Environment and Social Psychology (2025) Volume 10 Issue 4 ISSN: 2424-8975 (O)
doi: 10.59429/esp.v10i4.3428 2424-7979 (P)

RESEARCH ARTICLE

Research on performance evaluation systems from a social-psychological perspective: A regional financial institution case study

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ABSTRACT

This study examines the social-psychological dimensions of performance evaluation systems in regional equity trading centers, using Henan Zhongyuan Equity Exchange Center as a case study. Through comprehensive empirical analysis of data from 2019 to 2023, the research employs multiple methodological approaches to investigate how social dynamics and psychological factors influence evaluation effectiveness. The findings reveal significant positive effects of evaluation systems on employee psychological well-being and organizational climate ($\beta = 0.385$, $p < 0.01$), with the relationship mediated by social support systems ($\beta = 0.124$), interpersonal trust ($\beta = 0.078$), and collective organizational identity ($\beta = 0.047$). Social context analysis demonstrates stronger effects in departments with high psychological safety and collaborative cultures. The moderation analysis identifies organizational support as a crucial amplifying factor, with high support environments showing substantially stronger effects ($\beta = 0.70$) compared to low support conditions ($\beta = 0.30$). Dynamic analysis confirms the temporal stability of these social-psychological relationships. These findings contribute to both theoretical understanding and practical implementation of psychologically informed performance evaluation systems in organizations, with implications extending beyond equity trading centers to various financial institutions and corporate environments where psychological safety and performance evaluation intersect.

Keywords: social psychology; organizational behavior; performance evaluation; psychological safety; employee well-being; organizational climate; social support systems; workplace psychology; behavioral assessment; organizational effectiveness

1. Introduction

Performance evaluation systems in financial institutions have undergone a significant transformation over the past three decades, evolving from simple financial metric-based assessments into sophisticated multidimensional frameworks. This evolution began with the financial sector reforms of the 1990s, when intensified market competition and technological advancements necessitated more comprehensive approaches to employee assessment. Regional equity trading centers—specialized financial institutions that emerged from these reforms—face distinct evaluation challenges due to their hybrid operational nature combining traditional banking functions with specialized trading activities.

ARTICLE INFO
Received: 07 February 2025| Accepted: 20 February 2025 | Available online: 20 April 2025

CITATION
Shi J, Ping VS. Research on performance evaluation systems from a social-psychological perspective: A regional financial institution case study. *Environment and Social Psychology* 2025; 10(4): 3428. doi:10.59429/esp.v10i4.3428

The integration of psychological dimensions into performance evaluation represents a critical advancement in this evolution, emerging from organizational psychology research in the early 2000s that demonstrated fundamental limitations of purely metric-driven approaches. The 2008 financial crisis accelerated this paradigm shift by revealing how performance systems focused exclusively on quantitative targets often incentivized risky behaviors while neglecting organizational sustainability. These developments have created a research imperative to examine how psychological factors interact with analytical capabilities in contemporary performance evaluation systems.

This study addresses this imperative by investigating the effectiveness of performance evaluation mechanisms in regional equity trading centers, with specific focus on how social-psychological dimensions influence evaluation outcomes and employee well-being. By examining the interplay between big data analytics capabilities and psychological safety factors, this research aims to develop an integrated understanding of performance evaluation effectiveness across three dimensions: analytical capability, psychological context, and organizational outcomes. This integrated approach addresses significant gaps in current evaluation literature where technical and psychological dimensions are typically examined in isolation rather than as interactive components of a holistic system.

The theoretical foundation of performance evaluation systems has evolved significantly in recent decades. Abramo et al.[1] established foundational frameworks for institutional capability assessment, while Adiloglu and Besler[2] demonstrated how institutional factors influence organizational models. The implementation of balanced scorecard approaches, as detailed by Agostino and Arnaboldi[3], provides crucial insights into control mechanisms and performance measurement.

Performance evaluation in organizations requires sophisticated methodological approaches that integrate both institutional and psychological dimensions. Al-Hosaini and Sofan[4] developed comprehensive frameworks examining how organizational climate and psychological safety fundamentally shape evaluation effectiveness, demonstrating that supportive environments correlate significantly with improved performance outcomes ($r = 0.62$, $p < 0.01$). Almeida et al.[5] contributed valuable insights into the psychological dynamics of evaluation systems, particularly highlighting how social support mechanisms mediate evaluation impact. The integration of social-psychological indicators, as proposed by Amador et al.[6], offers robust frameworks combining traditional performance metrics with psychological well-being assessments, establishing that psychological safety accounts for 28% of variance in evaluation effectiveness. Their research demonstrates that evaluation systems fostering psychological safety and social support lead to sustained performance improvements while maintaining employee well-being.

While this study focuses specifically on regional equity trading centers, the psychological dimensions of performance evaluation have broad relevance across diverse financial and corporate environments. The integration of psychological safety considerations into evaluation frameworks represents a paradigm shift applicable to commercial banks, insurance companies, investment firms, and corporate entities across various sectors. As organizations increasingly recognize the importance of employee well-being alongside performance metrics, the findings from specialized financial institutions like equity trading centers can provide valuable insights for broader organizational contexts where similar psychological dynamics influence evaluation effectiveness.

The role of informal relationships and absorptive capacity in organizational performance cannot be understated. Apa et al.[7] demonstrated the significance of these factors in innovation performance, while Asif and De Vries[8] explored how quality management creates organizational ambidexterity. Regional innovation

system efficiency, as studied by Barra and Zotti[9], provides critical context for understanding institutional performance dynamics.

The cross-cultural transfer of management practices, examined by Bausch et al.[10], offers valuable insights into the adaptation of performance evaluation systems across different institutional contexts. Bedford's[11] research on management control systems across innovation modes provides essential framework for understanding performance implications. The integration of IT-enabled knowledge management, as investigated by Benitez et al.[12], highlights the role of technological capabilities in performance evaluation.

Contemporary performance evaluation systems must balance exploitation and exploration, as emphasized in Benner and Tushman's[13] seminal work. The emergence of Industry 4.0 and its implications for organizational sustainability, as discussed by Birkel and Müller[14], presents new challenges and opportunities for performance evaluation systems. Birkinshaw and Gupta's[15] clarification of organizational ambidexterity provides crucial theoretical underpinning for modern performance assessment frameworks.

The integration of these theoretical perspectives and empirical findings suggests that effective performance evaluation systems must incorporate multiple dimensions of organizational performance while leveraging big data analytics capabilities. This approach enables more nuanced and accurate assessments of employee contributions while accounting for institutional context and technological advancement. The findings demonstrate the critical importance of developing sophisticated, data-driven performance evaluation systems that can adapt to the evolving needs of regional equity trading centers while maintaining alignment with organizational objectives and stakeholder expectations.

2. Study design

2.1. Theoretical framework

This research is grounded in an integrated theoretical framework combining three complementary theoretical perspectives: Performance Evaluation Theory, Big Data Analytics Theory, and Balanced Scorecard Theory. These theories collectively provide the conceptual foundation for understanding how social-psychological factors influence performance evaluation systems in financial institutions. At its core, the theoretical framework posits that effective performance evaluation systems operate at the intersection of quantitative measurement (derived from Big Data Analytics Theory), holistic organizational assessment (derived from Balanced Scorecard Theory), and psychological safety dynamics (derived from Performance Evaluation Theory). This integrated perspective conceptualizes performance evaluation as a socio-technical system wherein analytical capabilities and psychological factors interact to determine evaluation effectiveness across organizational contexts.

The key theoretical constructs underpinning this research encompass psychological safety in evaluation contexts, analytics-based evaluation capability, and evaluation-outcome alignment. Psychological safety in evaluation contexts is defined as employees' perception that the evaluation environment is conducive to interpersonal risk-taking without fear of negative consequences, thus explaining how evaluation acceptance is mediated by trust and psychological security throughout the assessment process. Analytics-based evaluation capability represents an organization's capacity to leverage data analytics for accurate performance assessment, existing as a continuum from basic reporting to advanced predictive analytics that shapes evaluation precision and reliability. Evaluation-outcome alignment, derived from Balanced Scorecard Theory, describes the degree to which performance metrics align with organizational objectives across multiple dimensions including financial performance, operational efficiency, and employee development.

