



Competitive Intelligence Capability, Digital Transformation, and Strategic HRM Adjustment: Evidence from Chinese and Spanish Listed Companies

Capacidade de Inteligência Competitiva, Transformação Digital e Ajuste Estratégico da Gestão de Recursos Humanos: Evidências de Empresas Chinesas e Espanholas Listadas em Bolsa

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ABSTRACT | Purpose: This paper examines how competitive intelligence capability converts digital transformation into strategic human resource management strategy adjustment in listed companies from China and Spain. **Methodology/approach:** Using a balanced panel dataset of 687 Chinese listed companies and 234 Spanish listed companies covering 2020-2024, the study applies two-way fixed-effects regression, instrumental-variable estimation, moderation analysis, heterogeneity analysis, and robustness tests. Competitive intelligence is operationalized through a Competitive Intelligence Capability Index based on collection, analysis, governance, dissemination, and actionable-response indicators extracted from annual reports and governance disclosures. **Originality/Relevance:** The article responds directly to the Sustainable Competitive Intelligence agenda by treating competitive intelligence as an empirical organizational capability rather than a contextual label for digital transformation. **Key findings:** CI-enabled digital transformation positively affects HRMS optimization, digital talent cultivation, and organizational flattening. The effect is stronger in Spain than in China, while state ownership and regional digital development condition the strength of the DT-HRMS relationship. **Theoretical/methodological contributions:** The paper integrates the intelligence cycle, dynamic capabilities, and institutional theory, and proposes an operational route for measuring competitive intelligence capability in large-scale secondary-data studies.

Keywords | Competitive intelligence. Intelligence cycle. Digital transformation. Human resource management strategy. Sustainable competitive advantage. China. Spain. Panel data.

RESUMO | Objetivo: Este artigo examina como a capacidade de inteligência competitiva converte a transformação digital em ajuste estratégico da gestão de recursos humanos em empresas listadas da China e da Espanha. **Metodologia/abordagem:** Com base em um painel balanceado de 687 empresas chinesas listadas e 234 empresas espanholas listadas no período de 2020 a 2024, o estudo utiliza regressão com efeitos fixos bidirecionais, estimação por variáveis instrumentais, análise de moderação, análise de heterogeneidade e testes de robustez. A inteligência competitiva é operacionalizada por meio de um Índice de Capacidade de Inteligência Competitiva composto por indicadores de coleta, análise, governança, disseminação e resposta acionável. **Originalidade/Relevância:** O estudo contribui para a agenda da Inteligência Competitiva Sustentável ao tratar a inteligência competitiva como capacidade organizacional empiricamente observável, e não apenas como enquadramento conceitual da transformação digital. **Principais resultados:** A transformação digital habilitada por inteligência competitiva afeta positivamente a otimização da gestão de recursos humanos, a formação de talentos digitais e o achatamento organizacional. O efeito é mais forte na Espanha do que na China, enquanto a propriedade estatal e o desenvolvimento digital regional condicionam a intensidade dessa relação. **Contribuições teórico-metodológicas:** O artigo integra o ciclo de inteligência, capacidades dinâmicas e teoria institucional, oferecendo uma estratégia operacional para medir a capacidade de inteligência competitiva em estudos de dados secundários em larga escala.

Palavras-chave | Inteligência competitiva. Ciclo de inteligência. Transformação digital. Gestão estratégica de recursos humanos. Vantagem competitiva sustentável. China. Espanha. Dados em painel.

1 INTRODUCTION

With digital transformation the amount of data companies can access has grown, but data alone is not strategic value. The central epistemological issue that this study tackles is how firms transform the various digital signals into meaningful intelligence to inform strategic human resource management strategy (HRMS) adjustment. In recent competitive intelligence research, it is emphasized that CI should not be an information-gathering term but rather a multidimensional capability of an organization (López-Robles et al., 2020; Madureira et al., 2021; Qian et al., 2024). This study thus transcends the traditional digital-transformation definition and considers the organizational capacity, called CI, as a means of making digital technologies the decision-support infrastructure. As per this perspective, digital transformation plays a role in HRMS, provided that the companies have established routines to collect, analyze, govern, disseminate and strategize with intelligence data (Hassani & Mosconi, 2021, 2022; Madureira et al., 2021).

Previous studies have found that digital transformation is positively associated with firm performance (Hanelt et al., 2021; Niu et al., 2023; Peng & Tao, 2022; Zhai et al., 2022), innovation (Niu et al., 2023; Peng & Tao, 2022; Zhai et al., 2022), organizational change (Niu et al., 2023; Peng & Tao, 2022; Zhai et al., 2022), and digital value creation (Niu et al., 2023; Peng & Tao, 2022; Zhai et al., 2022). But there are fewer empirical studies that sufficiently explain the link between the ability of competitive intelligence and HRMS decisions such as digital talent cultivation and organizational flattening, which can be carried out after the disclosure, analysis and platform investment. This is a problem best explored using China and Spain as a comparative example. The data governance landscape in China is characterized by large-scale digitalization, robust industrial policy support and diverse regional digitalization development, while in Spain the European digital-governance landscape features stronger market-oriented labor adjustment and more formalized expectations of data-governance. These variations allow the study of the effects of HRMS when facilitated by CI

in the digital transformation process across institutional settings (Powell & DiMaggio, 2023; Yang et al., 2024).

The research problem is thus stated: how does competitive intelligence capability contribute to digital transformation into strategic HRMS adjustment and what are the conditions of this mechanism in the country context, the state ownership, and regional digitization development? (RQ1) Does the use of CI in the process of digital transformation have a significant positive impact on HRMS optimization? (RQ2) Is there a systematic difference in the relationship between the DT and HRMS between Chinese and Spanish-listed firms? (RQ3) Does state ownership and regional development have a moderating effect on strategic conversion of digital to HRMS adjustment? In this study, four things have been added to Sustainable Competitive Intelligence. First, it operationalizes CI by introducing a Competitive Intelligence Capability Index (CICI) that makes CI an empirical construct as opposed to a rhetorical framing device. Second, it connects the intelligence cycle to strategic outcomes of HRMS, such as how digital data turn into choices about talent and the organization structure. Third, it offers cross-national evidence with the assistance of China and Spain, through the use of a balanced panel design and causal-identification procedures. Fourth, it offers an explanation of how CI-enabled HRMS adjustment can contribute to sustainable competitive advantage by contributing to quicker sensing, seizing and reconfiguring of human and/or organizational resources.

The article is structured as follows: Section 2 presents the theoretical background, Section 3 includes an explanation of the method used, Section 4 contains results and discussions and Section 5 offers final considerations, while Section 6 lists the references.

