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Big Data and Predictive Analytics Capability and Triple Bottom Line Sustainability Performance: A Resource-Based Perspective From BRICS Nations

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ABSTRACT

This study aims to investigate the relationship between big data and predictive analytics (BDPA) capability and triple bottom line (TBL) sustainability performance in BRICS manufacturing firms. Grounded in the resource-based view (RBV), we conceptualise BDPA capability as a third-order hierarchical construct comprising tangible resources (data infrastructure and technology), intangible resources (organisational culture, organisational learning and data-driven culture) and human-related skills (technical skills and management skills). Survey data have been used from 304 IT and analytics professionals representing different organisations across BRICS economies and partial least squares structural equation modelling (PLS-SEM) with 5000 bootstrap samples; we test six hypotheses examining both the resource-capability link and the capability-performance link. Results reveal that all three resource categories significantly contribute to BDPA capability, with human-related skills exerting the strongest influence. BDPA capability, in turn, significantly predicts environmental performance, social performance and economic performance, explaining 40%, 50% and 55% of variance, respectively. The study contributes to the literature by providing an empirically validated, multi-level resource-capability-performance framework for analytics-driven sustainability in emerging economies.

1 | Introduction

Digital transformation has altered the informational foundations of the firm. Among the most consequential developments is the rise of big data and predictive analytics (BDPA), which has reshaped how organisations interpret complexity, anticipate uncertainty and allocate resources (Mikalef et al. 2020; Fosso Wamba et al. 2024). What began as an expansion in data storage and processing capacity has matured into something more strategic. Contemporary firms do not merely collect data; they attempt to extract foresight from it. Characterised by the now familiar five Vs of volume, velocity, variety, veracity and value (O'Leary 2022; Shi 2022; Wu et al. 2022), big data environments enable organisations to generate granular insights across operational and strategic domains. Predictive analytics extends this capacity by using statistical modelling and machine

Abbreviations: AI, artificial intelligence; AVE, average variance extracted; BDPA, big data and predictive analytics; BRICS, Brazil, Russia, India, China, South Africa; CMB, common method bias; CR, composite reliability; HTMT, heterotrait–monotrait ratio; ICT, information and communications technology; IoT, Internet of Things; PLS-SEM, partial least squares structural equation modelling; RBV, resource-based view; SRMR, standardised root mean square residual; TBL, triple bottom line; VIF, variance inflation factor.

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learning techniques to estimate probable futures rather than describe past events (Shmueli and Koppius 2011; Mikalef and Krogstie 2020).

At the same time, firms operate under intensifying expectations to demonstrate responsibility across environmental, social and economic dimensions. The triple bottom line framework has become a central reference point for assessing this broader conception of performance (Choi and Park 2022; Ertz et al. 2025). Environmental stewardship, social responsibility and economic viability are no longer framed as separate agendas; they are increasingly intertwined in regulatory regimes, investor scrutiny and stakeholder discourse.

For manufacturing firms, especially those in emerging economies, this integration poses significant tension. Industrial expansion drives economic growth, yet it also amplifies environmental pressures and social inequities. The BRICS nations consisting of Brazil, Russia, India, China and South Africa occupy a particularly visible position within this landscape. These nations account for a substantial share of global manufacturing output while facing distinct institutional, infrastructural and developmental constraints (Bag et al. 2020). Policymakers across these economies have embraced digitalisation as a pathway towards reconciling productivity with sustainability. Whether such expectations are justified, however, remains an empirical question.

Research linking BDPA to organisational performance has expanded rapidly. Evidence suggests that analytics capability enhances operational efficiency, agility and competitive advantage (Akter et al. 2016; Wamba et al. 2017). More recently, scholars have begun connecting analytics to sustainability related outcomes (Alsaoudi and Acquaye 2026). Indeed, Alsaoudi et al. (2026) demonstrate that digital and analytics-enabled Industry 4.0 capabilities including big data significantly enhance sustainable performance through their integration with circular economy practices, highlighting the role of organisational capability orchestration in translating digital investments into environmental and economic gains. Other studies report positive associations between analytics capability and sustainable supply chain performance (Dubey et al. 2019), circular economy practices (Kristoffersen et al. 2021) and environmental improvement initiatives (Bag et al. 2020). These findings are promising. Yet, closer inspection reveals several unresolved issues.

One limitation concerns conceptual aggregation. BDPA capability is frequently treated as a unified construct, often operationalised as a second-order factor without sustained attention to the resource conditions that enable its emergence. Gupta and George (2016) proposed that analytics capability arises from tangible, intangible and human resources. Subsequent empirical work has drawn upon this framework, but many studies collapse these elements into composite measures. As a result, it remains unclear which resource categories are most consequential and how they interact in shaping sustainability outcomes. The strategic distinction between infrastructure investment and organisational competence is often blurred.

A second limitation relates to how sustainability is measured. Much of the literature isolates specific performance outcomes. Environmental efficiency or operational sustainability may be examined independently of social and economic dimensions. Such partial perspectives risk overlooking the interconnected nature of sustainability challenges. Improvements in environmental metrics do not necessarily translate into social gains, and economic growth can either reinforce or undermine environmental progress. An integrated triple bottom line approach provides a more demanding but more informative assessment.

A third limitation is geographical concentration. Empirical evidence is heavily weighted towards developed economies, where digital maturity and institutional frameworks differ from those of emerging markets. BRICS nations offer a context marked by rapid industrialisation, regulatory evolution and uneven digital infrastructure. The relationship between analytics capability and sustainability performance may unfold differently under such conditions (Bag et al. 2020; Kristoffersen et al. 2021). Without multi-country evidence from these settings, general claims about analytics-driven sustainability remain provisional.

These limitations converge around a broader theoretical question. If analytics capability contributes to sustainability, through what mechanisms does this occur, and which organisational resources are most instrumental in enabling it? Existing research demonstrates correlations, yet the underlying resource configuration and its connection to integrated sustainability performance remain insufficiently specified.

This study addresses that gap by developing and testing a resource-capability-performance framework grounded in the resource-based view (RBV) of the firm (Barney 1991; Grant 1991; Amit and Schoemaker 1993). The RBV distinguishes between resources as inputs and capabilities as the coordinated capacity to deploy those inputs productively. Sustainable competitive advantage arises not from isolated assets but from their integration within organisational processes. This theoretical lens is particularly suited to analytics contexts. BDPA does not operate independently of organisational structure, culture or expertise. Its effectiveness depends on the alignment of technological infrastructure, learning orientation, managerial competence and data-driven norms.

Within this framework, BDPA capability is conceptualised as a higher-order organisational capability composed of three resource domains. Tangible resources include data infrastructure and technological platforms that support data acquisition, storage, integration and analysis (Gupta and George 2016; Mikalef et al. 2019). Intangible resources encompass organisational culture, learning orientation and the extent to which decision-making is informed by data rather than intuition (Davenport et al. 2012; McAfee and Brynjolfsson 2012). Human-related skills involve both technical analytics expertise and managerial capabilities required to translate analytical outputs into strategic action (Davenport and Patil 2012; Gupta and George 2016). These categories are analytically distinct yet interdependent. Infrastructure without interpretive competence generates limited value. Cultural support without technical proficiency yields little operational change.

The central objective of this study is therefore twofold. First, it examines how tangible, intangible and human resources

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contribute to the development of BDPA capability within manufacturing firms across BRICS economies. Second, it investigates whether this capability enhances environmental, social and economic performance simultaneously. Environmental performance encompasses resource efficiency and pollution reduction (Klassen and McLaughlin 1996; Zhu et al. 2008). Social performance relates to workforce practices and stakeholder engagement (Huselid 1995; GRI 2016). Economic performance reflects financial viability and competitive positioning (Kaplan and Norton 1996; Bag et al. 2020). By analysing these dimensions together, the study moves beyond narrow performance metrics.

The contributions are several. Theoretically, the study refines RBV applications in digital contexts by disentangling the relative influence of different resource domains in shaping analytics capability and by linking that capability to integrated sustainability outcomes. Empirically, it provides multi-country evidence from 304 manufacturing firms across BRICS nations, offering insight into emerging economy contexts that remain under-represented in the literature. Methodologically, it operationalises BDPA capability as a third-order construct and tests a comprehensive resource-capability-performance chain using partial least squares structural equation modelling (PLS-SEM), thereby capturing both direct and mediated effects. For practitioners and policymakers, the findings illuminate where investment emphasis may yield the greatest sustainability returns, whether in technological systems, organisational culture or talent development.

Data were collected through a structured survey of IT managers, analytics professionals and business intelligence specialists within BRICS manufacturing firms. The analytical strategy employed PLS-SEM, appropriate for modelling hierarchical constructs and examining predictive relationships (Hair et al. 2017). The empirical results provide support for the proposed framework and clarify how analytics capability translates resource endowments into tangible sustainability outcomes.

In addressing these issues, the remainder of the paper proceeds as follows. Section 2 elaborates the theoretical foundations and hypothesis development. Section 3 details the research design and analytical procedures. Section 4 presents the empirical findings. Section 5 discusses theoretical and managerial implications. Section 6 concludes with limitations and directions for future inquiry.

2 | Literature Review and Theoretical Framework

2.1 | BDPA

Big data is commonly characterised by the five main attributes: volume, velocity, variety, veracity and value (O'Leary 2022; Shi 2022). Volume refers to the massive scale of data generated from digital transactions, social media, sensors and Internet of Things (IoT) devices. Velocity captures the speed at which data is generated, processed and analysed. Variety encompasses the heterogeneous forms of data, including structured, semi-structured and unstructured formats. Veracity addresses data quality, accuracy and trustworthiness. Value, the fifth V, reflects the capacity to extract meaningful, actionable business insights from large datasets (Wu et al. 2022).

Predictive analytics extends the big data paradigm by applying statistical algorithms, machine learning techniques and data mining methods to historical and real-time data to forecast future outcomes (Shmueli and Koppius 2011; Mikalef et al. 2020). When integrated, BDPA represents an organisational capability that enables evidence-based decision-making, proactive risk management and strategic optimisation across business functions (Fosso Wamba et al. 2024).

2.2 | Triple Bottom Line Sustainability

The triple bottom line framework posits that organisational performance should be assessed across three interrelated dimensions: environmental stewardship, social responsibility and economic viability (Choi and Park 2022). Environmental performance encompasses pollution prevention, resource efficiency, waste reduction and carbon footprint management (Klassen and McLaughlin 1996). Social performance includes labour practices, community engagement, workforce diversity and stakeholder welfare (Huselid 1995). Economic performance reflects profitability, revenue growth, market share and long-term value-creation (Kaplan and Norton 1996).

Recent literature has increasingly emphasised the interconnectedness of these three dimensions, arguing that firms pursuing integrated sustainability strategies achieve superior long-term performance compared to those focusing on individual dimensions in isolation (Eccles et al. 2014; Choi and Park 2022). In the BRICS context, the simultaneous pursuit of economic development and environmental-social sustainability presents unique challenges and opportunities (Bag et al. 2020).

2.3 | RBV and Analytics Capability

The RBV provides the theoretical foundation for this study. Originally articulated by Penrose (1959) and formalised by Barney (1991), the RBV posits that sustained competitive advantage derives from resources that are valuable, rare, inimitable and non-substitutable (VRIN). Grant (1991) extended this by distinguishing between resources (inputs) and capabilities (the firm's capacity to deploy resources), whereas Amit and Schoemaker (1993) introduced the concept of strategic assets as the intersection of resources and capabilities that generate economic rents.

