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ARTICLE

# COMPETITIVE INTELLIGENCE-ENABLED DIGITAL TRANSFORMATION: A SUSTAINABLE OPTIMIZATION MODEL WITH EVIDENCE FROM CHINA AND SPAIN

# TRANSFORMAÇÃO DIGITAL HABILITADA POR INTELIGÊNCIA COMPETITIVA: UM MODELO DE OTIMIZAÇÃO SUSTENTÁVEL COM EVIDÊNCIAS DA CHINA E DA ESPANHA

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## ABSTRACT

**Purpose:** This study conceptualizes Competitive Intelligence (CI) as an intelligence-based decision governance capability that structures how organizations select, sequence, and govern digital transformation initiatives under conditions of competitive and sustainability uncertainty. Rather than modeling CI as a technological antecedent, the article positions CI as the decisional infrastructure through which digital transformation contributes to sustainable optimization outcomes.

**Methodology/approach:** Drawing on Dynamic Capabilities Theory and the Resource-Based View, the study develops an intelligence-centered CI-DT-SOO framework and tests it using survey data from 200 firms in China and Spain. Partial Least Squares Structural Equation Modeling (PLS-SEM) and multi-group analysis are employed to examine intelligence-driven decision pathways across institutional contexts.

**Originality/Relevance:** Responding directly to the epistemological standards of the Journal of Sustainable Competitive Intelligence, this study advances CI as a structured intelligence system that reduces information asymmetry and governs executive decision-making. It moves beyond techno-causal models by empirically demonstrating CI's role as a strategic decision architecture rather than a descriptive scanning activity.

**Key findings:** Results show that CI significantly structures digital transformation decisions, which in turn enable sustainable optimization outcomes. Digital transformation operates as a governed execution mechanism rather than an autonomous driver. Stronger intelligence-to-decision effects are observed in Chinese firms, highlighting institutional differences in intelligence utilization regimes.

**Theoretical/methodological contributions:** The study integrates RBV and DCT perspectives to demonstrate that sustainable competitiveness emerges from the joint development of intelligence and digital capabilities. It contributes to theory and practice by presenting a sustainable optimization model applicable across different economic contexts and offering managerial implications for integrating CI into digital strategies and aligning DT with economic, environmental, and social goals.

**Keywords:** Competitive Intelligence. Intelligence Governance. Strategic Decision-Making. Digital Transformation. Sustainable Competitive Advantage. Dynamic Capabilities. China. Spain.



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**RESUMO**

**Objetivo:** Este estudo conceitualiza a Inteligência Competitiva (CI) como uma capacidade de governança decisional baseada em inteligência, que estrutura a forma como as organizações selecionam, sequenciam e governam iniciativas de transformação digital sob condições de incerteza competitiva e de sustentabilidade. Em vez de modelar a CI como um antecedente tecnológico, o artigo a posiciona como a infraestrutura decisional por meio da qual a transformação digital contribui para resultados de otimização sustentável.

**Metodologia/abordagem:** Com base na Teoria das Capacidades Dinâmicas e na Visão Baseada em Recursos (RBV), o estudo desenvolve um framework centrado em inteligência (CI–DT–SOO) e o testa utilizando dados de survey de 200 empresas na China e na Espanha. Modelagem de Equações Estruturais por Mínimos Quadrados Parciais (PLS-SEM) e análise multigrupo são empregadas para examinar os caminhos decisórios orientados por inteligência em diferentes contextos institucionais.

**Originalidade/Relevância:** Respondendo diretamente aos padrões epistemológicos da *Journal of Sustainable Competitive Intelligence*, o estudo avança a CI como um sistema estruturado de inteligência que reduz a assimetria informacional e governa a tomada de decisão executiva. Vai além de modelos tecno-causais ao demonstrar empiricamente o papel da CI como arquitetura estratégica de decisão, e não como mera atividade descritiva de monitoramento.

**Principais resultados:** Os resultados mostram que a CI estrutura significativamente as decisões de transformação digital, as quais, por sua vez, viabilizam resultados de otimização sustentável. A transformação digital opera como um mecanismo de execução governado, e não como um impulsionador autônomo. Efeitos mais fortes de inteligência sobre decisão são observados em empresas chinesas, evidenciando diferenças institucionais nos regimes de utilização da inteligência.