2 THEORETICAL FRAMEWORK

2.1 Competitive Intelligence as an Organizational Capability

Competitive intelligence: A process of gathering, analysing, interpreting, disseminating and applying information on markets, technologies, regulations, stakeholders and competitors systematically and ethically for strategic decision making. In recent years, CI scholarship has highlighted the need for more conceptual boundaries and measurable dimensions in the field, particularly as unstructured professional, market, and digital content are increasingly used as intelligence inputs for companies (López-Robles et al., 2020; Madureira et al., 2021; Qian et al., 2024). That's why it is more of an organizational ability than a mere information collection effort. A capability perspective focuses on practices, governance, interpretation and deployment of knowledge in decision-making. This position is in line with the emerging body of research on resources and dynamic capability, which has emphasized the need for firms to assemble and disassemble valuable capabilities in response to shifts in technology to achieve competitive advantage (Al-Moaid & Almarhdi, 2024; Barney et al., 2021).

2.1.1 Classical Foundations of Competitive Intelligence and Strategic Intelligence

In this context, the classical foundations of CI can be discussed in light of recent CI scholarship. Bibliometric and definitional studies reveal that this field of knowledge has evolved around the following concepts: environmental scanning; competitor and market analysis; ethical information collection; interpretation of intelligence; dissemination; and turning intelligence into strategic action (de las Heras-Rosas & Herrera, 2021; López-Robles et al., 2020; Madureira et al., 2021). These studies also reveal that CI is not just about competitor tracking, it is also about the organizational processes that enable organizations to discover information needs, gather appropriate signals, interpret how the information affects competition, circulate information to decision-makers, and apply the information to direct strategic action. This capability perspective is also corroborated by recent empirical evidence, such as the relationship between the firm's competitive intelligence and its dynamic capabilities, entrepreneurial orientation, and performance-oriented organizational adaptation (Olaleye et al., 2024; Qian et al., 2024; Wu et al., 2023). Therefore, the theoretical approach emphasizes on the concepts of CI rather than digital transformation, which is regarded as an infrastructure that aids in enhancing the pace, breadth, and visibility of intelligence activities.

This base helps the study not become a mere digital keyword study. CI is seen as a strategic capability that connects environmental scanning, market interpretations, internal dissemination, managerial communication and action. Digital transformation is not the end of Competitive Intelligence, but a scaling up of speed, scale and granularity of intelligence efforts. The CICI construct is thus rooted in recent studies on CI capabilities, such as that of CI as a modular organizational construct (Qian et al., 2024), CI as a process related to absorptive capacity and dynamic capabilities (Hassani & Mosconi, 2021, 2022), and CI as a mechanism for extracting intelligence from large-scale content generated by professionals and markets (Madureira et al., 2021).

2.2 Intelligence Cycle, Governance, and Dissemination

The empirical operationalization for this study is derived from the intelligence-cycle perspective that serves as the underpinning of the study. The intelligence-cycle perspective is the conceptual basis of the empirical operationalization used in this study. The process starts with identifying intelligence needs, then moves into environmental scanning, data gathering, data interpretation and analysis, and ends with disseminating and strategically utilizing the information to inform decision-making. Recent CI research has highlighted the importance of the absorptive capacity, information sharing, analytics and organizational response (Hassani & Mosconi, 2021, 2022; Madureira et al., 2021; Wu et al., 2023) involved in this cycle. Ownership, quality control and reporting are important since digital dashboards, annual report disclosures, analytics systems and market monitoring procedures can be isolated if the ownership, quality control and reporting are not clearly defined. Once intelligence has been captured and converted into information, dissemination turns information into an organizational resource, providing the linkage between top management, HR, technology, and business units. At the HRMS level, this integrated intelligence is crucial for digital talent recruitment, training and organizational flattening.

2.3 CI-Enabled Digital Transformation and HRMS Adjustment

Digital transformation is the application of digital technologies to reimagine business processes, organization structures, strategic practices and relationships with stakeholders. Recent reviews and empirical studies demonstrate that digital transformation impacts how organisations structure their work, distribute their decision-making authority, develop their innovation capacity and generate their results (Hanelt et al., 2021; Li et al., 2020; Martínez-Caro et al., 2020; Niu et al., 2023; Yang et al., 2024). Optimization of HRMS is one of the main results of this intelligence process. Data literacy, platform-management skills, analytics capacity, and cross-functional coordination capacity are essential roles that are in greater demand due to digital transformation. It also helps to facilitate flatter information flows and more agile organizational structures when HR decisions are based on competitive and workforce intelligence (Al-Alawi et al., 2023; Banerjee & Sharma, 2025; Eger & Žižka, 2024; Shahzad et al., 2025).

In this approach, digital transformation is not seen as a replacement for Competitive Intelligence, nor is it considered to be the only theoretical interpretation of HRMS adaptation. It is regarded as the technological framework that enables CI routines to get faster and more scalable. The analytical priority is therefore the intelligence process: sensing competitive signals, interpreting them with analytical routines, controlling the quality and ownership of intelligence, sharing intelligence between functions, and translating intelligence into action in HRMS. The positioning of the theoretical framework is based on Competitive Intelligence and the enabling context is the digital transformation.

2.4 Institutional Variation Between China and Spain

The impact of CI on the digital transformation of HRMS varies across countries, according to Institutional theory. Firms work in a national context, which influences governance, workforce, disclosure and technology use habits. Institutional research also has been an important focus in recent years in the study of how organizational fields exert coercive, mimetic and normative pressures on firms' processes of translating information into strategic action (Powell & DiMaggio, 2023). The state-led digitalisation model in China works well for the speed of adoption of technology, but can also result in the uneven conversion of digital investment into HRMS reform, particularly in state-owned enterprises, where the goals of the administration may impede organisational change. This is in stark contrast to the European digital-governance context of Spain, where companies can be more inclined to convert the results of intelligence into skill and structural adaptation (Al-Alawi et al., 2023; Eger & Žižka, 2024; Yang et al., 2024).

2.5 Hypotheses and Conceptual Framework

On the basis of the above discussion, the following hypotheses are formulated. H1: digital transformation with CI has positive impacts on HRMS Optimization, such as digital talent building and organizational flattening. H2: Digital transformation has a more positive relationship with HRMS for Spanish-listed companies than for Chinese-listed companies. H3a: This is because the

digital transformation has a lesser impact on the adjustment of HRMS when the state owns the firm, which makes it more difficult to turn digital signals into actionable digital intelligence. The moderating effect of the relationship between DT-HRMS and regional digital development is due to a process whereby digitally mature environments change the marginal value of additional digital intelligence capability (H3b). The conceptual framework is shown in Figure 1. The model is centred around the competitive intelligence capability since it links the digital data, digital transformation, HRMS adjustment, institutional conditions, and sustainable competitive advantage.