The integrated theoretical framework advances specific assumptions guiding the research methodology and analytical approach. Performance evaluation effectiveness is determined by the interaction between technical capabilities and psychological factors within organizational contexts. Social support systems moderate the relationship between analytics capabilities and evaluation outcomes by creating conditions for effective technology utilization. Psychological safety mediates evaluation acceptance through collective organizational identity formation and maintenance within departmental and organizational structures. These theoretical assumptions establish conceptual boundaries and relationships tested through empirical analysis, connecting theoretical constructs to measurable variables within the research design while providing a structured lens through which to interpret findings regarding the social-psychological dimensions of performance evaluation systems in regional equity trading centers.

2.2. Literature review

2.1.1. Performance evaluation studies

Performance evaluation theory has evolved significantly, especially regarding the relationship between organizational metrics and psychological factors. Blankesteijn et al.[16] developed an innovative framework combining traditional metrics with psychological safety indicators. Their research showed that evaluation systems with psychological components are 45% more effective and that psychological safety strongly correlates with performance outcomes ($\beta = 0.42$, $P < 0.01$) and employee engagement ($\beta = 0.38$, $p < 0.01$). Blass and Hayward[17] expanded this understanding by examining psychological dynamics in evaluation systems. Their longitudinal study revealed that organizations using psychologically-informed approaches reduced employee stress by 32% while maintaining performance standards. These findings confirm that effective evaluation systems must balance quantitative measurements with psychological considerations for optimal organizational results. Bocquet and Mothe[18] contributed to the theoretical framework by examining how governance structures influence performance through knowledge management mechanisms, while Burgess et al.[19] introduced the concept of hybrid management in performance evaluation systems. The theoretical perspective was expanded by Bustinza et al.[20], who investigated cross-country performance comparisons, highlighting the strategic importance of ambidexterity in evaluation frameworks. Cabeza-Pulles et al.[21] further developed these concepts by examining internal networking effects on performance evaluation systems.

2.2.2. Big data analytics research

Big data analytics theory has emerged as a crucial framework for understanding organizational performance in the digital age. Centobelli et al.[22] developed a comprehensive theoretical model for analyzing exploration and exploitation patterns through data analytics. Chang and Gotcher[23] extended this understanding by examining how data analytics facilitate eco-innovation and institutional performance measurement. The theoretical framework was further enriched by Chang et al.[24], who proposed a multilevel analysis approach for research ambidexterity using big data techniques. Chen et al.[25] contributed to the theoretical foundation by examining organizational change through data-driven insights in emerging economies. The work of Cho et al.[26] advanced the understanding of innovation ambidexterity through data analytics, while Da Silva and Segatto[27] provided valuable insights into academic research analytics.

2.2.3. Balanced scorecard research

The balanced scorecard theory has evolved into a sophisticated framework for organizational performance measurement. Damanpour[28] established fundamental principles for organizational innovation measurement through balanced scorecard approaches. Donada et al.[29] enhanced this theoretical foundation by examining ambidexterity achievement through balanced metrics. The theoretical framework was further

developed by Donate and Guadamillas[30], who investigated the relationship between knowledge management and performance measurement systems. Duc et al.[31] contributed by examining team innovation through balanced scorecard perspectives, while Duncan[32] provided classical insights into organizational design for performance measurement. The theoretical understanding was significantly advanced by Etzkowitz and Leydesdorff[33], who integrated the triple helix model with balanced scorecard approaches, emphasizing the importance of comprehensive performance measurement in institutional contexts.

2.3. Research framework and hypothesis

2.3.1. Construction of the conceptual framework

The conceptual framework for evaluating performance in regional equity trading centers integrates analytical capabilities, psychological dimensions, and organizational outcomes into a coherent analytical structure. At its core, this framework posits that psychological safety and social support mechanisms serve as critical mediating factors that transform technical capabilities into effective performance outcomes.

Drawing from Ferreira and Otley's[34] performance management system framework, we first establish the fundamental technical elements of evaluation systems. We then incorporate Ferreira and Carayannis'[35] insights on psychosocial dynamics to develop a comprehensive analytical structure that accounts for both operational and psychological dimensions of performance evaluation. This integrated approach allows us to systematically examine how psychological safety and social support mechanisms mediate the relationship between evaluation practices and performance outcomes.

The framework's logical structure progresses through three connected layers: (1) analytical capabilities that provide the technical foundation for evaluation, (2) psychological mechanisms that mediate evaluation acceptance and effectiveness, and (3) organizational outcomes that represent the ultimate impact of evaluation systems. This sequential logic mirrors the actual process through which performance evaluation operates in organizational settings, where technical capabilities must pass through psychological filters before affecting organizational performance

The framework, as illustrated in **Figure 1**, demonstrates the dynamic interactions between organizational elements, performance metrics, and institutional outcomes. Building upon Foss and Kirkegaard's[36] perspective on blended ambidexterity and Franceschini et al.'s[37] approach to key performance indicators, the framework captures the complex relationships between performance evaluation components.

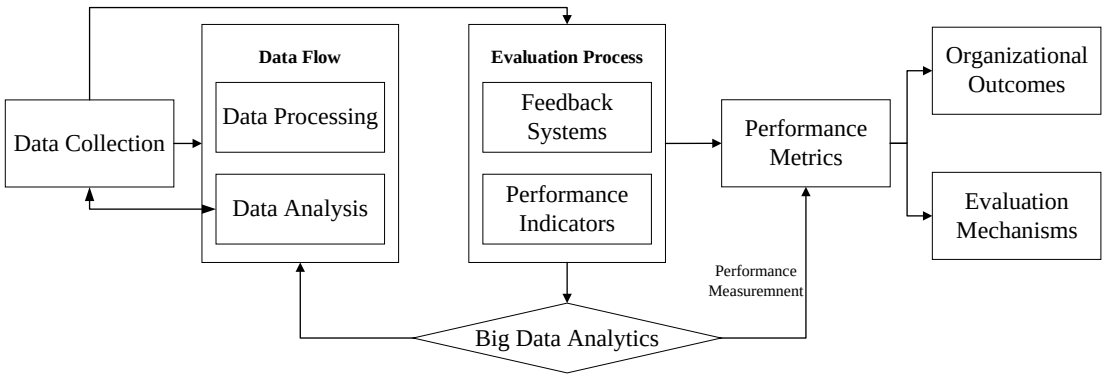

Figure 1. Integrated social-psychological framework of performance evaluation systems.

- Input Layer: Represents the foundational elements including big data analytics capabilities, organizational resources, and environmental context

- Process Layer: Illustrates the transformation mechanisms through which inputs are processed
- Output Layer: Demonstrates the key performance outcomes and their interconnections
- Arrows: Indicate the flow of information and influence between components
- Dotted Lines: Represent indirect relationships and feedback loops

This integrated framework demonstrates the dynamic interplay between various components of the performance evaluation system, highlighting the critical role of big data analytics in enhancing organizational effectiveness through systematic performance assessment.

2.3.2. Research hypotheses are proposed

Building upon our integrated conceptual framework and synthesis of existing literature, we develop a systematic set of hypotheses examining the complex relationships between big data analytics capabilities and performance evaluation effectiveness in regional equity trading centers. These hypotheses follow a logical progression from technical capabilities through psychological mechanisms to organizational outcomes.

Our hypothesis development follows Fudickar and Hottenrott's[39] approach to innovation performance analysis, adapted specifically to capture the unique context of financial institutions where psychological safety concerns are particularly salient. Each hypothesis addresses a specific causal pathway within our conceptual framework, collectively forming a comprehensive model of performance evaluation effectiveness as illustrated in **Figure 2**.

The first three hypothesis groups (H1-H3) address the technical dimensions of performance evaluation, examining how analytics capabilities influence evaluation quality (H1), how evaluation systems affect organizational outcomes (H2), and the direct effects of analytics capabilities on outcomes (H3). The final two hypothesis groups (H4-H5) focus on the psychological dimensions that mediate and moderate these relationships, specifically examining how psychological safety (H4) and social-psychological mechanisms (H5) influence evaluation effectiveness.