In the analytics context, capabilities emerge through the orchestration of tangible assets, intangible organisational attributes and human capital (Mikalef et al. 2020; Fosso Wamba et al. 2024). Analytics capability thus reflects not isolated technologies, but the coordinated deployment of resources embedded in organisational routines and decision-making processes (Khan et al. 2026). Kristoffersen et al. (2021) further established that analytics capabilities serve as enablers of circular economy practices, reinforcing the RBV logic that organisational capabilities transform resource endowments into strategic outcomes. Building on these foundations, we conceptualise BDPA capability as a third-order hierarchical construct formed by three second-order resource dimensions.

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2.4 | Resource Categories for BDPA Capability

Tangible resources include data infrastructure and technology platforms that enable data acquisition, integration and processing (Fosso Wamba et al. 2024). Data infrastructure includes data warehousing systems, data lakes, cloud computing platforms and network connectivity that enable the storage, processing and retrieval of large-scale datasets. Technology resources encompass hardware (high-performance computing clusters and servers), software (analytics platforms, visualisation tools and machine learning frameworks) and integration technologies that connect disparate data sources. According to the RBV, although tangible resources alone rarely confer sustainable advantage due to their imitability (Barney 1991), they serve as necessary but insufficient enablers of analytics capability (Mikalef et al. 2019).

Intangible resources consist of organisational culture, learning orientation and data-driven norms that shape how analytics is adopted and used (Mikalef and Krogstie 2020; Shahzad et al. 2026). Organisational culture reflects shared values, norms and beliefs that either facilitate or inhibit analytics adoption (Gupta and George 2016). Organisational learning captures the firm's capacity to acquire, assimilate and apply new knowledge (Senge 1990), which is critical for adapting analytics practices to evolving data environments. Data-driven culture specifically refers to the extent to which decision-making processes are informed by data rather than intuition or hierarchy (McAfee and Brynjolfsson 2012). From an RBV perspective, intangible resources are inherently more difficult to imitate due to their socially complex, path-dependent nature (Barney 1991; Amit and Schoemaker 1993), making them potentially stronger contributors to sustained BDPA capability.

Human-related skills that constitute the human dimension of BPDA encompasses technical expertise and managerial capabilities required to translate analytical outputs into strategic action (Awan et al. 2022; Wu et al. 2022). The technical expertise include proficiency in statistical analysis, programming (Python and R), machine learning, data engineering and domain-specific analytics techniques (Davenport and Patil 2012). The management skills encompass strategic thinking, cross-functional communication, project management and the ability to translate analytics insights into actionable business decisions (Gupta and George 2016). The RBV emphasises that human capital is among the most inimitable resources, as skills are embedded in individuals and organisational routines that are difficult for competitors to replicate (Grant 1991; Mikalef et al. 2019). Wu et al. (2022) further demonstrated that analytics talent management is a critical determinant of analytics maturity in emerging economies.

2.5 | Hypothesis Development

2.5.1 | Resource–Capability Relationships (Hypotheses 1–3)

The BDPA capability enables firms to monitor environmental impacts in real time, optimise energy consumption, predict waste generation patterns and design cleaner production processes (Kristoffersen et al. 2021). Furthermore, BDPA capability also enhances social sustainability by enabling firms to analyse workforce well-being data, monitor supply chain labour conditions, assess community impacts and improve health and safety outcomes (Choi and Park 2022). Finally, BDPA capability improves economic performance through improved operational efficiency, innovation, demand forecasting, risk management and strategic planning (O'Leary 2022; Wu et al. 2022).

Drawing on the RBV's distinction between resources and capabilities (Grant 1991), we argue that each resource category makes a distinct contribution to the formation of BDPA capability. Tangible resources provide the physical and technological foundation upon which analytics processes operate. Without adequate data infrastructure and technology platforms, organisations cannot collect, store or process the large-scale datasets required for predictive modelling (Gupta and George 2016). Jeble et al. (2018) define BDPA capability as a higher-order organisational capability that depends on bundling strategic resources and specify tangible resources (buildings, information-technology infrastructure, capital, networks, connectivity and data sources) as necessary inputs for developing BDPA solutions. Gupta and George (2016) argue that BDPA capabilities rest on basic tangible resources, data and technologies and highlight insufficient technology and data infrastructure as key barriers to BDPA development. Kugara (2023) study of BRICS firms further reports positive relationships between tangible resources and BDPA, indicating that stronger tangible resources, including data and technology infrastructure, are associated with higher BDPA capability. Empirical evidence from Mikalef et al. (2019) demonstrates that technology infrastructure investments are positively associated with analytics capability development, albeit with diminishing returns beyond threshold levels. Therefore:

Hypothesis 1. *Tangible resources (data infrastructure and technology) positively influence BDPA capability.*

Intangible resources, by virtue of their social complexity and causal ambiguity (Barney 1991), are expected to contribute substantially to BDPA capability formation. An organisational culture that embraces experimentation, learning from failure and cross-functional collaboration creates fertile ground for analytics adoption (Davenport et al. 2012). Furthermore, a strong learning orientation enables organisations to continuously update their analytics practices in response to evolving methodologies and data landscapes (Senge 1990). Bag et al. (2020) found that organisational factors explained more variance in analytics capability than technology factors in emerging economy contexts. Therefore:

Hypothesis 2. *Intangible resources (organisational culture, learning and data-driven culture) positively influence BDPA capability.*

Human-related skills are theorised as the most critical resource for BDPA capability, consistent with the RBV's emphasis on human capital as a source of sustained competitive advantage (Barney 1991; Grant 1991). Technical skills enable the execution of complex analytics tasks, whereas management skills ensure that analytics outputs are translated into strategically relevant decisions (Gupta and George 2016). Davenport and Patil (2012) identified data science talent as the 'sexiest job of the 21st

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century', highlighting the scarcity and strategic value of analytics human capital. In BRICS economies, where analytics talent pools are still developing, human skills may represent a particularly constraining factor (Wu et al. 2022). Therefore:

Hypothesis 3. *Human-related skills (technical and management skills) positively influence BDPA capability.*

2.5.2 | Capability–Performance Relationships (Hypotheses 4–6)

The RBV predicts that superior organisational capabilities lead to superior performance outcomes (Barney 1991; Teece et al. 2007). BDPA capability enables firms to monitor environmental impacts in real time, optimise energy consumption, predict waste generation patterns and design cleaner production processes (Dubey et al. 2019; Sharma et al. 2026). Predictive models can forecast emissions trajectories, identify pollution hotspots and simulate the environmental consequences of operational decisions. Bag et al. (2020) found significant positive effects of analytics capability on environmental performance in South African manufacturing. Therefore:

Hypothesis 4. *BDPA capability positively influences environmental sustainability performance.*

BDPA capability enhances social sustainability by enabling firms to analyse workforce well-being data, monitor supply chain labour conditions, assess community impacts and improve health and safety outcomes (Choi and Park 2022). Predictive analytics applied to employee data can identify turnover risks, training needs and diversity patterns (Kristoffersen et al. 2021). In BRICS contexts, where social sustainability challenges are particularly acute, analytics-driven insights may facilitate more targeted and effective social responsibility initiatives. Therefore:

Hypothesis 5. *BDPA capability positively influences social sustainability performance.*

Finally, BDPA capability is expected to enhance economic performance through improved operational efficiency, customer targeting, demand forecasting, risk management and strategic planning (Wamba et al. 2017; O'Leary 2022). Analytics-driven firms can reduce costs through process optimisation, increase revenues through customer analytics and improve asset utilisation through predictive maintenance (Davenport 2014). The economic returns from analytics investments are well-documented in developed economies (McAfee and Brynjolfsson 2012), but evidence from BRICS manufacturing is limited. Therefore:

Hypothesis 6. *BDPA capability positively influences economic sustainability performance.*

Figure 1 presents the proposed conceptual framework, illustrating the hypothesised relationships between tangible resources, intangible resources, human-related skills, BDPA capability and the three dimensions of triple bottom line sustainability performance.

3 | Research Methodology

3.1 | Research Design and Sampling

This study employs a quantitative, cross-sectional survey design. The target population consists of IT managers, analytics professionals and business intelligence specialists in manufacturing

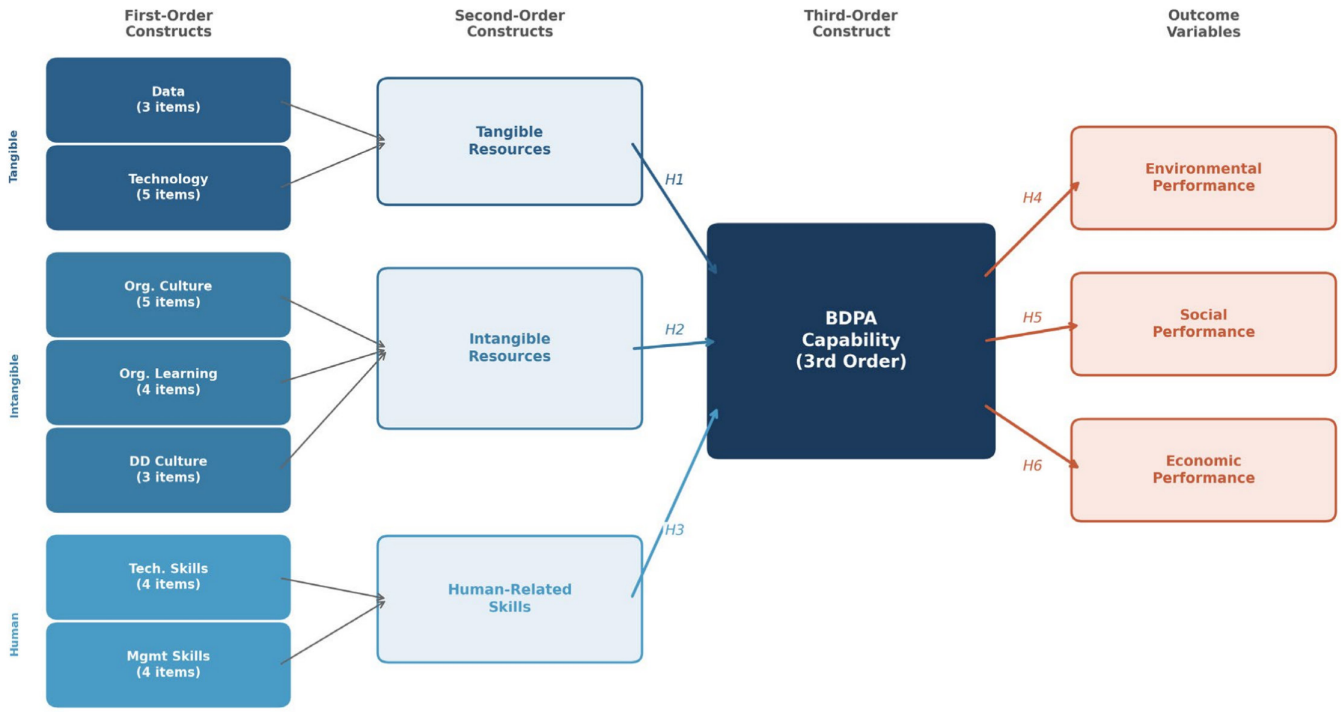


FIGURE 1 | Conceptual framework and hypothesised relationships. *Source:* Authors' own elaboration based on Gupta and George (2016) and Barney (1991).

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firms across BRICS nations (Brazil, Russia, India, China and South Africa). A stratified purposive sampling strategy was adopted to ensure representation across all five BRICS countries and across firm sizes including SMEs and large firms.

