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ARTICLE

Competitive-Intelligence Enabling Infrastructure, Psychological Adaptability, and Organizational Performance: Evidence from Chinese Manufacturing Firms

Infraestrutura Facilitadora da Inteligência Competitiva, Adaptabilidade Psicológica e Desempenho Organizacional: Evidências de Empresas Manufatureiras Chinesas

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ABSTRACT | Purpose: This study examines whether competitive-intelligence enabling infrastructure (CIEI) is associated with a cognitive-horizon proxy of psychological adaptability and subsequent organizational performance in Chinese manufacturing firms. It addresses the distinction between digital and analytical infrastructure and a complete competitive-intelligence system comprising intelligence planning, collection, analysis, dissemination, utilization, feedback, ethics, and governance. **Methodology/Approach:** The study analyzes 19,035 firm-year observations from 3,169 listed Chinese manufacturing firms during 2014–2023. CIEI is modeled as a formative archival index comprising big-data capability, digital-intelligence investment, and analytical capability. Low managerial myopia is used as a limited cognitive-horizon proxy of psychological adaptability, while organizational performance combines Tobin's Q, gross profitability, and asset turnover. The analytical hierarchy includes descriptive diffusion analysis, pooled models, firm and year fixed effects, one-year-lagged specifications, component-level and principal-component composition analyses, a 1,000-replication firm-cluster bootstrap, and dynamic-panel GMM. China's 2024 World Bank Enterprise Survey is used only as a separate contextual source because consistently defined 2024–2025 firm-level observations are unavailable for the primary panel. **Originality/Relevance:** The study does not equate digital infrastructure with competitive intelligence. Instead, it identifies an empirically observable enabling layer while explicitly separating it from unmeasured intelligence-cycle processes, including governance, dissemination, utilization, feedback, and accountable decision use. This distinction provides a more defensible basis for using archival corporate data in competitive-intelligence research. **Key Findings:** CIEI diffused substantially across the observed firms; 76.3% of the 772 firms in the ten-year balanced cohort moved to a higher infrastructure quartile. Prior-year CIEI was positively associated with subsequent organizational performance (b = 0.054, p = .019), while low managerial myopia showed a smaller positive association (b = 0.016, p = .048). Prior CIEI was not significantly associated with the adaptability

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proxy, and the cluster-bootstrap indirect-effect interval included zero. Component-level estimates were heterogeneous, and GMM results varied with instrument classification; consequently, the findings do not establish causality or validate a complete competitive-intelligence system. **Theoretical/Methodological Contributions:** The study reconnects archival analytics research with classical competitive-intelligence process, maturity, governance, and decision-use perspectives. Methodologically, it establishes explicit construct boundaries, treats CIEI as a formative enabling index rather than a reflective CI scale, separates primary from sensitivity specifications, and combines temporal ordering, firm fixed effects, clustered inference, bootstrap analysis, and dynamic-panel diagnostics. The results show that analytical infrastructure can be monitored through public data, but its conversion into competitive intelligence requires organizational processes that cannot be inferred from technology indicators alone.

Keywords | Competitive intelligence. Enabling infrastructure. Intelligence cycle. Intelligence governance. Psychological adaptability. Organizational performance. Chinese manufacturing.

RESUMO | Objetivo: Este estudo examina se a infraestrutura facilitadora da Inteligência Competitiva (*Competitive-Intelligence Enabling Infrastructure* – CIEI) está associada a uma proxy de horizonte cognitivo da adaptabilidade psicológica e, subsequentemente, ao desempenho organizacional em empresas manufatureiras chinesas. O estudo aborda a distinção entre infraestrutura digital e analítica e um sistema completo de Inteligência Competitiva, composto por planejamento da inteligência, coleta, análise, disseminação, utilização, feedback, ética e governança. **Metodologia/Abordagem:** O estudo analisa 19.035 observações empresa-ano de 3.169 empresas manufatureiras chinesas listadas em bolsa, durante o período de 2014 a 2023. A CIEI é modelada como um índice formativo baseado em dados de arquivo, composto por capacidade de big data, investimento em inteligência digital e capacidade analítica. O baixo nível de miopia gerencial é utilizado como uma proxy limitada de horizonte cognitivo da adaptabilidade psicológica, enquanto o desempenho organizacional combina Q de Tobin, rentabilidade bruta e giro do ativo. A estrutura analítica inclui análise descritiva de difusão, modelos agrupados (*pooled models*), efeitos fixos de empresa e ano, especificações com defasagem de um ano, análises de composição em nível de componentes e por componentes principais, *bootstrap* com agrupamento por empresa e 1.000 replicações e GMM para painel dinâmico. A *World Bank Enterprise Survey* de 2024 para a China é utilizada apenas como uma fonte contextual separada, uma vez que não estão disponíveis observações em nível de empresa, definidas de maneira consistente, para 2024–2025 no painel principal. **Originalidade/Relevância:** O estudo não equipara infraestrutura digital à Inteligência Competitiva. Em vez disso, identifica uma camada facilitadora empiricamente observável, ao mesmo tempo em que a distingue explicitamente dos processos não mensurados do ciclo de inteligência, incluindo governança, disseminação, utilização, feedback e uso responsável da inteligência na tomada de decisão. Essa distinção proporciona uma base mais defensável para a utilização de dados corporativos de arquivo em pesquisas sobre Inteligência Competitiva. **Principais Resultados:** A CIEI apresentou difusão substancial entre as empresas observadas; 76,3% das 772 empresas pertencentes à coorte balanceada de dez anos migraram para um quartil superior de infraestrutura. A CIEI do ano anterior apresentou associação positiva com o desempenho organizacional subsequente (b = 0,054; p = 0,019), enquanto o baixo nível de miopia gerencial apresentou uma associação positiva menor (b = 0,016; p = 0,048). A CIEI defasada não apresentou associação estatisticamente significativa com a proxy de adaptabilidade, e o intervalo do efeito indireto obtido por *cluster bootstrap* incluiu zero. As estimativas em nível de componentes mostraram-se heterogêneas, e os resultados do GMM variaram de acordo com a classificação dos instrumentos; consequentemente, os achados não permitem estabelecer causalidade nem validar um sistema completo de Inteligência Competitiva. **Contribuições Teóricas/Metodológicas:** O estudo reconecta a pesquisa baseada em análises de dados de arquivo às perspectivas clássicas de processo, maturidade, governança e utilização da Inteligência Competitiva na tomada de decisão. Metodologicamente, estabelece limites explícitos para os construtos, trata a CIEI como um índice formativo de infraestrutura facilitadora, em vez de uma escala reflexiva de Inteligência Competitiva, separa as especificações principais das análises de sensibilidade e combina ordenação temporal, efeitos fixos de empresa, inferência com erros agrupados, análise *bootstrap* e diagnósticos **de painel dinâmico**. Os resultados demonstram que a infraestrutura analítica pode ser monitorada por meio de dados públicos, mas sua conversão em Inteligência Competitiva requer processos organizacionais que não podem ser inferidos exclusivamente a partir de indicadores tecnológicos.

Palavras-chave | Inteligência competitiva. Infraestrutura facilitadora. Ciclo de inteligência. Governança da inteligência. Adaptabilidade psicológica. Desempenho organizacional. Manufatura chinesa.

1 INTRODUCTION

Manufacturing firms increasingly compete through their ability to detect environmental change, interpret dispersed signals, and connect evidence to timely decisions. Digital platforms, artificial intelligence, and large-scale data have expanded the information available to managers, but information becomes competitive intelligence (CI) only when it is deliberately collected, analyzed, communicated, challenged, and used. Classical research therefore defines CI as an ethical, managed, and decision-oriented process rather than the possession of technology (Calof & Wright, 2008; Dishman & Calof, 2008; Fleisher & Bensoussan, 2007). Recent analytics research reaches a compatible conclusion: technology creates value through complementary managerial capabilities, coordination, and organizational resilience (Hossain et al., 2022; Huang et al., 2022; Lin et al., 2025).

This distinction is particularly important in archival research. Public firm-level databases may record digital investment, analytical capability, innovation, financial structure, and performance, but they rarely observe intelligence requirements, source-selection procedures, environmental-scanning frequency, dissemination routines, decision utilization, post-decision feedback, ethical controls, or intelligence governance. Consequently, technology-related archival indicators cannot validly be interpreted as a direct measure of an organization's complete competitive-intelligence system. The present study therefore examines competitive-intelligence enabling infrastructure (CIEI), defined as the digital and analytical resource layer that may support the collection and analysis stages of intelligence work. CIEI is neither presented as a validated CI maturity score nor assumed to demonstrate that intelligence is disseminated, utilized, governed, or converted into strategic action.

This is not a terminological construct repositioning, but a substantive one. In a complete CI system, infrastructure is the means of information processing, and intelligence governance is the means of setting priorities, assigning responsibilities, judging the quality of information sources, controlling ethical behaviour, deciding on dissemination channels and linking intelligence outputs with accountable decision forums. This study has monitored only a portion of this larger architecture with an archival index. Thus, the empirical research question is not whether the sampled firms have mature CI systems, but whether an observable change in enabling infrastructure is related to a limited proxy of the cognitive horizon and to organizational performance.