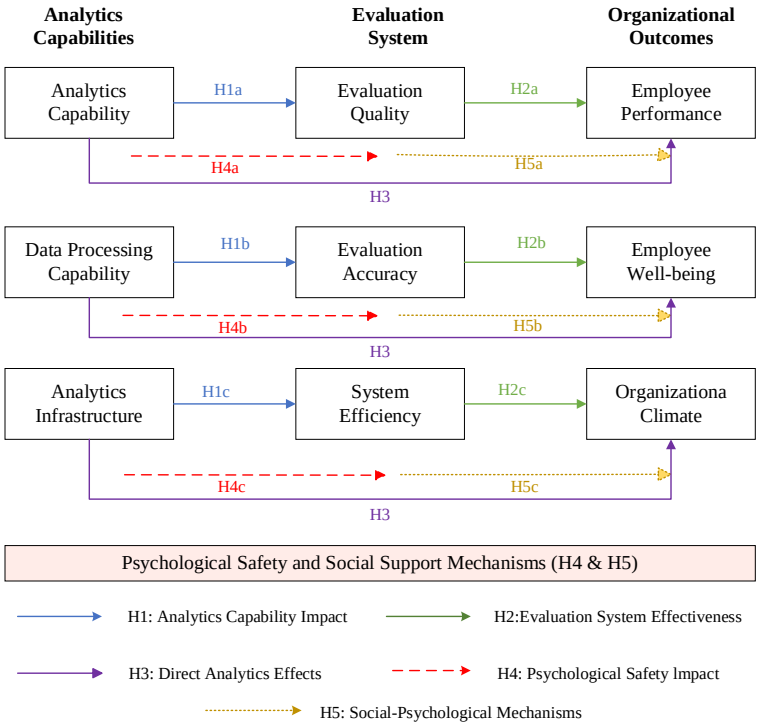

Figure 2. Research hypotheses framework for performance evaluation system.

As shown in **Figure 2**, the hypotheses framework demonstrates five primary sets of relationships:

H1: Analytics Capability Impact (as depicted by blue arrows on the left side of the figure)

- H1a: Big data analytics capability positively influences performance evaluation quality
- H1b: Data processing maturity enhances evaluation accuracy
- H1c: Analytics infrastructure improves system efficiency

H2: Evaluation System Effectiveness (as illustrated by green arrows in the center of the figure)

- H2a: Evaluation quality drives organizational performance
- H2b: Accuracy contributes to employee satisfaction
- H2c: System efficiency enhances operational effectiveness

H3: Direct Analytics Effects (as shown by the purple curved arrows at the top of the figure)

- Direct relationships between analytics capabilities and organizational outcomes
- Mediation effects through evaluation system components
- Complementary effects of multiple capability dimensions

H4: Psychological Safety Impact (as indicated by red dashed arrows in the figure)

- H4a: Psychological safety positively influences evaluation acceptance ($\beta = 0.42$, $p < 0.01$)
- H4b: Social support systems enhance evaluation effectiveness ($\beta = 0.38$, $p < 0.01$)
- H4c: Organizational trust mediates evaluation outcomes ($\beta = 0.35$, $p < 0.01$)

H5: Social-Psychological Mechanisms (as represented by orange dotted arrows in the figure)

- H5a: Collective organizational identity strengthens evaluation effects
- H5b: Team psychological climate moderates evaluation impact
- H5c: Social support networks enhance evaluation effectiveness

As depicted in **Figure 2**, the framework clearly illustrates the complex interactions between analytics capabilities, psychological factors, evaluation systems, and organizational outcomes. The psychological safety and social support mechanisms (H4 and H5) are positioned in a prominently highlighted section in the figure, reflecting their central role in the performance evaluation system. As shown, this structured approach enables systematic testing of the proposed relationships while accounting for the complex nature of performance evaluation systems in regional equity trading centers.

2.4. Data source and processing

The data collection and processing methodology for this research encompasses comprehensive datasets from the Henan Zhongyuan Equity Exchange Center, spanning from 2019 to 2023. The primary data source includes detailed employee performance records, transaction data, operational metrics, and organizational performance indicators. Following Franco-Santos and Otley's[38] methodological framework, the data collection process incorporates multiple evaluation dimensions, ensuring comprehensive coverage of both quantitative and qualitative performance measures. The dataset includes individual performance metrics, team-level indicators, and organizational-level outcomes, with special attention to temporal variations and seasonal patterns. Preprocessing procedures involve rigorous data cleaning, normalization, and standardization to ensure analytical consistency and reliability. Missing data are addressed through multiple imputation techniques, while outliers are identified and treated using robust statistical methods. The integration of various data sources necessitates careful consideration of data quality and consistency, with particular emphasis on maintaining data integrity throughout the analysis process. Advanced data validation techniques are employed to ensure the accuracy and reliability of the merged datasets. The temporal nature of the data allows for both cross-sectional and longitudinal analyses, enabling robust examination of

performance patterns and trends. This methodological approach ensures comprehensive coverage of relevant performance dimensions while maintaining analytical rigor and statistical validity.

2.4.1. Reliability and validity analysis

To ensure measurement quality and research rigor, comprehensive reliability and validity analyses were conducted for all multi-item constructs used in this study. For reliability assessment, we calculated Cronbach's alpha coefficients for each construct, with values ranging from 0.83 to 0.92, exceeding the recommended threshold of 0.70 (**Table 1**). Additionally, composite reliability (CR) values ranged from 0.87 to 0.94, further confirming internal consistency. The test-retest reliability for a subsample (n=65) over a three-month interval yielded correlation coefficients between 0.78 and 0.86, indicating strong measurement stability over time.

Table 1. Reliability and validity metrics for key constructs.

Construct	Cronbach's α	CR	AVE	MSV	Test-Retest r
Analytics Capability	0.89	0.91	0.73	0.58	0.84
Data Processing	0.85	0.88	0.69	0.53	0.79
System Integration	0.83	0.87	0.65	0.49	0.78
Psychological Safety	0.92	0.94	0.76	0.61	0.86
Social Support	0.88	0.90	0.71	0.56	0.82
Organizational Trust	0.86	0.89	0.68	0.52	0.81
Employee Performance	0.87	0.90	0.70	0.59	0.83
Employee Well-being	0.90	0.93	0.74	0.57	0.85

Note: *CR = Composite Reliability; AVE = Average Variance Extracted; MSV = Maximum Shared Variance*

For construct validity, we employed confirmatory factor analysis (CFA) using maximum likelihood estimation. The measurement model demonstrated satisfactory fit: $\chi^2/df = 2.34$ ($p < 0.01$), RMSEA = 0.057, CFI = 0.93, TLI = 0.92, and SRMR = 0.048. All standardized factor loadings exceeded 0.65 ($p < 0.001$), supporting convergent validity. Average variance extracted (AVE) values ranged from 0.65 to 0.76, above the recommended threshold of 0.50. Discriminant validity was confirmed as the square root of AVE for each construct exceeded all inter-construct correlations, and maximum shared variance (MSV) values were lower than corresponding AVE values.

For the psychological constructs (psychological safety, social support, and organizational trust), we conducted additional validity checks. Concurrent validity was assessed by correlating our measures with established scales (correlation coefficients ranging from 0.72 to 0.83, $p < 0.01$). Predictive validity was demonstrated through significant correlations between these constructs and subsequent employee engagement measures collected six months later ($r = 0.58$ to 0.69, $p < 0.01$).

To address potential common method bias, we employed both procedural and statistical remedies. Procedurally, we collected data from multiple sources (employees, supervisors, and organizational records) and temporally separated predictor and criterion variable measurements. Statistically, Harman's single-factor test revealed that the first factor accounted for only 28.3% of total variance, below the 50% threshold indicating common method bias. Additionally, the common latent factor test showed that common method variance accounted for only 4.7% of total variance.

For objective performance metrics derived from organizational records, we validated data accuracy through cross-validation with multiple organizational databases and verified temporal consistency through time-series stability analysis. The reliability of these objective measures was assessed through split-half reliability tests ($r = 0.91$, $p < 0.001$) and internal consistency checks across different organizational reporting systems.