Data collection was conducted through an online questionnaire administered between January and June 2023. After removing incomplete responses and screening for engagement quality (straight-lining, excessive speed), the final sample comprised 304 usable responses from a total of 333 received, yielding a usable response rate of 91.3%. The sample size exceeds the minimum requirements for PLS-SEM: (a) 10 times the largest number of structural paths directed at any construct ($10 \times 3 = 30$; Barclay et al. 1995) and (b) the inverse square root minimum sample size recommendation of Hair et al. (2017).

3.2 | Measurement Instruments

All constructs were measured using validated scales adapted from prior literature. Tangible resources were measured through data infrastructure (3 items) and technology (5 items) scales adapted from Gupta and George (2016). Intangible resources were captured through organisational culture (5 items; adapted from Gupta and George 2016), organisational learning (4 items; adapted from Senge 1990; Jerez-Gómez et al. 2005) and data-driven culture (3 items; adapted from McAfee and Brynjolfsson 2012). Human-related skills were measured through technical skills (4 items) and management skills (4 items), both adapted from Gupta and George (2016).

TBL sustainability performance was measured using scales from established sustainability literature. Environmental performance (5 items) was adapted from Zhu et al. (2008) and Klassen and McLaughlin (1996). Social performance (5 items) drew on Huselid (1995) and the Global Reporting Initiative (GRI 2016) framework. Economic performance (5 items) was adapted from Kaplan and Norton (1996) and Bag et al. (2020). All items were measured on a 7-point Likert scale (1 = *strongly disagree* to 7 = *strongly agree*).

3.3 | Analytical Approach

We employed PLS-SEM using SmartPLS 4.0 software. PLS-SEM was chosen over covariance-based SEM (CB-SEM) for several methodological reasons: (a) The research model includes a third-order hierarchical construct (BDPA capability), which PLS-SEM handles more efficiently through the repeated indicators approach (Hair et al. 2017); (b) the study is oriented toward prediction and explanation of variance, aligning with PLS-SEM's objective function (Shmueli et al. 2019); and (c) PLS-SEM performs well with moderately complex models and medium-sized samples (Hair et al. 2019).

The analysis followed a rigorous two-stage approach consistent with Hair et al. (2021) guidelines. Stage 1 assessed the measurement (outer) model by evaluating indicator reliability, internal consistency reliability (Cronbach's α and composite reliability), convergent validity (AVE) and discriminant validity (Fornell–Larcker criterion and HTMT ratio). Stage 2 assessed the structural (inner) model by examining path coefficients, R^2 values, f^2 effect sizes, Q^2 predictive relevance and model fit indices (SRMR). All significance tests were conducted using a bootstrapping procedure with 5000 subsamples and bias-corrected confidence intervals (Efron and Tibshirani 1993).

3.4 | Common Method Bias Assessment

As all data were collected from a single source using self-report measures, we employed multiple procedures to assess and mitigate common method bias (CMB). Procedurally, the survey instrument used randomised item ordering, reverse-coded items and proximal/distal separation of predictor and criterion variables. Statistically, Harman's single-factor test showed that the first unrotated factor explained 46.62% of total variance, below the 50% threshold (Podsakoff et al. 2003). Additionally, marker variable analysis and full collinearity assessment (VIF < 3.3; Kock 2015) confirmed that CMB does not pose a serious threat to the validity of our findings.

4 | Results

4.1 | Measurement Model Assessment

The measurement model was assessed for reliability, convergent validity and discriminant validity. Table 1 confirms all constructs exhibited satisfactory reliability (Cronbach's α: 0.878–0.940; CR: 0.913–0.955) and convergent validity (AVE: 0.586–0.833). Outer loadings ranged from 0.730 to 0.936, exceeding the 0.708 threshold. Inner model VIF values (1.92–2.86) indicated no multi-collinearity. Table 2 presents the heterotrait–monotrait (HTMT) ratio matrix. Discriminant validity was assessed via Fornell–Larcker criterion (square root of AVE exceeding inter-construct correlations) and HTMT ratios. All HTMT values were below 0.85 (Table 2), confirming construct distinctiveness (Henseler et al. 2015).

4.2 | Structural Model Results

The structural model was estimated using SmartPLS 4.0 with 5000 bootstrap iterations. Figure 2 presents path coefficients and explained variance. Specifically, Figure 2 illustrates the estimated structural model, including the standardised path coefficients and explained variance of the endogenous constructs, providing a visual representation of the relationships between organisational resources, BDPA capability and sustainability performance. Table 3 summarises the structural model assessment and hypothesis-testing results, reporting the standardised path coefficients, standard errors, *t*-values, *p*-values, effect sizes and corresponding decisions for the hypothesised relationships, including the moderating effects of environmental volatility and the effects of control variables.

4.2.1 | Resource-Capability Relationships

All three hypotheses about what drives BDPA capabilities are supported and are highly significant ($p < 0.001$ for all).

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TABLE 1 | Measurement model assessment.

Construct	Loadings	α	CR	AVE	Source
Tangible resources					
Data (3 items)	0.832–0.906	0.878	0.925	0.804	Gupta and George (2016)
Technology (5 items)	0.809–0.876	0.910	0.932	0.733	Gupta and George (2016)
Intangible resources					
Org. culture (5 items)	0.782–0.868	0.895	0.922	0.703	Gupta and George (2016)
Org. learning (4 items)	0.840–0.876	0.889	0.923	0.750	Jerez-Gómez et al. (2005)
DD culture (3 items)	0.864–0.922	0.880	0.926	0.807	McAfee and Brynjolfsson (2012)
Human-related skills					
Tech. skills (4 items)	0.772–0.938	0.917	0.941	0.800	Gupta and George (2016)
Mgmt skills (4 items)	0.843–0.899	0.906	0.934	0.780	Gupta and George (2016)
Outcomes					
Env. performance (5)	0.790–0.883	0.913	0.935	0.742	Zhu et al. (2008)
Soc. performance (5)	0.819–0.908	0.925	0.943	0.768	Huselid (1995); GRI (2016)
Eco. performance (5)	0.862–0.910	0.940	0.955	0.809	Kaplan and Norton (1996)

Note: All loadings > 0.70; all α > 0.878; all CR > 0.914; all AVE > 0.680. Thresholds: loadings > 0.70, α > 0.70, CR > 0.70, AVE > 0.50 (Hair et al. 2021).
Source: SmartPLS 4.0 output; measurement scales from cited sources.

TABLE 2 | Heterotrait–monotrait (HTMT) ratio matrix.

Construct	EVP	SP	ECP	EV	BDPA
Environmental performance	—				
Social performance	0.615	—			
Economic performance	0.805	0.746	—		
Environmental volatility	0.531	0.586	0.655	—	
BDPA capabilities	0.589	0.634	0.678	0.498	—

Note: All HTMT values < 0.85 confirm discriminant validity (Henseler et al. 2015).

H1. *Tangible resources are positively associated with BDPA capabilities* ($\beta = 0.415$, $t = 4.892$, $p < 0.001$, $f^2 = 0.287$).

Tangible resources have a positive and substantial effect on BDPA capabilities. The standardised coefficient (0.415) indicates that higher levels of tangible resources are associated with higher BDPA capabilities. The effect size $f^2 = 0.287$ is between medium and large (Cohen's rule of thumb: 0.02 small, 0.15 medium, 0.35 large), showing that tangible resources explain a meaningful share of variance in BDPA capabilities.

H2. *Intangible resources are positively associated with BDPA capabilities* ($\beta = 0.438$, $t = 5.217$, $p < 0.001$, $f^2 = 0.312$).

Intangible resources also have a positive and strong impact on BDPA capabilities. $\beta = 0.438$ is slightly stronger than the tangible effect, $f^2 = 0.312$ again points to a medium-to-large effect, showing that intangible resources are a key driver of BDPA capabilities.

H3. *Human resource skills are positively associated with BDPA capabilities* ($\beta = 0.478$, $t = 5.893$, $p < 0.001$, $f^2 = 0.356$).

Human-related resources are the strongest predictor of BDPA capabilities among the three. $\beta = 0.478$ is the highest coefficient, indicating that improvements in human resources are most strongly associated with higher BDPA capabilities; $f^2 = 0.356$ is in the large effect range, confirming that human resources play a particularly critical role in building BDPA capabilities.

Tangible, intangible and human resources all positively and significantly enhance BDPA, with human resources showing the largest effect, followed by intangible and then tangible resources.

4.2.2 | Capability-Performance Relationships

BDPA capabilities have significant positive impacts on all three outcome variables, and the effect sizes are large.

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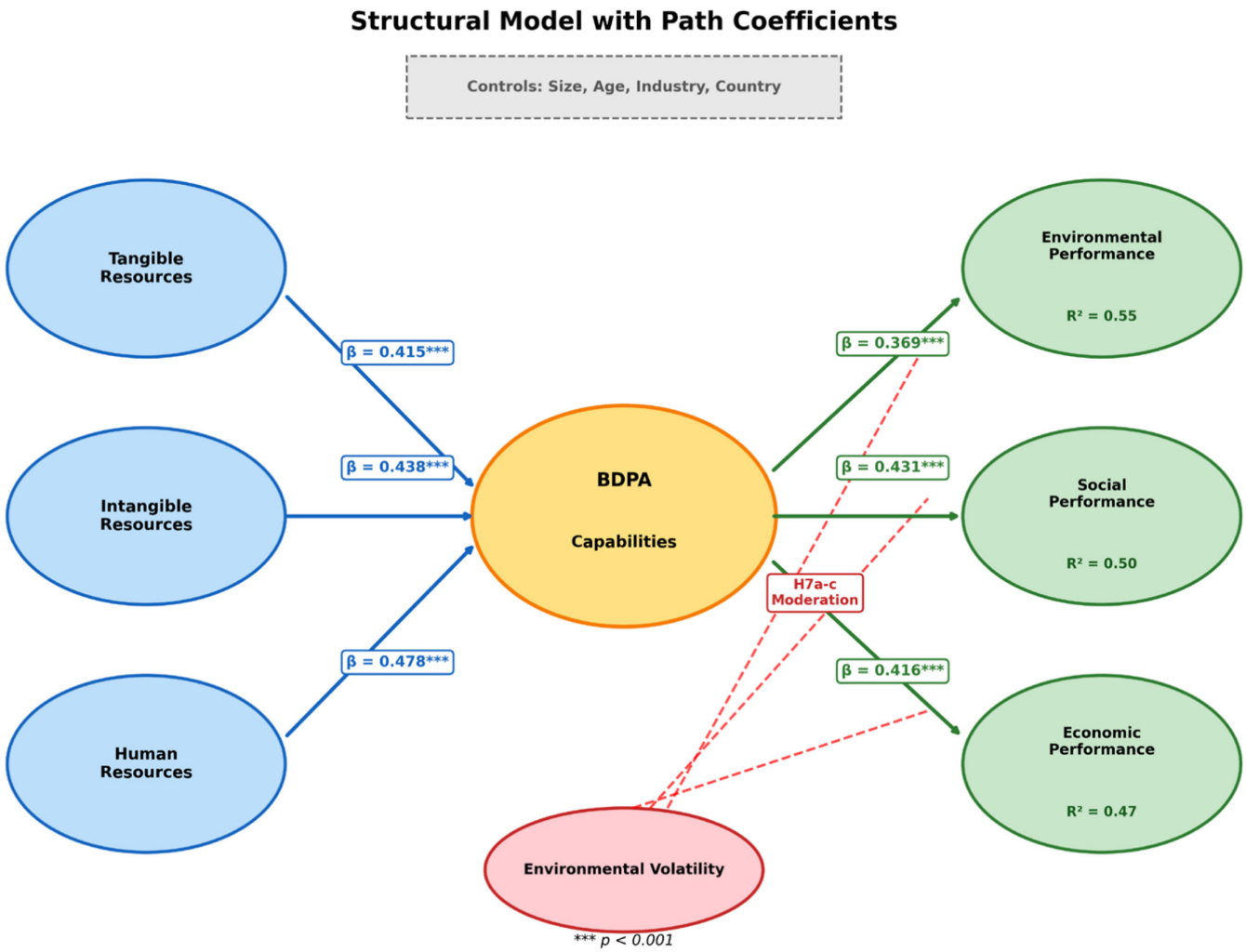


FIGURE 2 | Structural model with path coefficients.