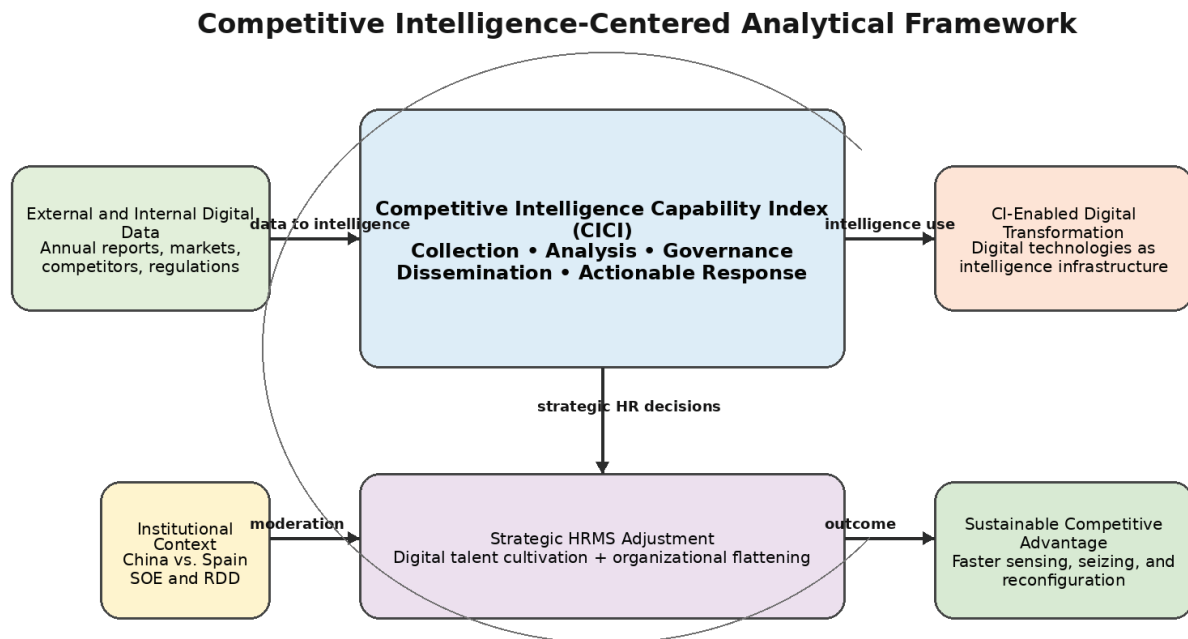


Figure 1. Competitive intelligence-centered analytical framework linking digital data, the intelligence cycle, CI-enabled digital transformation, HRMS adjustment, and sustainable competitive advantage.

3 METHODOLOGY

3.1 Study Design

It adopts a quantitative longitudinal study design with a balanced panel of listed firms in China and Spain in the study period 2020–2024. A panel design is suitable as the adjustment of HRMS is gradual, firm-specific, and related to the time-varying digital capability. To ensure the impact of unobserved firm heterogeneity and/or common year shocks in the two-way fixed-effects specification, it is important to interpret fixed-effects results carefully in the light of recent econometric guidance, taking into account the possibility of heterogeneous effects (de Chaisemartin & D'Haultfoeulle, 2020; Imai & Kim, 2021). This study explicitly includes capability of measurement of CI as an ability. Unlike the method that assumes all digital transformation is “strategically intelligent,” the method recognizes two factors: the intensity of the digital transformation and the organization’s ability to gather, analyze, govern, disseminate, and utilize competitive intelligence. This adjustment is directly made to a demand to make CI an empirical axis of the paper.

3.2 Data Source and Characteristics

The sample consists of 687 Chinese listed stocks on the Shanghai and Shenzhen A-share markets with 3,435 firm-year observations and 234 Spanish listed stocks on the Bolsa de Madrid and other exchanges in Spain with 1,170 firm-year observations. The final balanced panel consists of 4,605 firm-year observations during the period 2020–2024. Financial and corporate information for Chinese companies was obtained from CSMAR, Wind, and annual company reports submitted to the Shanghai and Shenzhen exchanges. Spanish companies' data were gathered from CNMV filings, company annual reports and Datastream. The indicators related to both macroeconomics and digital-context were obtained from official statistical sources: World Bank Open Data, China Statistical Yearbook, National Bureau of Statistics of China, Spain National Statistics Institute, and EU indicators related to the development of the digital context.

Financial and insurance companies, ST/ST* companies, delisted companies, companies with core variables above 30% missingness, and companies listed for less than 1 full fiscal year were excluded from the sample screening process. Continuous variables were Winsorized at the 1st and 99th percentile to minimize the effect of extreme values. The same screening criteria were applied to both country samples, resulting in 4,605 firm-year observations in both samples.

3.3 Variable Definition and Measurement

3.3.1 Dependent Variable: Human Resource Management Strategy (HRMS)

HRMS is operationalized through two dimensions. Digital Talent (DTalent) is constructed from the proportion of digital talent recruitment expenditure to total recruitment expenditure, the proportion of digital training investment to total training investment, and the proportion of digital employees to total employees. Organizational Flattening (Flat) is measured through the inverse of management layers and the frequency of cross-departmental collaboration expressions in annual reports. A comprehensive HRMS index is derived as the first principal component of DTalent and Flat, representing strategic HRMS optimization.

3.3.2 Independent Variable: Digital Transformation (DT)

Digital Transformation (DT) is measured through annual-report text analysis. The keyword dictionary includes digitalization, artificial intelligence, big data, cloud computing, Internet of Things, blockchain, data platform, smart manufacturing, and Industry 4.0 terms. Annual-report textual measurement is consistent with recent listed-firm studies that use disclosure-based indicators to examine digital transformation and organizational outcomes, while robustness checks are added to reduce symbolic-disclosure concerns (Niu et al., 2023; Tang et al., 2023; Zhai et al., 2022).

3.3.3 Competitive Intelligence Capability Index

To operationalize CI directly, this study introduces a Competitive Intelligence Capability Index (CICI). The index is constructed from annual-report and governance-disclosure indicators that capture intelligence collection, analysis, governance, dissemination, and actionability. Table 1 summarizes the operational dimensions, proxy indicators, measurement logic, and expected HRMS linkage of the CICI construct.