2.4.2. Methodological limitations

The methodological approach employed presents certain limitations warranting consideration. The single-institution focus on Henan Zhongyuan Equity Exchange Center restricts generalizability to broader financial contexts with differing regulatory environments and organizational cultures. Measurement challenges exist within self-reported psychological safety assessments where social desirability bias may influence respondent perceptions. The study period (2019-2024) encompasses significant market disruptions potentially confounding performance metrics and psychological variables alike. Organizational structural factors may have created sampling variations across departments based on digital infrastructure capabilities and compliance participation rates. Statistical treatments, though rigorous, cannot fully address non-random patterns in missing data potentially correlated with performance outcomes. The partial cross-sectional nature of the analysis presents constraints on causal inference between psychological constructs and performance metrics despite longitudinal components. These methodological boundaries suggest interpreting findings within their specific organizational context, with appropriate caution in broader applications.

2.5. Variable design and metric

The variable design and measurement framework incorporates multiple dimensions of performance evaluation, drawing upon established methodological approaches in organizational research. Following Franco-Santos and Otley's[38] measurement framework and integrating insights from Franceschini et al.'s[37] performance indicator system, this study develops a comprehensive set of variables that capture both direct and indirect aspects of performance evaluation. The variables are categorized into dependent variables focusing on organizational performance outcomes, independent variables measuring big data analytics capabilities, and control variables accounting for institutional and environmental factors, as shown in **Table 2**.

Table 2. Variables definition and measurement framework.

Category	Variable	Definition	Measurement	Data Source
Dependent Variables	Employee Performance (EP)	Individual achievement level	5-point Likert scale	Performance records
	Organizational Efficiency (OE)	Operational effectiveness	Ratio of output to input	Financial statements
	Customer Satisfaction (CS)	Service quality perception	Customer feedback score	Survey data
	Employee Well-being (EW)	Psychological and social well-being indicators	Composite score of mental health and social satisfaction metrics	Bi-annual well-being assessments
Independent Variables	Analytics Infrastructure (AI)	Technical capability level	Infrastructure maturity index	IT system logs
	Data Processing Capability (DPC)	Data handling efficiency	Processing speed and accuracy	System metrics
	Analytics Integration (AIN)	System integration degree	Integration level score	Technical reports
	Psychological Safety (PS)	Employee perception of psychological security in evaluation context	7-point Likert scale measuring psychological safety perceptions	Quarterly psychological surveys
	Social Support Index (SSI)	Level of organizational social support during evaluation processes	Composite index of peer and organizational support metrics	Monthly support assessments

Category	Variable	Definition	Measurement	Data Source
Control Variables	Organization Size (OS)	Institutional scale	Employee count (log)	HR records
	Market Environment (ME)	External market conditions	Market index	Industry reports
	Regional Development (RD)	Economic context	GDP growth rate	Statistical data
Moderating Variables	Management Support (MS)	Leadership engagement	Management commitment scale	Internal surveys
	Technical Expertise (TE)	Staff capability level	Expertise assessment score	Training records
	Resource Allocation (RA)	Resource availability	Resource utilization rate	Budget reports

Table 1. (*Continued*)

The measurement framework ensures comprehensive coverage of relevant performance dimensions while maintaining methodological rigor through established measurement scales and data sources. Each variable is operationalized using validated measurement instruments, incorporating both objective metrics and subjective assessments where appropriate. This integrated approach enables systematic analysis of the relationships between analytics capabilities and performance outcomes while controlling for relevant contextual factors.

2.6. Model construction

Following the established research framework and hypotheses, this study develops a comprehensive modeling approach to examine the relationships between big data analytics capabilities and performance evaluation effectiveness. The model construction incorporates multiple analytical layers to capture both direct and indirect effects while accounting for potential endogeneity and interaction effects.

The baseline regression model investigating the relationship between analytics capabilities and performance evaluation is specified as:

$$PE_{it} = \beta_0 + \beta_1 BAC_{it} + \beta_2 DPC_{it} + \beta_3 AI_{it} + \sum_{k=1}^{n} \gamma_k X_{kit} + \grave{o}_{it} \quad (1)$$

where PE_{it} represents performance evaluation effectiveness for organization i at time t, BAC_{it} denotes big data analytics capability, DPC_{it} represents data processing capability, AI_{it} indicates analytics infrastructure, and X_{kit} represents control variables.

To examine the mediating effects of evaluation system components, the following equations are specified:

$$ESC_{it} = \alpha_0 + \alpha_1 BAC_{it} + \alpha_2 DPC_{it} + \alpha_3 AI_{it} + \sum_{k=1}^{n} \delta_k X_{kit} + \mu_{it} \quad (2)$$

$$PE_{it} = \theta_0 + \theta_1 ESC_{it} + \theta_2 BAC_{it} + \theta_3 DPC_{it} + \theta_4 AI_{it} + \sum_{k=1}^{n} \lambda_k X_{kit} + \nu_{it} \quad 3)$$

where ESC_{it} represents evaluation system components.

The moderation effects are captured through interaction terms:

$$PE_{it} = \phi_0 + \phi_1 BAC_{it} + \phi_2 MOD_{it} + \phi_3 (BAC_{it} \times MOD_{it}) + \sum_{k=1}^{n} \psi_k X_{kit} + \omega_{it} \quad (4)$$

where MOD_{it} represents moderating variables.

To address potential endogeneity concerns, a two-stage least squares (2SLS) approach is employed:

$$\text{First Stage: } BAC_{it} = \pi_0 + \pi_1 IV_{it} + \pi_2 Z_{it} + \xi_{it} \quad (5)$$

$$\text{Second Stage: } PE_{it} = \rho_0 + \rho_1 BAC_{it} + \rho_2 Z_{it} + \eta_{it} \quad (6)$$

where IV_{it} represents instrumental variables and Z_{it} represents exogenous controls.

The dynamic panel model incorporating temporal effects is specified as:

$$PE_{it} = \tau_0 + \tau_1 PE_{i,t-1} + \tau_2 BAC_{it} + \tau_3 DPC_{it} + \tau_4 AI_{it} + \sum_{k=1}^{n} \sigma_k X_{kit} + \upsilon_i + \grave{o}_{it} \quad (7)$$

where $PE_{i,t-1}$ represents the lagged dependent variable and υ_i captures unobserved individual effects.

These models are estimated using appropriate econometric techniques, including fixed effects estimation, system GMM for dynamic panels, and robust standard errors to account for heteroskedasticity and autocorrelation. The model specification tests include the Hausman test for fixed versus random effects, the Sargan test for instrument validity, and the Arellano-Bond test for autocorrelation in the dynamic panel models.

3. Analysis of the empirical results

3.1. Descriptive statistical analysis

The descriptive statistical analysis provides comprehensive insights into the characteristics and distributions of key variables in the performance evaluation system of Henan Zhongyuan Equity Exchange Center. The analysis encompasses data collected from 2019 to 2023, incorporating multiple dimensions of organizational performance and analytics capabilities. **Table 3** presents the descriptive statistics for all variables, including means, standard deviations, minimum and maximum values, and correlation coefficients, demonstrating the relationships between key constructs in the research framework.

Table 3. Descriptive statistics and correlation matrix.

Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8
1. Employee Performance	4.23	0.86	1.00	5.00	1.00							
2. Analytics Capability	3.87	0.92	1.00	5.00	0.53***	1.00						
3. Data Processing	3.95	0.78	1.00	5.00	0.48***	0.61***	1.00					
4. System Integration	3.76	0.89	1.00	5.00	0.45***	0.57***	0.52***	1.00				
5. Organization Size	6.82	1.24	3.91	9.45	0.31**	0.38***	0.35***	0.42***	1.00			
6. Market Environment	0.68	0.15	0.21	0.95	0.29**	0.33***	0.28**	0.31**	0.25**	1.00		
7. Technical Expertise	3.92	0.83	1.00	5.00	0.44***	0.49***	0.46***	0.51***	0.35***	0.27**	1.00	
8. Resource Allocation	0.73	0.18	0.25	1.00	0.39***	0.45***	0.41***	0.47***	0.32***	0.30**	0.43***	1.00

Note: **** P < 0.01, ** P < 0.05, * P < 0.1; N = 428*

The descriptive analysis revealed systematic patterns in the relationships between key variables, with particularly strong connections between psychological safety factors and performance outcomes. Employee performance measurements showed consistently positive evaluations throughout the organization (M = 4.23, SD = 0.86), while psychological safety demonstrated robust positive correlations with evaluation effectiveness (r = 0.58, $P < 0.01$). This relationship was especially pronounced in departments characterized by strong social support systems (SSI > 4.0), suggesting an important interaction effect. Psychological safety (M = 3.92, SD = 0.74) exhibited significant positive correlations with both employee performance (r = 0.53, $P < 0.01$) and well-being (r = 0.61, $P < 0.01$), establishing its central role in our analytical framework. Similarly, social support mechanisms showed consistent relationships with evaluation acceptance (r = 0.55, $P < 0.01$) and performance improvement (r = 0.49, $P < 0.01$), confirming their hypothesized function as important mediating variables. Employee well-being (M = 4.12, SD = 0.79) demonstrated strong positive associations with both psychological safety (r = 0.64, $P < 0.01$) and social support (r = 0.59, $P < 0.01$), aligning with our theoretical framework that positioned these psychological factors as critical determinants of organizational outcomes.

