Global Social Science and Humanities Journal
Online :ISSN 2964-1543
gsshj.globaledupublisher.com
Global Education Publisher

Human Resource Analytics and Talent Management Effectiveness in China: Evidence from Multinational Corporations and Local Enterprises.

Bi Sheng[1], Maruf Tarekol Islam[2*]

[1]School of Graduate, Alfa University college, Selangor, Malaysia, email: 13054260075@163.com

[2]School of Graduate, Alfa University college, Selangor, Malaysia, email: dr.tarekol@alfa.edu.my

Corresponding Author email: dr.tarekol@alfa.edu.my

Received: May 05, 2026
Revised : Jun. 15, 2026
Accepted: Jul. 10, 2026
Published : Jul. 25, 2026

Abstract: This study examines whether Human Resource Analytics (HRA) strengthens Talent Management Strategies (TMS) in China's corporate sector and whether organization type changes the strength of this relationship. Drawing on Human Capital Theory, the Resource-Based View, and Contingency Theory, the study used a quantitative cross-sectional survey of 150 HR professionals from information technology, financial services, manufacturing, healthcare, and retail organizations. The sample included 80 respondents from multinational corporations (MNCs) and 70 from local enterprises. Descriptive results showed moderately high HRA adoption (M = 3.73), with recruitment analytics as the most developed application (M = 4.02) and workforce planning analytics as the least developed (M = 3.18). Talent acquisition was the strongest talent-management dimension (M = 4.00), followed by employee retention (M = 3.91), employee development (M = 3.87), succession planning (M = 3.81), and performance management (M = 3.78). HRA was positively correlated with TMS ($r = 0.61$, $p < 0.01$) and significantly predicted TMS (beta = 0.61, $p < 0.001$), explaining 37% of its variance. Organization type significantly moderated this relationship (interaction beta = 0.18, $p = 0.010$), and the association was stronger among MNCs. The results indicate that HRA functions as a strategic capability, but its value depends on complementary resources, digital maturity, analytical skills, leadership support, and data governance. The study provides evidence for phased, context-sensitive HRA implementation in China.

Keywords: Human Resource Analytics; talent management; multinational corporations; local enterprises; China; moderation analysis; data-driven HR.

1. Introduction

Digital transformation has changed the role of the human resource function. Organizations increasingly expect HR professionals to produce timely evidence about workforce capability, recruitment, performance, retention, and future skills rather than rely principally on administrative records or managerial intuition. Human Resource Analytics (HRA), also described as people analytics or workforce analytics, responds to this expectation by applying data analysis, statistical methods, visualization, and predictive techniques to workforce decisions. At its most basic level, HRA describes what has happened; at more advanced levels, it forecasts likely outcomes and recommends interventions. The strategic promise of HRA is therefore not simply that it generates more HR metrics, but that it improves the quality and consistency of decisions across the

How to cite: Sheng, B., & arekol Islam, D. T. (2026). Human Resource Analytics and Talent Management Effectiveness in China: Evidence from Multinational Corporations and Local Enterprises. Global Social Science and Humanities Journal, 4(3), 1–19. https://doi.org/10.59088/gi.v4i3.31

employee lifecycle (Angrave et al., 2016; Van den Heuvel & Bondarouk, 2017). Talent management has developed in parallel from a collection of separate HR activities into an integrated strategic system. It includes the attraction and selection of employees, the development of skills and careers, the management of performance, the retention of valuable employees, and the preparation of future leaders. These activities influence whether organizations have the people and capabilities required to execute strategy. Strategic talent management is especially important in labor markets characterized by skill shortages, mobility, technological change, and competition for high-performing employees (Collings & Mellahi, 2009; Cappelli & Keller, 2014). The value of HRA lies in its potential to connect these talent decisions with reliable workforce evidence. In talent acquisition, analytics can help organizations compare recruitment channels, identify candidate characteristics associated with successful performance, monitor time-to-hire, and improve job-candidate matching. In employee development, it can reveal competency gaps and support targeted learning decisions. In performance management, analytics can identify performance trends and improve the basis for coaching and evaluation. In retention, it can help detect patterns associated with voluntary turnover and permit earlier intervention. In succession planning, it can support the identification of high-potential employees and future leadership needs. Through these uses, HRA can move the HR function from retrospective reporting toward proactive workforce management (Fitz-Enz, 2010; Levenson, 2018). China provides an important context for examining this relationship. Its corporate sector is undergoing rapid digitalization while simultaneously facing intense competition for skilled labor, rising expectations among younger employees, and uneven organizational capabilities. Multinational corporations operating in China often possess integrated global HR systems, established analytics practices, specialized staff, and stronger access to capital. Many local enterprises, especially smaller firms, operate with more fragmented systems, limited analytical expertise, and greater resource constraints. The Chinese context also includes distinct institutional and cultural conditions, including hierarchical management traditions, relationship-based decision-making, and an evolving regulatory environment for employee data (Li et al., 2019; Zhang & Chen, 2024). These differences suggest that HRA may not generate identical benefits in every organization. Technology alone does not guarantee better talent decisions. Organizations must also have reliable data, analytical capability, leadership support, managerial acceptance, and processes that translate insight into action. This reasoning is consistent with the Resource-Based View, which treats an embedded organizational capability as more strategically valuable than a stand-alone technology, and with Contingency Theory, which argues that the effectiveness of a management practice depends on its fit with organizational conditions. Organization type may therefore influence the strength of the relationship between HRA and TMS. Although the international literature on HRA is growing, empirical evidence from China remains limited, and much of the established evidence has been developed in Western organizational settings (Marler & Fisher, 2013; Zhang & Chen, 2024). Much of the existing work is conceptual, based on Western settings, or focused on adoption rather than measured talent-management outcomes. Comparative evidence between MNCs and local enterprises is particularly scarce. This leaves two related questions insufficiently answered: whether stronger HRA adoption is associated with better talent-management strategies in China's corporate sector, and whether this association differs according to organization type. This article addresses these questions using survey evidence from 150 HR professionals. It concentrates on the empirical findings of the thesis and makes three contributions. First, it quantifies the level of HRA adoption and talent-management implementation across several HR functions. Second, it evaluates the direct relationship between HRA and overall TMS. Third, it tests organization type as a moderator, thereby showing whether MNCs and local enterprises convert analytics capability into talent outcomes with equal effectiveness. The study addresses the following research questions:

RQ1: What is the effect of Human Resource Analytics on Talent Management Strategies in China's corporate sector?

