-square/df, CFI, TLI, GFI, and RMSEA. The model demonstrated an acceptable fit, with CFI and TLI values above 0.90, GFI above 0.85, and RMSEA below 0.08 (Hair et al., 2019). Structural paths were then analyzed to test the hypothesized relationships among HR Analytics, Talent Management, HR Decision Making, and Organizational Performance. Standardized path coefficients (β), critical ratios (C.R.), and significance levels (p-values) were used to interpret direct effects, while mediation effects were tested using bootstrapping with 5,000 resamples at a 95 percent confidence interval. Mediation was confirmed when the confidence interval did not include zero (Preacher & Hayes, 2008). The model's explanatory power was evaluated using R^2 values for the endogenous variables, reflecting the proportion of variance explained. Ethical considerations were carefully observed throughout the study. Respondents were assured of confidentiality, anonymity, and voluntary participation. Data were used solely for academic purposes in compliance with ethical standards recommended by the American Psychological Association.

IV. RESULTS AND FINDINGS

The preliminary analysis addressed data quality and assumptions. Out of 167 responses, six with random missing values were excluded (Sekaran and Bougie, 2016). Using Mahalanobis distance ($p < 0.000$) across 20 indicators, four extreme outliers were removed (Kline, 2011), leaving 157 valid cases. Normality was confirmed, with Skewness and Kurtosis within ±1 and ±3 (Byrne, 2016). Correlations were below 0.85, indicating no multicollinearity (Tabachnick et al., 2007). Harman's single-factor test showed one factor explaining 17.10% of the variance, confirming no significant common method variance.

Construct Reliability and Convergent Validity

The assessment of reliability and validity ensured that all measurement items met the statistical standards required for further analysis. Table 1 should be inserted here to summarize the results of Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and factor loadings for each construct. Cronbach's alpha values ranged from 0.785 to 0.853, all exceeding the threshold value of 0.70 (Nunnally & Bernstein, 1994), confirming internal consistency. Composite reliability values were between 0.87 and 0.91, indicating acceptable measurement precision. The AVE for each construct ranged from 0.60 to 0.66, meeting the minimum recommended value of 0.50 as per Fornell and Larcker (1981), thus establishing convergent validity. Factor loadings for individual items ranged from 0.62 to 0.77, demonstrating that all indicators contributed significantly to their respective latent variables. Discriminant validity was also confirmed, as the square root of AVE for each construct was greater than its correlations with other constructs, ensuring that the measures were conceptually distinct. These results collectively verified the measurement reliability and validity of the constructs.

Table 1: Construct Reliability and Convergent Validity

Construct		Factor Loadings	Cronbach Alpha	Composite Reliability	Average Variance Extracted AVE
	HR Analytics				
HRA1		0.62	0.785	0.87	0.63
HRA2		0.68			
HRA3		0.68			
HRA4		0.65			
HRA5		0.64			
	Talent Management				
TM1		0.63	0.800	0.88	0.60
TM2		0.62			
TM3		0.73			
TM4		0.77			
TM5		0.62			
	HR Decision Making				
HRDM1		0.68	0.844	0.89	0.62
HRDM2		0.77			
HRDM3		0.73			
HRDM4		0.73			
HRDM5		0.70			
	Organizational Performance				
OP1		0.77	0.853	0.91	0.66
OP2		0.74			
OP3		0.75			
OP4		0.67			
OP5		0.75			

Descriptive Statistics and Correlations

Descriptive statistics were computed to provide an overview of respondents' perceptions of HR Analytics, Talent Management, HR Decision Making, and Organizational Performance. The results showed that all constructs had mean values above the midpoint of 3.00, suggesting a positive perception among respondents regarding the implementation of HR analytics and its impact on organizational functions. Specifically, HR Analytics had a mean value of 3.97 (SD = 0.44), indicating moderate to high usage levels within organizations. Talent Management recorded a mean of 4.06 (SD = 0.46), reflecting strong agreement on practices related to attracting and retaining skilled employees. HR Decision Making showed a mean of 3.99 (SD = 0.48), suggesting that analytical data is increasingly being utilized in strategic HR decisions. Organizational Performance had the mean value of 3.99 (SD = 0.54), implying that respondents perceive a positive link between data-driven HR practices and performance outcomes. The correlations among variables were very low. All were less than 0.12. This means that each construct was empirically distinct, and there was no multicollinearity found.