The China manufacturing context is analytically relevant because listed companies were rapidly digitalized and had high levels of competition and significant technology and management capability heterogeneity between 2014 and 2023. Studies of Chinese companies correlate digital transformation and analytics with innovation, risk, resilience and performance (Chen et al., 2024; Sun et al., 2024; Zhuo & Chen, 2023). However, four gaps remain. Much of this evidence is interpreted with analytics – and not the classical CI process and maturity models. Secondly, positive cross-sectional relationships are sometimes talked about but existing studies do not establish the extent to which changes within the firm precede later performance. Third, the studies conducted in the archives have not been able to distinguish between a measured infrastructure component and the unobserved governance and decision-use processes that CI theory requires. A fourth gap is in the area of construct validation. In archival research, digital indicators are often used together in composite scores without separating formative resource indicators from formative psychological and/or organizational indicators. In the current context, big-data capability, digital-intelligence investment, and analytical capability are not synonymous as a result of a single latent trait, but rather they are a set of capabilities that work together as a resource. This is an early interpretation that alters the proper validation criteria. Theoretically justified content coverage and alternative weighting and comparison with a direct criterion are relevant; internal-consistency statistics are not sufficient. The study cannot be a claim of formative redundancy or independent external validation due to the lack of a direct global CI criterion in the public panel.

Psychological adaptability is theoretically relevant because intelligence can influence strategic behavior only when decision makers reconsider assumptions and respond to changing evidence. The public panel contains no validated individual-level adaptability scale. The empirical analysis therefore uses low managerial myopia as a single-indicator organizational proxy for a longer cognitive and decision horizon. Green innovation is not treated as a psychological measure; it is retained as a separate behavioral sensitivity indicator. This design narrows the empirical claim to an observable cognitive-horizon proxy and does not identify employees' emotional states or behavioral flexibility.

The study addresses four research questions. RQ1 asks how CIEI changed across Chinese manufacturing firms from 2014 to 2023. RQ2 asks whether CIEI is associated with the adaptability proxy and performance in pooled and within-firm models. RQ3 asks whether prior-year CIEI and adaptability are associated with subsequent outcomes after firm and year effects are absorbed. RQ4 asks whether the findings survive alternative index construction and dynamic-panel assumptions, and what recent 2024–2025 public indicators contribute to contextual interpretation.

The contribution is threefold. Theoretically, the study reconnects digital analytics to the CI cycle, empirical CI typologies, maturity, governance, and decision use (Madureira et al., 2021a, 2021b, 2023; Maluleka & Chummun, 2023; Wright et al., 2002, 2009). Methodologically, it defines a temporally lagged two-way fixed-effects model as the primary test and treats pooled models, contemporaneous fixed effects, component sensitivity, cluster-bootstrap indirect effects, and GMM as distinct forms of evidence. Empirically, it documents diffusion of analytical infrastructure in both the full and balanced cohorts while showing that performance estimates depend on timing, component composition, and instrument classification. The conclusion is bounded: infrastructure expansion and a cognitive-horizon proxy are observable; a complete CI system and direct psychological adaptability are not independently validated by these public data.

2 THEORETICAL FRAMEWORK

2.1 Competitive Intelligence, Governance, And Maturity

Competitive intelligence is an anticipatory organizational practice that transforms information about the external and competitive environment into actionable knowledge. It has at its heart elements of purposeful direction, lawful and ethical data collection, analysis and interpretation, dissemination, utilization, and feedback (Fuld, 1995; Pellissier & Nenzhelele, 2013; Prescott & Miller, 2001). Empirical typologies reveal that CI practice is characterised by attitude, collecting, using and locating intelligence, while implementation research highlights that the intelligence needs to be linked to a strategy, and not be left as a separate information activity (Maluleka & Chummun, 2023; Wright et al., 2002, 2009). These models clarify that digital investment alone does not constitute CI maturity.

Governance coordinates the intelligence cycle. It includes who sets the intelligence requirements, how the quality and ethics of intelligence are managed, which intelligence products are delivered to decision makers, how disagreement is resolved, and whether intelligence products have feedback into them for further monitoring. If governance is lacking, the output of analysis can be contained in technical units or too late to impact strategy. Governance is a recurring organizational practice that is connected to an accountable decision forum (Calof & Wright, 2008; Cavallo et al., 2021; Dishman & Calof, 2008).

Maturity models further the process view by evaluating development in terms of people, practices, process, products, technology, management, and decision use. Madureira et al. (2023) combine the fourteen models in a multidimensional model and earlier work offers a unified definition of the concept of CI and construct validation (Madureira et al., 2021a, 2021b). These studies set the standard that the current archival index does not comply with, namely a validated measure of CI maturity should not look at analytical infrastructure. As such, the sample-relative quartiles below are descriptive, rather than maturity-level quartiles.

Viviers et al. (2002) provide an empirically operationalized process model that distinguishes planning and focus, collection, analysis, communication, process and structure, and organizational awareness and culture. This framework is especially relevant to the present study because it demonstrates that Competitive Intelligence cannot be reduced to data infrastructure or analytical technology. Planning determines the intelligence questions to be investigated; collection establishes the quality and diversity of information inputs; analysis transforms information into actionable interpretations; communication transfers intelligence to authorized decision-makers; process and structure establish coordination and responsibility; and organizational awareness supports intelligence sharing and managerial use. The present study therefore treats CIEI as a technological and analytical antecedent and develops a separate direct CI-process instrument based on these process dimensions, supplemented by explicit measures of utilization, feedback, governance, and ethics (Appendix A), for the supplementary managerial validation specified in the future-research agenda.

2.2 CIEI as a Formative Enabling Resource

CIEI is conceptualized as a formative bundle of digital and analytical resources. Big-data capability (BD) represents capacity to handle large and complex information; digital-intelligence investment (DI) represents commitment to digital systems; and analytical capability (AC) represents the capacity to extract interpretable patterns. Together these indicators relate most directly to collection and analysis. They do not directly observe planning priorities, dissemination, feedback, ethics, or whether intelligence changes a decision.

The resource-based view of the firm provides a rationale for the importance of infrastructure as elements are paired with complementary routines, dynamic-capabilities reasoning offers a temporal logic; firms perceive change, exploit opportunity, and realign resources. Governance, learning and coordinated action is needed for seizing and transformation, as analytical infrastructure can support sensing (AlNuaimi et al., 2022; Chen et al., 2024). The research based on analytics further reveals that data capability has a positive relationship with performance, not only in terms of technology, but also in terms of innovation, resource integration as well as resilience (Hossain et al., 2022; Huang et al., 2022; Lin et al., 2025; Su et al., 2021). To address the organizational question, whether infrastructure is oriented towards specific intelligence needs and applied to decisions, CI theory provides the necessary input.

2.3 Psychological Adaptability and Its Archival Boundary

Psychological adaptability is a state of adjustment in a novel and uncertain situation involving cognitive, emotional and behavioral responses. Adaptive-performance and psychological-capital research suggests that actors who are flexible are more likely to alter their mental models, learn from disruption, and change their behaviour (Carter & Youssef-Morgan, 2022; Katsaros, 2024; Kim & Yoon, 2025; Loghman et al., 2023; Ma et al., 2024; Tang et al., 2024). The dimensions are typically captured in the form of direct individual-level responses, and generally cannot be reconstructed from financial information alone.

The panel's managerial-myopia indicator captures only a narrow cognitive-horizon component of the broader adaptability construct. Low myopia (LM) is a longer period of managerial decision making and is the main adaptability proxy (PA). This proxy does not capture emotional regulation, uncertainty tolerance, or behavioral flexibility. The variable on green-innovation is analysed separately as an observable renewal behaviour, instead of being renamed as psychological adaptability. Two indicators for low myopia plus GI are kept as a composite to determine if it is necessary to combine cognition and behavior indicators to make a conclusion. The growth of the firm is not included in any of the adaptability measures as it is an organizational outcome and would contaminate mediation.

Adaptation can include short-run costs since changes to routine, re-allocation of resources, and innovation can lead to a fall in efficiency in the short term. Thus, between-firm associations could be pooled in this way without having to be the same size as the contemporaneous or lagged relationship. The hypotheses are about temporally-ordered associations, not about causation.

2.4 Organizational Performance and Hypotheses

Organizational performance is represented by market valuation, profitability, and operating efficiency. Tobin's Q captures market expectations, gross profitability captures the productive return on resources, and asset turnover captures operating utilization. Standardizing and averaging these indicators reduce dependence on one accounting or market measure.

The framework generates four testable expectations. H1: prior-year CIEI is positively associated with the subsequent low-myopia adaptability proxy. H2: prior-year low myopia is positively associated with subsequent organizational performance. H3: prior-year CIEI is positively associated with subsequent organizational performance. H4: low myopia carries an indirect association between prior CIEI and later organizational performance. H4 is evaluated as an exploratory three-wave pathway because no direct psychological scale is available.