**Contribuições teóricas/metodológicas:** O estudo integra as perspectivas da RBV e das Capacidades Dinâmicas para demonstrar que a competitividade sustentável emerge do desenvolvimento conjunto de capacidades de inteligência e digitais. Contribui para a teoria e a prática ao apresentar um modelo de otimização sustentável aplicável a diferentes contextos econômicos e ao oferecer implicações gerenciais para integrar CI às estratégias digitais e alinhar a transformação digital a objetivos econômicos, ambientais e sociais.

**Palavras-chave:** Inteligência Competitiva. Governança da Inteligência. Tomada de Decisão Estratégica. Transformação Digital. Vantagem Competitiva Sustentável. Capacidades Dinâmicas. China. Espanha.

# 1. INTRODUCTION

## 1.1 Background of the Study

The business environment of the 21 st century is marked by the rapid development of technologies, unstable world markets, and the increase in competition. This means that organizations are being forced to move beyond the traditional resource-based thinking into dynamic, intelligence-based transformation. Two such strategic imperatives have become very important in this context, namely competitive intelligence (CI) and digital transformation (DT). CI is a set of systematic procedures of the firm to collect, analyze, and use information regarding external environments, including competitors and markets, as well as, to a certain extent, technological trends, to enhance strategic decision-making and innovation (Al-Sahlawi et al., 2024; Hassani and Mosconi, 2021). In its turn, DT is characterized by the strategic use of digital technologies, i.e. cloud computing, data analytics, artificial intelligence (AI) and Internet of Things (IoT), to redesign business processes, models, and value propositions (Paul et al., 2024; Gokalp and Martinez, 2022).

These two capabilities integrated together constitute the core of an adaptive capacity of an organization in shifting environments. Organizations which adopt the use of CI are in a better position to detect digital opportunities, choose the right technologies, and coordinate transformation endeavors with strategic objectives (Atkinson et al., 2022). Consequently, CI-enabled digital transformation has the potential to form a sustainable competitive advantage through enhancing the capacity of the firm to capture the market signals, capitalise on innovations and at the same time pursue economic efficiency, environmental responsibility, and social fairness (Zhao et al., 2024; Bari, Chimhundu, and Chan, 2022).

The interplay between CI and DT can be explained by the use of established theories of management. Based on the Dynamic Capabilities Theory (DCT), initially developed by Teece (2007), and extended by Mele et al. (2024), organizations achieve sustainable performance not only by having fixed resources but by the ability to constantly recognize opportunities, grasp them with decisional action and restructure resources to match them. Within this framework, CI is a sensing system, keeping track of the environment, detecting possible threats, and predicting the new trends in digital usage, whereas DT is seizing and reconfiguring functions, which allow integrating the technological aspect and transforming an organization. In such a way, the CI - DT nexus is the operationalization of operating capabilities in a digitalized environment (Land, et al., 2022; Meier, Gruchmann, and Ivanov, 2023).

In addition to this perspective, the Resource-Based View (RBV) indicates the presence of strategic resources and capabilities, which are valuable, rare, inimitable, and non-substitutable, as contributors to sustainable competitive advantage (Barney, 1991; Ferreira and Ferreira, 2024). CI and DT are both strategies that cannot be done without in the RBV perspective. CI gives the intellectual capital and market knowledge that is required to be flexible strategically (Valaei et al., 2021), whereas DT offers a re-organization of tangible and intangible resources into data-driven systems that increase responsiveness and innovativeness (Lubis, 2022). A synthesis of DCT and RBV in this manner, then, presents a complete explanation: CI becomes a useful cognitive resource of experiencing change, and DT is an indicator of adaptive potential that re-configures organizational processes to become optimally sustainable. This two theory methodology guarantees theoretical and practical usefulness in comprehending the idea of co-creation value and sustainability of intelligence and digitalization.