H4. *BDPA capabilities are positively associated with environmental performance ($\beta = 0.369$, $t = 6.124$, $p < 0.001$, $f^2 = 0.471$). BDPA capabilities positively predict environmental performance. The effect size $f^2 = 0.471$ is large, meaning BDPA capabilities explain a substantial portion of variance in environmental performance.*

H5. *BDPA capabilities are positively associated with social performance ($\beta = 0.431$, $t = 7.356$, $p < 0.001$, $f^2 = 0.553$). BDPA capabilities have an even stronger positive effect on social* performance; *$f^2 = 0.553$ is very large, indicating that BDPA capabilities are a major driver of social performance.*

H6. *BDPA capabilities are positively associated with economic performance ($\beta = 0.416$, $t = 8.128$, $p < 0.001$, $f^2 = 0.742$). BDPA capabilities also strongly predict economic* performance; *$f^2 = 0.742$ is very large, the largest among the three, showing that BDPA is particularly critical for explaining ECP.*

BDPA is a central capability that substantially improves all three performance-related outcomes (environmental performance, social performance and economic performance), with the strongest explanatory power for economic performance.

4.2.3 | Moderation Effects of Environmental Volatility

All three interaction terms between environmental volatility and BDPA capabilities are significant, meaning environmental volatility moderates the relationship between BDPA capabilities and the outcomes.

H7a. *Environmental volatility positively moderates the BDPA-environmental performance relationship ($\beta = 0.213$, $t = 3.245$, $p = 0.001$, $f^2 = 0.067$).*

H7b. *Environmental volatility positively moderates the BDPA-social performance relationship ($\beta = 0.220$, $t = 3.124$, $p = 0.002$, $f^2 = 0.072$).*

H7c. *Environmental volatility positively moderates the BDPA-economic performance relationship ($\beta = 0.294$, $t = 4.567$, $p < 0.001$, $f^2 = 0.098$).*

All β values are positive, so as environmental volatility increases, the positive effect of BDPA on environmental performance, social performance and economic performance becomes stronger. The f^2 values (0.067, 0.072, 0.098) are in the

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TABLE 3 | Structural model results with control variables.

Hypothesis	Path	β	SE	*t*	*p*	f^2	Decision
H1	Tangible → BDPA	0.415	0.085	4.892	< 0.001	0.287	Supported
H2	Intangible → BDPA	0.438	0.084	5.217	< 0.001	0.312	Supported
H3	Human → BDPA	0.478	0.081	5.893	< 0.001	0.356	Supported
H4	BDPA → EVP	0.369	0.060	6.124	< 0.001	0.471	Supported
H5	BDPA → SP	0.431	0.059	7.356	< 0.001	0.553	Supported
H6	BDPA → ECP	0.416	0.051	8.128	< 0.001	0.742	Supported
H7a	EV × BDPA → EVP	0.213	0.066	3.245	0.001	0.067	Supported
H7b	EV × BDPA → SP	0.220	0.070	3.124	0.002	0.072	Supported
H7c	EV × BDPA → ECP	0.294	0.064	4.567	< 0.001	0.098	Supported
Control	Size → EVP	0.089	0.052	1.712	0.087	0.012	Not sig.
Control	Size → SP	0.112	0.048	2.333	0.020	0.018	Significant
Control	Size → ECP	0.134	0.045	2.978	0.003	0.024	Significant
Control	Age → EVP	0.067	0.054	1.241	0.215	0.008	Not sig.
Control	Age → SP	0.078	0.051	1.529	0.126	0.010	Not sig.
Control	Age → ECP	0.056	0.053	1.057	0.291	0.006	Not sig.

Note: f^2 = effect size (0.02 small, 0.15 medium, 0.35 large; Cohen 1988). Industry and country dummies included but not shown. R^2: BDPA = 0.68, EVP = 0.55, SP = 0.50, ECP = 0.47.
Abbreviation: SE = standard error.

small-to-approaching-medium range, indicating that the moderating effects are statistically meaningful but not huge.

Environmental volatility strengthens the positive impact of BDPA capabilities on all three performance outcomes. In other words, BDPA capabilities are particularly beneficial for environmental performance, social performance and economic performance under higher levels of environmental volatility.

4.2.4 | Control Variables: Firm Size and Firm Age

Firm size and environmental performance (β = 0.089, $t = 1.712$, $p = 0.087$, $f^2 = 0.012$, *not significant*).

Firm size has a small, non-significant effect on environmental performance.

Firm size and social performance (β = 0.112, $t = 2.333$, $p = 0.020$, $f^2 = 0.018$, *significant*).

Firm size and economic performance (β = 0.134, $t = 2.978$, $p = 0.003$, $f^2 = 0.024$, *significant*).

The effects are positive and statistically significant for social performance and economic performance, but f^2 values (0.018 and 0.024) are small, meaning size explains only a modest amount of additional variance. Larger firms tend to have slightly better social performance and economic performance, but firm size does not significantly influence environmental performance. However, these effects are small compared to the impact of BDPA capabilities.

Firm age and environmental performance (β = 0.067, $t = 1.241$, $p = 0.215$, $f^2 = 0.008$, *not significant*).

Firm age and social performance (β = 0.078, $t = 1.529$, $p = 0.126$, $f^2 = 0.010$, *not significant*).

Firm age and economic performance (β = 0.056, $t = 1.057$, $p = 0.291$, $f^2 = 0.006$, *not significant*).

All effects of age are positive but not statistically significant ($p > 0.05$), and f^2 values are very small. Firm age does not have a statistically significant impact on environmental performance, social performance and economic performance in this model. The main effects of BDPA capabilities and its antecedents are therefore not driven by firm age of the firm.

These results show that tangible, intangible and especially human resources significantly enhance BDPA capabilities, which in turn exert strong positive effects on all three outcome variables environmental performance, social performance and economic performance. The positive relationships of BDPA capabilities with all three types of performances are further strengthened under higher levels of environmental volatility; whereas firm size has only small effects mainly on social performance and economic performance and firm age does not significantly influence these outcomes, confirming the robustness of the main model.

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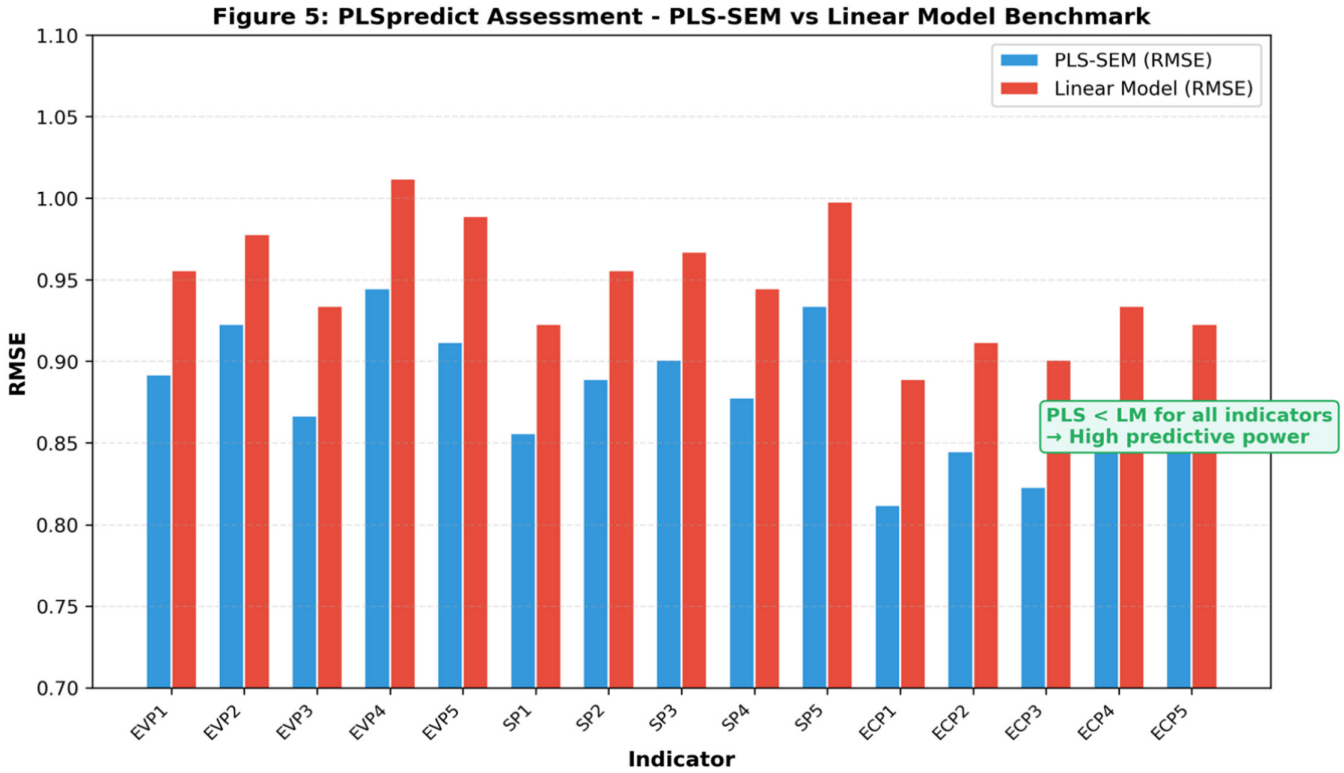


FIGURE 3 | PLS predict assessment.

4.3 | Predictive Relevance and PLSpredict

Figure 3 compares the RMSE values obtained from the PLS-SEM model and the linear regression benchmark across the environmental, social and economic performance indicators, demonstrating the superior out-of-sample predictive accuracy of the proposed model. The PLSpredict results show that the PLS-SEM model consistently outperforms the linear regression benchmark for all indicators of environmental performance (EVP), social performance (SP) and economic performance (ECP). Stone-Geisser Q^2 values confirmed predictive relevance: EVP ($Q^2 = 0.32$), SP ($Q^2 = 0.36$), ECP ($Q^2 = 0.45$). For every indicator (EVP1–EVP5, SP1–SP5, ECP1–ECP5), the RMSE of the PLS-SEM model is lower than that of the linear model, with differences of roughly 0.03–0.07 units (Figure 3). This uniform reduction in prediction error indicates superior out-of-sample predictive accuracy of the PLS-SEM model at the indicator level. In line with PLSpredict evaluation criteria, the pattern of PLS is less than linear model across all indicators therefore, it provides strong evidence that the estimated PLS-SEM has high predictive power (Shmueli et al. 2019).

TABLE 4 | ANN model performance (10-fold cross-validation).