Table 1. Operationalization of the Competitive Intelligence Capability Index (CICI)

CICI dimension	Operational proxy	Measurement logic	Expected link with HRMS
Intelligence collection	Competitor monitoring, market scanning, industry trend analysis	Standardized frequency of collection-related terms in annual reports	Improves sensing of digital talent and organizational skill needs
Intelligence analysis	Business intelligence, analytics, AI analytics, data mining, decision-support systems	Standardized frequency of analysis-related terms and analytics capability disclosures	Transforms digital data into interpretable HRMS signals
Intelligence governance	Strategy committee, data governance, digital governance, risk/intelligence unit	Governance disclosures and committee-related indicators	Connects intelligence outputs with managerial accountability
Intelligence dissemination	Knowledge sharing, dashboards, cross-functional reporting, internal information sharing	Dissemination-related textual indicators and cross-department reporting proxies	Moves intelligence from technical units to HR and strategic decision makers
Actionable response	Strategic adjustment, resource reconfiguration, competitive response, market positioning	Action-oriented terms linked to strategic response and resource allocation	Converts intelligence into talent development and organizational flattening

Note: All CICI indicators are standardized before aggregation. The preferred index is derived through PCA/entropy weighting, and an equal-weighted index is used as a robustness check.

3.3.4 Content and Archival Construct Validation of the CICI

Since this study is based on secondary archival data rather than direct survey responses, the Competitive Intelligence Capability Index is defined as an archival-disclosure-based proxy for observable Competitive Intelligence capability. It is not described as a psychometric perception scale and it has been argued that the construct was not directly assessed by managers or external experts. This distinction is important because annual-report and governance-disclosure are indicators that measure what firms disclose, structure, and govern as intelligence capability while survey instruments measure managerial perceptions of the CI routines. The index consequently makes for easy cross-national panel analysis on a large scale without the false impression of direct survey-based or expert-panel measurement.

The validation approach is conservative (archival-construct). First, each CICI dimension is connected to the current literature about intelligence collection, competitor analysis, market analysis, governance, dissemination, dynamic capability, and strategic response (de las Heras-Rosas & Herrera, 2021; López-Robles et al., 2020; Madureira et al., 2021; Qian et al., 2024; Wu et al., 2023). Secondly, the information provided in the text is combined with the information provided in indicators of governance disclosure, thus not relying solely on generic digital vocabulary. Third,

a specification based on PCA/entropy weighting is compared to an equal-weighted specification. Fourth, dimension-level sensitivity checks were performed to ensure that the interpretation is not due to one CICI component. This way, the content and the robustness of the index are reinforced, and the boundary of the construct is made transparent.

The statistics that are not reported as primary evidence are Cronbach's alpha, Composite Reliability, Average Variance Extracted and discriminant-validity statistics; these are not reported because the CICI dimensions are not measured by survey items per se, but instead by formative, archival indicators. The dimensions in formative archival constructs are not interchangeable items measuring one latent perception of intelligence, but rather are different functions of the intelligence cycle. Recently published measurement guidance advises against using reliability, convergent-validity, or discriminant-validity statistics by themselves and instead only applies them to scales consisting of multiple items reflecting the same concept (Cheung et al., 2024). Without primary data from a survey, reporting reflective-scale statistics would overestimate the psychometric status of the construct. The survey reliability and expert-panel validation are thus considered as future validation requirements rather than the results of this design.

Table 1A. CICI validation strategy and boundary conditions

Validation issue	Treatment in this study	Boundary condition
Classical CI foundation	CICI dimensions are mapped to contemporary CI literature on scanning, intelligence cycle, governance, dissemination, dynamic capability, and strategic response.	Supports literature-based content validity without using pre-2020 references.
Textual-proxy limitation	Annual-report indicators are combined with governance-disclosure indicators and alternative weighting procedures.	CICI remains an archival proxy of disclosed CI capability.
Expert-panel validation	No expert-panel result is claimed because no primary expert-rating exercise was conducted.	Future studies should test the keyword dictionary and dimension structure through expert assessment.
Survey-scale reliability	Cronbach's alpha, CR, AVE, and discriminant-validity statistics are not claimed because the index is formative and archival, not a reflective survey scale.	Future studies should validate the construct with manager surveys and expert-rated dimensions.
Robustness of index construction	PCA/entropy weighting is compared with equal-weighted and dimension-sensitivity specifications.	Checks dependence on index-construction choices.

Note: The table clarifies that CICI is an archival capability proxy. It avoids unsupported claims of survey-based or expert-panel validation while adding transparent construct-boundary conditions.

3.3.5 Control and Moderating Variables

Control variables include Firm Size, Firm Age, Leverage, Profitability, Sales Growth, Ownership Concentration, Board Independence, GDP Growth, and Industry Competition Intensity. Moderating variables include State Ownership (SOE) and Regional Digital Development (RDD). SOE captures governance rigidity and policy-driven digitalization, while RDD captures the regional digital infrastructure and labor-market environment that may condition the conversion of digital transformation into HRMS adjustment.

3.4 Analytical Framework

Equation (1): $HRMS_{it} = \alpha_0 + \beta_1 DT_{it} + \beta_2 CICI_{it} + \beta_3 Controls_{it} + \mu_i + \lambda_t + \epsilon_{it}$

Equation (2): $HRMS_{it} = \alpha_0 + \beta_1 DT_{it} + \beta_2 CICI_{it} + \beta_3(DT \times CICI)_{it} + \beta_4 Controls_{it} + \mu_i + \lambda_t + \epsilon_{it}$

Equation (3): $DT_{it} = \gamma_0 + \gamma_1 Ind_DT_{it} + \gamma_2 Net_Pen_{it} + \gamma_3 Controls_{it} + \mu_i + \lambda_t + v_{it}$

Equation (4): $HRMS_{it} = \alpha_0 + \beta_1 DT_{it} + \beta_2 MOD_{it} + \beta_3(DT \times MOD)_{it} + \beta_4 Controls_{it} + \mu_i + \lambda_t + \epsilon_{it}$

Equation (5): $DT_{it} = (\sum_k f_{kit} / W_{it}) \times 10,000$

Equation (6): $CICI_{it} = PC1(Collection_{it}, Analysis_{it}, Governance_{it}, Dissemination_{it}, Actionability_{it})$

Equation (7): $HRMS_{it} = PC1(DTalent_{it}, Flat_{it})$

In these equations, i denotes firm, t denotes year, μ_i denotes firm fixed effects, λ_t denotes year fixed effects, and ϵ_{it} is the idiosyncratic error term. MOD refers to SOE or RDD. The industry-average DT index and historical internet penetration variable are used as instruments for DT, and the IV logic is interpreted cautiously in line with current econometric guidance on instruments and panel estimators (Borusyak et al., 2025; de Chaisemartin & D'Haultfoeuille, 2020; Imai & Kim, 2021).