Figure 1 distinguishes the measured infrastructure, cognitive-horizon proxy, and performance variables from the unobserved CI-process boundary. Governance, dissemination, utilization, feedback, and ethics are theoretically necessary mechanisms, not empirically demonstrated outcomes.

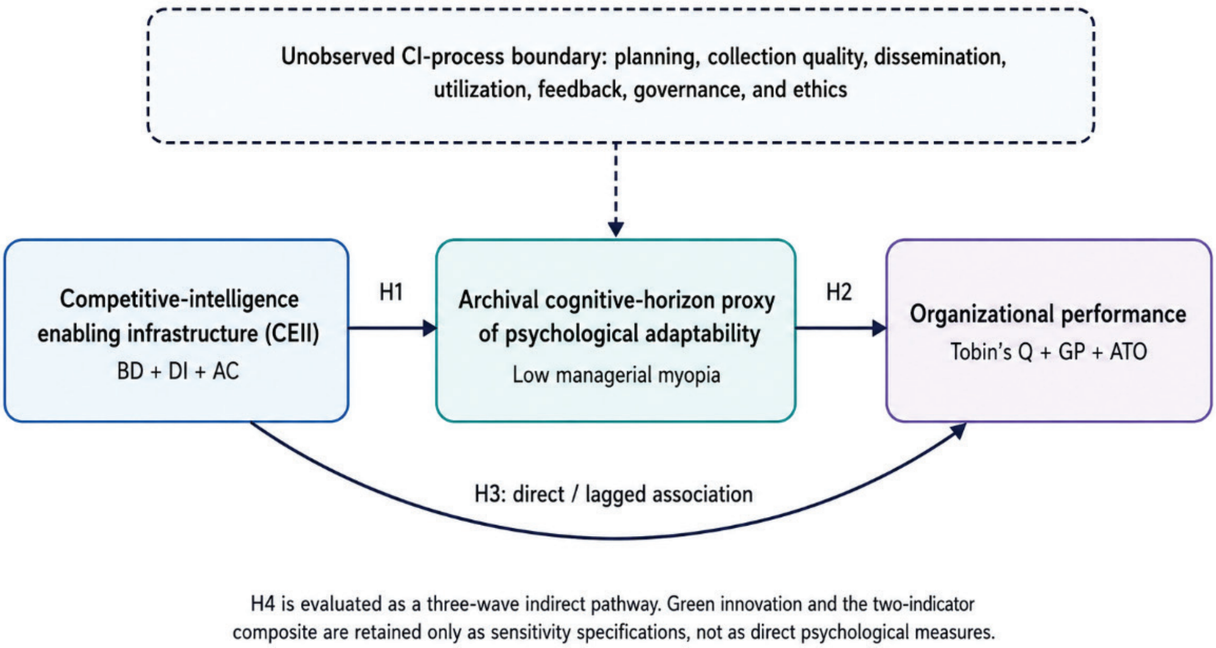

Figure 1. Conceptual framework, cognitive-horizon adaptability proxy, and unobserved intelligence-cycle boundary.

3 METHODOLOGY

3.1 Research Design and Data Sources

The inferential layer is the publicly distributed China's Manufacturing Firms panel (Oliveira Gibin, n.d.), downloaded on June 18, 2026. After numeric conversion, duplicate checks, complete-case screening, and winsorization, it contains 19,035 firm-year observations from 3,169 listed Chinese manufacturers during 2014–2023. The panel is unbalanced; 1,044 firms are observed at both endpoints and 772 are observed in all ten years. Firm-year is the unit of analysis.

The repository provides coded firm-year variables but does not identify a complete upstream institutional provider or a full construction manual for every indicator. Table 2 therefore preserves the repository labels, reports the transformations applied in this study, and avoids unsupported claims about unverified source units. The calculations are reproducible from the public file, but measurement provenance is less complete than it would be in a first-party accounting database. This limitation is treated as a boundary of inference rather than resolved through assumed metadata.

The contextual layer is the China 2024 World Bank Enterprise Survey (WBES), reference ID CHN_2024_WBES_v01_M. Fieldwork occurred from January 2024 to February 2025 and covered 2,189 establishments. The survey uses stratified random sampling, had a 20.2% overall response rate, and requires sampling weights for population inference (World Bank Group, 2025). The downloaded aggregate custom-query file contains published indicators rather than establishment-level records; it is used only for contemporary context and is never merged with the listed-firm panel.

The historical panel ends in 2023 because the public repository does not provide a consistently defined 2024–2025 extension for all focal and control variables. Combining partial indicators from different sources would change the unit of analysis and measurement system. The WBES evidence therefore reduces the contextual lag but does not create a same-firm longitudinal extension.

Table 1 distinguishes the inferential and contextual data layers before they appear.

Table 1. Data sources, units of analysis, and permissible analytical roles.

Source	Coverage and unit	Sample	Role and boundary
China's Manufacturing Firms panel	Listed manufacturing firm-year; China; 2014–2023	19,035 observations; 3,169 firms	Inferential models; public repository lacks complete upstream construction metadata
China 2024 WBES (CHN_2024_WBES_v01_M)	Stratified establishment survey; Jan. 2024–Feb. 2025	2,189 establishments; 20.2% response rate	Weighted contextual indicators only; no merge or external validation

3.2 Variable Operationalization and Data Dictionary

CIEI and OP use separately standardized components. CIEI is the standardized mean of z(BD), z(DI), and z(AC); OP is the standardized mean of z(Tobin's Q), z(GP), and z(ATO). The primary adaptability proxy PA is z(−Myopia), so higher values indicate a longer managerial decision horizon. GI and the standardized mean of z(−Myopia) and z(GI) are sensitivity specifications only. Controls are SIZE, LEV, AGE, and TOP10.

Formally, $\mathrm{CIEI} = z\{[z(\mathrm{BD}) + z(\mathrm{DI}) + z(\mathrm{AC})]/3\}$, $\mathrm{PA} = z(-\mathrm{Myopia})$, and $\mathrm{OP} = z\{[z(\mathrm{TobinQ}) + z(\mathrm{GP}) + z(\mathrm{ATO})]/3\}$. This construction prevents scale differences from mechanically dominating the composites. Equal weighting is transparent but not assumed to be uniquely correct; principal-component and component-specific models assess sensitivity.

Table 2 reports raw labels, observed transformations, empirical roles, and measurement boundaries. "Repository-coded measure" is retained where the public source does not support a more precise unit definition.

Table 2. Variable definitions, observed scales, analytical direction, and measurement boundaries.

Variable	Observed construction	Direction	Role	Boundary
BD	Repository-coded continuous capability measure	Higher = more big-data capability	CIEI component	Does not identify monitored sources or collection quality
DI	Repository-coded continuous investment measure	Higher = more digital-intelligence investment	CIEI component	Investment does not demonstrate utilization or governance
AC	Repository-coded continuous analytical-capability measure	Higher = more analytical capability	CIEI component	Does not observe dissemination or decision influence
Myopia / PA	Repository-coded managerial myopia; PA = z(−Myopia)	Higher PA = longer managerial horizon	Primary adaptability proxy	Single cognitive-horizon indicator; not direct emotion or behavior
GI	Repository-coded green-innovation measure	Higher = more green innovation	Behavioral sensitivity only	Not relabeled as psychological adaptability
GROW	Repository-coded firm-growth measure	Higher = more realized growth	Outcome sensitivity only	Excluded from all adaptability measures
TobinQ; GP; ATO	Market valuation; gross profitability; asset turnover	Higher = stronger dimension	OP components	Do not measure decision quality directly
SIZE; LEV; AGE; TOP10	Repository-coded controls; TOP10 is a percentage	Original analytical scales	Controls	Time-varying leadership and shocks remain unobserved

Table 2A. Direct CI-process operationalization based on Viviers et al. (2002).

CI domain	Archival CIEI coverage	Direct managerial measurement (Appendix A)	Role in the model
Planning and focus	Not measured	CIP1–CIP3	Defines strategic intelligence requirements
Collection quality	Only technical capacity	CIC1–CIC3	Assesses source diversity, verification, and reliability
Analysis	Partially represented by AC	CIA1–CIA3	Measures actual conversion of information into intelligence
Dissemination	Not measured	CID1–CID3	Measures timely and recipient-specific communication
Utilization	Not measured	CIU1–CIU3	Measures use of intelligence in decisions
Governance	Not measured	CIG1–CIG3	Measures responsibility, oversight, and procedures
Feedback	Not measured	CIF1–CIF3	Measures post-decision evaluation and learning
Ethics	Not measured	CIE1–CIE3	Measures lawful and ethical CI conduct
Overall direct CI capability	Not measured	GCI1–GCI3	External criterion for the multidimensional CI process

3.3 Data Preparation and Measurement Assessment

European decimal commas were converted to numeric values. Firm-year identifiers were examined for duplication, and the variables required for the reported models contained no missing observations after numeric conversion. Continuous variables were winsorized at the first and ninety-ninth percentiles. No observations were imputed. The preprocessing procedure was applied before composite construction and was held constant across the primary and sensitivity models.