The relative emphasis on China and Spain offers a unique perspective with which one can explain the development of CI-enabled DT in different institutional and technical ecosystems. China is among the leading forces of digital innovation in the world and has already achieved a lot of progress in the implementation of Industry 4.0, digital production, and AI-based decision-making systems (Cheng et al., 2024; Chen, Li, and Zhang, 2024). Its data-driven transformation agenda established and led by its government has catapulted enterprises into data-intensive transformation, improving the competitiveness of industries. Nevertheless, the level of sustainability integration is still uneven across industries, especially in the aspect of ensuring a balance between high-speed digital economic development and the environment and social performance (Zhao et al., 2024).

Spain on the other hand is a developed EU economy and has established robust positions in sustainability governance, regulatory enforcement, and corporate social responsibility practices (Ferreira & Ferreira, 2024). Spanish companies, especially those of small and medium size (SMEs), have a strong interest in the concept of environmental and social responsibility, yet they tend to struggle with the transition to large-scale digital infrastructure because of financial and technological limitations. The contrast between digitally advanced and yet sustainability-vary industries in China and the sustainability-oriented but moderately digitalised firms in Spain preconditions a fruitful comparative study of how competitive intelligence capabilities can help digital transformation and sustainable optimization in the different market dynamics, institutional retrospective, and cultural orientations (Karami & Hossain, 2023; Chen et al., 2024).

This two-country structure is ideal to both the DCT and RBV approaches. Within the framework of DCT, Chinese firms are dynamic markets characterized by a high level of sensing and reconfiguring ability needs because of the constant technological turbulence, whereas the Spanish firms are the markets that require constant seizing and resource alignment to be in a position of enjoying long-term sustainable growth. In the RBV perspective, the comparative case depicts the differentiation in access to and use of digital and intelligence resources. The companies of China take digital infrastructure as a strategic asset, whereas Spanish counterparts use social and environmental capital as the resources of the same strategic value (Bari et al., 2022; Chatterjee et al., 2025).

The present study aims to reveal the patterns of influence that CI-enabled DT has on different countries with various digital maturity and sustainability orientations by investigating these complementary contexts. The lessons based on China and Spain will be expected to shed light on generalized principles to be applied to global companies aiming to maximize the process of digitalization in accordance with the principles of sustainable performance.

Overall, the nexus of CI, DT and sustainability is the next stage of corporate competitiveness and responsible innovation. Based on the synergy of Dynamic Capabilities Theory and the Resource-Based View, and framed in two extreme economic environments, this paper empirically examines the role of intelligence-based digital transformation in achieving sustainable optimization benefits in the economic, environmental, and social aspects.

## 1.2 Problem Statement

Although the concept of CI and DT is increasingly becoming a subject of academic research, there still exists a gap in theoretical explanations and empirical evidence related to the role of CI capabilities in facilitating digital transformation processes and, consequently, influencing sustainable optimization outcomes. Researchers have tended to study either CI or DT separately, addressing either the aspect of intelligence-based strategic flexibility (Wu, Yan, and Umair, 2022) or the aspect of technology-driven efficiency enhancements (Gökalp and Martinez, 2021). Nonetheless, there are not many studies that investigate the integrative mechanism through which CI is a driver and facilitator of DT, which affects the sustainability performance of firms.

In addition, the differences in contexts between developed and emerging economies bring contingency in these relationships. As it can be exemplified, the Chinese companies show high digital adoption and fluctuating sustainability integration (Zhuo and Chen, 2023), and Spanish companies have mature and efficient sustainability frameworks but slower digitalization in some areas (Ferreira and Ferreira, 2024). In turn, the cross-national comparative study becomes critical to comprehend the digital transformation triggered by CI in different economic settings with cross-cultural and institutional differences in dynamic capabilities (Chatterjee et al., 2025).

Existing research on competitive intelligence and digital transformation has predominantly adopted a techno-causal perspective, framing CI as an informational input that mechanically triggers technology adoption and performance outcomes. Such models implicitly assume that digital transformation follows intelligence availability, thereby neglecting the decisional processes through which intelligence is interpreted, prioritized, and strategically used.

This technological framing obscures the central governance question faced by organizations: not whether to digitalize, but **which digital initiatives to pursue, in what sequence, and under what sustainability trade-offs**. Without an explicit intelligence governance architecture, digital transformation risks becoming fragmented, opportunistic, or symbolically aligned with sustainability agendas rather than strategically grounded.