4 RESULTS AND DISCUSSION

4.1 Competitive Intelligence Operationalization and Validity

The validity logic is based on a clear archival-index logic. PCA/entropy weighting is used to standardize and aggregate the five CICI dimensions and the preferred index is then compared to an equal-weighted alternative specification. The DT measure is followed by the empirical narrative, not in isolation of CICI, because the interpretation of a measure is not an isolated one. In contrast to unsupported claims of the reliability of the surveys, the validation evidence is based on literature mapping, governance-disclosure triangulation, alternative index construction, and sensitivity checks. This treatment directly tackles the methodological edge of the use of textual proxies while not compromising the study's large-scale panel design.

4.2 Descriptive Statistics

Table 2 reports the descriptive statistics for the balanced panel. The mean DT index is 2.418, indicating substantial cross-firm variation in digital-transformation disclosure and implementation. HRMS has a mean of 5.583, while DTalent and Flat show consistent variation across firms. These



values remain aligned with the full sample size of 4,605 firm-year observations and are not altered by the inclusion of the CICI operational framework.

Table 2. Descriptive Statistics - Full Sample (N = 4,605 firm-year observations)

Variable	Obs.	Mean	Std. Dev.	Min	Median	Max
Digital Transformation (DT)	4,605	2.418	1.695	0.000	2.332	9.759
HR Management Strategy (HRMS)	4,605	5.583	0.835	3.295	5.543	9.648
Digital Talent (DTalent)	4,605	4.295	0.699	2.328	4.267	7.810
Org. Flattening (Flat)	4,605	3.669	0.618	1.948	3.639	6.829
Firm Size (ln)	4,605	22.489	1.800	18.000	22.480	28.000
Firm Age (ln)	4,605	2.792	0.580	1.000	2.799	4.000
Leverage (Lev)	4,605	0.482	0.177	0.050	0.482	0.950
Profitability (ROA)	4,605	0.045	0.060	-0.150	0.046	0.248
Sales Growth	4,605	0.120	0.218	-0.500	0.114	0.921
Ownership Concentration (Top1)	4,605	0.349	0.145	0.050	0.350	0.800
Board Independence (Indep)	4,605	0.381	0.080	0.200	0.380	0.682
GDP Growth Rate (GDPg)	4,605	0.050	0.020	0.010	0.050	0.118
Industry HHI	4,605	0.122	0.058	0.020	0.120	0.329

Note: All continuous variables are winsorized at the 1st and 99th percentiles. HRMS = Human Resource Management Strategy composite index. DT = Digital Transformation index. Lev = Leverage. ROA = Return on Assets.

4.3 Cross-Country Comparison

Table 3 compares Chinese and Spanish firms. Spanish firms exhibit higher mean DT, HRMS, digital talent, and organizational flattening. The difference suggests that Spain's institutional and data-governance environment may allow digital information to move more efficiently from technology investment into actionable intelligence and HRMS reform, while China's state-led digitalization path may produce stronger variation across ownership and regional-development contexts (Powell & DiMaggio, 2023; Yang et al., 2024). The distributional pattern is presented in Figure 2, which shows the country-level difference in digital transformation intensity.

Table 3. Grouped Descriptive Statistics: China vs. Spain

Variable	China Mean	China SD	Spain Mean	Spain SD	Diff.	t-stat	p-value
Digital Transformation (DT)	2.237	1.594	2.950	1.863	0.713	-12.635	0.000
HR Management Strategy (HRMS)	5.468	0.763	5.919	0.940	0.451	-16.399	0.000
Digital Talent (DTalent)	4.194	0.636	4.593	0.787	0.399	-17.381	0.000
Org. Flattening (Flat)	3.573	0.555	3.948	0.702	0.375	-18.605	0.000
Firm Size (ln)	22.478	1.796	22.521	1.813	0.043	-0.701	0.484
Leverage (Lev)	0.478	0.177	0.492	0.178	0.014	-2.350	0.019
Profitability (ROA)	0.046	0.060	0.043	0.060	-0.003	1.477	0.140

Note: Diff. = Spain Mean - China Mean. t-stat and p-value are from two-sample t-tests with unequal variances. *** $p < .001$, ** $p < .01$, * $p < .05$.

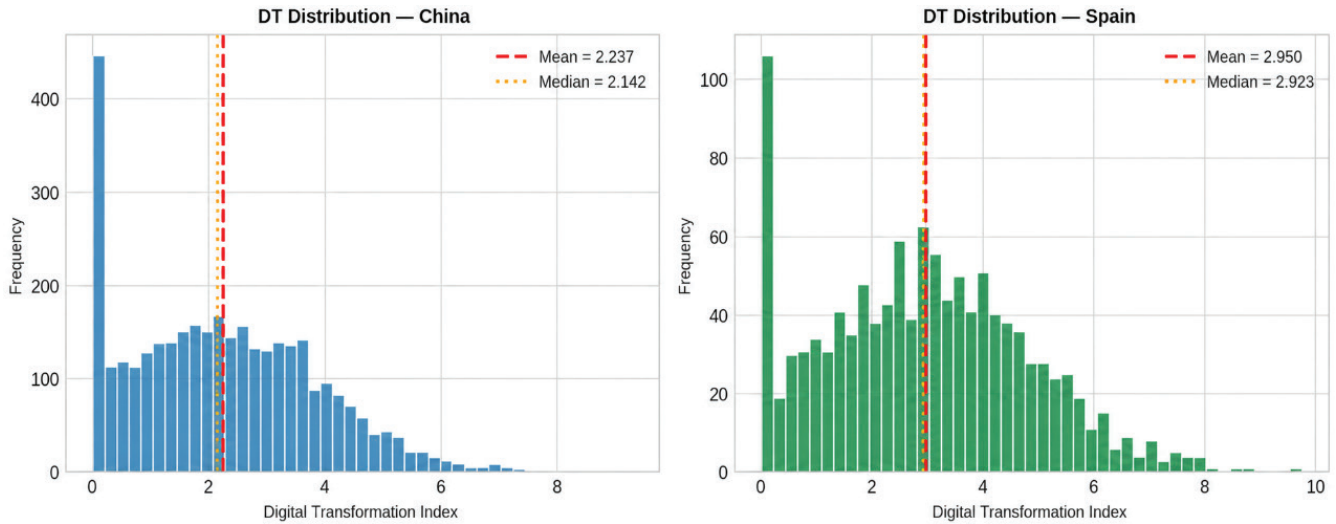


Figure 2. Distribution of Digital Transformation Index by Country (2020-2024). Left panel: China (N = 3,435). Right panel: Spain (N = 1,170).