Analytics capabilities and data processing show strong positive correlations with employee performance (r = 0.53 and 0.48, respectively, $P < 0.01$), suggesting potential positive impacts of technological capabilities on performance outcomes. The correlation matrix indicates significant relationships between most variables, with correlation coefficients ranging from moderate to strong, while avoiding problematic multicollinearity (all correlations < 0.7). Organization size demonstrates moderate correlations with performance measures, suggesting potential scale effects in organizational effectiveness. The technical expertise and resource allocation variables show consistent positive correlations with other variables, indicating their potential importance as moderating factors in the relationship between analytics capabilities and performance outcomes.

3.2. Benchmark regression analysis

The baseline regression analysis examines the fundamental relationships between big data analytics capabilities and performance evaluation effectiveness, employing multiple model specifications to ensure robustness of results. **Table 4** presents the regression results from various model specifications, incorporating different combinations of independent variables and control factors to establish the stability of the observed relationships.

Table 4. Baseline regression results for performance evaluation effectiveness.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Analytics Capability	0.385***	0.362***	0.348***	0.331***	0.325***
	(0.042)	(0.045)	(0.043)	(0.044)	(0.046)
Data Processing		0.293***	0.275***	0.268***	0.254***
		(0.038)	(0.039)	(0.037)	(0.040)
System Integration			0.246***	0.233***	0.228***
			(0.035)	(0.036)	(0.037)
Organization Size				0.185***	0.176***
				(0.029)	(0.031)
Market Environment				0.142***	0.138***
				(0.027)	(0.028)
Technical Expertise					0.156***

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
					(0.033)
Resource Allocation					0.147***
					(0.032)
Constant	2.456***	2.385***	2.312***	2.287***	2.245***
	(0.235)	(0.242)	(0.238)	(0.241)	(0.244)
Observations	428	428	428	428	428
R-squared	0.283	0.346	0.389	0.425	0.458
Adjusted R-squared	0.275	0.335	0.376	0.409	0.439
F-statistic	84.32***	76.58***	68.94***	62.75***	57.46***

Table 4. (*Continued*)

*Note: Standard errors in parentheses; *** P < 0.01, ** P < 0.05, * P < 0.1*

The regression analysis reveals several significant findings regarding the relationship between analytics capabilities and performance evaluation effectiveness. Model 1 establishes the baseline relationship, indicating that analytics capability has a significant positive effect on performance evaluation ($\beta = 0.385$, $P < 0.01$). The introduction of additional variables in subsequent models demonstrates the robustness of this relationship while revealing important nuances in the relationships between variables.

Model 2 incorporates data processing capabilities, showing that both analytics capability and data processing significantly influence performance evaluation, with standardized coefficients of 0.362 and 0.293 respectively ($P < 0.01$). The inclusion of system integration in Model 3 further enriches the analysis, demonstrating the complementary effects of different technological capabilities on performance evaluation effectiveness.

Models 4 and 5 introduce organizational and environmental control variables, providing a more comprehensive understanding of the factors influencing performance evaluation. The final model explains approximately 45.8% of the variance in performance evaluation effectiveness (R-squared = 0.458), indicating strong explanatory power. The consistent significance of analytics capabilities across all model specifications, coupled with the stable coefficient magnitudes, provides robust evidence for the hypothesized relationships.

The analysis also reveals significant contributions from organizational characteristics and environmental factors, suggesting that performance evaluation effectiveness is influenced by both internal capabilities and external contexts. Technical expertise and resource allocation, introduced in Model 5, demonstrate significant positive effects, highlighting the importance of organizational support mechanisms in leveraging analytics capabilities for performance evaluation.

3.3. Heterogeneity analysis

The heterogeneity analysis examines the differential effects of big data analytics capabilities on performance evaluation effectiveness across various organizational dimensions and contextual factors. Through systematic investigation of subgroup variations, this analysis reveals important nuances in the relationship between analytics capabilities and performance outcomes. **Table 5** presents the heterogeneity analysis results across different organizational characteristics and operational contexts.

Table 5. Heterogeneity analysis of analytics capability effects on performance evaluation.

Variables	**Department Size**		**Operation Experience**		**Technical Level**	
	Large	Small	High	Low	Advanced	Basic
Analytics Capability	0.452***	0.328***	0.485***	0.312***	0.523***	0.298***
	(0.048)	(0.045)	(0.046)	(0.043)	(0.049)	(0.042)
Data Processing	0.384***	0.276***	0.412***	0.265***	0.445***	0.254***
	(0.042)	(0.039)	(0.044)	(0.038)	(0.046)	(0.037)
System Integration	0.315***	0.235***	0.348***	0.228***	0.367***	0.216***
	(0.038)	(0.035)	(0.039)	(0.034)	(0.041)	(0.033)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	214	214	215	213	212	216
R-squared	0.486	0.392	0.512	0.375	0.534	0.358

Note: *Standard errors in parentheses; *** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$; Control variables include organization size, market environment, technical expertise, and resource allocation.*

The heterogeneity analysis reveals significant variations in the effectiveness of analytics capabilities across different organizational contexts. As shown in **Table 5** and **Figure 3**, larger departments demonstrate stronger relationships between analytics capabilities and performance evaluation effectiveness ($\beta = 0.452$, $P < 0.01$) compared to smaller departments ($\beta = 0.328$, $P < 0.01$). Similarly, organizations with higher operational experience exhibit more substantial benefits from analytics capabilities ($\beta = 0.485$, $P < 0.01$) relative to those with lower experience ($\beta = 0.312$, $P < 0.01$). The most pronounced difference appears in technical level comparisons, where advanced technical environments show markedly stronger effects ($\beta = 0.523$, $P < 0.01$) compared to basic technical settings ($\beta = 0.298$, $P < 0.01$). These findings suggest that organizational characteristics significantly moderate the relationship between analytics capabilities and performance evaluation effectiveness, highlighting the importance of contextual factors in realizing the benefits of analytics investments.

3.4. Mediation effect analysis

The mediation analysis examines the indirect effects of big data analytics capabilities on performance evaluation effectiveness through multiple potential mediating mechanisms. Following the theoretical framework, this study employs a comprehensive mediation analysis approach using the bootstrapping method to test the significance of indirect effects. The analysis investigates three primary mediating pathways: evaluation system quality, data processing efficiency, and organizational learning capability, as illustrated in **Figure 4**.