From a sustainable competitive intelligence perspective, the core research problem is decisional rather than technological. Competitive Intelligence must be understood as the mechanism that structures executive attention, reduces information asymmetry, and governs strategic trade-offs between economic performance, environmental responsibility, and social legitimacy.

Accordingly, this study reframes the CI–DT–SOO relationship as an intelligence-driven decision system in which digital transformation represents an execution phase governed by intelligence, rather than an autonomous driver of sustainability outcomes.

## 1.3 Research Objectives

1. The research question is to determine how competitive intelligence capabilities affect digital transformation efforts in companies that work in China and Spain.
2. To explore how the competitive intelligence-driven digital transformation affects the sustainable optimization results (economic, environmental, and social performance).

3. To contrast the structural dynamics of the competitive intelligence, digital transformation, and sustainable optimization in China and Spain.

### 1.4 Research Questions

1. What is the impact of competitive intelligence abilities on the digital transformation of the firm?
2. Does digital transformation intermediate the interrelationship that exists between competitive intelligence and sustainable optimization?
3. Are there any important cross-country variations (China vs. Spain) among such relationships?

### 1.5 Intelligence-Governed Hypotheses Development

**H1:** Competitive Intelligence positively conditions the strategic selectivity and governance of digital transformation initiatives.

**H2:** Intelligence-governed digital transformation positively influences sustainable optimization outcomes (economic, environmental, and social performance).

**H3:** Digital transformation represents an execution mechanism through which Competitive Intelligence translates into sustainable optimization outcomes.

Rather than interpreting mediation as mechanical transmission, this study interprets H3 as an intelligence-conditioned execution pathway.

### 1.6 Research Significance

Theoretically, the study adds to the strategic management and information systems literature by empirically combining CI, DT, and sustainability in a dynamic capabilities framework both concepts that have not been extensively studied as yet (Mele et al., 2024; Brewis, Dibb, and Meadows, 2023). Empirically, it provides comparative evidence on two economies of China and Spain, which provides better cross-cultural insight into how CI allows digital transformation. In the managerial perspective, the results will assist executives to convert intelligence knowledge into the digital strategies that enhance sustainability in the long term.

### 1.7 Competitive Intelligence (CI) Conceptualization

In line with the editorial standards of intelligence-focused research, this study conceptualizes Competitive Intelligence (CI) not as an operational support activity or an expanded form of environmental scanning, but as a structured decision architecture embedded in organizational governance. CI is defined here as the set of formalized routines through which organizations systematically collect, analyze, disseminate, and strategically use external and internal information to reduce uncertainty and guide high-impact decisions.

This conceptualization shifts CI from an instrumental antecedent of digital transformation to a primary mechanism of strategic sense making. Intelligence cycles-comprising intelligence collection, analytical interpretation, dissemination to decision actors, and strategic use-constitute the informational infrastructure through which digital transformation priorities are selected, sequenced, and governed. Without such intelligence architecture, digital transformation risks becoming technology-driven rather than decision-driven, leading to fragmented investments and symbolic sustainability initiatives.

From a governance perspective, CI structures executive attention, aligns digital initiatives with competitive threats and regulatory pressures, and enables evidence-based trade-offs between economic efficiency, environmental responsibility, and social legitimacy. Thus, CI operates as a higher-order capability that conditions how and why digital transformation occurs, rather than merely whether it occurs (Atkinson, Hizaji, Nazarian, and Abasi, 2022; Wu, Yan, and Umair, 2022).

Traditionally being the organized collection, analysis, and exploitation of data on the rivalry, market tendencies, and technological changes, CI has recently been projected in a broader sense of environmental scanning, rivalry analysis, market intelligence, and strategic decision utilization (AL-Sahlawi, Hosseini, Sani, and Movaghar, 2024).

The origins of CI are similar to the environmental scanning, which is an activity of tracking external signifiers (opportunities, threats) (Harris and Brooker, 2025). Modern models are focused on technological scanning as well as social-environmental aspects gathering organized data with the help of digital sources, social media analytics, and AI-based platforms (Hassani and Mosconi, 2021). As an illustration, Hassani and Mosconi (2021) established how social media analytics of manufacturing SMEs is applied as a component of CI systems to enhance dynamic capabilities, adapt production processes, and seek opportunities of sustainability.