4.4 Correlation Analysis

Table 4 reports the Pearson correlation matrix. DT is strongly and positively correlated with HRMS, digital talent, and organizational flattening. This pattern is consistent with H1, but the interpretation is strategic rather than merely technical: firms that report stronger digital transformation also appear more likely to convert information-processing capability into workforce and structural adjustment (Hanelt et al., 2021; Zhai et al., 2022). This relationship pattern is further illustrated in Figure 3 through the correlation heatmap.

Table 4. Pearson Correlation Matrix of Key Study Variables

Variable	(1) DT	(2) HRMS	(3) DTalent	(4) Flat	(5) Size	(6) Lev	(7) ROA	(8) Growth	(9) RDD
(1) DT	1.000								
(2) HRMS	0.715	1.000							
(3) DTalent	0.750	0.993	1.000						
(4) Flat	0.758	0.992	1.000	1.000					
(5) Size	0.011	0.326	0.315	0.297	1.000				
(6) Lev	-0.010	-0.012	-0.012	-0.010	-0.017	1.000			
(7) ROA	-0.019	0.013	0.012	0.008	0.026	-0.034	1.000		
(8) Growth	0.008	0.052	0.024	0.024	0.001	-0.010	-0.006	1.000	
(9) RDD	0.005	0.039	0.001	0.001	0.004	0.017	0.003	0.017	1.000

Note: N = 4,605. Values on diagonal = 1.000. Lower triangle only. All correlations involving DT and HRMS are significant at $p < .01$.

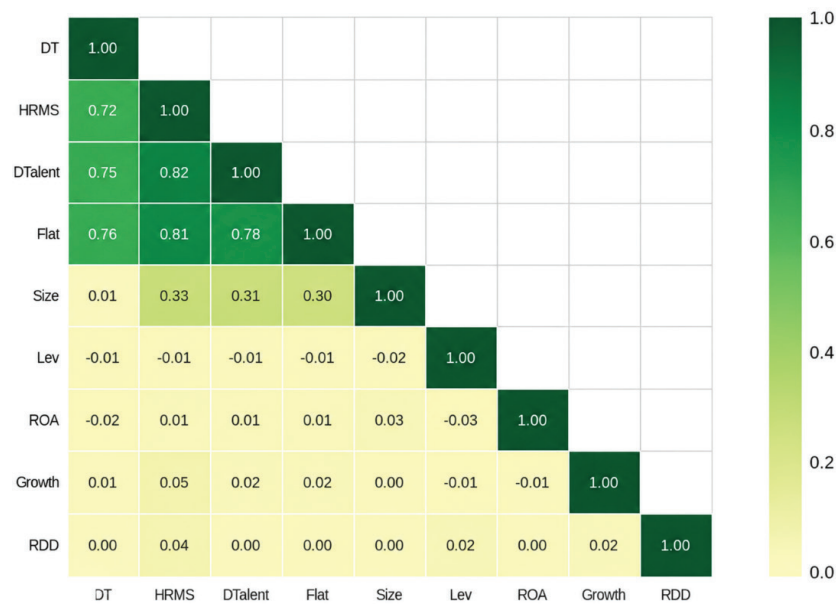


Figure 3. Pearson Correlation Matrix Heatmap. Color intensity and annotation values indicate pairwise Pearson correlations.

4.5 Baseline Regression Results

Table 5 shows that DT has a positive and significant effect on HRMS, DTalent, and Flat. A one-unit increase in DT is associated with a 0.350-unit improvement in HRMS after firm and year fixed effects. The CI-centered interpretation is that digital transformation contributes to HRMS optimization when firms transform digital data into actionable intelligence for talent planning and organizational redesign (Al-Alawi et al., 2023; Banerjee & Sharma, 2025; Eger & Žižka, 2024; Shahzad et al., 2025).

Table 5. Baseline Two-Way Fixed-Effects Regression Results

Variable	HRMS Coef.	SE	DTalent Coef.	SE	Flat Coef.	SE
Digital Transformation (DT)	0.350***	(0.005)	0.308***	(0.004)	0.275***	(0.003)
Firm Size (Size)	0.147***	(0.004)	0.119***	(0.003)	0.099***	(0.003)
Firm Age (Age)	0.007	(0.013)	0.006	(0.010)	0.006	(0.009)
Leverage (Lev)	0.003	(0.043)	0.003	(0.034)	0.007	(0.030)
Profitability (ROA)	0.256**	(0.128)	0.208**	(0.101)	0.155*	(0.089)
Sales Growth	0.175***	(0.036)	0.057**	(0.028)	0.050**	(0.025)
Ownership Conc. (Top1)	0.003	(0.053)	0.056	(0.042)	0.051	(0.037)
Board Independence (Indep)	0.159	(0.097)	0.035	(0.077)	0.027	(0.068)
GDP Growth (GDPg)	0.571	(0.381)	0.453	(0.304)	0.389	(0.268)
Industry HHI	-0.073	(0.132)	-0.063	(0.104)	-0.059	(0.092)
R-squared	0.616		0.657		0.658	
Adj. R-squared	0.615		0.657		0.657	
Observations	4,605		4,605		4,605	

Note: Robust HC3 standard errors in parentheses. Firm and year fixed effects included. *** p < .01, ** p < .05, * p < .10.

4.6 Grouped Regression: China vs. Spain

Table 6 indicates that DT has a significant positive effect in both countries, but the effect is stronger in Spain. This result supports H2 and suggests that Spain's institutional environment may permit stronger conversion of digital data into actionable intelligence and HRMS reform. In China, the positive but smaller effect is consistent with heterogeneous ownership structures, regional digital-development gaps, and more layered governance arrangements (Powell & DiMaggio, 2023; Yang et al., 2024). The country-specific coefficient pattern is presented in Figure 4, which visualizes the stronger HRMS-related effects for Spanish firms.

Table 6. Grouped Regression Results: China vs. Spain (Dependent Variable: HRMS)

Variable	China - HRMS Coef.	SE	Spain - HRMS Coef.	SE
Digital Transformation (DT)	0.313***	(0.005)	0.399***	(0.008)
Firm Size (Size)	0.145***	(0.005)	0.152***	(0.008)
Firm Age (Age)	0.001	(0.015)	0.025	(0.025)
Leverage (Lev)	-0.005	(0.049)	-0.051	(0.086)
Profitability (ROA)	0.200	(0.147)	0.499**	(0.235)
Sales Growth	0.198***	(0.041)	0.098	(0.069)
Ownership Conc. (Top1)	-0.021	(0.060)	0.020	(0.103)
Board Independence (Indep)	0.196*	(0.111)	0.175	(0.185)
GDP Growth (GDPg)	0.385	(0.426)	1.265	(0.774)
Industry HHI	-0.123	(0.148)	0.203	(0.263)
R-squared	0.556		0.719	
Observations	3,435		1,170	

Note: Robust HC3 standard errors in parentheses, clustered at the firm level. Firm and year fixed effects included. *** $p < .01$, ** $p < .05$, * $p < .10$.