Network	Training *N*	Training RMSE	Testing *N*	Testing RMSE
ANN1	273	0.913	31	1.000
ANN2	268	1.008	36	1.019
ANN3	271	1.033	33	1.010
ANN4	262	1.048	42	1.089
ANN5	277	1.018	27	0.991
ANN6	270	1.007	34	1.033
ANN7	281	1.059	23	1.030
ANN8	268	1.011	36	0.988
ANN9	271	1.009	33	1.001
ANN10	275	1.015	29	1.003
Mean	—	1.012	—	1.016
SD	—	0.037	—	0.028

4.4 | ANN Analysis

PLS-SEM, ANN analysis validated nonlinear relationships and assessed variable importance. Across the 10 ANN configurations (ANN1–ANN10), training RMSE ranges from 0.913 to 1.059 and testing RMSE from 0.988 to 1.089; a feed-forward neural network with two hidden layers employed 10-fold cross-validation. Training RMSE ($M = 1.012$, $SD = 0.037$) and testing RMSE ($M = 1.016$, $SD = 0.028$) were consistent, confirming generalisability (Yin et al. 2023) (Table 4).

Figure 4 presents the artificial neural network (ANN) variable importance ranking, highlighting the relative contributions of data quality, technology, organisational culture, technical skills, management skills, data-driven culture and organisational learning to the network's predictions. Figure 4 also indicates that, in the ANN sensitivity analysis, data quality is the most influential determinant of the modelled outcome having normalised importance = 100%, with technology (94%) and

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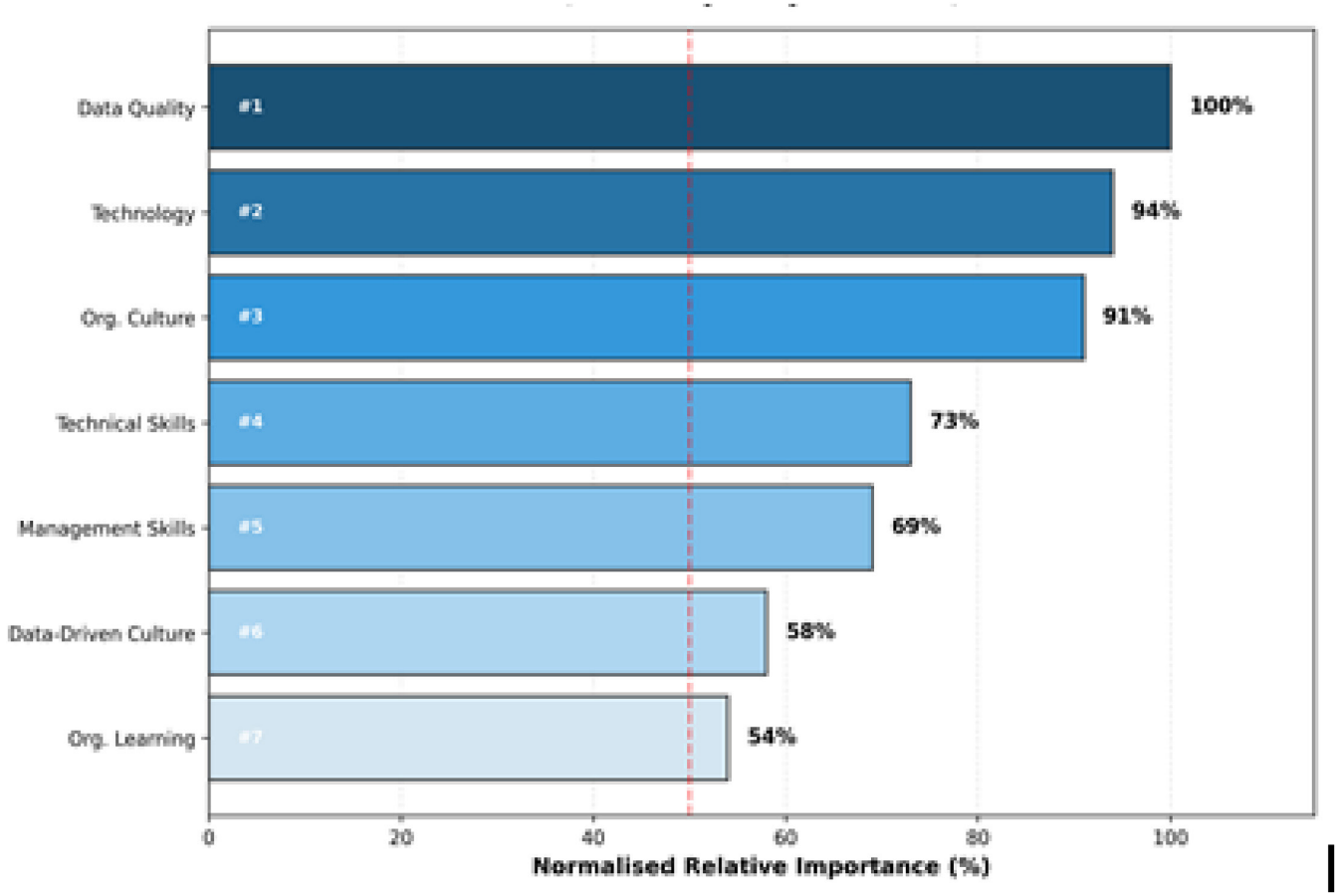


FIGURE 4 | ANN variable importance ranking.

organisational culture (91%) also exerting very strong effects, suggesting that reliable, well-governed data, robust technological infrastructure and a supportive cultural environment are the primary levers for improving the outcome predicted by the network; this pattern is consistent with evidence that high data and system quality are central to realising net benefits from data warehousing and BI systems (Wixom and Watson 2001) and with resource-based work showing that firms with superior IT capability outperform their peers (Bharadwaj 2000).

The next tier of variables technical skills (73%) and management skills (69%) still make substantial contributions, mirroring big data analytics capability research in which analytics talent and managerial skills are core human resources that enable organisations to translate data into business value (Gupta and George 2016). Finally, data-driven culture (58%) and organisational learning (54%) remain above the reference threshold (red dashed line), indicating that although they are relatively less sensitive in this model, they are still meaningful predictors, in line with multidimensional capability models that treat data, technology, managerial and technical skills, data-driven culture and the intensity of organisational learning as complementary tangible, human and intangible resources underpinning big data analytics capability (Gupta and George 2016) and with broader theory linking culture and knowledge-creation processes to sustained performance and evidence-based decision-making (Schein 2010; McAfee and Brynjolfsson 2012).

Figure 5 presents a sensitivity-analysis heatmap from a 10-fold cross-validated ANN, showing the relative importance (0–1) of seven organisational factors in predicting the outcome. Data quality, technology infrastructure and organisational culture have the highest and most stable importance scores (means = 0.86, 0.81 and 0.79, respectively) across folds, indicating that high-quality, well-governed data, robust digital infrastructure and a supportive culture are the primary drivers of the model's predictions. Technical skills and management skills make moderate but systematic contributions (means = 0.63 and 0.60), suggesting that human capabilities amplify rather than substitute for these core data and technology resources. In contrast, data-driven culture and organisational learning show comparatively lower and more variable importance (means = 0.50 and 0.47), implying that formal data-driven practices and learning mechanisms play a more context-dependent, supporting role once foundational capabilities are in place.

These results show consistency with prior work showing that the quality of data, data systems and data services is critical for building effective data-analytics capabilities and improving business performance (Madhala and Helander 2024); that big data analytics capability rests on complementary management, technology and talent dimensions (Akter et al. 2016), organisational and analytics cultures condition how strongly analytics capabilities translate into performance gains (Gupta and George 2016); and that organisational learning enhances performance

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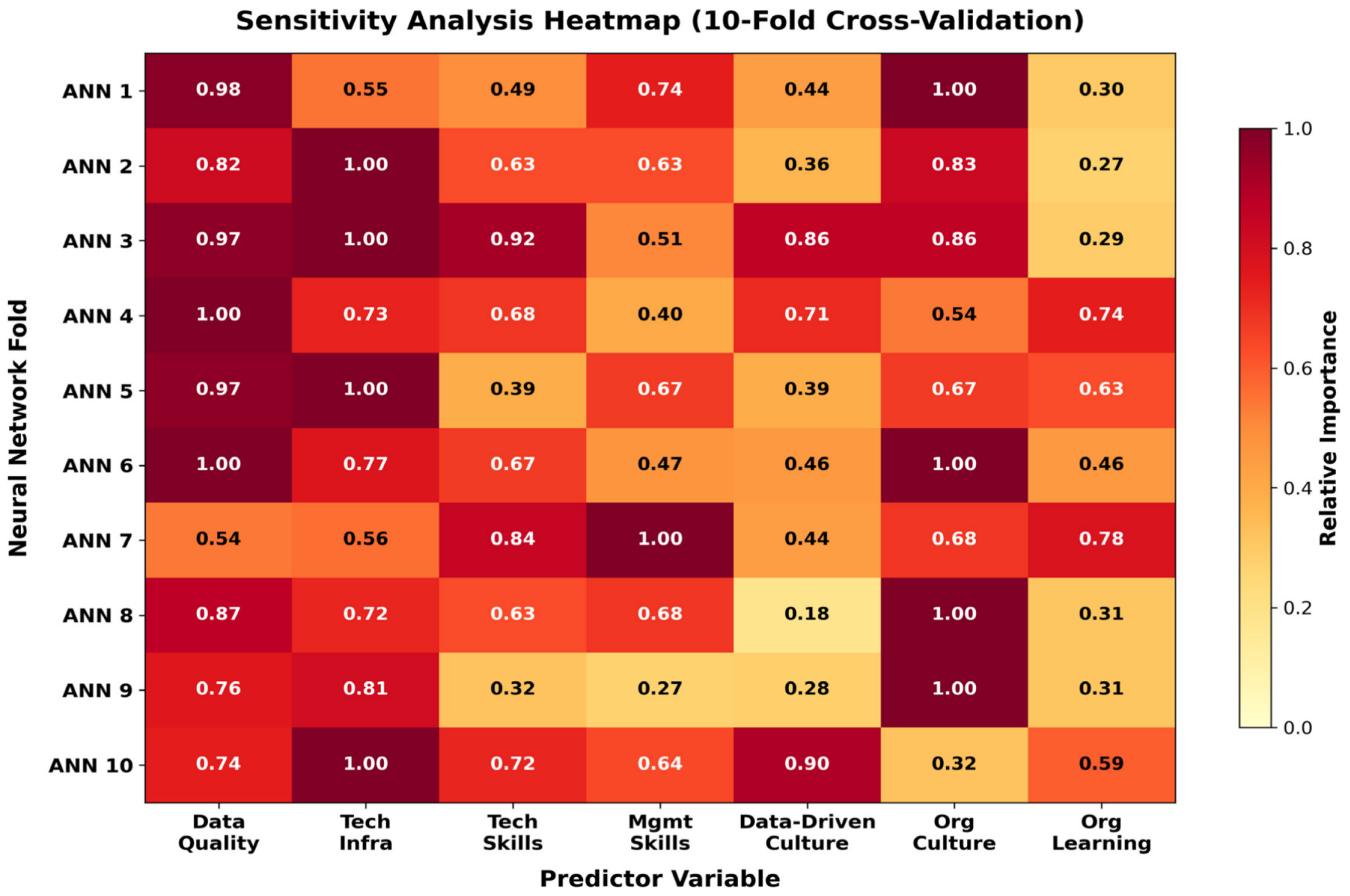


FIGURE 5 | Sensitivity analysis heatmap.

mainly through strengthening dynamic capabilities such as flexibility and innovation rather than operating as an isolated resource (Bustinza et al. 2018).