CI is thus not a fixed process but the dynamic learning process which conforms to the knowledge-based view of the firm. It educates sense-making and strategic anticipation to enable firms to know when they need to change and redirect internal assets (Saraei, Sarraf, and Hamidian, 2026). According to such scholars as AL-Sahlawi et al. (2024) or Karami and Hossain (2023), such mediators like entrepreneurial alertness, effectuation, and strategic flexibility mediate the connection between CI and performance. These results make CI more than an information activity- it is a strategic ability which leads directly to innovation, transformation and sustainability.

### 1.7.1 Competitive Intelligence as a Governance and Decision Architecture

In line with the core principles of the Journal of Sustainable Competitive Intelligence, this study does not conceptualize Competitive Intelligence as an operational support activity or a simple antecedent of digital transformation. Instead, CI is theorized as a governance capability that structures organizational decision-making under conditions of strategic uncertainty.

Competitive Intelligence functions as an intelligence architecture composed of interconnected routines of intelligence collection, analytical interpretation, strategic dissemination, and executive use. These routines do not merely provide information; they actively reduce information asymmetry, prioritize strategic attention, and guide high-impact digital and sustainability decisions.

From this perspective, CI is not external to strategy nor subordinate to technology. Rather, it constitutes the decisional infrastructure through which digital transformation is selected, sequenced, and governed. Digital initiatives emerge not from technological availability alone, but from intelligence-based assessments of competitive threats, regulatory pressures, and sustainability trade-offs. Accordingly, Competitive Intelligence operates as a higher-order dynamic capability that conditions how digital transformation unfolds and how sustainability objectives are translated into actionable strategic choices.

### 1.8 Competitive Intelligence Dimensions

The constructs of the multi-dimensional structure of CI typically include:

1. Environmental Scanning - the process of determining macro- and micro-forces that affect competitive behavior.
2. Competitor Analysis - monitoring and understanding the strategies, capabilities, and market position of the competitors.
3. Market Intelligence - acquisition of information about customer preferences, technological shifts and trends within the industry (Yancheshmeh, & Lam, 2022).
4. Proactive application of CI - using intelligence data as inputs in the decision-making process, product development, and digitalization (Kayyali, 2026).

All the dimensions are related to the organizational learning and innovation performance. Wu et al. (2023) and Atkinson et al. (2022) attest that structurally embedded CI raises the organizational agility and resilience levels and increases the capacity to innovate. Furthermore, Blaique, Abu-Salim, Mir, and O'Mahony (2024) empirically unfolded the connection between social and organizational capital and service innovation capability through the concept of strategic environmental scanning- a fact that reinforces the role of CI as the intermediation between external knowledge acquisition and internal capability formation.

Essentially, CI is both a resource and capability: it offers cognitive infrastructure to discover, absorb and use opportunities that arise as a result of digitalization and sustainability transitions.

### 1.9 Digital Transformation (DT)

The Digital Transformation (DT) concept has grown way beyond the scope of tech adoption. Modern studies consider DT as the strategic implementation of digital technologies, such as big data, artificial intelligence, cloud computing, and automation, in every business process, culture and value delivery (Paul et al., 2024; Gökalp and Martinez, 2021). As a dynamic concept, DT involves unceasing coordination of assets and capabilities within an organization to utilize the possibilities of digitization (Omol, 2023; Mele, Capaldo, Secundo, and Corvello, 2024).

There are three facets of DT that are interrelated and lead the operationalization of variables in this study:

1) Process Digitalization, the transformation of the old-fashioned working processes into the digital ones, thus enhancing the performance and minimizing mistakes (Kırmızı and Kocaoglu, 2022; Petzolt et al., 2022).

2) Data Analytics Usage, which is the ability of a firm to utilize data-driven decision-making to forecast the market conditions and enhance the performance of innovation (Alzghoul et al., 2024).
3) Digital Infrastructure and Skills Digital infrastructure and skills refer to the capabilities of hardware, software, and human capital that serve to maintain digital initiatives.