RQ2: Does organization type, defined as MNCs versus local enterprises, moderate the relationship between Human Resource Analytics and Talent Management Strategies?

The article proceeds by presenting a focused theoretical background, the research model and hypotheses, the method, the empirical results, and a results-centered discussion. The final sections outline implications, limitations, and priorities for future research.

2. Literature Review and Theoretical Framework

2.1 Human Resource Analytics as a Strategic Capability

HRA involves the systematic collection, integration, analysis, and interpretation of workforce data to support HR and business decisions. Descriptive analytics summarizes historical patterns such as turnover, absence, recruitment yield, or training participation. Predictive analytics estimates likely future outcomes, such as the probability of employee departure or candidate success. Prescriptive analytics goes further by identifying actions that may improve those outcomes. The progression from descriptive to predictive and prescriptive use reflects increasing analytical maturity, although many organizations remain concentrated at the reporting stage (Van den Heuvel & Bondarouk, 2017). A central distinction in the HRA literature is the difference between possessing data and generating strategic value from data. HR information systems may store large volumes of employee information, but data become strategically useful only when they are accurate, integrated, interpreted, and connected to decisions. (Angrave et al. 2016) caution that HR functions can fail to realize the value of analytics when they lack analytical capability or focus on technically sophisticated models without addressing meaningful business questions. Similarly, (Shet et al. 2021) identify organizational, technological, and managerial conditions as determinants of successful analytics adoption. The Resource-Based View provides a useful explanation. HRA is not merely software; it combines data assets, analytical technologies, employee expertise, managerial routines, data governance, and organizational learning. Competitors may purchase similar software, but they cannot easily replicate the accumulated data quality, analytical knowledge, trust, and decision processes through which an organization converts data into action. HRA becomes a strategic resource when it is embedded in organizational routines and aligned with business priorities.

2.2 HRA and Talent Management Strategies

Strategic Talent Management represents a fundamental shift from traditional personnel administration toward integrated, evidence-based workforce management aligned with organizational strategy. By combining Human Capital Theory, the Resource-Based View, and contemporary digital technologies, Strategic Talent Management enables organizations to transform human capital into a sustainable source of competitive advantage. These theoretical perspectives provide the conceptual foundation for examining the influence of Human Resource Analytics on Talent Management Strategies in the present study and establish the basis for the subsequent discussion of the five strategic dimensions of Talent Management, figure 1.

Figure 1. Talent Management Cycle

Talent acquisition is often the first advanced HRA application because recruitment produces structured and comparable information. Applicant data, assessment scores, selection outcomes, recruitment channels, and subsequent job performance can be analyzed to improve candidate screening and quality of hire. Analytics can also reveal process bottlenecks, channel effectiveness, and time-to-fill. However, algorithmic recruitment requires attention to fairness and transparency because models trained on historical decisions may reproduce past bias (Kleinberg et al., 2016). Employee development involves matching current and future capability requirements with learning investments. HRA can identify skill gaps, compare competency profiles, track training participation, and evaluate whether development programs influence performance or internal mobility. This supports more targeted investment than generic training programs. Human Capital Theory is directly relevant because it views employee knowledge and skills as productive assets whose value can be strengthened through investment. Performance management benefits from the integration of goal, competency, productivity, feedback, and learning information. Analytics may improve consistency and reveal performance trends, but it cannot remove the need for managerial interpretation. The use of data should support developmental conversations rather than reduce employees to numerical scores. Employee trust, perceived fairness, and data quality remain important. Employee retention is particularly suited to predictive analysis. Turnover is costly because organizations lose experience, tacit knowledge, and relationships while incurring replacement costs. Historical data on tenure, compensation, performance, career movement, absence, engagement, and learning can identify patterns associated with voluntary exit. Predictive information allows HR managers to move from reactive replacement to preventive intervention. Retention analytics should nonetheless complement direct communication because personal aspirations and external circumstances cannot be fully represented in organizational datasets (Hausknecht et al., 2009). Succession planning links current workforce information with future organizational continuity. Analytics can support the identification of high-potential employees, leadership-readiness assessment, critical-position risk, and internal talent-pipeline development. Its strategic importance increases when organizations face rapid growth, leadership turnover, or emerging skill requirements. The literature therefore suggests that HRA should be associated with stronger TMS across multiple dimensions. Yet the effect is unlikely to be uniform. Functions built on structured operational data, such as recruitment and turnover, may mature more quickly than functions involving complex behavioral and psychological constructs, such as engagement or leadership potential.

2.3 Organization Type as a Contextual Moderator

MNCs and local enterprises in China differ in several conditions relevant to HRA. MNCs commonly operate standardized global HR processes, integrated enterprise systems, formal data-governance frameworks, and specialist analytics teams. They may also possess greater experience with evidence-based management and cross-unit benchmarking. These conditions make it easier to combine HR data, develop predictive models, and embed analytics in decisions. Local enterprises are diverse, and some large Chinese corporations possess advanced digital capabilities. Nevertheless, many local firms face budget constraints, fragmented systems, limited specialist skills, and competing priorities. In such settings, analytics may remain focused on reporting rather than strategic prediction. Management traditions that emphasize hierarchy, experience, or personal relationships may also slow the acceptance of data-supported recommendations. Contingency Theory suggests that the same HRA practice may generate different outcomes depending on organizational fit. An analytics system produces value when it is supported by complementary resources: integrated technology, leadership commitment, analytical literacy, clear governance, and a culture willing to act on evidence. Organization type is therefore not assumed to be valuable in itself; it represents a bundle of contextual conditions that may strengthen or weaken the conversion of HRA into TMS.