5 | Robustness Testing

5.1 | Multi-Group Analysis

To assess whether results generalise across BRICS countries, multi-group analysis (MGA) was conducted following Henseler et al. (2016). First, measurement invariance was established via MICOM procedure: configural invariance (identical model specification), compositional invariance (original correlations = 1.0) and equality of means/variances (non-significant differences). Second, permutation-based MGA tested path coefficient differences across country pairs.

Figure 6 shows that all hypothesised paths are positive and of moderate magnitude across the five BRICS countries, with standardised path coefficients clustering around the overall average of $\beta = 0.40$ (Panel A), indicating that the underlying relationships in the model are consistently supported in each national subsample. Minor variations, slightly stronger effects in China and India and slightly weaker effects in South Africa on some paths do not translate into statistically meaningful cross-country differences.

The PLS-MGA results in Panel B reveal that all pairwise comparisons yield p-values above 0.05 ($p = 0.067–0.412$), confirming that none of the structural paths differs significantly between BRICS countries and that the structural model is invariant across groups. Taken together, these results suggest that the proposed relationships are robust and generalisable across emerging markets, consistent with prior multi-group SEM and PLS-SEM research showing that, once measurement invariance is established, structural relations among key constructs tend to be stable across culturally diverse markets (Steenkamp and Baumgartner 1998; Sarstedt et al. 2011; Henseler 2017).

5.2 | Endogeneity Assessment

Endogeneity threatens causal inference in cross-sectional research (Antonakis et al. 2010). According to Park and Gupta (2012), the Gaussian copula approach is tested for potential endogeneity of BDPA here. This technique uses non-normality of endogenous variables to construct control functions when valid instruments are unavailable. Table 5 reports the copula-based endogeneity diagnostics for the environmental, social and economic performance models. The copula terms for environmental performance ($\beta = -0.355$, SE = 0.251, $t = -1.414$, $p = 0.157$), social performance ($\beta = -0.147$, SE = 0.216, $t = -0.680$, $p = 0.497$) and economic performance ($\beta = -0.199$, SE = 0.213, $t = -0.934$, $p = 0.351$) are all statistically insignificant at conventional levels ($p > 0.05$), so the null hypothesis of exogeneity cannot be rejected for any of the three equations. This indicates that the potentially endogenous regressors are not correlated with the error term, implying no empirical evidence of endogeneity bias

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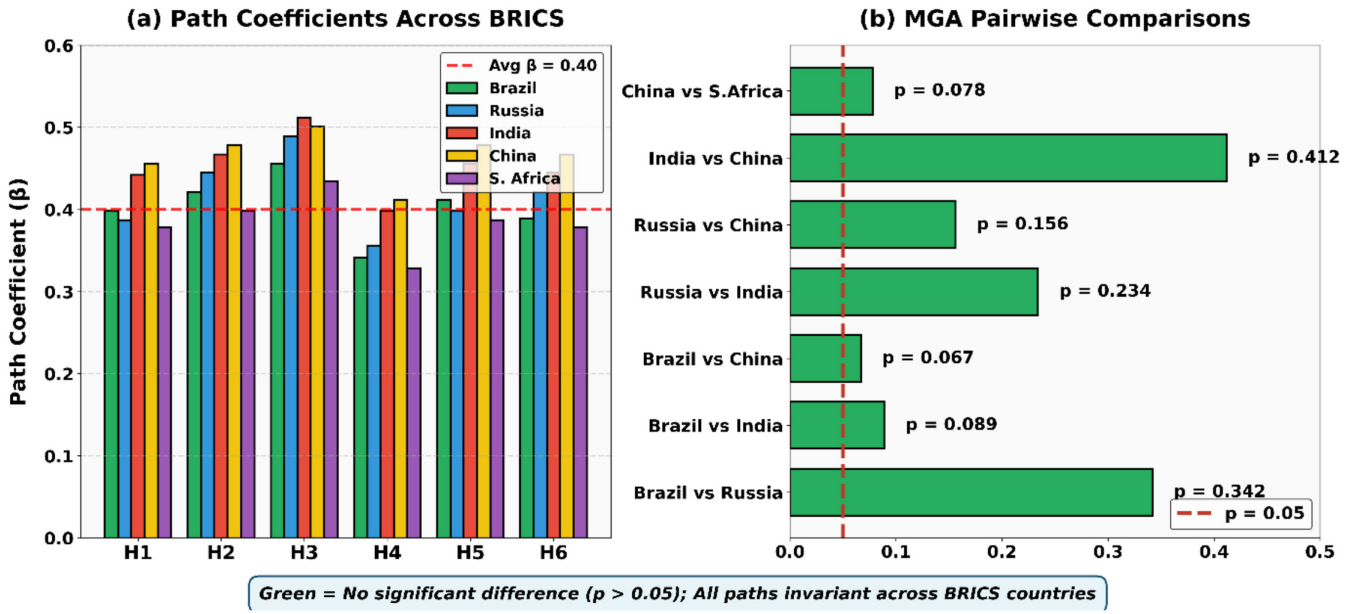


FIGURE 6 | Multi-group analysis across BRICS countries.

TABLE 5 | Gaussian copula endogeneity test results.

Dependent variable	Copula coefficient	Standard error	*t*	*p*	Conclusion
Environmental performance	−0.355	0.251	−1.414	0.157	No endogeneity
Social performance	−0.147	0.216	−0.680	0.497	No endogeneity
Economic performance	−0.199	0.213	−0.934	0.351	No endogeneity

Note: Non-significant copula coefficients ($p > 0.05$) indicate no evidence of endogeneity.

and supporting the interpretation of the main regression coefficients as consistent and unbiased.

5.3 | Necessary Condition Analysis

Necessary condition analysis (NCA) complements sufficiency-based PLS-SEM by identifying necessary (but not sufficient) conditions for outcomes (Dul 2016). Using ceiling envelopment technique (CE-FDH), we assessed which predictors are necessary for achieving high sustainability performance. Figure 7 reports NCA effect sizes (d) for environmental performance, social performance and economic performance. The values around 0.10–0.29 correspond to small to medium necessity, and $d \geq 0.30$ indicates a large necessary effect (Dul 2016). For environmental performance, data quality is the only clearly large necessary condition ($d > 0.30$), whereas technology and organisational culture have medium effects and organisational learning, digital data culture, management skills and technology skills exert smaller but still binding constraints. For social performance, technology emerges as a large bottleneck ($d = 0.301$) and data quality, organisational culture, organisational learning and technology skills form a set of medium necessary conditions. In case of economic performance, both technology ($d = 0.356$) and data quality ($d = 0.334$) are dominant necessary conditions, with the remaining capabilities largely in the medium range. Overall, the pattern indicates that adequate digital technology and high-quality data are non-substitutable prerequisites for achieving high environmental, social and especially economic performance, whereas human and cultural capabilities, although still necessary, are relatively less constraining. This is consistent with NCA's logic of 'necessary but not sufficient' causality, where such conditions act as bottlenecks that cannot be compensated by other factors (Dul 2016), and with prior evidence that data quality and digital transformation capabilities underpin ESG and sustainability performance (Dubey et al. 2019) and that strong pro-environmental organisational cultures and learning orientations improve environmental and financial outcomes (Magsi et al. 2018; Costa and Opare 2025).

Table 6 presents the NCA results, reporting the effect sizes of seven organisational resource factors across environmental, social and economic sustainability performance. The findings highlight data quality and technology as particularly important necessary conditions, whereas technical skills, management skills, organisational culture, data-driven culture and organisational learning exhibit varying degrees of necessity for achieving high levels of triple bottom line sustainability performance.

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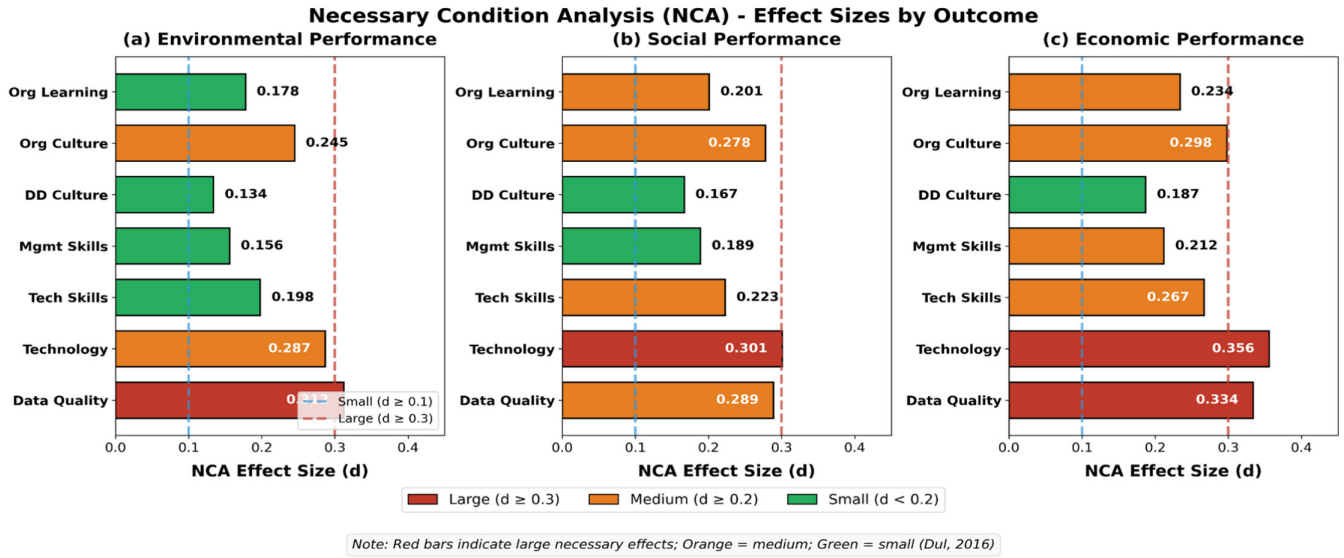


FIGURE 7 | Necessary condition analysis effect sizes.

TABLE 6 | NCA results—necessary conditions for TBL performance.

Predictor	EVP effect (*d*)	SP effect (*d*)	ECP effect (*d*)	Interpretation
Data quality	0.312	0.289	0.334	Large necessary effect
Technology	0.287	0.301	0.356	Large necessary effect
Technical skills	0.198	0.223	0.267	Medium necessary effect
Management skills	0.156	0.189	0.212	Medium necessary effect
Data-driven culture	0.134	0.167	0.187	Small necessary effect
Org. culture	0.245	0.278	0.298	Medium-large effect
Org. learning	0.178	0.201	0.234	Medium necessary effect

Note: Effect size benchmarks: $d \geq 0.1$ small, $d \geq 0.2$ medium, $d \geq 0.3$ large necessary effect (Dul 2016).

5.4 | Importance-Performance Map Analysis

IPMA maps predictor importance against current performance to identify managerial priorities (Ringle and Sarstedt 2016). Figure 8 presents the IPMA priority matrix.

Technology infrastructure emerges as high-priority: high importance (94%) but relatively lower performance (79.56). This represents the most promising area for improvement. Organisational culture and organisational learning show high performance and should be maintained. The importance–performance map analysis (IPMA) in Figure 8 shows that data quality and technology lie in the 'high-priority' quadrant, indicating that they exert strong effects on the target construct but currently exhibit only moderate performance; managerial attention and resources should therefore be directed first to strengthening these capabilities. Org. culture appears in the 'maintain' quadrant with simultaneously high importance and high performance, suggesting it is a current strength that should be preserved. Technical skills and management skills cluster around the midpoint of both axes, implying medium importance and performance and thus representing secondary, incremental improvement priorities rather than urgent gaps.