CIEI is specified as a formative enabling index because big-data capability, digital-intelligence investment, and analytical capability jointly define the resource bundle rather than function as interchangeable effects of a single latent construct. Removing one component can therefore alter the substantive domain represented by the index. Cronbach's alpha, exploratory factor analysis, and confirmatory factor analysis are not treated as decisive validation procedures for this specification because they assume a reflective measurement logic that is not maintained here.

The formative assessment follows four stages. First, content correspondence is established by mapping each archival component to the collection-and-analysis infrastructure of the intelligence cycle while explicitly excluding planning, dissemination, utilization, feedback, ethics, and governance. Second, indicator collinearity is assessed using variance-inflation factors calculated from the three standardized CIEI components. Third, composition dependence is examined through component-specific models and an alternative principal-component weighting. Fourth, criterion sensitivity is evaluated through temporally ordered associations with subsequent organizational-performance outcomes. These procedures assess whether the archival index is computationally stable and theoretically bounded; they do not establish that it measures a complete competitive-intelligence system.

To make this measurement boundary fully explicit, the empirical construct contains only big-data capability, digital-intelligence investment, and analytical capability; it does not empirically measure intelligence planning, collection quality, dissemination, managerial utilization, feedback, governance, or ethics. Direct operationalization of Competitive Intelligence would require a supplementary managerial CI instrument capturing at least seven process domains: (i) planning, including whether formal intelligence priorities and requirements are established; (ii) collection quality, including the reliability, diversity, timeliness, and verification of sources; (iii) dissemination, including whether intelligence reaches appropriate decision-makers in a useful form; (iv) utilization, including whether managers use intelligence in strategic decisions; (v) feedback, including whether the usefulness and accuracy of intelligence are evaluated; (vi) governance, including responsibility, decision rights, oversight, and accountability; and (vii) ethics, including lawful collection, confidentiality, and privacy controls. The strongest empirical design would then estimate a mediated model in which CIEI operates through direct CI-process capability to influence organizational performance (CIEI → direct CI-process capability → organizational performance). Because such primary managerial data are not available for the sampled firm-years, CIEI is interpreted strictly as an enabling-infrastructure antecedent aligned with the analytics, digital-transformation, and business-intelligence literatures, and all empirical claims are bounded accordingly.

The primary adaptability variable is a single archival cognitive-horizon indicator, PA = z(−Myopia). Internal-consistency reliability is therefore not applicable. PA does not directly measure emotional regulation, behavioral flexibility, uncertainty tolerance, or individual adaptive performance. Green innovation is retained only as an organizational-behavior sensitivity variable and is not relabeled as psychological adaptability. Organizational performance is a standardized multidimensional summary of Tobin's Q, gross profitability, and asset turnover. The reported coefficient therefore represents an association with the joint standardized performance index and should not be interpreted as demonstrating an identical relationship with each individual performance dimension.

No direct global CI item, validated CI maturity instrument, managerial assessment, expert panel, or organization-level benchmark is available for the sampled firm-years. Consequently, convergent redundancy validation and independent external validation cannot be performed with the current secondary data. The comparison with previously validated CI frameworks and Delphi evidence is used exclusively to evaluate theoretical content correspondence and must not be interpreted as external validation of the present CIEI index.

Because independent external validation cannot be performed with the current secondary data, the absence of external validation is acknowledged as a substantive limitation of this study rather than a resolved methodological step. The structured expert content-validation protocol and the managerial criterion-validation design required to address this limitation are specified in the future-research directions presented in the Conclusion, and the adapted direct CI-process instrument developed for this purpose is presented in Appendix A.

To partially mitigate this limitation within the present study, an independent organizational benchmark was incorporated. Published survey evidence from 302 small and medium-sized enterprises containing six directly measured Competitive Intelligence indicators was used to assess whether a directly measured CI construct exhibits acceptable measurement properties and the expected association with an organizational outcome. This benchmark is used strictly for nomological triangulation of directly enacted CI practice; it is not treated as matched criterion validation of the Chinese CIEI scores because the samples, countries, organizations, and measurement systems differ. The manuscript accordingly distinguishes three forms of evidence: (i) formative assessment of the Chinese enabling-infrastructure index, (ii) independent direct-CI nomological triangulation, and (iii) the still-required matched Chinese managerial criterion validation. The corresponding benchmark results are reported in Section 4.1.1.

CIEI scores are divided using fixed pooled-sample quartile thresholds only for longitudinal description. Q1–Q4 represent positions within the observed sample distribution and are not stages of CI maturity. Movement between quartiles indicates relative diffusion of the measured infrastructure bundle; it does not demonstrate improvement in dissemination, utilization, governance, or decision quality. Accordingly, the study does not use CIEI quartiles as CI-maturity levels; they indicate only relative positions in the observed distribution of digital and analytical infrastructure. A firm in the highest CIEI quartile cannot be assumed to possess formal intelligence priorities, verified collection routines, effective dissemination, accountable decision use, feedback procedures, or ethical governance.

3.3.1 Indicator Collinearity

Indicator collinearity was evaluated by regressing each standardized CIEI component on the remaining two components and calculating the corresponding variance-inflation factor. VIF values below 3.3 were interpreted as indicating that no component was made redundant by excessive linear overlap; values between 3.3 and 5.0 were treated as requiring caution, and values above 5.0 as evidence of problematic collinearity. The assessment concerns redundancy among the formative indicators and is not presented as reflective-scale reliability. The corresponding collinearity diagnostics are reported in Table 3A. Tolerance was calculated as the reciprocal of VIF.

3.4 Estimator Hierarchy, Equations, And Endogeneity

The estimator hierarchy is defined in advance of result interpretation. The primary tests of H1–H3 use one-year-lagged predictors with firm and year fixed effects because this model absorbs time-invariant firm heterogeneity and places the predictor before the outcome. Contemporaneous two-way fixed effects are the principal within-firm robustness models. Pooled year-effects models describe combined between- and within-firm association and are not used for final hypothesis decisions. Standard errors are clustered by firm in all linear models.

$$OP_{it} = \beta_1 CIEI_{i,t-1} + \beta_2 PA_{i,t-1} + \gamma X_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

$$PA_{it} = \alpha_1 CIEI_{i,t-1} + \delta X_{i,t-1} + \mu_i + \lambda_t + \upsilon_{it} \quad (2)$$

Principal-component analysis was used as a composition-sensitivity diagnostic for the three standardized CIEI indicators. The proportion of variance represented by the first component and its component coefficients were examined alongside component-specific fixed-effects estimates. This procedure evaluates whether the equal-weight index conceals heterogeneous component behavior; it is not treated as a reflective-factor validity test or as an independently validated CI measure.

Dynamic-panel GMM is an endogeneity sensitivity analysis, not the primary estimator. All specifications include lagged OP and collapsed instruments. The analysis contrasts CIEI and PA treated as predetermined (lag 1 instruments) with the more conservative classification of both as endogenous (lag 2 instruments), reports one- and two-step system estimates, difference GMM, and a specification that treats SIZE and LEV as predetermined. AGE and TOP10 remain standard instruments under the maintained exogeneity assumption. Hansen and AR(2) non-rejection are necessary diagnostics, not proof of exogeneity; instrument counts remain well below the number of firms (Arellano & Bond, 1991; Blundell & Bond, 1998; Roodman, 2009; Windmeijer, 2005).

All data preparation and linear models were implemented in Python. Dynamic models were estimated with pydynpd (Wu et al., 2023). Analysis scripts, derived outputs, bootstrap distributions, GMM diagnostics, and figures accompany the manuscript.

3.5 Ethical and Reproducibility Considerations

The study relies on public secondary firm/establishment data that is anonymized for human participants and does not involve direct contact with them. No ethics approval number is reported because the analysis uses publicly available secondary organizational data and involved no direct participant contact. The analytical panel, scripts, model outputs and files for figure generation are also retained in order that the reported calculations can be replicated from the distributed datasets, dependent on the limitations of the metadata as stated above.

4 RESULTS AND DISCUSSION

4.1 Descriptive Statistics and Construct Checks

Table 3 reports the focal variables, components, and controls. CIEI, PA, and OP are standardized. PA now corresponds only to low managerial myopia and is not mechanically influenced by GI or firm growth. Its raw correlations with CIEI and OP are 0.160 and 0.040, respectively; these descriptive relationships do not control for stable firm differences.

Table 3. Descriptive statistics for the analytical panel after winsorization.