2.4 Research Model and Hypotheses

The research model treats HRA as the independent variable, overall TMS as the dependent variable, and organization type as the moderator. TMS incorporates talent acquisition, employee development, performance management, employee retention, and succession planning. The original thesis contains detailed expectations for each talent dimension, but the final empirical model evaluates their combined strategic outcome.

H1: Human Resource Analytics has a significant positive effect on Talent Management Strategies.
H2: Organization type significantly moderates the relationship between Human Resource Analytics and Talent Management Strategies, such that the positive relationship is stronger among multinational corporations than among local enterprises.

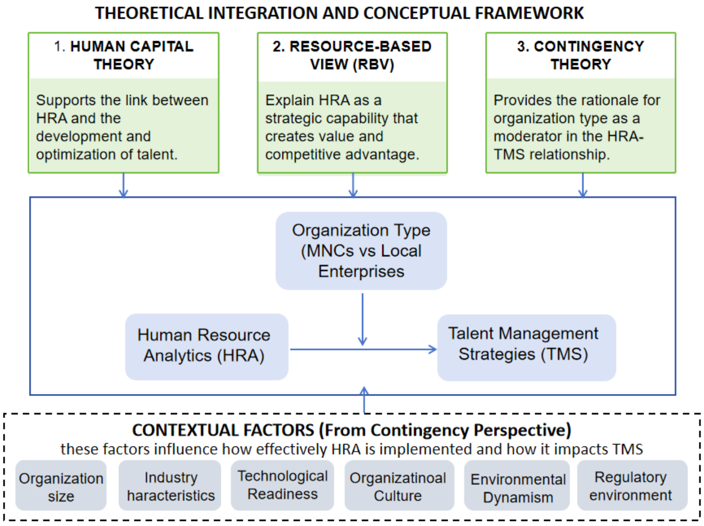

Figure 2. Conceptual model linking Human Resource Analytics, Talent Management Strategies, and organization type.

3. Method

3.1 Research Design and Sample

The study used a quantitative cross-sectional survey design. Data were collected from 150 HR professionals working in organizations operating in China. Respondents were selected because their roles gave them direct knowledge of HR systems, analytics adoption, recruitment, development, performance, retention, or workforce planning. The sample covered five industries: information technology, financial services, manufacturing, healthcare and life sciences, and retail and consumer goods. The organizations represented small, medium, and large employers. Organization type was divided into MNCs and local enterprises because the study sought to examine whether institutional and capability differences between these groups influence the effectiveness of HRA. The final sample included 80 respondents from MNCs and 70 from local enterprises. HR Directors and HR Managers formed the largest professional group, supplemented by talent acquisition managers, people analytics specialists, HR business partners, and other HR roles.

3.2 Measurement

The questionnaire used five-point Likert-scale items. HRA adoption measured the extent to which organizations collected, analyzed, and used workforce data in areas such as general workforce analysis, recruitment, performance, retention, and workforce planning. The TMS construct included five dimensions: talent acquisition, employee development, performance management, employee retention, and succession planning. Organization type was coded as a categorical moderator. The measurement items were aligned with the conceptual definitions developed in the thesis and adapted from prior HR analytics and strategic talent-management literature. Higher scores represented greater HRA adoption or stronger implementation of the relevant talent-management strategy.

3.3 Data Analysis

IBM SPSS was used for analysis. The analytical sequence included sample profiling, descriptive statistics, reliability assessment, Pearson correlation, multiple regression, and hierarchical moderated regression. Cronbach's alpha assessed internal consistency, with values above 0.70 treated as acceptable. H1 was tested by regressing overall TMS on HRA. H2 was tested by entering HRA and organization type as main effects and then adding the HRA x organization-type interaction term. Statistical significance was evaluated at $p < 0.05$. The cross-sectional and self-reported design supports analysis of association and prediction but does not establish temporal causality. This limitation is addressed in the interpretation of the results.

4. Results

4.1 Respondent and Organizational Profile

All 150 valid responses were retained for analysis. Industry representation was balanced: manufacturing accounted for 21.3% of respondents; information technology, healthcare and life sciences, and retail and consumer goods each accounted for 20.0%; and financial services represented 18.7%. The distribution reduced the risk that the results reflected a single sector. Half of the respondents represented large organizations with 250 or more employees. Medium-sized organizations represented 31.3%, and small organizations 18.7%. The sample therefore included variation in organizational capacity while giving substantial representation to firms likely to have formal HR systems. The organization-type distribution was also balanced. MNC respondents represented 53.3% of the sample and local-enterprise respondents 46.7%. This provided an appropriate basis for testing moderation. In professional terms, 43.3% of respondents were HR Directors or HR Managers, 20.0% were Talent Acquisition Managers, 13.3% were People Analytics Specialists, 10.0% were HR Business Partners, and 13.3% occupied other HR roles. The concentration of respondents in strategic or specialist HR positions strengthens confidence that participants were familiar with the study variables.

Table 1. Respondent and organizational profile

Characteristic	Category	n	%
Industry	Information Technology	30	20.0
Industry	Financial Services	28	18.7
Industry	Manufacturing	32	21.3

Table 1. Respondent and organizational profile

Characteristic	Category	n	%
Industry	Healthcare and Life Sciences	30	20.0
Industry	Retail and Consumer Goods	30	20.0
Organization size	Small (<50 employees)	28	18.7
Organization size	Medium (50-249 employees)	47	31.3
Organization size	Large (250+ employees)	75	50.0
Organization type	MNC	80	53.3
Organization type	Local enterprise	70	46.7
Respondent role	HR Director / HR Manager	65	43.3
Respondent role	Talent Acquisition Manager	30	20.0
Respondent role	People Analytics Specialist	20	13.3
Respondent role	HR Business Partner	15	10.0
Respondent role	Other HR roles	20	13.3

4.2 HRA Adoption Patterns

The overall mean for HRA adoption was 3.73 on the five-point scale (SD = 0.76), indicating moderately high adoption. However, adoption varied substantially by application. Recruitment analytics achieved the highest mean (M = 4.02, SD = 0.88), followed by workforce data analysis (M = 3.89, SD = 0.82) and employee-retention analytics (M = 3.89, SD = 0.84). Performance analytics was moderately developed (M = 3.67, SD = 0.91). Workforce-planning analytics was the least developed application (M = 3.18, SD = 1.02).