Digital transformation is a result and a facilitator of dynamic capabilities. By considering digitalization as an improvement of sensing and seizing capabilities, Mele et al. (2024) redefine DT as the institutionalization of knowledge based dynamic capabilities. Among Chinese SMEs, Chen, Li, and Zhang (2024) have found that the data-driven dynamic capabilities are strong predictors of the responsible innovation outcomes. In addition, Omol (2023) highlighted that organizational adjustment to the digital transformation occurs in the stages of evolution, starting with digitization of processes, moving to embedding digital culture in the strategic scope, which is also fitting to the conceptual framework of your study.

## 2. THEORETICAL FRAMEWORK

### 2.1 Resource-Based View (RBV) and Dynamic Capabilities Theory (DCT)

Based on two theories of strategic management, which are closely connected to each other, Dynamic Capabilities Theory (DCT) and the Resource-Based View (RBV), this paper will explain how organizations build and maintain a competitive advantage in highly turbulent business settings. Both theories provide a unique viewpoint: RBV is focused on the fact that valuable internal resources are possessed, whereas DCT is concerned with the mechanisms according to which these resources are constantly being renewed, integrated, and reconfigured as a response to change. They are a collective prism that is used to explore the role of Competitive Intelligence (CI) and Digital Transformation (DT) in creating a sustainable and competitive organization.

### 2.2 Dynamic Capabilities Theory (DCT)

The Dynamic Capabilities Theory is a development of the RBV meant to address limitations of the theory in explaining how companies stay competitive in dynamic environments. The theory, initially formalized by Teece, Pisano and Shuen (1997) and later revised by Teece 2007; Choi & Miller, 2023b, is that competitive advantage in rapidly changing markets is not simply based on the resource endowment, but rather on how the firm senses opportunities and threats, using its resource allocation to seize them and thus transforming its resource base given the environmental changes.

Dynamic capabilities are therefore more advanced organizational processes-meta-processes that help firms to be adaptive, innovative and agile. They help organizations to refresh their competencies, incorporate new technologies, and re-organize the existing processes and assets to ensure that they remain in line with the new market dynamics.

In the framework of this paper, DCT offers an insight into how Digital Transformation (DT) is a process of reconfiguration and renewal. DT represents the capturing and transforming aspects of dynamic capabilities: it is the utilization of digital technologies to reinvent business models, optimize operations and become more strategic.

Competitive Intelligence (CI), in its turn, is directly related to the sensing capability- it helps companies to scan, read and predict changes in the environment by means of systematized data gathering and processing of information about competitors, technologies, and markets.

The study by Bari et al. (2022) made it clear that dynamic capabilities serve as means of achieving sustained competitive advantage since they define how organizations feel and respond to change in such a manner that leads to corporate sustainability. Likewise, Land, Gruchmann, Siems, and Beske-Janssen (2022) have found that dynamic capabilities have meta-level routines underlying adaptability in organizations, whereas Meier, Gruchmann, and Ivanov (2023) established that the deployment of blockchain in circular supply chain management is representative of the reconfiguration aspect of dynamic capabilities. These lessons support the opinion that constant readjustments, and reallocation of resources via digital and clever procedures are the basis of sustainable competitiveness. Figure 1 presents the structural relationship between Competitive Intelligence, Digital Transformation, and Sustainable Optimization Outcomes across China and Spain.