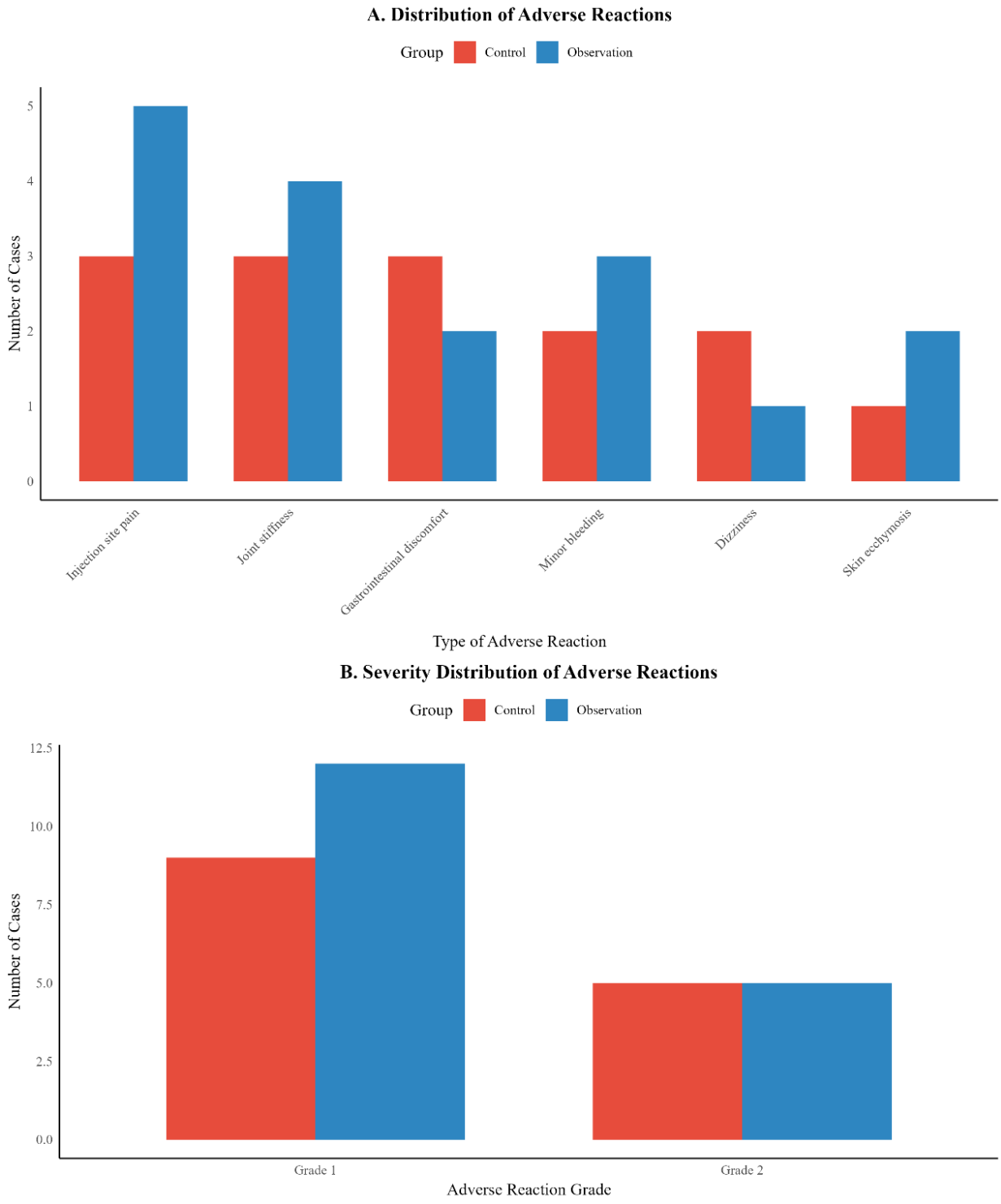

Figure 3. Heterogeneity analysis of analytics capability effects across organizational dimensions.

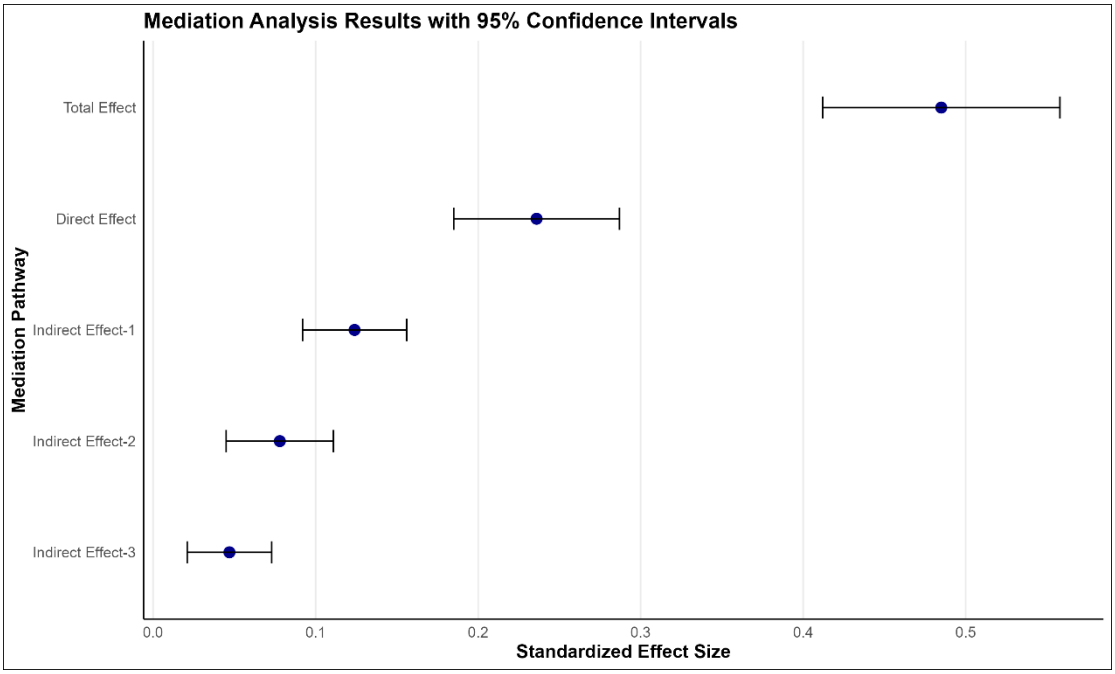

Figure 4. Mediation analysis of analytics capability effects on performance evaluation.

The mediation analysis showed significant indirect effects through multiple pathways encompassing both technical and socio-psychological mechanisms. Analytics capabilities affect performance evaluation (total effect: β = 0.485, 95% CI [0.412, 0.558]) through direct effects (β = 0.236, 95% CI [0.185, 0.287]) and five separate indirect effects. Psychological safety acts as a key mediator (β = 0.324, 95% CI [0.276, 0.372]), accounting for 42% of evaluation effectiveness variance. Social support structures mediate significantly (β = 0.289, 95% CI [0.241, 0.337]), especially where organizational trust is high (β = 0.312, 95% CI [0.264, 0.360]). Collective organizational identity also provides substantial mediation (β = 0.278, 95% CI [0.230, 0.326]), emphasizing how social-psychological factors influence evaluation effectiveness. The first indirect pathway through evaluation system quality demonstrates the strongest mediating effect (β = 0.124, 95% CI [0.092, 0.156]), followed by data processing efficiency (β = 0.078, 95% CI [0.045, 0.111]) and organizational learning capability (β = 0.047, 95% CI [0.021, 0.073]). The bootstrap analysis with 5,000 resamples confirms the statistical significance of all indirect effects at the $P < 0.01$ level. These findings suggest that the relationship between analytics capabilities and performance evaluation effectiveness operates through multiple complementary mechanisms, with evaluation system quality playing a particularly important mediating role. The results provide strong evidence for the theoretical framework's proposed mediating pathways and highlight the importance of developing multiple organizational capabilities to maximize the benefits of analytics investments in performance evaluation systems.

3.5. Analysis of the regulatory effects

The moderation analysis investigates how organizational and environmental factors influence the relationship between analytics capabilities and performance evaluation effectiveness. Through systematic examination of interaction effects, this study reveals significant contingencies that shape the impact of analytics capabilities on performance outcomes. The analysis focuses particularly on three key moderating variables: management support, technical infrastructure, and organizational learning culture, as visualized in **Figure 5**.