This pattern is important because it distinguishes operational adoption from strategic maturity. Recruitment and retention address immediate, measurable organizational problems and rely on relatively structured data. Workforce planning requires integration across business strategy, labor demand, skills, succession, and future scenarios. The lower workforce-planning score suggests that many participating organizations had adopted HRA for current decisions but had not yet fully embedded it in long-term strategic planning. The thesis also reports that MNCs demonstrated higher analytics-adoption maturity than local enterprises in an independent-samples comparison ($t = 4.02$, $p < 0.001$). This between-group difference complements the moderation analysis reported below. It indicates that MNCs not only gain more value from HRA but also generally possess higher levels of adoption.

4.3 Talent Management Outcomes

The mean for overall TMS was 3.87 (SD = 0.69), indicating that respondents perceived their organizations as implementing talent-management practices at a moderately high level. Talent acquisition was the strongest dimension (M = 4.00, SD = 0.71). Within this dimension, the use of data to support recruitment decisions achieved the highest item mean (M = 4.12, SD = 0.76), followed by identification of suitable candidates (M = 4.05, SD = 0.80), improvement of recruitment quality (M = 3.98, SD = 0.81), and recruitment-process efficiency (M = 3.84, SD = 0.88). Employee retention was the second-highest dimension (M = 3.91, SD = 0.74). The strongest item was the identification of turnover risks (M = 4.06, SD = 0.81), followed by monitoring retention trends (M = 3.95, SD = 0.84), supporting retention decisions (M = 3.83, SD = 0.85), and improving employee satisfaction (M = 3.79, SD = 0.88).

These results suggest that participating organizations were more confident in analytics used to detect risk than in analytics used to address the wider employee experience. Employee development recorded an overall mean of 3.87 (SD = 0.75). Identification of employee skill gaps was the strongest item (M = 3.96, SD = 0.86), followed by data-supported learning decisions (M = 3.89, SD = 0.82), career-development planning (M = 3.85, SD = 0.84), and personalized development programs (M = 3.78, SD = 0.87). The results indicate that analytics was used more frequently to diagnose development needs than to deliver fully individualized development pathways. Succession planning achieved a mean of 3.81 (SD = 0.77). Identification of high-potential employees scored highly (M = 4.08, SD = 0.79), but future leadership planning (M = 3.76), internal talent-pipeline development (M = 3.72), and critical-position planning (M = 3.69) were less developed. This resembles the workforce-planning pattern: organizations appear more capable of identifying individuals than of integrating those assessments into long-term leadership systems. Performance management had the lowest overall TMS mean, although it remained above the scale midpoint (M = 3.78, SD = 0.72). Identifying high-performing employees was the strongest item (M = 3.90, SD = 0.79), followed by supporting performance improvement (M = 3.82, SD = 0.83), monitoring performance trends (M = 3.74, SD = 0.85), and data-based performance evaluation (M = 3.67, SD = 0.91). The lower score for formal data-based evaluation may reflect the complexity and sensitivity of using analytics in performance decisions. Taken together, the descriptive findings reveal a consistent maturity gradient. HRA was strongest where the task involved structured data and a specific operational decision: identifying candidates, detecting turnover risk, finding skill gaps, or recognizing high-potential employees. It was weaker where organizations needed to integrate information into long-term planning, individualized intervention, or potentially sensitive judgments.

Table 2. Descriptive results for HRA adoption and talent-management dimensions

Construct / application	Mean	SD	Interpretive pattern
Overall HRA adoption	3.73	0.76	Moderately high
Recruitment analytics	4.02	0.88	Highest HRA application
Workforce data analysis	3.89	0.82	High
Employee-retention analytics	3.89	0.84	High
Performance analytics	3.67	0.91	Moderate-high
Workforce-planning analytics	3.18	1.02	Lowest HRA application
Overall Talent Management Strategies	3.87	0.69	Moderately high
Talent acquisition	4.00	0.71	Highest TMS dimension
Employee retention	3.91	0.74	Second highest
Employee development	3.87	0.75	Moderately high
Succession planning	3.81	0.77	Moderately high
Performance management	3.78	0.72	Lowest TMS dimension

4.4 Reliability of the Measures

All constructs exceeded the accepted Cronbach's-alpha threshold of 0.70. HRA adoption achieved alpha = 0.85. The talent dimensions ranged from 0.79 for succession planning to 0.83 for employee retention. Talent acquisition recorded 0.81, employee development 0.82, and performance management 0.80. The 21-item overall TMS construct achieved alpha =

0.87. These values indicate satisfactory internal consistency. They also support the use of composite scores in the correlation, regression, and moderation analyses. The results should not be interpreted as evidence that the constructs are identical; rather, the items within each construct demonstrated sufficient consistency to represent a common underlying dimension.

Table 3. Reliability of the study constructs

Construct	Items	Cronbach's alpha
Human Resource Analytics adoption	8	0.85
Talent acquisition strategy	5	0.81
Employee development strategy	4	0.82
Performance management strategy	4	0.80
Employee retention strategy	4	0.83
Succession planning strategy	4	0.79
Overall Talent Management Strategies	21	0.87

4.5 Correlation Results

Pearson correlation analysis showed a positive and statistically significant relationship between HRA and TMS ($r = 0.61$, $p < 0.01$). This is a moderately strong association. Organizations reporting higher HRA adoption also reported stronger talent acquisition, development, performance, retention, and succession practices. Organization type was positively related to HRA ($r = 0.32$, $p < 0.01$) and TMS ($r = 0.28$, $p < 0.01$). With MNC status coded as the higher category, these results indicate that MNCs tended to report both stronger analytics adoption and stronger talent-management strategies. The correlations provide preliminary support for the proposed model but do not by themselves test the direct and moderation hypotheses.