Variable	N	Mean	SD	Minimum	Median	Maximum
CIEI	19,035	0.000	1.000	-2.089	-0.166	5.870
PA	19,035	-0.000	1.000	-3.700	0.224	1.191
OP	19,035	0.000	1.000	-2.310	-0.119	4.929
BD	19,035	4.244	0.437	3.135	4.263	5.468
DI	19,035	0.007	0.015	0.000	0.002	0.109
AC	19,035	0.053	0.046	0.000	0.042	0.285
Myopia	19,035	0.062	0.052	0.000	0.050	0.255
GI	19,035	0.340	0.109	0.200	0.307	0.784
GROW	19,035	0.203	0.485	-0.616	0.098	2.803
TobinQ	19,035	2.101	1.252	0.861	1.704	8.038
GP	19,035	1.870	1.334	0.000	1.792	5.877
ATO	19,035	0.612	0.325	0.121	0.549	2.019
SIZE	19,035	22.218	1.155	20.194	22.055	25.804
LEV	19,035	0.392	0.185	0.061	0.385	0.851
AGE	19,035	2.081	0.815	0.000	2.197	3.367
TOP10	19,035	57.985	14.534	24.333	58.380	88.787

Note. PA is the standardized inverse of the repository-coded managerial-myopia indicator. GI and GROW are reported separately and are not included in the primary adaptability proxy.

Indicator-collinearity diagnostics are presented in Table 3A. VIF values ranged from 1.01 to 1.12 and were therefore well below the pre-specified threshold of 3.3. The corresponding tolerance values ranged from 0.896 to 0.987. These results indicate that the three formative indicators provide overlapping but non-redundant information and that no component is affected by problematic linear collinearity.

Table 3A. Formative-indicator collinearity diagnostics for CIEI

Indicator	Tolerance	VIF	Assessment
Big-data capability (BD)	0.896	1.12	No problematic collinearity
Digital-intelligence investment (DI)	0.987	1.01	No problematic collinearity
Analytical capability (AC)	0.906	1.10	No problematic collinearity
Maximum VIF	—	1.12	Below the 3.3 threshold

Note. Tolerance = 1/VIF. Diagnostics concern collinearity among the three formative CIEI indicators and do not constitute reflective-scale reliability, convergent validity, or independent external validation.

4.1.1 Independent Direct-CI Nomological Benchmark

Independent organizational evidence was used to assess whether a directly measured Competitive Intelligence construct exhibits acceptable measurement properties and the expected association with an organizational outcome. In a survey of 302 SMEs, six direct-CI indicators produced standardized loadings of .757–.808, Cronbach's alpha of .900, composite reliability of .901, and average variance extracted of .604 (square root of AVE = .777). HTMT ratios with absorptive capacity, frugal innovation, and value creation ranged from .605 to .643, supporting discriminant validity. Direct CI was positively associated with value creation (β = .300, SE = .089, 95% CI [.131, .478]) and frugal innovation (β = .183, SE = .083, 95% CI [.038, .358]), and exhibited a significant indirect effect on value creation through frugal innovation (indirect effect = .064, 95% CI [.011, .137]). The structural model explained 54.2% of the variance in value creation (R^2 = .542) and 36.3% of the variance in frugal innovation (R^2 = .363).

These findings provide independent nomological triangulation for directly enacted CI practice: directly measured CI can be empirically distinguished from adjacent organizational capabilities and predicts an organizational outcome. They do not constitute matched criterion validation of the Chinese CIEI scores because the samples, countries, organizations, and measurement systems differ. The study therefore reports three forms of evidence—formative assessment of the Chinese infrastructure index, independent direct-CI nomological triangulation, and the still-required matched Chinese managerial criterion validation—and this boundary is maintained in the Methodology, Results, Discussion, Conclusion, and Data Availability Statement.

4.2 Diffusion of CIEI Quartiles

Figure 2 applies fixed pooled-sample thresholds. Across all available observations, Q1 declined from 60.5% in 2014 to 6.0% in 2023, while Q4 increased from 9.8% to 38.6%. Table 4 shows that this shift is not explained solely by entry and exit: among the 772 firms observed in every year, 76.3% moved upward, only 2.1% moved downward, mean CIEI rose from −0.565 to 0.483, and Q4 increased from 11.8% to 39.5%. The result documents diffusion within the observed listed-firm cohorts, not maturity of the full CI cycle.

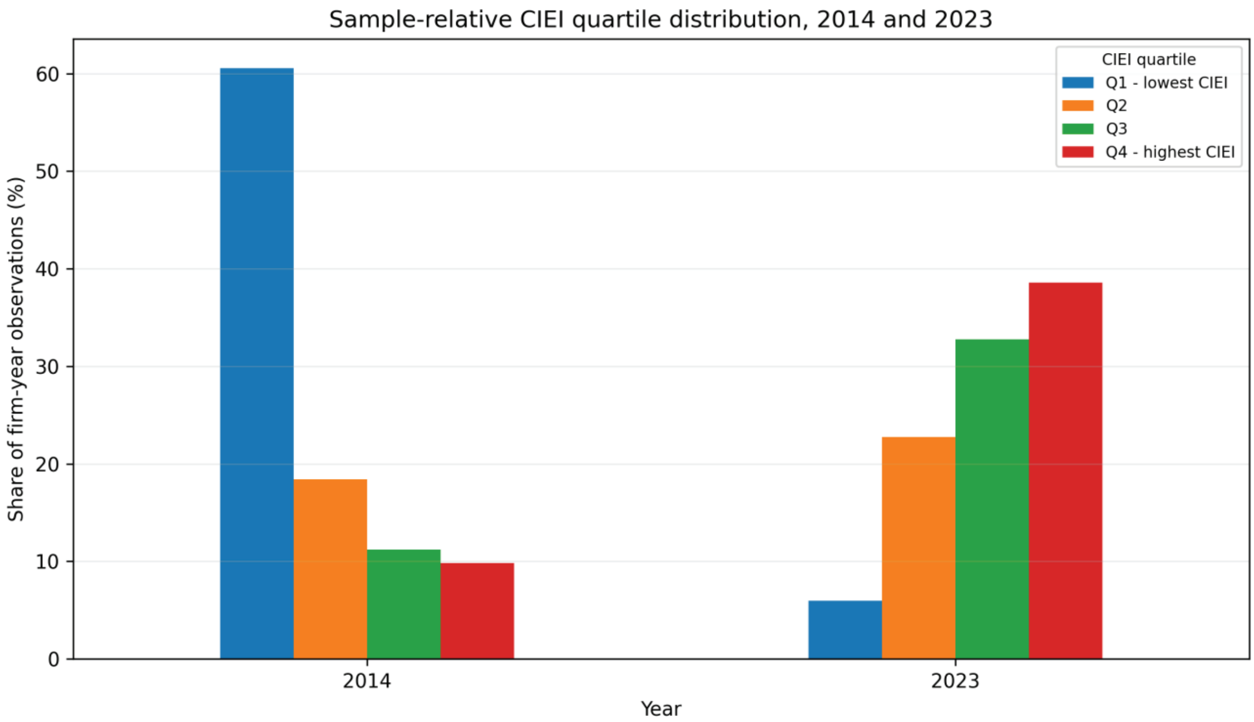

Figure 2. Sample-relative CIEI quartile distribution in 2014 and 2023.

Table 4. CIEI diffusion sensitivity in firms observed at both endpoints and in all ten years.

Cohort	Firms	Upward	Same	Downward	Mean CIEI 2014	Mean CIEI 2023
Endpoint cohort	1,044	76.3%	21.5%	2.2%	-0.619	0.411
Ten-year balanced cohort	772	76.3%	21.6%	2.1%	-0.565	0.483

4.3 Organizational Performance Models

Table 5 separates between-firm association, contemporaneous within-firm change, and the primary lagged model. In the pooled model, CIEI (b = 0.237, p < .001) and PA (b = 0.048, p < .001) are positively associated with OP. After firm and year effects are absorbed, contemporaneous CIEI is null (b = −0.015, p = .523), while PA remains small and positive (b = 0.025, p = .001).

The primary lagged model provides temporally ordered but non-causal evidence. Prior CIEI is positively associated with subsequent OP (b = 0.054, SE = 0.023, p = .019), and prior low myopia has a smaller positive association (b = 0.016, SE = 0.008, p = .048). Within-R^2 is .017, indicating limited explanatory power for annual within-firm change. Figure 3 displays the focal coefficients and confidence intervals from this primary model. Because the dependent variable combines market valuation, profitability, and operating efficiency, the primary coefficient pertains to their joint standardized index. It does not demonstrate that CIEI has an identical association with Tobin's Q, gross profitability, and asset turnover separately.

Table 5. Organizational-performance models under pooled, contemporaneous fixed-effects, and primary lagged specifications.

Predictor	Pooled OP	Contemporaneous FE OP	Primary lagged OP
CIEI	0.237*** (0.019)	-0.015 (0.024)	0.054* (0.023)
PA	0.048*** (0.011)	0.025** (0.008)	0.016* (0.008)
Firm size	0.121*** (0.019)	-0.188*** (0.033)	-0.152*** (0.032)
Leverage	0.087 (0.093)	-0.047 (0.107)	0.306** (0.106)
Firm age	0.188*** (0.023)	0.292*** (0.039)	0.162*** (0.042)
Ownership concentration	0.006*** (0.001)	0.003* (0.001)	0.004** (0.002)
R^2 / within-R^2	0.148	0.021	0.017
Observations	19,035	19,035	15,866

Note. Firm-clustered standard errors are in parentheses. Pooled models include year effects; FE models include firm and year effects. CIEI, PA, and OP are standardized; controls retain their analytical scales. *** p < .001; ** p < .01; * p < .05; † p < .10.