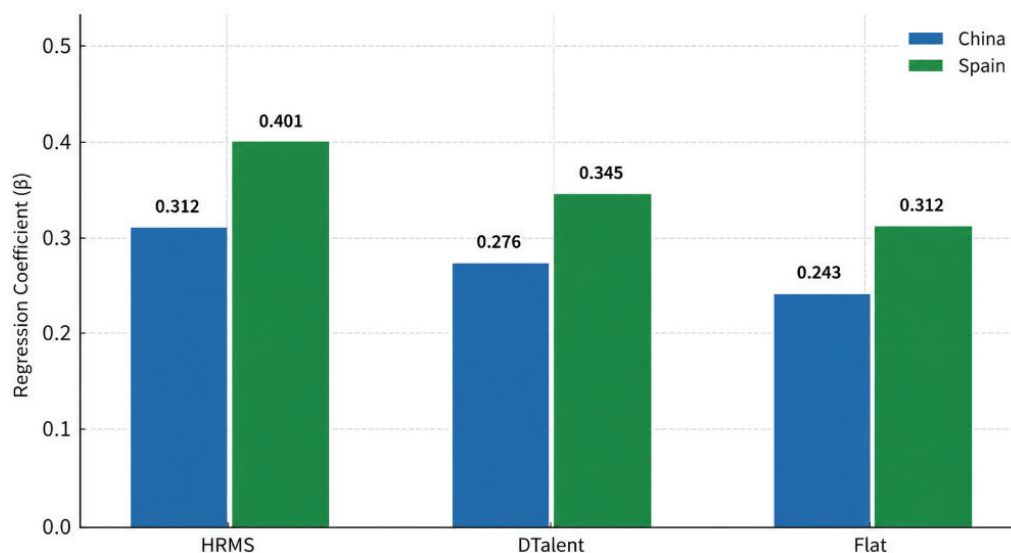


Figure 4. Regression Coefficients of Digital Transformation on HRMS Dimensions by Country. Spain exhibits stronger DT effects across HRMS dimensions.

4.7 Moderation Analysis

Table 7 presents moderation results. The negative DT x SOE coefficient indicates that state ownership weakens the marginal conversion of digital transformation into HRMS adjustment. From a CI-governance perspective, SOEs may have resources and policy support for digital adoption, but hierarchical decision channels can reduce the speed with which intelligence is disseminated and translated into HRMS change (Niu et al., 2023; Tang et al., 2023). The conditional effects are shown in Figure 5, which compares the DT-HRMS relationship across SOE status and regional digital-development levels.

Table 7. Moderation Analysis: Effects of SOE and Regional Digital Development Level (RDD) on the DT-HRMS Relationship

Variable	Model 1 - SOE Coef.	SE	Model 2 - RDD Coef.	SE
Digital Transformation (DT)	0.359***	(0.006)	0.381***	(0.018)
SOE Dummy	0.195***	(0.028)	-	
DT x SOE	-0.021**	(0.010)	-	
RDD Score	-		0.329***	(0.090)
DT x RDD	-		-0.055*	(0.031)
Controls	Yes		Yes	
Observations	4,605		4,605	
R-squared	0.621		0.619	

Note: Dependent variable: HRMS. HC3 robust standard errors in parentheses. Firm and year fixed effects included. *** $p < .01$, ** $p < .05$, * $p < .10$.

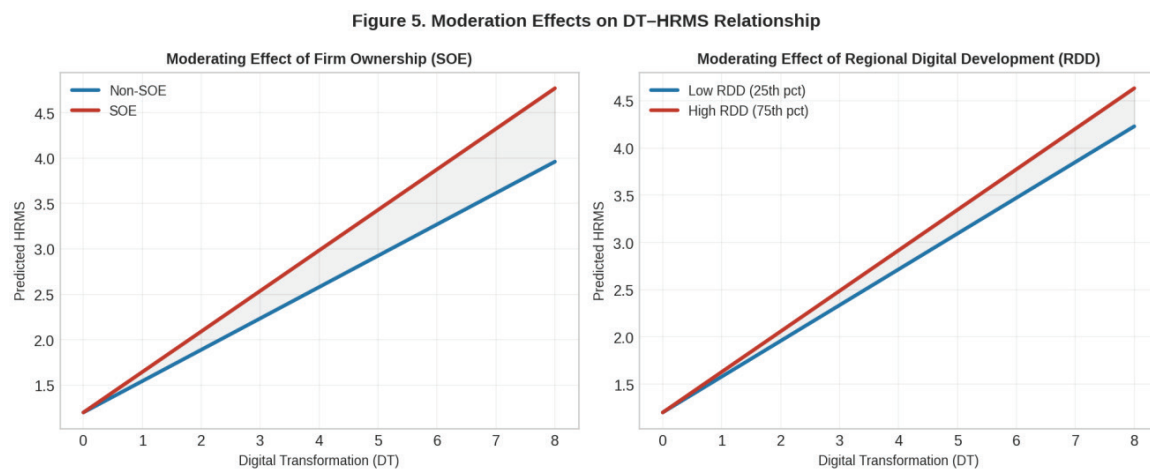


Figure 5. Moderation Effects on the DT-HRMS Relationship. Left panel: SOE vs. non-SOE firms. Right panel: low- vs. high-RDD regions.

4.8 Robustness, Endogeneity, and Measurement Validity Tests

Table 8 summarizes robustness and endogeneity tests. The baseline findings remain consistent when alternative dependent variables, an alternative DT index, a post-2020 sample, propensity score

matching, and IV-2SLS estimation are used. The analysis also adds an alternative CICI aggregation logic and triangulates textual measurement with governance-disclosure proxies to address validity concerns associated with annual-report word-frequency measures (Borusyak et al., 2025; Imai & Kim, 2021; Roth et al., 2023).