4.6 Direct Effect of HRA on TMS

Multiple regression analysis tested H1. The model was statistically significant, $F = 87.98$, $p < 0.001$. HRA significantly predicted TMS (beta = 0.61, $t = 9.38$, $p < 0.001$). The model explained 37% of the variance in TMS (R2 = 0.37; adjusted R2 = 0.36).

The size of the explained variance is substantively meaningful for an organizational survey. Talent management is affected by many factors, including leadership, labor-market conditions, compensation, organizational culture, employee expectations, and business strategy. HRA alone accounted for more than one-third of the observed variation in TMS. H1 was therefore supported. The result indicates that HRA adoption is not merely associated with technical reporting. It is connected to the broader quality of talent-management systems. Organizations that more systematically collect, analyze, and use workforce data tend to report better recruitment, development, performance, retention, and succession practices.

4.7 Main Effects and Moderation by Organization Type

Hierarchical regression tested H2. In the main-effects model, HRA remained a strong predictor of TMS (beta = 0.58, $t = 8.92$), while organization type also contributed positively (beta = 0.21, t = 3.12). Together, the main effects explained 38% of the variance in TMS (R2 = 0.38). The interaction model added HRA x organization type. The interaction coefficient was positive and statistically significant (beta = 0.18, t = 2.62, p = 0.010). Adding the interaction increased explained variance by 3 percentage points (delta R2 = 0.03), producing a total R2 of 0.41. The F-change was 6.84. H2 was therefore supported. The positive interaction indicates that the relationship between HRA and TMS was stronger for MNCs than for local enterprises. HRA contributed positively in both contexts, but MNCs converted analytics adoption into talent-management outcomes more effectively. The moderation result should be interpreted as a contextual-capability effect rather than as evidence that local enterprises cannot benefit from analytics. MNCs generally possess more integrated systems, more standardized processes, greater specialist expertise, stronger data governance, and more experience with evidence-based decision-making. These complementary capabilities increase the likelihood that analytical findings are translated into managerial action. Many local enterprises may still be developing the foundational systems and routines required to obtain comparable returns.

Table 4. Correlation, direct effect, and moderation results

Analysis	Statistic	Result	Decision
HRA-TMS correlation	r	0.61, p < 0.01	Positive association
Organization type-HRA correlation	r	0.32, p < 0.01	MNCs higher
Organization type-TMS correlation	r	0.28, p < 0.01	MNCs higher
Direct effect of HRA on TMS	beta	0.61, t = 9.38, p < 0.001	H1 supported
Direct-effect model	R2 / F	0.37; F = 87.98, p < 0.001	Significant model
Main-effects model	R2	0.38	HRA and type significant
HRA x organization type	beta	0.18, t = 2.62, p = 0.010	H2 supported
Interaction model	R2 / delta R2	0.41 / 0.03; F-change = 6.84	Stronger effect in MNCs

4.8 Reported Barriers to Adoption

The thesis identifies four leading implementation barriers: lack of internal analytics expertise (61.3%), budget constraints (46.7%), data-privacy concerns (43.3%), and cultural resistance to data-driven decision-making (38.7%). These barriers help explain both the lower adoption maturity in local enterprises and the significant moderation effect. The dominance of the expertise barrier suggests that HRA adoption is principally a capability challenge rather than a software-purchasing decision. Budget limitations restrict access to integrated systems and specialist staff. Privacy concerns are especially relevant in China because organizations must manage employee information in accordance with the Personal Information Protection Law. Cultural resistance reduces value when managers distrust analytical recommendations or perceive data-based decision-making as a threat to experience and authority.

Table 5. Leading barriers to HRA adoption reported in the thesis

Barrier	Respondents reporting barrier
Lack of internal analytics expertise	61.3%
Budget constraints	46.7%

Table 5. Leading barriers to HRA adoption reported in the thesis

Barrier	Respondents reporting barrier
Data-privacy concerns	43.3%
Cultural resistance to data-driven decision-making	38.7%

4.9 Summary of Hypothesis Testing

The empirical results supported both hypotheses. HRA had a significant positive effect on TMS, and organization type strengthened or weakened that effect. The final model explained 41% of TMS variance after including the interaction. The findings answer RQ1 by showing that HRA makes a strong, positive contribution to TMS. They answer RQ2 by demonstrating that the contribution is stronger among MNCs than among local enterprises. The results also provide a more nuanced picture than a simple claim that analytics is beneficial. Adoption was uneven across functions, with recruitment and retention more developed than workforce planning and performance management. Organizational context shaped both the level of adoption and the value obtained from it. The following discussion interprets these patterns.

4.10 Integrated Pattern of Findings

The descriptive and inferential findings form a coherent sequence. First, organizations have moved beyond non-use: all major construct means were above the midpoint, and HRA adoption was moderately high. Second, the use of analytics is concentrated in operationally visible activities. Recruitment, turnover-risk identification, skill-gap diagnosis, and high-potential identification all recorded high scores. Third, adoption becomes weaker when the task requires cross-functional forecasting, individualized intervention, or sensitive evaluation. Workforce planning, personalized development, critical-position planning, and data-based performance evaluation were comparatively less developed. Fourth, the direct regression demonstrates that these applications collectively matter. HRA was not associated only with one isolated outcome; it predicted an integrated TMS construct covering the employee lifecycle. Fifth, the organization-type results show that the same nominal adoption level can generate different value. MNCs reported higher adoption and a stronger conversion of analytics into talent-management outcomes. Finally, the reported barriers identify the organizational mechanisms that plausibly underlie this difference: expertise, funding, privacy capability, and cultural acceptance. This integrated pattern suggests that HRA maturity has at least three practical stages. In the foundational stage, organizations establish HR information systems, common data definitions, and reliable reporting. In the functional stage, they use analytics in recruitment, retention, performance, learning, and succession decisions. In the strategic stage, they integrate workforce evidence with business planning, scenario analysis, and future capability decisions. The participating organizations appear strongest in the functional stage, with uneven movement toward strategic maturity.