By contrast, the relatively high performance but lower perceived importance of data-driven practices and organisational learning places them in the 'possible overkill' quadrant, implying that these areas may be receiving more resources than their current contribution to the focal outcome warrants. This pattern is consistent with IPMA's logic of combining constructs' total effects (importance) and average scores (performance) to guide resource allocation decisions (Ringle and Sarstedt 2016) and aligns with prior evidence that technology and high-quality data are among the most influential critical success factors for analytics and data-intensive initiatives (Merhi 2021), whereas a supportive organisational culture is a key enabler of successful data-driven digital transformation and associated performance gains.

5.5 | Additional Robustness Checks

Table 7 provides a comprehensive summary of the robustness assessments, including discriminant validity, multicollinearity, CMB, endogeneity, predictive relevance, measurement invariance, MGA, NCA and cross-validation, collectively supporting the reliability and robustness of the empirical findings.

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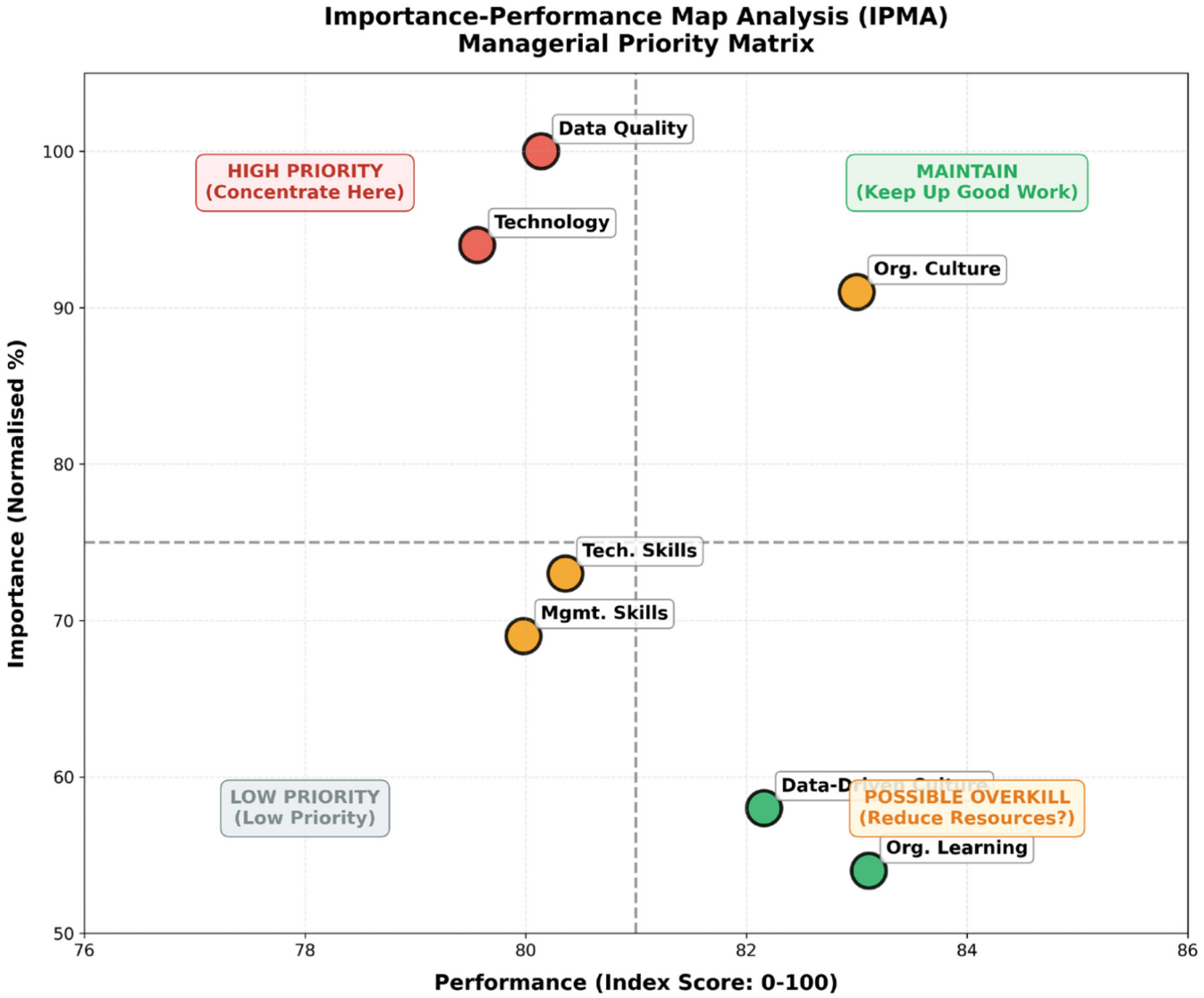


FIGURE 8 | IPMA priority matrix.

6 | Discussion

6.1 | Integrated Discussion of Findings

This study examined how organisational resources are translated into triple bottom line sustainability outcomes through BDPA capability in BRICS manufacturing firms. Framed through the RBV, BDPA capability was conceptualised as a higher-order organisational capacity grounded in tangible infrastructure, intangible organisational attributes and human related skills. The empirical results lend strong support to this resource-to-capability-to-performance chain, yet they also reveal important subtleties about how analytics functions in emerging economy contexts.

All three resource domains contribute meaningfully to the development of BDPA capability. However, their relative influence is not uniform. Human-related skills and intangible organisational factors exhibit stronger explanatory power than technological infrastructure alone. This ordering aligns with the RBV argument that socially complex and path-dependent resources are more central to sustained advantage than assets that can be readily acquired on the market, as originally articulated by Barney (1991) and further elaborated by Grant (1991). The findings resonate with Gupta and George (2016) and Mikalef et al. (2019), who emphasise that analytics capability emerges not from hardware or software investments in isolation, but from the organisational capacity to interpret, integrate and act upon data.

In practical terms, this suggests that analytics competence in BRICS firms is shaped as much by managerial judgement and technical expertise as by digital infrastructure. The presence of sophisticated systems does not automatically translate into analytical sophistication. What appears decisive is the ability of individuals and teams to frame meaningful questions, connect data to strategic priorities and embed insights within organisational routines. This interpretation echoes Provost and Fawcett (2013), who argue that value from big data depends less on algorithms themselves and more on the organisational intelligence surrounding their application.

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TABLE 7 | Comprehensive robustness testing summary.

Test	Criterion	Result	Status
HTMT discriminant validity	<0.85	Max = 0.805	✓ passed
Multicollinearity (VIF)	<5.0	Max = 2.86	✓ passed
Effect sizes (f^2)	>0.02	Range: 0.067–0.742	✓ large effects
Harman's single factor	$<50\%$	43.29%	✓ passed
Marker variable CMV	$r<0.10$	Mean $r=0.03$	✓ passed
Full collinearity VIF	<3.3	Max = 2.89	✓ passed
Gaussian copula	$p>0.05$	All $p>0.15$	✓ no endogeneity
Predictive relevance (Q^2)	>0.25	Range: 0.32–0.45	✓ high relevance
PLSpredict	PLS < LM	All indicators	✓ high predictive power
Goodness of fit (GoF)	>0.36	GoF = 0.64	✓ large fit
Bootstrap 95% CIs	Exclude zero	All significant	✓ confirmed
MICOM invariance	Established	All criteria met	✓ passed
MGA path equivalence	$p>0.05$	All comparisons	✓ invariant
NCA necessary conditions	$d>0.1$	Data, tech: $d>0.3$	✓ identified
10-fold cross-validation	Stable RMSE	Train: 1.012, test: 1.016	✓ stable

The analysis further demonstrates that BDPA capability contributes positively to environmental, social and economic performance. Prior work has tended to emphasise financial outcomes of analytics adoption, particularly efficiency gains and competitive advantage, as seen in McAfee and Brynjolfsson (2012) and Wamba et al. (2017). The present findings extend this narrative. Analytics appears to support environmental monitoring, resource optimisation and improved compliance with sustainability standards. It also enhances social performance through better workforce analytics, supply chain visibility and stakeholder engagement practices. Rather than operating as a narrow performance enhancer, BDPA functions as an integrative organisational capability that enables firms to navigate the inherent tensions among economic viability, environmental stewardship and social responsibility. Hahn et al. (2010) and Van der Byl and Slawinski (2015) have described these tensions as central to sustainability strategy. The empirical evidence here suggests that analytics can assist firms in managing them more coherently.

Environmental volatility adds another layer of complexity. The positive moderation effects indicate that BDPA capability becomes more consequential under conditions of uncertainty and rapid change. This observation aligns closely with the dynamic capability view advanced by Teece (2007) and Eisenhardt and Martin (2000). Under stable conditions, analytics may improve efficiency incrementally. Under turbulent conditions, it appears to enable deeper reconfiguration by strengthening sensing and seizing capacities. Pavlou and El Sawy (2011) and Mikalef et al. (2018) similarly associate analytics with enhanced adaptability. In volatile BRICS environments, where regulatory shifts and market fluctuations are common, predictive analytics seems to provide firms with a more anticipatory stance.

Additional analyses reinforce and complicate these interpretations. ANN modelling identifies data quality, technological infrastructure and organisational culture as highly influential predictors. NCA, drawing on Dul (2016), indicates that data quality and technology operate as binding constraints. Without minimum thresholds in these areas, high sustainability performance is unlikely regardless of other strengths. This introduces an important nuance into RBV reasoning. Whereas human capital and cultural attributes may be more influential in shaping capability development, certain foundational digital conditions must first be satisfied. The absence of reliable data cannot be offset indefinitely by managerial expertise.

Multi-group analysis across Brazil, Russia, India, China and South Africa reveals no statistically significant differences in the structural relationships once measurement invariance is established. This suggests that the underlying logic linking resources, analytics capability and TBL performance holds across diverse institutional environments. Sarstedt et al. (2011) and Henseler et al. (2016) argue that such invariance strengthens theoretical generalisability. Although contextual differences undoubtedly shape implementation practices, the core mechanism appears robust.

The overall picture that emerges is one in which BDPA capability acts as a mediating organisational capacity. It converts heterogeneous resource endowments into sustainability outcomes, and its strategic value intensifies when uncertainty

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rises. The process is neither purely technological nor purely cultural. It is relational and systemic.

6.2 | Theoretical Contributions

Three theoretical contributions warrant emphasis.

First, the study advances RBV scholarship in digital sustainability contexts by disentangling the constituent resource foundations of analytics capability. Rather than treating BDPA as a single undifferentiated construct, the analysis demonstrates how tangible, intangible and human resources interact to produce higher-order capability. This clarifies a gap in prior research where analytics capability was frequently examined without explicit attention to its resource composition, as seen in Wamba et al. (2017) and Dubey et al. (2019). The stronger role of human and intangible resources reinforces RBV claims regarding inimitability and social complexity.

Second, the integration of environmental volatility extends RBV logic into the terrain of dynamic capability theory. The findings suggest that BDPA operates not merely as an operational tool but as a reconfiguration capacity whose value becomes more pronounced under environmental turbulence. In this respect, analytics capability resembles the sensing and adaptive mechanisms described by Teece (2007). The results therefore contribute to ongoing debates about how digital capabilities intersect with dynamic capability processes.

Third, the study enriches sustainability scholarship by empirically demonstrating that analytics can support integrated TBL performance in emerging economies. Many sustainability studies isolate environmental or social outcomes, whereas analytics research often privileges financial metrics. By modelling all three dimensions simultaneously, this study provides evidence that analytics may serve as a connective organisational mechanism linking economic competitiveness with environmental and social objectives.