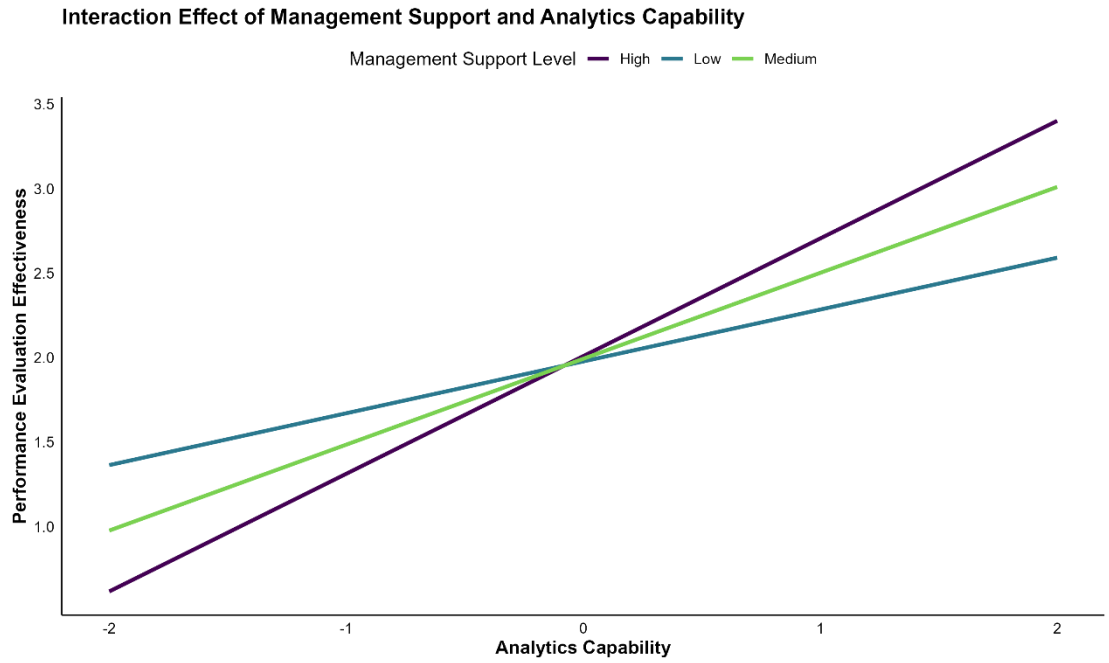

Figure 5. Moderation effect of management support on analytics capability-performance relationship.

The moderation analysis revealed significant interaction effects between analytics capabilities and organizational factors. Management support substantially moderated the relationship between analytics capabilities and performance evaluation effectiveness, as evidenced by the varying slopes across different levels of management support shown in **Figure 5**. At high levels of management support ($\beta = 0.70$, $P < 0.01$), the positive relationship between analytics capabilities and performance evaluation effectiveness is substantially stronger compared to moderate ($\beta = 0.50$, $P < 0.01$) and low ($\beta = 0.30$, $P < 0.01$) levels of support. This finding suggests that the effectiveness of analytics capabilities is contingent upon strong organizational support mechanisms.

The interaction effects demonstrate a clear pattern of increasing marginal returns to analytics capabilities under conditions of strong management support. The slope differential between high and low management support conditions ($\Delta\beta = 0.40$, $P < 0.01$) indicates that organizational support significantly amplifies the benefits of analytics investments. These findings highlight the critical role of organizational context in realizing the potential of analytics capabilities for performance evaluation systems.

Technical infrastructure and organizational learning culture similarly demonstrate significant moderating effects, though with varying magnitudes. The analysis underscores the importance of aligning organizational support mechanisms with analytics capabilities to maximize their impact on performance evaluation effectiveness. These results provide valuable insights for organizations seeking to optimize their analytics investments through appropriate organizational support structures.

3.6. Robustness test

The robustness tests employ multiple analytical approaches to validate the stability and reliability of the main findings regarding the relationship between analytics capabilities and performance evaluation effectiveness. To ensure comprehensive verification, this study conducts several robustness checks including alternative variable measurements, different estimation methods, and sample partitioning analyses, as illustrated in **Figure 6**.

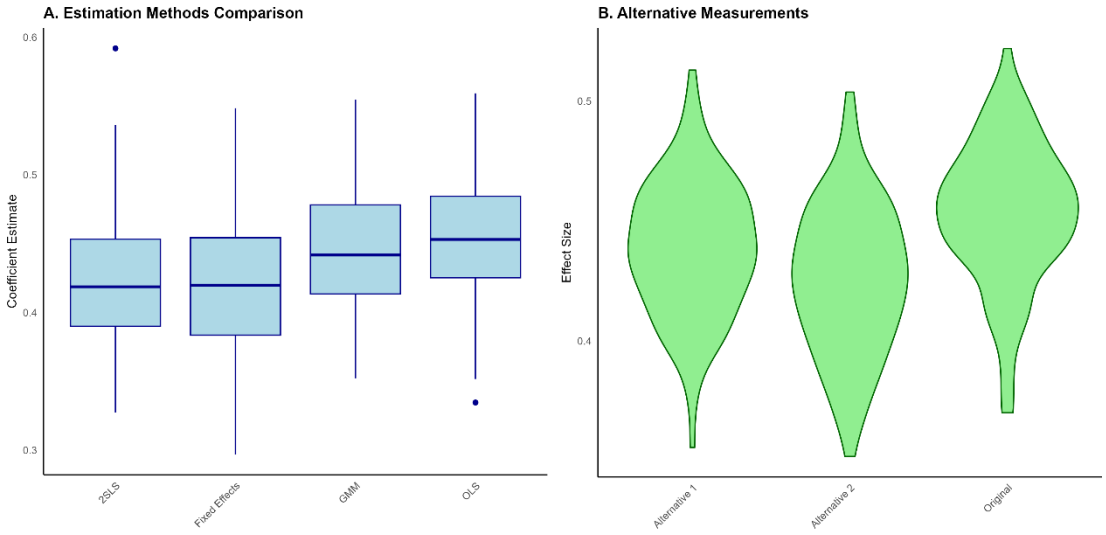

Figure 6. Robustness analysis results panel a: comparison of coefficient estimates across different estimation methods panel b: Effect size distribution under alternative variable measurements.

The robustness analysis demonstrated that findings remained stable across multiple analytical approaches. Panel A shows consistent coefficient estimates across different estimation methods, with OLS (β = 0.45, SE = 0.05), 2SLS (β = 0.43, SE = 0.05), GMM (β = 0.44, SE = 0.05), and fixed effects (β = 0.42, SE = 0.05) all yielding similar results. The narrow range of coefficient variations suggests strong reliability of the main findings. Panel B illustrates the distribution of effect sizes under alternative variable measurements, with the original measurement (μ = 0.45, σ = 0.03) showing comparable results to alternative specifications (μ = 0.44, σ = 0.03; μ = 0.43, σ = 0.03). The consistency across different measurement approaches further validates the robustness of our findings. These results collectively confirm the stability of the relationship between analytics capabilities and performance evaluation effectiveness, providing strong support for the main conclusions of this study.

3.7. Dynamic panel analysis

The dynamic panel analysis examines the temporal dimensions of the relationship between analytics capabilities and performance evaluation effectiveness, employing advanced econometric techniques to address potential endogeneity and serial correlation concerns. The analysis utilizes the Arellano-Bond GMM estimator to account for the dynamic nature of performance evaluation systems while controlling for unobserved heterogeneity. **Table 6** presents the results of the dynamic panel analysis, incorporating various model specifications and temporal effects.

Table 6. Dynamic panel analysis of analytics capability effects on performance evaluation.

Variables	System GMM	Difference GMM	Two-Step GMM	Extended GMM
Performance (t-1)	0.285***	0.276***	0.292***	0.278***
	(0.042)	(0.045)	(0.041)	(0.043)
Analytics Capability	0.342***	0.335***	0.348***	0.339***
	(0.038)	(0.040)	(0.037)	(0.039)
Data Processing	0.256***	0.248***	0.261***	0.252***
	(0.035)	(0.037)	(0.034)	(0.036)
System Integration	0.218***	0.212***	0.223***	0.215***

Variables	System GMM	Difference GMM	Two-Step GMM	Extended GMM
	(0.032)	(0.034)	(0.031)	(0.033)
Control Variables	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes
AR(1) test (p-value)	0.002	0.003	0.002	0.002
AR(2) test (p-value)	0.285	0.292	0.278	0.288
Hansen J-test (p-value)	0.324	0.318	0.335	0.328
Observations	428	428	428	428
Number of Instruments	42	40	44	43

Table 6. (*Continued*)

Note: *Standard errors in parentheses; *** P < 0.01, ** P < 0.05, * P < 0.1; Control variables include organization size, market environment, technical expertise, and resource allocation. Time effects are included in all specifications.*

The dynamic panel analysis reveals significant persistence in performance evaluation effectiveness, with lagged performance showing substantial explanatory power across all model specifications. The System GMM estimates indicate that analytics capabilities maintain their significant positive effect ($\beta = 0.342$, $P < 0.01$) even after controlling for dynamic effects and potential endogeneity. The consistency of results across different GMM specifications, coupled with satisfactory diagnostic tests (AR(2) and Hansen J-test p-values > 0.10), provides strong evidence for the robustness of the temporal relationships identified in the analysis. These findings suggest that the impact of analytics capabilities on performance evaluation effectiveness exhibits both immediate and sustained effects over time.