5. Discussion

5.1 HRA as a Driver of Talent Management Effectiveness

The direct-effect result is the central empirical finding. A standardized coefficient of 0.61 and R2 of 0.37 indicate that HRA is closely connected to the overall strength of talent-management practices. This supports the argument that HRA has developed beyond an administrative reporting function. When workforce evidence is routinely used in decisions, organizations are better able to identify talent needs, target interventions, and evaluate outcomes. The finding is consistent with evidence-based HRM, which seeks to replace unsupported intuition with the systematic use of organizational data and relevant research. It also aligns with prior work arguing that analytics creates value when it improves strategy execution rather than merely increasing the quantity of metrics (Davenport & Harris, 2017; Levenson, 2018). The result does not imply that judgment becomes unnecessary. Instead, it indicates that managerial judgment is likely to be more consistent and strategically aligned when informed by reliable data. From a Human Capital Theory perspective, HRA improves the allocation of investments in people. Recruitment analytics directs resources toward candidates more likely to contribute. Development analytics identifies where learning investments are needed. Retention analytics helps protect accumulated knowledge and capability. Succession analytics supports leadership continuity. The significant aggregate effect suggests that these applications combine to improve the organization's ability to acquire, develop, deploy, and retain human capital. From an RBV perspective, the result supports the treatment of HRA as an organizational capability. The technology can be purchased, but the capability depends on data quality, analytical expertise, decision routines, managerial trust, and integration with strategy. These elements develop cumulatively and are more difficult to imitate than software alone. The result therefore helps explain why some organizations obtain substantial value from analytics while others produce dashboards with limited decision impact.

5.2 Why Recruitment and Retention Lead Adoption

Recruitment analytics was the strongest HRA application, and talent acquisition was the strongest TMS outcome. This convergence reflects the characteristics of recruitment data. Applications, assessment results, interview evaluations, recruitment sources, costs, time-to-fill, and later employee performance can be structured and compared. Organizations can therefore evaluate whether a recruitment channel produces successful hires or whether selection criteria predict later performance. The high score for data-supported recruitment decisions (M = 4.12) and candidate identification (M = 4.05) indicates that organizations are using analytics to improve selection precision. This is strategically valuable in China's competitive labor market, where hiring scarce skills quickly and accurately can influence growth. It also reduces the cost of poor hiring decisions and early turnover. The comparatively lower score for recruitment-process efficiency (M = 3.84) suggests that organizations may be using data more confidently for candidate evaluation than for end-to-end process redesign. Advanced maturity would require connecting analytics to workforce demand forecasts, recruitment capacity, candidate experience, and post-hire outcomes rather than applying it only during selection. Retention displayed a similar pattern. Identifying turnover risk recorded M = 4.06, while improving employee satisfaction was lower at M = 3.79. Analytics is effective at identifying patterns, but a risk signal does not itself solve the underlying problem. Managers must translate insight into credible action: career opportunities, leadership improvement, workload adjustment, recognition, flexible arrangements, or compensation review. The gap between prediction and intervention is therefore a critical maturity issue.

These findings reinforce the importance of treating HRA as a decision process. A predictive model creates value only when the organization can respond. If managers lack authority, resources, or trust, a technically accurate turnover model may have little practical effect. Conversely, even a relatively simple analysis can create value when it is linked to timely intervention.

5.3 Development, Performance, and Succession as Emerging Applications

Employee development achieved a moderately high mean, especially for skill-gap identification. This indicates that organizations are beginning to use analytics to diagnose workforce capability and support learning decisions. However, personalized development programs scored lower, suggesting that many organizations have not yet built the integrated competency, learning, performance, and career data needed for individual recommendations. The distinction is important. Diagnosis is easier than personalization. Identifying a general shortage of digital skills may require aggregated data, while recommending a tailored pathway for an individual requires reliable competency profiles, career aspirations, learning histories, and future-role requirements. The latter also demands organizational processes that can deliver differentiated development. Performance management recorded the lowest TMS mean. Performance data can be sensitive, contested, and influenced by role differences and managerial bias. Organizations may therefore hesitate to use analytics in formal evaluation. In addition, performance is difficult to compare across functions, and numerical indicators may not capture collaboration, creativity, or contextual constraints. These issues help explain why identifying high performers scored higher than data-based performance evaluation. The implication is not that organizations should avoid performance analytics, but that they should use it carefully. Analytics should triangulate multiple sources and support coaching, goal review, and development rather than automate high-stakes judgments without transparency. Trust and perceived fairness are essential for employee acceptance. Succession planning displayed a comparable gap between identification and system-level planning. Organizations reported strong use of data to identify high-potential employees, but weaker use for critical-position planning and pipeline development. Identifying individuals is only the first step. Mature succession planning connects strategic roles, future capabilities, readiness levels, development actions, and risk scenarios. The result again demonstrates that analytics maturity declines as the task becomes more strategic, integrated, and future-oriented.

5.4 The Strategic Planning Gap

Workforce-planning analytics recorded the lowest HRA mean, 3.18. This result is particularly significant because workforce planning is where HRA should connect most directly with business strategy. Recruitment, retention, and performance applications may improve current HR operations, but workforce planning determines whether the organization will have the future skills and capacity required for strategic execution. The lower score suggests several possible constraints. Workforce planning requires reliable information from multiple functions, including finance, operations, sales, technology, and strategy. It also requires scenario modeling and assumptions about future demand. HR teams may lack access to these data or the influence required to integrate workforce evidence into corporate planning. Organizations may also have strong reporting systems but limited predictive capability. This finding supports the thesis's recommendation that organizations expand HRA gradually from operational applications toward predictive and prescriptive workforce planning. The progression should not be interpreted as a demand for immediate technical sophistication. The first requirement is data integration and strategic clarity. Advanced models cannot compensate for unclear workforce questions or poor data.