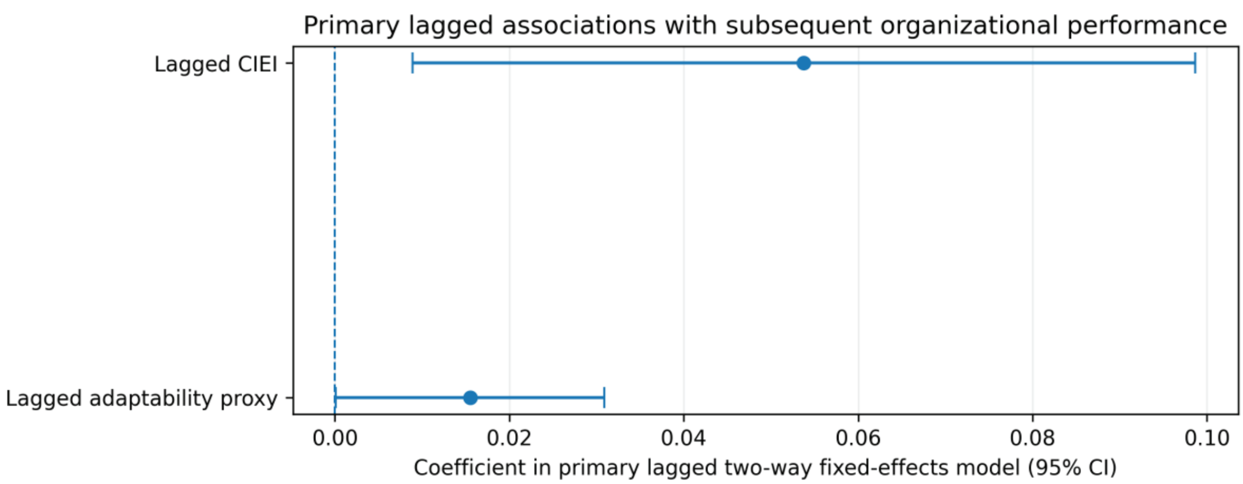

Figure 3. Focal coefficients in the primary lagged two-way fixed-effects performance model.

4.4 Adaptability Models, Component Sensitivity, And Indirect Effects

Table 6 reports the adaptability models and sensitivity analyses. CIEI is positively associated with PA in the pooled model (b = 0.116, p < .001), but the contemporaneous FE coefficient is only marginal (b = 0.041, p = .089) and the primary lagged coefficient is not statistically supported (b = 0.044, p = .108); H1 is therefore not supported. H2 receives narrow associational support because prior low myopia is positively associated with subsequent OP (b = 0.016, p = .048). GI is not significantly associated with subsequent OP, and the earlier two-indicator composite is only marginal.

Table 6. Adaptability models, component sensitivity, and firm-cluster bootstrap indirect effects.

Analysis	Estimate (SE)	p	95% CI / bootstrap CI	Interpretation
Pooled CIEI → PA	0.116 (0.015)	< .001	[0.086, 0.146]	Between-firm descriptive association
Contemporaneous FE CIEI → PA	0.041 (0.024)	= .089	[-0.006, 0.088]	Marginal within-firm association
Primary lagged CIEI → PA	0.044 (0.027)	= .108	[-0.010, 0.097]	H1 not supported
Primary lagged PA → OP	0.016 (0.008)	= .048	[0.000, 0.031]	Small positive association; H2 supported
Low myopia indirect effect	0.00047	= .242	[-0.00023, 0.00166]	Firm-cluster bootstrap; interval includes zero
GI sensitivity indirect effect	0.00004	= .944	[-0.00067, 0.00091]	Firm-cluster bootstrap; interval includes zero
Two-indicator composite indirect effect	0.00035	= .332	[-0.00029, 0.00154]	Firm-cluster bootstrap; interval includes zero
Lagged GI → OP	-0.013 (0.029)	= .661	[-0.070, 0.045]	Sensitivity only
Lagged two-indicator composite → OP	0.017 (0.010)	= .090	[-0.003, 0.037]	Sensitivity only

4.5 CIEI Component and Composition Sensitivity

The CIEI bundle is empirically heterogeneous. The first principal component accounted for 44.7% of the variance in the three standardized indicators, with component coefficients of 0.691 for BD, 0.303 for DI, and 0.656 for AC. The first component therefore captured only moderate common variation and did not establish unidimensionality. Component-specific fixed-effects estimates also differed materially: DI was positively associated with organizational performance in contemporaneous and lagged models, AC was negatively associated in both specifications, and BD was statistically unsupported. Together with the low VIF values, these results indicate that the components are not statistically redundant but also do not behave as interchangeable indicators of a homogeneous capability. CIEI should consequently be interpreted as an exploratory formative resource bundle.

Table 7. Principal-component composition, collinearity, and component-level performance sensitivity.

Indicator	PC1 coefficient	VIF	Contemporaneous FE OP	Lagged FE OP	Interpretation
Big-data capability (BD)	0.691	1.12	0.012 (0.017)	0.015 (0.017)	Statistically unsupported in both specifications
Digital-intelligence investment (DI)	0.303	1.01	0.189*** (0.024)	0.145*** (0.024)	Positive in both specifications
Analytical capability (AC)	0.656	1.10	−0.184*** (0.021)	−0.056* (0.022)	Negative in both specifications
PC1 variance explained	44.7%	—	—	—	Moderate common variance; no evidence of unidimensionality

Note. Firm-clustered standard errors are reported in parentheses. Contemporaneous and lagged models include firm and year fixed effects and the controls reported in Table 5. PC1 coefficients describe index composition and are not reflective factor loadings or evidence of complete CI validity. *** p < .001; ** p < .01; * p < .05.

4.6 Dynamic-Panel Endogeneity Sensitivity

Table 8 shows that GMM conclusions depend on instrument classification. When CIEI and PA are treated as predetermined, CIEI is positive ($b = 0.232$, $p < .001$) and PA is negative ($b = -0.078$, $p < .001$). When both are treated as endogenous, two-step and one-step system GMM produce positive CIEI coefficients of approximately 0.147, while PA is null. Difference GMM and the specification treating SIZE and LEV as predetermined also produce positive CIEI coefficients. Hansen tests are not rejected and AR(2) tests are non-significant, but these diagnostics do not validate the exclusion assumptions. GMM is therefore reported as sensitivity evidence consistent with a positive CIEI association, not as causal identification.

Table 8. Dynamic-panel GMM sensitivity across alternative instrument classifications.

Diagnostic / term	System pred. 2-step	System endog. 2-step	System endog. 1-step	Difference endog. 2-step	SIZE/LEV pred. 2-step
Lagged OP	0.584*** (0.019)	0.597*** (0.020)	0.595*** (0.020)	0.600*** (0.022)	0.585*** (0.020)
CIEI	0.232*** (0.028)	0.147*** (0.033)	0.147*** (0.033)	0.116** (0.041)	0.104** (0.038)
PA	-0.078*** (0.020)	0.066 (0.079)	0.068 (0.078)	0.028 (0.065)	0.041 (0.084)
Hansen p	0.756	0.824	0.824	0.059	0.772
AR(2) p	0.616	0.488	0.494	0.512	0.637
Instruments	19	19	19	18	21
Firms / observations	3,169 / 12,351	3,169 / 12,351	3,169 / 12,351	3,169 / 12,351	3,169 / 12,351

Note. Models use collapsed instruments and time effects. Two-step models use finite-sample corrected robust standard errors. CIEI/PA “predetermined” uses lag 1 instruments; “endogenous” uses lag 2 instruments. Non-rejection of Hansen and AR(2) tests is not proof of instrument exogeneity.

Table 9 consolidates the hypothesis decisions using the pre-specified primary lagged fixed-effects models and the three-wave firm-cluster bootstrap. Pooled and contemporaneous estimates are not used for final hypothesis decisions.

Table 9. Summary of hypothesis evaluation

Hypothesis	Primary test	Estimate	p / 95% CI	Decision
H1: Prior CIEI is positively associated with subsequent PA	Lagged firm and year FE	b = 0.044, SE = 0.027	p = .108; 95% CI [−0.010, 0.097]	Not supported
H2: Prior PA is positively associated with subsequent OP	Lagged firm and year FE	b = 0.016, SE = 0.008	p = .048; 95% CI [0.000, 0.031]	Limited associational support
H3: Prior CIEI is positively associated with subsequent OP	Lagged firm and year FE	b = 0.054, SE = 0.023	p = .019	Supported as a temporal association
H4: PA carries an indirect association between prior CIEI and later OP	Three-wave firm-cluster bootstrap	Indirect effect = 0.00047	p = .242; 95% CI [−0.00023, 0.00166]	Not supported

Note. Decisions are based on the pre-specified primary models. Statistical support does not establish causal identification.