Table 2: Descriptive Statistics and Correlations

Variables	1	2	3	4	Mean	SD
1. HR Analytics	-				3.97	0.44
2. Talent Management	0.105	-			4.06	0.46
3. HR Decision Making	-0.011	0.115	-		3.99	0.48
4. Organizational Performance	-0.012	0.008	-0.045	-	3.99	0.54

Confirmatory Factor Analysis

For Confirmatory Factor Analysis (CFA), this study followed Kline's (2011) to assess the values of model fit "i.e., $x^2/df < 3.0$, comparative fit index (CFI) ≥ 0.90, tucker–lewis index (TLI) ≥ 0.90, standardized root mean residual (SRMR) ≤ 0.10, and root mean square error of approximation (RMSEA) ≤ 0.08)." The measurement model of the study was found to be fit as per the suggested criteria i.e., $x^2/df = 1.54$, CFI = 0.957, TLI= 0.946, RMSEA = 0.054, SRMR = 0.048.

Hypothesis Testing

This section presents the CB-SEM results for the hypothesized relationships. Table 3 reports the standardized coefficients (β), standard errors (SE), 95% confidence intervals (CI), and hypothesis support status. Significance was evaluated at the 5% level, where CIs excluding zero indicate significance (Hair et al., 2019; Kline, 2011). The direct effect of HR Analytics on Organizational Performance was not significant (β = –0.018, SE = 0.129, 95% CI [–0.197, 0.160]). Similarly, HR Analytics showed no significant effect on Talent Management (β = 0.138, SE = 0.095, 95% CI [–0.083, 0.349]) or HR Decision Making (β = 0.000, SE = 0.104, 95% CI [–0.184, 0.184]). Talent Management also failed to significantly predict Organizational Performance (β = 0.041, SE = 0.139, 95% CI [–0.165, 0.246]), and HR Decision Making had no significant effect on performance (β = –0.048, SE = 0.116, 95% CI [–0.218, 0.133]).

Table 3: Results of Hypothesis Testing

Variables	β	S.E.	Bootstrapping at 95%		Conclusion
			Lower	Upper	
Direct Effect					
HRA -> OP	-0.018	0.129	-0.197	0.160	Not Significant
HRA -> TM	0.138	0.095	-0.083	0.349	Not Significant
HRA -> HRDM	0.000	0.104	-0.184	0.184	Not Significant
TM -> OP	0.041	0.139	-0.165	0.246	Not Significant
HRDM -> OP	-0.048	0.116	-0.218	0.133	Not Significant
Indirect Effect					
HRA -> TM -> OP	0.007	0.028	-0.024	0.110	Not Significant
HRA ->HRDM -> OP	0.000	0.013	-0.027	0.027	Not Significant

Regarding mediation, neither Talent Management (β = 0.007, SE = 0.028, 95% CI [–0.024, 0.110]) nor HR Decision Making (β = 0.000, SE = 0.013, 95% CI [–0.027, 0.027]) significantly mediated the relationship between HR Analytics and Organizational Performance. All CIs included zero, and β values were below the 0.10 threshold for small effects, indicating no substantive or statistical significance. Therefore, all hypotheses (H1–H7) were not supported, suggesting that HR Analytics, Talent Management, and HR Decision Making did not exert measurable direct or indirect effects on Organizational Performance (Hair et al., 2019; Kline, 2011).