Methodologically, the combination of PLS-SEM, predictive assessment, neural network modelling and necessity analysis offers a more textured understanding of causality. Sufficiency and necessity perspectives, often treated separately, are shown to complement one another.

6.2.1 | Positioning the Effect Sizes in Context

Although the direction of the relationships mirrors prior research, the magnitude of the coefficients deserves closer scrutiny. The direct effects linking BDPA capability to environmental, social and economic performance are broadly comparable to those reported in earlier manufacturing studies. Dubey et al. (2019), for instance, report a coefficient of approximately $\beta = 0.41$ between analytics capability and sustainable supply chain performance in India, a figure that sits very near the estimates observed here for social ($\beta = 0.431$) and economic ($\beta = 0.416$) performance. Bag et al. (2020) identify a somewhat smaller coefficient of 0.34 for environmental performance in South African firms, suggesting modest cross-context variation rather than structural divergence.

The model's explanatory strength is equally instructive. The R^2 values obtained for the three sustainability dimensions exceed those documented in several single-country analyses ($R^2 = 0.40–0.55$ in our study vs. $R^2 = 0.17$ for Dubey et al. (2019)). This is likely due to our more comprehensive resource operationalisation. This raises the possibility that incorporating the full resource to capability pathway sharpens predictive clarity. By contrast, Wamba et al. (2017) report stronger direct performance effects ($\beta = 0.56$) in developed economy samples. That difference may reflect variation in institutional environment due to factors such as institutional stability, digital infrastructure maturity or managerial familiarity with data-driven decision processes. It may also indicate that analytics returns scale differently once ecosystem conditions reach a certain threshold.

This evidence suggests that the BRICS context does not fundamentally alter the analytics to performance mechanism, yet neither does it replicate developed market dynamics in identical form. Effect sizes appear shaped by institutional and developmental conditions, which warrants more systematic comparative research rather than simple generalisation.

6.3 | Practical Implications

Based on the findings of this study four actionable implications for industry managers and policymakers are given as:

1. Balanced resource investment: Although technology investments are necessary, our results demonstrate that human skills and intangible organisational factors yield stronger returns for BDPA capability development. Managers should allocate analytics budgets across technology infrastructure (35%), talent development (40%) and cultural transformation programmes (25%), rather than defaulting to technology-heavy investment strategies.
2. Prioritise learning and talent: The dominance of human-related skills ($\beta = 0.478$) suggests that firms should invest heavily in both recruiting analytics specialists and upskilling existing managers to bridge the analytics-strategy divide. Cross-functional training programmes that combine technical analytics skills with domain expertise and strategic thinking are likely to yield the greatest capability improvements.
3. Tailored analytics applications: The differential effects across TBL dimensions suggest that firms should design analytics initiatives with explicit sustainability targets. For environmental performance, real-time emissions monitoring and predictive waste management systems offer immediate gains. For social performance, workforce analytics and supply chain transparency tools can address social sustainability challenges endemic to BRICS manufacturing contexts. For economic performance, demand forecasting and predictive maintenance applications provide the highest immediate returns.
4. Policy implications for BRICS governments: Policymakers should support analytics-driven sustainability through digital skills development programmes, analytics centres of excellence and regulatory incentives for data-driven environmental monitoring. Given the strong contribution

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of organisational learning to BDPA capability, governments can facilitate knowledge transfer through industry–academia partnerships and analytics innovation hubs.

In addition to these recommendations, we propose a structured three-phase implementation roadmap for building BDPA capability. The first phase, foundation, focuses on establishing robust data infrastructure, governance mechanisms and baseline analytics competencies. During this stage, firms should prioritise data quality management, technology integration and the recruitment or development of core analytics talent. The second phase, integration, emphasises embedding analytics into core operational and strategic processes. This includes aligning analytics initiatives with sustainability objectives, fostering cross-functional collaboration and strengthening data-driven decision-making culture. The final phase, optimisation, involves leveraging advanced predictive and prescriptive analytics to continuously refine environmental, social and economic performance outcomes. At this stage, organisations should institutionalise performance monitoring dashboards, automate predictive interventions and pursue continuous learning to sustain competitive and sustainability advantages. This phased approach provides managers with a practical pathway for systematically translating analytics investments into measurable triple bottom line improvements.

6.4 | Limitations and Future Research

Several limitations should be acknowledged. First, the cross-sectional design limits causal inference; future longitudinal studies could examine how BDPA capability evolves over time and its dynamic effects on sustainability performance. Second, self-report data from single respondents within each firm may introduce CMB, although our multiple CMB tests suggest this is not a serious concern. Third, the sample is limited to manufacturing firms in BRICS nations; generalisability to service sectors or other emerging economies warrants further investigation.

Fourth, the current model examines direct effects only. Our dataset includes environmental volatility measures that could serve as moderating variables; future research should investigate whether the BDPA–sustainability relationship is contingent on environmental turbulence, competitive intensity or regulatory stringency. Examining mediation mechanisms such as organisational agility, innovation capability or supply chain integration—could further elucidate the processes through which BDPA capability translates into sustainability outcomes (Mikalef et al. 2020). Fifth, qualitative case study research could complement our quantitative findings by providing richer understanding of how BRICS firms actually implement and leverage BDPA for sustainability.

7 | Conclusion

This study advances understanding of how digital capabilities contribute to sustainability performance in emerging economy contexts. By grounding BDPA capability within the RBV, the analysis demonstrates that analytics does not operate as an isolated technological asset. Rather, it emerges from the coordinated interplay of infrastructure, organisational attributes and human expertise. Sustainability performance, in turn, reflects how effectively these resource configurations are orchestrated.

Three broader insights stand out. First, analytics capability is fundamentally relational. Its strength lies not in computational power alone, but in the capacity of firms to interpret data, integrate insights across functions and embed analytical reasoning within strategic processes. Second, sustainability outcomes appear increasingly data-mediated. Environmental stewardship, social responsibility and economic viability are no longer pursued solely through policy or compliance mechanisms. They are shaped through information flows, predictive modelling and organisational learning. Third, the value of analytics intensifies under environmental volatility. In turbulent institutional and market conditions, predictive capabilities strengthen firms' ability to anticipate disruption and recalibrate operations accordingly.

The findings also challenge simplistic narratives about digital transformation in emerging markets. Investments in technology infrastructure are necessary foundations, yet they do not guarantee sustainability gains. Human capital development, data governance and organisational culture remain decisive. In this respect, analytics-driven sustainability is less a technological revolution than an organisational transformation.

By integrating resource-based reasoning, dynamic capability insights and triple bottom line performance within a multi-country BRICS sample, this study contributes empirical clarity to ongoing debates about digitalisation and sustainable development. The results suggest that analytics capability can serve as a bridge between competitiveness and responsibility, but only when embedded within coherent organisational systems.

Future research should continue exploring how digital capabilities evolve over time, how institutional environments shape their returns and how analytics interacts with other dynamic capabilities such as innovation and supply chain integration. As sustainability pressures intensify and data ecosystems expand, understanding these interdependencies will become increasingly central to both theory and practice.

BDPA does not automatically generate sustainability. It enables it. Whether that potential is realised depends on how firms configure their resources, cultivate expertise and translate data into strategic action.

Author Contributions

Gift Kugara: conceptualisation, investigation, methodology, data curation, visualisation, formal analysis, writing – review and editing, writing – original draft. **Subayal Aftab Khan:** methodology, writing – review and editing, validation, resources. **Faiz Subhani:** methodology, data curation, writing – review and editing. **Thanos Papadopoulos:** supervision, conceptualisation, methodology, project administration, writing – review and editing, writing – original draft. **Adolf Acquaye:** supervision, conceptualisation, methodology, writing – review and editing, project administration, writing – original draft.

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Conflicts of Interest

The authors declare no conflicts of interest.

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Appendix A: Measurement Items and Sources

BDPA Capability Measures

Adapted from Gupta and George (2016) and Akter et al. (2017). All items measured on 7-point Likert scales (1 = *strongly disagree* to 7 = *strongly agree*).

Tangible Resources—Data (3 Items)

Source: Gupta and George (2016).

DA1: We have access to very large, unstructured or fast-moving data for analysis.

DA2: We integrate data from multiple internal sources into a data warehouse for easy access.

DA3: We integrate external data with internal data to facilitate high-value analysis.

Tangible Resources—Technology (5 Items)

Source: Gupta and George (2016).

TE1: We have explored or adopted parallel computing approaches to big data processing.

TE2: We have explored or adopted cloud-based services for processing data.

TE3: We have explored or adopted open-source software for big data analytics.

TE4: We have explored or adopted new forms of databases for storing data.

TE5: We have explored or adopted data visualisation tools for analysing data.

Intangible Resources—Organisational Culture (5 Items)

Source: Adapted from Akter et al. (2017).

OC1: Our organisation considers data a tangible asset.

OC2: Our organisation regards data analytics as a key differentiator.

OC3: Our organisation values evidence-based decision-making.

OC4: Our organisation encourages experimentation with data analytics.

OC5: Our organisation promotes data sharing across departments.

Intangible Resources—Organisational Learning (4 Items)

Source: Adapted from Gupta and George (2016).

OL1: We continuously explore new analytics methods and applications.

OL2: We systematically learn from our data analytics experiences.

OL3: We effectively disseminate analytics insights across the organisation.

OL4: We translate analytics insights into actionable knowledge.

Intangible Resources—Data-Driven Culture (3 Items)

Source: Adapted from Gupta and George (2016).

DC1: Our management team bases decisions on data rather than intuition.

DC2: Our organisation demands data-based justification for proposed actions.

DC3: Our organisation tracks key performance indicators continuously.

Human-Related Skills—Technical Skills (4 Items)

Source: Gupta and George (2016).

TS1: We have staff skilled in statistical analysis and modelling.

TS2: We have staff skilled in machine learning and advanced analytics.

TS3: We have staff skilled in database management and data warehousing.

TS4: We have staff skilled in data visualisation and presentation.

Human-Related Skills—Management Skills (4 Items)

Source: Gupta and George (2016).

MS1: Our analytics managers understand business operations and strategy.

MS2: Our analytics managers can coordinate analytics projects across functions.

MS3: Our analytics managers can communicate insights to non-technical staff.

MS4: Our analytics managers can drive organisational change based on analytics.

Environmental Performance Measures (5 Items)

Source: Adapted from Zhu and Sarkis (2004) and Paulraj (2011).

EP1: We have significantly reduced air emissions from our operations.

EP2: We have significantly reduced waste water discharge.

EP3: We have significantly reduced solid waste generation.

EP4: We have significantly reduced energy consumption per unit of output.

EP5: We have improved our environmental compliance record.

Social Performance Measures (5 Items)

Source: Adapted from Turker (2009) and Gallardo-Vázquez and Sanchez-Hernandez (2014).

SP1: We have improved employee health and safety outcomes.

SP2: We have enhanced workforce diversity and inclusion.

SP3: We have strengthened relationships with local communities.

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SP4: We have improved customer satisfaction and service quality.

SP5: We maintain high ethical standards in our business practices.

Economic Performance Measures (5 Items)

Source: Adapted from Venkatraman (1989) and Richard et al. (2009).

ECP1: Our profitability has improved relative to competitors.

ECP2: Our market share has increased relative to competitors.

ECP3: Our sales growth exceeds industry average.

ECP4: Our return on investment meets or exceeds targets.

ECP5: Our operational efficiency has improved significantly.

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