4.7 Discussion

4.7.1 Contemporary 2024–2025 Context

The China 2024 WBES contextual layer is kept separate from the panel. Official metadata identify 2,189 establishments, January 2024–February 2025 fieldwork, stratified sampling, a 20.2% response rate, and weighting requirements. The aggregate custom-query export downloaded on June 18, 2026 reports a management-practices index of 92.6 and a performance-monitoring score of 76.2 for medium and large firms, process innovation of 9.4%, real annual sales growth of 9.6%, and real labor-productivity growth of 2.9%. These weighted indicators describe the contemporary environment; they neither extend the listed-firm panel nor externally validate CIEI or PA.

4.7.2 Integrated Discussion

The principal empirical pattern is a separation between infrastructure diffusion and verified CI conversion. CIEI increased substantially in the full panel and in balanced cohorts, yet the contemporaneous within-firm coefficient is null. The positive lagged association suggests that analytical infrastructure may require time before appearing in valuation, profitability, or asset use. It does not demonstrate that planning, dissemination, utilization, feedback, governance, or information-asymmetry reduction occurred; those mechanisms remain unobserved.

The distinction between infrastructure and effective CI conversion is consistent with the process model tested by Viviers et al. (2002). Their framework separates intelligence planning, collection, analysis, communication, process and structure, and organizational awareness. Their results further indicate that favorable managerial attitudes toward CI can coexist with weak formal processes, inadequate analytical practices, limited coordination, and incomplete communication. The implication for the present findings is that expanding digital and analytical resources may be insufficient when intelligence requirements are not formally identified, sources are not systematically verified, outputs are not tailored to decision-makers, or intelligence results are not evaluated and incorporated into strategic action.

4.7.3 Intelligence Governance, Dissemination, and Utilization

The performance relevance of CIEI is likely to depend on intelligence governance. Digital and analytical systems can expand access to information, but governance determines who defines intelligence priorities, which sources are considered acceptable, who evaluates analytical quality, and which managers are accountable for responding to intelligence outputs. The null contemporaneous relationship and the heterogeneous component estimates are consistent with the possibility that infrastructure investment does not immediately create value when responsibilities, decision rights, and accountability mechanisms are underdeveloped. This interpretation remains theoretical because formal CI roles, governance procedures, and decision forums are not directly observed in the panel (Calof & Wright, 2008; Madureira et al., 2023).

Dissemination provides a second potential boundary between analytical capacity and organizational performance. Intelligence may possess technical quality but have little strategic effect when it is delivered too late, communicated in an unsuitable format, restricted to technical departments, or not directed to managers with relevant decision authority. The positive lagged CIEI coefficient may therefore be consistent with the time required to integrate analytical output into reporting and decision routines. Nevertheless, the dataset contains no evidence regarding dissemination frequency, recipients, communication channels, timeliness, or the perceived usefulness of intelligence products (Dishman & Calof, 2008; Wright et al., 2009).

Utilization must also be distinguished from the availability of information. Managers may ignore, delay, selectively interpret, or politically filter analytical findings, particularly where those findings conflict with established strategies or managerial interests. Psychological adaptability could theoretically facilitate intelligence utilization by increasing openness to changing evidence; however, the absence of a significant relationship between prior CIEI and subsequent low myopia provides no support for this pathway. The findings therefore suggest complementarity between infrastructure and managerial orientation rather than demonstrating that intelligence was actively incorporated into decisions (Cavallo et al., 2021; Wright et al., 2002).

4.7.4 Information-Asymmetry Reduction

A possible explanation for the positive lagged association is that digital integration and analytical capacity reduce information asymmetries within and outside the firm. Internally, shared systems may reduce information gaps among operational departments, analysts, and senior managers. Externally, stronger monitoring capabilities may reduce uncertainty concerning competitors, customers, suppliers, technology, and regulation. Improved information access could subsequently support more timely resource allocation and strategic adjustment. This mechanism cannot be considered empirically verified because the study contains no direct measure of information asymmetry, forecast accuracy, intelligence timeliness, managerial information access, or decision quality. It should therefore be presented as a theoretically plausible pathway for future testing rather than as an established explanation of the estimated coefficient (Madureira et al., 2021a; Maluleka & Chummun, 2023).

The independent direct-CI benchmark reinforces this interpretation. In the external survey of 302 SMEs (Section 4.1.1), directly measured CI practice—rather than infrastructure alone—was reliably measurable and positively associated with value creation, both directly and indirectly through frugal innovation. Read together with the heterogeneous Chinese component estimates, this pattern is consistent with the theoretical claim that the performance value of intelligence depends on enacted CI processes such as planning, dissemination, utilization, and governance, which the archival panel does not observe. The benchmark provides nomological support for the direct-CI construct but does not validate the Chinese CIEI scores; matched managerial criterion validation remains a requirement for future research.

Component results qualify the aggregate CIEI finding. DI is positive, AC is negative, and BD is null in fixed-effects models. These opposing coefficients may reflect different investment stages, reactive capability building, adjustment costs, or repository measurement differences. The moderate PC1 variance and uneven loadings reinforce the conclusion that CIEI is an exploratory formative resource bundle rather than a validated unidimensional maturity score.

The adaptability findings are narrower and more interpretable than in the earlier composite specification. Low managerial myopia is positively associated with subsequent performance, whereas GI is not. CIEI is not significantly associated with subsequent low myopia, and the 1,000-replication firm-cluster bootstrap interval for the three-wave indirect effect includes zero (indirect effect = 0.00047, 95% firm-cluster bootstrap CI [−0.00023, 0.00166]). H4 is therefore not supported. The data provide evidence about a managerial decision horizon, not a complete psychological adaptability mechanism.

Pooled and fixed-effects estimates answer different questions. Pooled models capture persistent between-firm advantages in leadership, talent, data quality, market position, and organizational routines that better-equipped firms retain over time, whereas fixed-effects models isolate within-firm change. The low within-R^2 values indicate that CIEI explains only a small share of annual within-firm performance variation, which is consistent with the fact that CIEI itself changes slowly from year to year. Most of the annual performance variation therefore remains unexplained by CIEI in within-firm models.

The central element of the CI scholarship is a disciplined measurement boundary. To reach the level of maturity of CI, there are inputs such as analytics and digital systems, together with five additional elements—people, governance, processes, intelligence products, and decision use. Sample-relative CIEI quartiles can be used to track infrastructure diffusion, but not rank CI maturity. This distinction is not a replacement of empirical typologies, implementation research, and expert-validated CI elements, but an addition to them (Madureira et al., 2021b, 2023; Maluleka & Chummun, 2023; Somiah et al., 2021; Wright et al., 2002, 2009).

For managers, the results caution against treating technology acquisition as a guaranteed business case. Infrastructure investment should be paired with explicit intelligence priorities, source-evaluation protocols, analyst–decision-maker interaction, dissemination responsibilities, scenario routines, evidence trails, and post-decision feedback. These recommendations are grounded in CI theory and the observed instability of infrastructure coefficients; they are not presented as mechanisms measured in this dataset.

For policy and data institutions, the findings support adding non-sensitive process items to public enterprise surveys: responsibility for environmental scanning, frequency of intelligence distribution, evidence use in strategic decisions, feedback after decisions, and ethical-governance procedures. Such measures would enable redundancy analysis and external validation of archival infrastructure indices without falsely equating technology with CI.

5 CONCLUSION

This study examined competitive-intelligence enabling infrastructure, a low-myopia cognitive-horizon proxy of psychological adaptability, and organizational performance in 3,169 listed Chinese manufacturing firms during 2014–2023. Official WBES aggregates were used only to document the 2024–2025 context. The most stable descriptive finding is broad diffusion of the measured infrastructure bundle, including within the 772-firm ten-year balanced cohort.

H3 receives associational support because prior CIEI is positively related to subsequent performance in the primary lagged fixed-effects model. H2 receives small, qualified support because prior low myopia is positively associated with subsequent performance. H1 is not supported, and H4 is not supported by the firm-cluster bootstrap. Contemporaneous CIEI is null after firm effects, the bundle's components diverge, and GMM coefficients depend on instrument classification. The evidence does not establish a causal effect or a psychological mediation mechanism.

The theoretical implication is that enabling infrastructure and a functioning CI system are not interchangeable. Infrastructure may support collection and analysis, but mature CI also requires planning, dissemination, utilization, feedback, ethics, and accountable governance. Public archival variables cannot validate those dimensions merely because they correlate with performance.

The study has seven major limitations. First, the panel does not observe the full intelligence cycle, so CI-cycle measurement is incomplete. Second, CIEI lacks independent external validation, including managerial redundancy validation, expert-panel assessment, and criterion benchmarking. Third, psychological adaptability is captured only through a limited single-indicator cognitive-horizon proxy, complemented by a separately defined behavioral sensitivity indicator. Fourth, the repository metadata are incomplete because the upstream institutional provider and full construction manuals for every indicator are not identified. Fifth, the repository does not provide a comparable extension to the 2024–2025 period with the same focal variables, controls, firm identifiers, and measurement procedures. Sixth, residual endogeneity cannot be fully excluded despite temporal ordering, firm fixed effects, and dynamic-panel GMM diagnostics. Seventh, generalizability is limited to listed Chinese manufacturing firms. Expecting to add a few indicators from another source would change the sampling frame, the unit of analysis, the definitions of the indicators, and the way the data were generated, making the resulting panel technically and nominally newer but not comparable. The study therefore keeps the window of the longitudinal view between 2014 and 2023. The China 2024 WBES is not merged with the observations for listed firms because it was conducted between January 2024 and February 2025. This method enhances contemporary interpretation, but does not include unrelated establishments as “later observations” of the sampled firms.