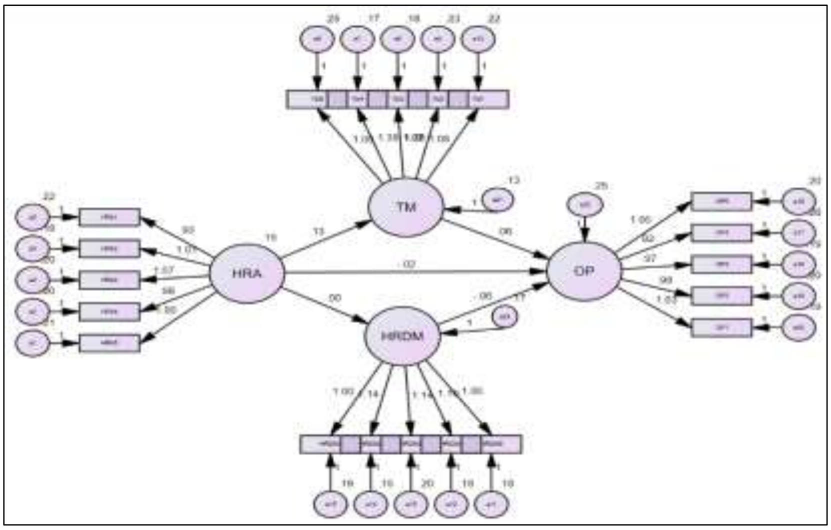

Fig 2: Structural Equation Modeling

Discussion of Findings

The first hypothesis (H1) proposed that HR Analytics (HRA) would positively and significantly influence Organizational Performance (OP), consistent with the Resource-Based View (Barney, 1991). Prior research supported this expectation, reporting substantial gains in performance through HR analytics adoption (Angrave et al., 2016; Tessema et al., 2025; Siddiqua et al., 2023). However, this study found no significant direct effect ($\beta = -0.018$, CI including zero), diverging from earlier evidence. This non-significance likely reflects the limited maturity of HR analytics practices in Bangladesh, where many organizations still rely on traditional HR methods and lack the necessary infrastructure and analytical skills (Taher et al., 2025). The benefits of analytics may not emerge without strategic integration, as suggested by McCartney and Fu (2022), and organizations often fail to convert analytical insights into strategic decisions. The absence of measurable effects could also result from contextual and methodological factors such as sample size (N = 157), cross-sectional design, and reliance on perceptual data, which might overlook delayed or nuanced effects. Overall, the findings imply that analytics alone cannot enhance performance without the requisite strategic alignment, resources, and cultural readiness.

The mediating roles of HR Decision Making (HRDM) and Talent Management (TM) were also examined, anticipating that HRA would strengthen these processes and thereby improve OP. Despite theoretical support for analytics enabling evidence-based decisions and strategic talent initiatives (Boudreau & Cascio, 2017; Minbaeva, 2018; Collings & Mellahi, 2013), none of the indirect paths were significant, leading to the rejection of H2–H5. This indicates that analytics adoption did not translate into better HR practices or outcomes. Contributing factors include underdeveloped HR systems (Marler & Boudreau, 2017), reliance on intuition (Angrave et al., 2016), perceptual measurement limitations, and contextual barriers such as weak digital infrastructure, leadership disengagement, and poor institutional support (Khokon & Hossain, 2020; Taher et al., 2025; Hossain & Mahmood, 2021; Roy et al., 2024). Consequently, the study concludes that the success of HR analytics depends on organizational capability, strategic alignment, and contextual readiness rather than mere technology implementation.

V. IMPLICATIONS

The statistically non-significant findings of this study offer critical insights into the boundary conditions of the Resource-Based View (RBV) and Dynamic Capabilities Theory (DCT) within the context of HR analytics. Theoretically, the results indicate that the mere presence of analytical capabilities does not automatically translate into improved organizational performance. This challenges the assumption that HR analytics represents a universally strategic resource under RBV. Instead, it supports a more conditional interpretation, where analytics yields value only when embedded within complementary capabilities such as analytical culture, leadership commitment, and data-driven processes. From a dynamic capabilities' perspective, the findings imply that HR analytics may constitute a potential capability that requires integration, learning, and reconfiguration to generate tangible outcomes. The absence of significant mediating effects of Talent Management and Evidence-Based HR Decision Making suggests that these processes, in their current form, may not be sufficiently mature or aligned to activate analytics-driven performance improvements. Hence, the study refines theoretical expectations by suggesting that the translation of analytics into performance is contingent upon contextual readiness rather than inherent capability.