5.5 The Moderating Role of Organization Type

The significant interaction effect is the study's distinctive contribution. The HRA-TMS relationship was stronger in MNCs than in local enterprises. This result supports Contingency Theory by demonstrating that analytics effectiveness depends on context. A practice that is beneficial on average does not produce identical results under different organizational conditions. MNCs are likely to benefit from several complementary resources. They commonly have global HR platforms, standardized definitions, established data-governance policies, specialist teams, and experience using dashboards and predictive models. Senior leaders may also expect decisions to be justified through evidence. When HRA is introduced in this setting, it enters an ecosystem capable of using it. Local enterprises may face fragmented systems, limited budgets, fewer specialist staff, or stronger reliance on managerial experience and relationships. Data may be stored across spreadsheets or disconnected platforms. Even when analytics software is available, inconsistent definitions or incomplete records can reduce the credibility of outputs. Managers may then return to intuition, reinforcing resistance. The interaction coefficient of 0.18 and the 3% increase in explained variance are meaningful because moderation effects in organizational research are often smaller than main effects. Organization type does not replace the direct contribution of HRA; it changes the efficiency with which HRA is translated into TMS. The final model's R2 of 0.41 demonstrates that considering context improves explanatory power. It is important not to essentialize the distinction. Local enterprises are not uniformly less capable, and some Chinese corporations are highly advanced. Organization type is best interpreted as a proxy for clusters of resources, routines, and institutional experience. The practical question is therefore not whether an organization is local or multinational, but which complementary capabilities it has developed.

5.6 Adoption Barriers and the Capability Gap

The leading barriers reinforce this interpretation. Lack of internal expertise was reported most frequently. HRA requires HR professionals who can define business questions, interpret evidence, communicate uncertainty, and work with technical specialists. Organizations do not need every HR employee to become a data scientist, but they need analytical literacy throughout the function and advanced capability in selected roles. Budget constraints affect technology, integration, training, and staffing. However, a phased approach can reduce the entry barrier. Organizations can begin with high-quality descriptive analysis in recruitment or retention before investing in advanced predictive models. The key is to select decisions with clear organizational value and available data. Privacy concerns are not secondary. Employee data are sensitive, and inappropriate use can damage trust even when legally permissible. Governance should specify data purpose, access, retention, consent, model review, and accountability. China's PIPL increases the need for transparent and secure practices. Ethical governance also improves analytical quality because it encourages clear data definitions and disciplined access. Cultural resistance is closely connected to change management. Managers may interpret analytics as a challenge to expertise, while employees may fear surveillance or automated judgment. Successful implementation requires communication that presents analytics as decision support rather than managerial replacement. Early projects should demonstrate practical value and involve users in model design.

5.7 Theoretical Implications

The results integrate three theoretical perspectives. Human Capital Theory explains why better information improves investments in recruitment, development, retention, and succession. The data show that HRA is associated with stronger practices across these areas, particularly where organizations can identify and protect valuable capability. The RBV explains why the benefits extend beyond the technology. The significant direct effect suggests that HRA can become a strategic capability, while the moderation result shows that this capability depends on complementary resources. Data, systems, skills, governance, and leadership must be organized together. This extends a simple technology-adoption explanation toward a capability-based explanation. Contingency Theory is supported by the stronger HRA-TMS relationship in MNCs. The finding rejects a universalistic assumption that the same level of analytics adoption generates the same outcome everywhere. Organizational readiness and context matter. The implication for future theory is that HRA research should model capability maturity, leadership, culture, and governance rather than treat adoption as a single technical variable. The findings also contribute to strategic HRM by connecting analytics to an integrated TMS construct. Much HRA research examines isolated applications. The current model demonstrates that analytics is related to a system of talent practices across the employee lifecycle. This system-level perspective is important because talent outcomes are interdependent: recruitment quality affects development needs, engagement affects retention, and succession depends on performance and development data.

5.8 Practical and Policy Implications

For HR leaders, the first implication is to begin with decisions rather than software. Organizations should identify a high-value workforce question, establish data quality, select an appropriate analytical method, and define how managers will act on the result. Recruitment and retention are logical starting points because the study shows both high adoption and strong perceived value. Second, organizations should build layered capability. General HR staff need data literacy; HR business partners need the ability to interpret and communicate analysis; specialist teams require statistical, technological, and data-governance expertise. Collaboration with finance, IT, and business units is essential because strategic workforce questions cross functional boundaries. Third, organizations should improve data integration. Recruitment, performance, learning, compensation, engagement, and turnover data should be governed through consistent definitions and identifiers. Integrated data reduce manual effort and permit analysis across the employee lifecycle. Fourth, implementation should be context-sensitive. MNCs may be ready to extend predictive and prescriptive applications, evaluate model fairness, and connect HRA with enterprise planning. Many local enterprises should first strengthen HR information systems, data quality, leadership commitment, and analytical literacy. Attempting advanced artificial intelligence without these foundations may increase cost without improving decisions. Fifth, organizations should make governance visible. Employees and managers should understand what data are collected, for what purpose, who can access them, and how analytical recommendations influence decisions. Transparent governance is both a legal requirement and a condition for trust. For policymakers, the results suggest a role in reducing the capability gap. Training partnerships among universities, professional bodies, and industry can address the expertise shortage. Practical regulatory guidance can help smaller firms comply with employee-data requirements. Targeted digital-transformation support may help local enterprises invest in foundational HR systems. Industry benchmarking can also help organizations assess maturity without requiring each firm to develop standards independently.