With respect to the second limitation, an independent organizational survey benchmark containing direct Competitive Intelligence measures has been added. The six-item scale, based on 302 SMEs, demonstrated strong reliability, convergent validity, discriminant validity, and a positive relationship with organizational value creation. These results provide independent nomological evidence that directly measured CI practices can be empirically distinguished from adjacent organizational capabilities and can predict an organizational outcome. This evidence is deliberately not described as matched criterion validation of the Chinese CIEI scores; the study distinguishes formative assessment of the Chinese infrastructure index, independent direct-CI nomological triangulation, and the still-required matched Chinese managerial criterion validation.

The other time restriction is content-related. However, the primary models are unable to account for the firms' changes that occurred during the 2024–2025 period, such as faster adoption of generative artificial intelligence, shifting investments in digital, new intelligence-governance systems and emerging competitive indicators. The estimated relationships, therefore, refer to the competitive environment in 2014–2023 and should not be treated as any direct prediction about the 2026 competitive environment.

Future studies should connect firm accounts to various multi-respondent CI measures related to planning, collection, analysis, dissemination, utilization, feedback, and governance. A separate global CI item would allow for formative redundancy analysis and validated adaptability scales would be needed to investigate cognition, emotion, and behavior directly. Future studies should use quasi-experimental variation or external instruments only when the relevant identification and exclusion assumptions can be credibly justified. The study therefore provides a reproducible account of what the available public data can establish: analytical infrastructure expanded across the observed firms and was temporally associated with performance, but infrastructure alone does not constitute Competitive Intelligence. Its strategic value depends on organizational planning, collection quality, dissemination, utilization, feedback, ethical safeguards, and accountable governance.

As the required next validation step, future research should execute a structured expert content-validation protocol involving a panel of approximately 8–15 qualified experts comprising Competitive Intelligence scholars, CI or strategic-intelligence practitioners, and manufacturing analytics or digital-governance specialists. Each expert should independently rate the BD, DI, and AC indicators for relevance, clarity, representativeness, domain coverage, and whether each indicator measures CI-enabling infrastructure rather than a complete CI process, using a four-point relevance scale. Reporting should include expert-selection criteria, academic–practitioner composition, years of experience, number of evaluation rounds, item-level and scale-level content-validity indices (I-CVI and S-CVI), the content-validity ratio (CVR), percentage agreement, qualitative recommendations, and any modifications made to the index after expert evaluation. Even a fully executed protocol of this kind would validate only the content relevance of CIEI as enabling infrastructure; criterion validation is therefore also required, in which a supplementary managerial CI instrument covering planning, collection quality, dissemination, utilization, feedback, governance, and ethics is administered to managers of a matched subset of the sampled firms, together with global criterion items, so that the correspondence between the archival CIEI index and directly measured CI-process capability can be tested within the mediated model CIEI → direct CI-process capability → organizational performance.

To operationalize this agenda, the adapted direct CI-process instrument is presented in Appendix A. It contains 24 items across eight domains—intelligence planning, collection quality, analysis, dissemination, utilization, governance, feedback and evaluation, and ethics and legality—together with three global criterion items, adapted from the CI-process questionnaire developed and tested by Viviers et al. (2002), which covered planning and focus, collection, analysis, communication, process and structure, and organizational awareness and culture. Consistent with the original study, the instrument should be pretested with academic and industry experts, pilot-tested with manufacturing managers, and examined through cognitive follow-up interviews before full administration, and each domain should be validated separately before any higher-order direct CI-process capability index is formed. Three additional hypotheses are stated for future matched-sample testing and are not tested in the present study: H5, competitive-intelligence enabling infrastructure is positively associated with directly measured CI-process capability; H6, directly measured CI-process capability is positively associated with organizational performance; and H7, directly measured CI-process capability mediates the relationship between CIEI and organizational performance.

Data Availability Statement: The primary dataset, *China's Manufacturing Firms*, is publicly available through Kaggle at https://www.kaggle.com/datasets/willianoliveiragibin/chinas-manufacturing-firms. The analytical file used in this study was downloaded on June 18, 2026. The contemporary contextual source is the China 2024 World Bank Enterprise Survey, reference ID CHN_2024_WBES_v01_M. Its aggregate custom-query indicators were downloaded on June 18, 2026 and were not merged with the listed-firm panel. The final submission package includes the preprocessing and variable-construction scripts, pooled and fixed-effects specifications, component-level sensitivity analyses, firm-cluster bootstrap procedure, dynamic-panel GMM specifications and diagnostics, derived tables, and figure-generation files.

The independent direct-CI benchmark statistics summarized in Section 4.1.1 were obtained from a published organizational survey of 302 SMEs containing directly measured Competitive Intelligence indicators. These external benchmark values were used only for nomological triangulation; they were not merged with the Chinese listed-firm panel and do not constitute matched criterion validation of the CIEI scores.

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APPENDIX A

Adapted Direct CI-Process Instrument (Based on Viviers et al., 2002)

The following instrument was adapted from the CI-process questionnaire employed by Viviers et al. (2002) and extended with explicit utilization, governance, feedback, and ethics dimensions. It is presented as the developed instrument for the supplementary managerial validation study specified in the future-research directions; it has not been administered in the present study, and no responses or validation statistics are reported. Responses are recorded on a five-point scale: 1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly agree. Expert content ratings use a four-point relevance scale: 1 = Not relevant, 2 = Somewhat relevant, 3 = Quite relevant, 4 = Highly relevant.

Code	Survey item
A. Intelligence planning and focus	
CIP1	Senior managers formally identify the organization's priority competitive-intelligence requirements.
CIP2	Competitive-intelligence priorities are explicitly linked to organizational strategy.
CIP3	Intelligence requirements are reviewed when competitive, technological, regulatory, or customer conditions change.
B. Intelligence collection quality	
CIC1	The organization obtains competitive information from a sufficiently diverse range of credible internal and external sources.
CIC2	Important competitive information is verified through at least one additional independent source.
CIC3	The reliability, date, ownership, and relevance of important information sources are documented.
C. Intelligence analysis	
CIA1	The organization applies formal analytical techniques to convert competitive information into decision-relevant intelligence.
CIA2	Competitor, customer, supplier, regulatory, and emerging-technology profiles are systematically updated.
CIA3	Intelligence analysis considers alternative scenarios, threats, opportunities, and likely competitor responses.
D. Intelligence dissemination	
CID1	Intelligence findings are delivered promptly to managers with the authority to act on them.
CID2	Intelligence outputs are tailored to the information needs and responsibilities of different decision-makers.
CID3	Decision-makers can request clarification, challenge assumptions, and provide feedback to intelligence analysts.
E. Intelligence utilization	
CIU1	Senior managers routinely consider competitive intelligence when making strategic decisions.
CIU2	Intelligence findings influence resource allocation, market response, innovation, and competitive positioning.
CIU3	The organization can identify important decisions that were informed by competitive-intelligence evidence.
F. Intelligence governance	
CIG1	Formal responsibility for coordinating Competitive Intelligence is clearly assigned.
CIG2	Senior management oversees the alignment of intelligence activities with organizational strategy.
CIG3	Formal procedures govern intelligence quality, access, storage, approval, escalation, and accountability.

Code	Survey item
G. Feedback and evaluation	
CIF1	The accuracy, relevance, timeliness, and usefulness of intelligence are evaluated after important decisions.
CIF2	Decision-makers are periodically consulted to determine whether intelligence products meet their needs.
CIF3	Lessons from previous decisions are used to improve subsequent intelligence requirements, sources, analysis, and dissemination.
H. Ethics and legality	
CIE1	The organization has formal legal and ethical guidelines for Competitive Intelligence activities.
CIE2	Confidentiality, privacy, data-security, and authorized-access requirements are followed throughout the intelligence process.
CIE3	Employees involved in intelligence activities receive training on lawful and ethical information collection and use.
Global criterion items	
GCI1	Overall, our organization operates a systematic and integrated Competitive Intelligence process.
GCI2	The organization produces timely and actionable intelligence that senior managers trust and use.
GCI3	Competitive-intelligence activities in this organization are strategically directed, properly governed, ethically controlled, and regularly evaluated.

Note. Dissemination is measured with three distinct items because Viviers et al. (2002) reported that their communication construct contained too few unambiguous items for reliable evaluation. Scores should be calculated separately for each of the eight domains, and the domain scores may form a higher-order direct CI-process capability index only if the measurement results support this structure.