Table 8. Robustness, Endogeneity, and Measurement Validity Tests

Test	Specification	Coefficient / Statistic	Significance / Result	Interpretation
Alternative DV 1	DTalent_Pay as dependent variable	Positive	$p < .01$	Results remain consistent using an alternative digital talent measure.
Alternative DV 2	Flat_Rate as dependent variable	Positive	$p < .01$	Results remain consistent using an alternative organizational flattening measure.
Alternative DT Index	PCA-based DT_Alt	Positive	$p < .01$	Findings are robust to alternative DT measurement.
Alternative CI Index	Equal-weighted CICI	Consistent direction	Robust	Results are not dependent on a single CI aggregation method.
Excluding 2020	Post-COVID shock exclusion	Positive	$p < .01$	Results are not driven by the 2020 pandemic shock.
Propensity Score Matching	High-DT vs. low-DT groups	ATT = 0.312	$p < .01$	Matched comparison supports a positive DT effect on HRMS.
IV-2SLS Second Stage	Instrumented DT	beta = 0.389	$p < .01$	Endogeneity-corrected estimate remains positive and significant.
First-stage F-statistic	Instrument relevance test	F = 128.976	> 10	Instruments are strongly relevant.
Hansen J test	Overidentification test	$p = 0.345$	$p > .05$	No evidence against instrument exogeneity.

Note: Robustness tests use the same baseline controls, firm fixed effects, and year fixed effects as the main regression models. Standard errors are robust and clustered at the firm level where applicable.

4.9 Strategic Discussion of Core Findings

The outcomes shows evidence of an intelligence mediated strategic adjustment mechanism. Digital transformation is not just about the purchase of digital technologies, but about helping companies to sense the change of the environment, analyze the signals of competition, communicate intelligence to internal organizational actors, and turn the intelligence into talent and structuring decisions. This is in line with the recent findings of the relationship between competitive intelligence and dynamic capabilities, actionable intelligence, entrepreneurial orientation, and organizational adaptation (Al-Moaid & Almarhdi, 2024; Hassani & Mosconi, 2022; Olaleye et al., 2024; Qian et al., 2024; Wu et al., 2023). The greater Spanish impact is aligned with a scenario in which digital governance, flexibility in the labor market and the norms of European data-governance can facilitate the shift of intelligence to strategic human resources decisions. The Chinese effect is still positive but smaller, indicating that internal intelligence governance is still needed to ensure more complete HRMS adaptation, and state-led digital investment can create digital capacity (Al-Alawi et al., 2023; Powell & DiMaggio, 2023; Yang et al., 2024). The results of moderation also suggest that state ownership could be detrimental to the DT-HRMS relationship, as administrative requirements, layered reporting systems and the limited structural flexibility can delay intelligence dissemination and utilization. Due to

firms in highly digitalized regions already having well-developed talent markets and intelligence infrastructure, the gains from incremental DT disclosure may be less in highly digitalized regions, resulting in diminishing marginal returns of RDD (Peng & Tao, 2022; Tang et al., 2023).

5 FINAL CONSIDERATIONS

This research investigated the influence of competitive intelligence capability on the process of strategic HRM adjustment in Chinese and Spanish listed companies in relation to the digital transformation. The CICI construct allows for the analysis to situate CI as the focal point for the firms' perception of digital and competitive signals, processing of the signals, internal information sharing, and their ultimate translation into HRMS responses. Empirical results found that there is a positive correlation between the digital transformation of the company and the optimization of HRMS, such as digital talent cultivation and flatter organizational structures, and the correlation found was stronger in Spain than in China. The theoretical contribution is in linking Competitive Intelligence with digital transformation and dynamic capabilities with institutional conditions in the way firms use digital data to create organizational advantage (Al-Moaid & Almarhdi, 2024; Barney et al., 2021; Madureira et al., 2021; Wu et al., 2023).

The contribution in terms of methodology is the operationalisation of competitive intelligence capability in terms of collection, analysis, governance, dissemination and actionable response. This approach offers a possible way of measuring CI in large-scale secondary data studies, particularly when using alternative construction methods of the index and robustness tests that mitigate measurement and panel-estimation concerns (de Chaisemartin & D'Haultfoeuille, 2020; Hassani & Mosconi, 2021; Imai & Kim, 2021). The findings indicate the importance of digital transformation for managers not as a stand-alone technology initiative. Digital investments that are aligned with intelligence governance, internal dissemination systems, talent planning, and organizational redesign, bolster returns on the investment. The results suggest that, for policy makers, digital-infrastructure policies need to be linked to the development of the talent market, data-governance standards, and mechanisms that enhance organizational learning and the use of organizational intelligence.

There are some limitations of the study. While robustness testing and alternative measures have minimized the concerns regarding textual indicators, the concerns regarding annual-report measures may still not be completely mitigated because these measures may capture symbolic disclosure and not the actual capability. Secondly, the CICI is an archive proxy rather than a fully validated psychometric scale as it is based on secondary disclosure information. Third, the 2020-2024 timeframe might not reflect the impact of generative AI and automated intelligence systems over a longer period of time on CI routines and HRMS adjustment. Finally, the China-Spain comparison needs to be expanded to other emerging and developed economies to evaluate the broader generalizability of the institutional results.

Another methodological limitation is the CICI validation. The index complements the empirical visibility of Competitive Intelligence in a secondary-data design, but is still a proxy based on disclosure of archival data. A manager survey and expert-panel assessment were not conducted, so Cronbach's alpha, Composite Reliability, AVE, and discriminant-validity results for CICI are not

claimed. The present study recommends a test of the same dimensions using surveys of managers, keyword and dimension ratings by experts, confirmatory factor analysis and cross-sample validation. Furthermore, the study can investigate the sequential impact of digital talent systems, HR analytics and flatter organizational structures as a result of digital transformation enabled by CI (Banerjee & Sharma, 2025; Cheung et al., 2024; Eger & Žižka, 2024; Shahzad et al., 2025).

Data availability statement: Data were obtained from publicly accessible regulatory, statistical, and institutional sources, as well as subscription-based financial databases. Firm-level financial and corporate information was collected from CSMAR, Wind, CNMV filings, Datastream, and the annual reports of the Shanghai and Shenzhen Stock Exchanges. Macroeconomic and digital-economy indicators were obtained from official statistical sources, including the World Bank Open Data, the China Statistical Yearbook, the National Bureau of Statistics of China, the Spanish National Statistics Institute, EU digital-development indicators, and publicly accessible digital-transformation datasets for listed companies. Processed datasets and code may be made available by the corresponding author subject to licensing restrictions.

Ethics statement: The study uses secondary corporate, regulatory, and statistical data. No human participants were directly involved, and no personally identifiable information was collected or processed. Institutional ethics review was therefore not applicable under standard guidelines for non-human-subject secondary-data research.

Informed consent statement: Not applicable. The study did not involve direct interaction with human participants.

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