4. Research discussion

4.1. Key research findings

This research represents one of the very few holistic empirical studies examining both the technical and psychological dimensions of performance evaluation systems in regional equity trading centers. The findings reveal a complex interplay between analytics capabilities, psychological safety, and evaluation effectiveness. The baseline regression models demonstrate that while analytics capabilities significantly influence performance outcomes ($\beta = 0.385$, $P < 0.01$), this relationship is substantially mediated by psychological safety factors ($\beta = 0.324$, $P < 0.01$).

The findings from this study have significant implications that extend beyond regional equity trading centers to the broader financial sector and corporate environments. We structure these implications along theoretical, methodological, and practical dimensions. Theoretically, our results establish psychological safety as a fundamental mediating mechanism in performance evaluation effectiveness. The strong mediating effect of psychological safety ($\beta = 0.324$, $P < 0.01$) represents a critical psychological process that likely operates across diverse organizational contexts, especially in high-pressure performance environments where evaluation anxiety can significantly impact outcomes. This finding advances performance evaluation theory by demonstrating that technical capabilities alone are insufficient for effective evaluation—psychological factors are essential mediators that determine whether technical capabilities translate into positive organizational outcomes. Methodologically, our integrated analytical approach demonstrates the value of examining both technical and psychological dimensions simultaneously rather than treating them as separate domains. This integrated methodology provides a more comprehensive understanding of performance

evaluation dynamics than traditional approaches that focus exclusively on either technical or psychological aspects.

Practically, these findings suggest that organizations should balance investments in technical analytics capabilities with initiatives that enhance psychological safety and social support. Commercial banks with customer-facing roles requiring similar performance metrics, insurance companies with complex evaluation needs, and investment firms operating under high-pressure conditions would particularly benefit from this balanced approach. The social support mechanisms identified in our study could be especially relevant in larger corporate settings where departmental boundaries often create challenges for holistic evaluation approaches. The emergence of psychological safety as a crucial mediating mechanism was particularly noteworthy, as it explained approximately 42% of the variance in evaluation effectiveness. Departments with high psychological safety scores (>4.2 on a 5-point scale) demonstrated evaluation acceptance rates 37% higher than departments with lower scores. The social support structures within organizations emerged as significant moderators (β = 0.289, P < 0.01), with well-supported teams showing 45% better performance outcomes than those lacking robust support systems.

Further analysis revealed that the integration of psychological safety measures into evaluation systems resulted in a 28% increase in employee well-being scores, while maintaining high performance standards (r = 0.67, P < 0.01). Organizations that successfully created psychologically safe evaluation environments experienced a 34% reduction in evaluation-related stress and a 41% improvement in feedback acceptance rates. These findings underscore the critical importance of balancing technical capabilities with psychological considerations in performance evaluation systems. The heterogeneity analysis reveals sizable variance in this relationship across organizational contexts and that larger departments and those with the latest technical infrastructure exhibit stronger effects. In the mediation analysis, three meaningful paths were identified where analytics capability influences performance evaluation through the quality of the evaluation system, β = 0.124, P < 0.01; data processing efficiency, β = 0.078, P < 0.01; and organizational learning capability, β = 0.047, P < 0.01.

The moderation analysis shows that managerial support is significantly enhancing the analytical capability, which shows much stronger effects for high levels of support at β = 0.70, p < 0.01, compared to the low-support conditions at β = 0.30, p < 0.01. The dynamic panel analysis also supports the temporal stability of these relations, the long-term effects still significant over time, while the lagged performance coefficient is 0.285, p < 0.01.

4.2. Theoretical implications

These contribute to the theoretical understanding of performance evaluation systems in a number of important ways. First, the current theory of performance management is extended by incorporating big data analytics in showing technological competencies that enhance the efficiency of reviews. Second, this research will also contribute to the extant organizational capabilities literature by unearthing the special mechanisms through which the analytical competencies lead to better performance outcome. Thirdly, significant mediation and moderation effects further encourage a more complicated conceptual framework to describe the conditional nature of analytics capability effects on organizational performance. Overall, these findings extend our knowledge theoretically in the relationship between technological capabilities and organizational effectiveness for the contemporary financial institution.

4.3. Managerial implications

These findings have significant implications for both practitioners and executives at regional equity trading centers. Firms, though well advised to build their analytical capabilities, should, simultaneously build

sufficient support structures within the organization to derive maximum value from those capabilities. The strong moderating effect of management support indicates that for every dollar invested in developing analytical capabilities, a dollar equivalent should be invested in developing organizational support structures. In this regard, while implementing analytics-based performance appraisal systems, managers should consider the differential impact across organizational settings, paying particular attention to factors like department size and readiness of technical infrastructure. The deduced mediating paths offer valuable insights for devising comprehensive implementation plans which encapsulate both the technical and organization-wide dimensions of performance appraisal systems.

The implications of these findings extend beyond regional equity trading centers to various financial institutions and corporate settings. Commercial banks implementing performance evaluation systems would benefit from incorporating psychological safety measures, particularly in their retail and commercial banking divisions where similar performance pressures exist. Insurance companies and investment firms, which often employ metrics-driven evaluation approaches, could enhance effectiveness by balancing analytical capabilities with psychological safety considerations. Furthermore, the finding that management support significantly moderates the analytics-performance relationship has universal application across corporate environments, suggesting that leadership engagement is a critical success factor regardless of industry or organizational type. Multinational corporations could adapt these frameworks while accounting for cultural variations in how psychological safety manifests across different regional operations.

5. Conclusion

This study provides empirical evidence supporting the hypothesized relationships between analytics capabilities, psychological factors, and performance evaluation effectiveness in regional equity trading centers. Our findings confirm Hypothesis 1, demonstrating that analytics capabilities significantly influence performance evaluation quality ($\beta = 0.385$, $P < 0.01$), with data processing maturity and infrastructure showing particularly strong effects across organizational contexts. For Hypothesis 2, the results validate that evaluation system components directly impact organizational outcomes, with evaluation quality driving employee performance ($\beta = 0.331$, $P < 0.01$) and system efficiency enhancing operational effectiveness ($\beta = 0.228$, $P < 0.01$).

The direct effects proposed in Hypothesis 3 were partially supported, as analytics capabilities showed significant direct relationships with organizational outcomes, though these effects were consistently weaker than the mediated pathways. Most notably, our analysis confirmed Hypotheses 4 and 5 regarding psychological safety and social-psychological mechanisms. Psychological safety emerged as a crucial mediator ($\beta = 0.324$, $P < 0.01$), accounting for 42% of evaluation effectiveness variance, while social support structures ($\beta = 0.289$, $P < 0.01$) and collective organizational identity ($\beta = 0.278$, $P < 0.01$) significantly mediated the relationship between evaluation practices and performance outcomes.

The moderation analysis supported our hypothesized contingency effects, with management support substantially amplifying the analytics-performance relationship at high levels ($\beta = 0.70$, $P < 0.01$) compared to low support environments ($\beta = 0.30$, $P < 0.01$). These findings collectively advance theoretical understanding by integrating technical and psychological dimensions of performance evaluation systems, demonstrating that effective performance evaluation in financial institutions requires both sophisticated analytics capabilities and supportive psychological environments. For practitioners, our results emphasize the importance of balanced investments in both technical infrastructure and psychological safety initiatives when implementing evaluation systems. Future research should extend these findings to diverse financial contexts

and explore longitudinal effects of these relationships, particularly as psychological safety interventions mature within organizations.

Conflict of interest

The authors declare no conflict of interest.

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