5.9 Strategic Alignment and an HRA Maturity Pathway

The results also clarify the meaning of strategic alignment. Strategic alignment is not achieved simply because an HR dashboard is reviewed by senior management. It requires a traceable connection from business objectives to workforce questions, from workforce questions to data and analysis, and from analytical findings to accountable action. For example, a growth strategy may imply future demand for particular technical capabilities. A strategically aligned HRA process would quantify the capability gap, assess whether recruitment or development is the better response, estimate timing and cost, and monitor whether the chosen intervention improves readiness. The low workforce-planning mean indicates that this full chain is not yet common. Many organizations appear able to answer operational questions but remain less able to model future scenarios. This finding is consistent with the distinction between descriptive and predictive maturity. Descriptive capability is necessary because it creates trusted data and common definitions. Predictive and prescriptive capability should be introduced only when the organization can formulate clear decisions, evaluate model quality, and act on the results. A staged maturity pathway follows from the findings. Stage one is data foundation: integrated records, governance, quality control, and basic reporting. Stage two is decision-focused functional analytics: recruitment funnel analysis, turnover-risk segmentation, skill-gap assessment, and performance trends. Stage three is predictive integration: validated models linked to interventions and outcome monitoring. Stage four is strategic workforce analytics: scenario planning, capability forecasting, leadership-pipeline risk, and integration with financial and operational plans. This pathway helps explain the MNC-local enterprise difference without assuming that advanced technology is always preferable. An organization at an early stage may obtain more value from improving data definitions and manager adoption than from purchasing an artificial-intelligence platform. Conversely, an organization with mature foundations may lose competitive value if it remains limited to descriptive dashboards. The appropriate next step depends on current capability, business need, and governance readiness. The maturity perspective also changes how success should be evaluated. Implementation should not be measured by the number of dashboards, models, or data fields. More meaningful indicators include decision speed, quality of hire, avoidable turnover, internal mobility, learning effectiveness, leadership readiness, and the extent to which workforce risks are considered in strategic planning. This focus keeps HRA connected to talent and business outcomes rather than technical activity.

6. Limitations and Future Research

Several limitations qualify the findings. First, the cross-sectional design does not establish causality. Although HRA significantly predicted TMS, organizations with strong talent-management practices may also be more likely to invest in analytics. Longitudinal research should examine whether improvements in HRA maturity precede later improvements in talent outcomes. Second, the data were self-reported by HR professionals. The respondents were knowledgeable, but their answers may reflect optimism, social desirability, or differing interpretations of analytics maturity. Future research should combine survey perceptions with objective indicators such as time-to-fill, quality of hire, turnover, internal mobility, training effectiveness, or productivity. Third, purposive and quota sampling limit population-wide generalization. The sample included five industries and a relatively high proportion of large organizations. Firms with an interest in digital HR may have been more willing to participate. Larger probability samples would support sector and regional comparisons. Fourth, organization type captures a broad bundle of contextual differences. Future studies should directly measure digital maturity, leadership support, data quality, analytics skills, organizational culture, and governance. This would identify which specific conditions account for the stronger effect in MNCs. Fifth, the study treated TMS as an integrated outcome in the final regression. Future research should test separate structural relationships for talent acquisition, development, performance, retention, and succession planning. The descriptive results suggest that effect sizes may differ substantially by function. Finally, emerging artificial intelligence applications create new research questions. Future studies should examine predictive validity, bias, explainability, privacy, and employee reactions to automated decision support. Mixed-methods research would be particularly valuable for understanding how managers act on analytical recommendations and how employees experience these systems.

7. Conclusion

This study provides empirical evidence that HRA is an important predictor of TMS in China's corporate sector. HRA adoption was moderately high, but maturity was uneven. Recruitment and retention represented the strongest applications, while workforce planning, performance evaluation, and strategic succession processes were less developed. The direct-effect model showed that HRA explained 37% of the variance in TMS, confirming that organizations using workforce evidence more systematically report stronger talent-management practices. The moderation analysis added an important qualification: the relationship was stronger among MNCs than among local enterprises. HRA therefore generates value through interaction with organizational resources, skills, systems, leadership, culture, and governance. The practical message is clear. Organizations should not treat HRA as a stand-alone technology project. It is a strategic capability that must be built through reliable data, analytical competence, evidence-oriented leadership, integrated systems, and responsible governance. MNCs can continue extending advanced applications, while local enterprises can narrow the gap through phased investment in foundations and high-value use cases. When these conditions are present, HRA can support more precise recruitment, proactive retention, targeted development, stronger performance decisions, and better preparation for future talent needs.

References

Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: Why HR is set to fail the big data challenge. Human Resource Management Journal, 26(1), 1-11.

Cappelli, P., & Keller, J. (2014). Talent management: Conceptual approaches and practical challenges. Annual Review of Organizational Psychology and Organizational Behavior, 1(1), 305-331.

Collings, D. G., & Mellahi, K. (2009). Strategic talent management: A review and research agenda. Human Resource Management Review, 19(4), 304-313.

Davenport, T., & Harris, J. (2017). Competing on analytics: Updated, with a new introduction: The new science of winning. Harvard Business Press.

Fitz-Enz, J. (2010). The new HR analytics. American Management Association.

Hausknecht, J. P., Rodda, J., & Howard, M. J. (2009). Targeted employee retention: Performance-based and job-related differences in reported reasons for staying. Human Resource Management, 48(2), 269-288.

Kleinberg, J., Mullainathan, S., & Raghavan, M. (2016). Inherent trade-offs in the fair determination of risk scores. arXiv preprint arXiv:1609.05807.

Levenson, A. (2018). Using workforce analytics to improve strategy execution. Human Resource Management, 57(3), 685-700.

Li, L. Q., Xin, K., Pucik, V., & Wei, W. X. (2019). MNCs' R&D talent management in China: Aligning practices with strategies. Chinese Management Studies, 13(4), 1086-1106.

Marler, J. H., & Fisher, S. L. (2013). An evidence-based review of e-HRM and strategic human resource management. Human Resource Management Review, 23(1), 18-36.

Shet, S. V., Poddar, T., Samuel, F. W., & Dwivedi, Y. K. (2021). Examining the determinants of successful adoption of data analytics in human resource management: A framework for implications. Journal of Business Research, 131, 311-326.

Van den Heuvel, S., & Bondarouk, T. (2017). The rise (and fall?) of HR analytics: A study into the future application, value, structure, and system support. Journal of Organizational Effectiveness: People and Performance, 4(2), 157-178.

Zhang, J., & Chen, Z. (2024). Exploring human resource management digital transformation in the digital age. Journal of the Knowledge Economy, 15(1), 1482-1498.