For practitioners, these findings underscore those investments in HR analytics technologies alone are unlikely to enhance performance outcomes. Managers should recognize that analytical systems must be accompanied by supportive organizational conditions, such as leadership advocacy, data literacy, and cross-functional collaboration to realize their potential (Roy & Islam., 2025; Roy et al., 2025). The lack of significant effects through Talent Management and HR Decision Making further highlights that analytics-driven insights must be operationalized through coherent HR processes and actionable decision frameworks. In emerging economies like Bangladesh, where technological adoption and analytical expertise are still developing, organizations must focus on cultivating a data-oriented mindset, improving data quality, and aligning analytics with strategic HR objectives before expecting measurable performance gains. The study thus offers a pragmatic caution against overreliance on technological tools without parallel human and structural enablers.

Methodologically, the non-significant results emphasize the complexity of capturing analytics-related phenomena using cross-sectional, perceptual data. Future studies should employ longitudinal or multi-source research designs to better assess causality and temporal effects. Moreover, expanding sample diversity and incorporating objective performance metrics could improve external validity. Researchers should also consider alternative modeling approaches or moderating variables, such as organizational culture or digital maturity that may explain variance in analytics–performance relationships. These methodological refinements would strengthen future empirical inquiries and enhance the precision of theoretical testing in HR analytics research.

VI. LIMITATIONS AND FUTURE DIRECTIONS

This study carries several limitations that qualify the interpretation and generalization of its findings. First, the sample size was relatively small (N=157) and restricted to a single national context, Bangladesh, and specific industries. Although it contributes valuable evidence from an emerging economy, these contextual boundaries limit the generalizability of the conclusions. The small sample size also reduces statistical power, making it difficult to detect subtle relationships or small effect sizes. Second, the research employed a cross-sectional design, offering only a single-time snapshot. Because organizational performance and strategic HR initiatives evolve gradually, cross-sectional data cannot fully establish causality or reveal delayed effects. Longitudinal approaches might better capture the temporal dynamics of HR analytics outcomes.

A third limitation concerns the use of self-reported data from HR and managerial respondents, which may introduce common-method bias and perceptual distortions. Although preventive steps such as validated scales and CFA diagnostics were undertaken, social desirability and subjective misjudgments could still influence responses. For instance, participants might have overstated their organization's analytics use or inaccurately assessed performance outcomes. Incorporating multi-source or objective data, such as audited HR reports or financial performance indicators, could improve validity. Fourth, measurement issues remain possible despite employing established scales (Marler & Boudreau, 2017; Huselid, 2018). The constructs of HRA, HRDM, and TM are inherently multidimensional, and some sub-dimensions such as data quality or decision credibility might not have been fully captured. Similarly, the measure of "organizational performance" was broad and open to varying interpretations. Future studies could use more specific or objective performance indicators to ensure greater precision. Unmeasured contextual influences may also have shaped the results. Variables such as firm size, industry type, and leadership support may moderate the HRA–performance relationship but were not included in this model. Their exclusion might have introduced omitted-variable bias, as large firms could benefit more from analytics compared to smaller ones. Therefore, these findings should be interpreted cautiously as they may reflect both genuine contextual constraints and methodological limitations.

The unexpected null results offer valuable direction for future research. Scholars should replicate this model using larger, cross-national samples to improve external validity and enable comparisons across industries and organizational types. Longitudinal and experimental studies are recommended to clarify causality and delayed effects of analytics adoption. Future models could include moderators such as strategic alignment (McCartney & Fu, 2022), analytics maturity, organizational culture, and leadership support to explain when and why HR analytics succeeds or fails. Mixed-method approaches involving case studies or interviews would provide deeper insights into the practical application and barriers of analytics. Additionally, exploring alternative mediators and outcomes such as decision quality, employee engagement, or cost efficiency could uncover more proximal effects. Future work might also examine "dark side" outcomes, such as privacy risks or data fatigue (Chatterjee et al., 2022), to present a more balanced understanding of HR analytics in diverse organizational contexts.

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