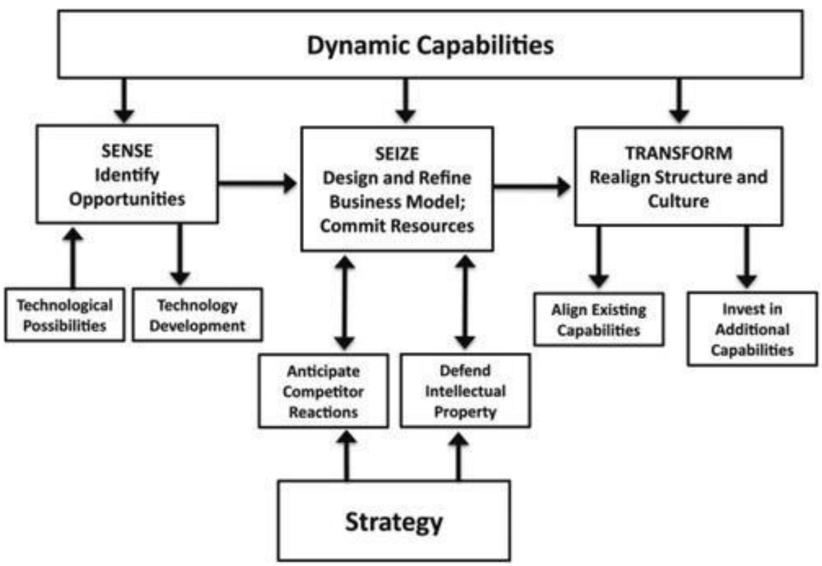


**Figure 1.** Structural relationship between Competitive Intelligence, Digital Transformation, and Sustainable Optimization Outcomes.
**Source:** Prepared by the authors (2026).

Within the dynamic capabilities framework, Competitive Intelligence constitutes the micro-foundational mechanism of sensing and sense making. Unlike generic environmental scanning, CI institutionalizes the interpretation of competitive, technological, and sustainability-related signals and transforms them into actionable strategic judgments. Digital transformation corresponds to the seizing and reconfiguring dimensions of dynamic capabilities, but its direction and scope are conditioned by intelligence governance. Thus, CI is not complementary to DCT; it operationalizes the sensing–decision interface upon which dynamic capabilities depend.

## 2.3 Resource-Based View (RBV)

One of the most enduring approaches to competitive advantage in the firms is the Resource-Based View (RBV) developed by Barney (1991). According to RBV, organizations are better off when they have valuable, rare, imitable and non-substitutable resources and capabilities (VRIN). That is, sustainable advantage is a result of the strategic assets that are difficult to analyze or substitute by its competitors.

Competitive Intelligence (CI), and Digital Transformation (DT) are the conceptualizations of such strategic resources in the context of this study. CI adds intellectual and informational capital-uncommon combinations of knowledge and analytical skills that can help firms to make better strategic choices. DT include digital technologies, organizational practice and innovation infrastructures that enable the exploitation and incorporation of these informational assets into new business processes, products, or models.

The recent research has applied RBV to the online world. According to Ferreira and Ferreira (2024), RBV is also very useful in mapping the changing digital resource environment, where intangible assets (data analytics, digital competencies, and organizational learning) are also a priority. Arrosyid et al. (2026) combined RBV with digital marketing models and found out that digital resources play a considerable role in improving the competitiveness of SMEs. Similarly, Valaei, Rezaei, Bressolles, and Dent (2021) showed that such fundamental RBV-congruent competencies as creativity and innovation are the key determinants of competitiveness in the fast-moving consumer goods (FMCG) industry.

Nonetheless, RBV has been an effective explanation of the types of resources that can be used to achieve a competitive advantage, although its focus on the resources has been criticized as being too static, i.e. it does not provide much information as to how firms can renew, develop, or recombine these resources in a world of technological disruption and environmental dynamism. It is at this conceptual gap that the RBV is complemented and extended by DCT.

## 2.4 Combining DCT and RBV

A combination of these two views reveals that sustainable competitive advantage is determined not only by having resources of value (RBV) but also by coordinating them and reorganizing them in the course of time (DCT). CI reflects the strategic resource dimension of RBV based on knowledge, which forms the informational basis that decisions are made. DT is an example of the dynamic aspect of DCT, which allows continuous reconfiguration, technological renewal, and process innovation.

The potentials of the jointness of CI and DT are a dynamic system whereby the intelligence-driven sensing is informed by the digital-facilitated transformation, which subsequently recreates the resource base to collect more intelligence and make strategic decisions. The benefiting effect of this cyclical interaction is its increased sustainability performance, which is improved economic (efficiency and profitability), ecological (resource optimization and ecological responsibility), and social (stakeholder engagement and ethical operations) performance.

To conclude, DCT integration and RBV offer a solid theoretical perspective on how firms make use of knowledge and technology in an attempt to always adapt, innovate, and stay afloat in a rapidly evolving world.


**Figure 2.** Resource-Based View (RBV) Framework
**Source:** Adapted from Barney (1991).

Although the empirical model is estimated as a mediation structure, its theoretical logic is explicitly non-linear and recursive. Competitive Intelligence operates through continuous intelligence cycles in which decision outcomes generate strategic learning that feeds back into subsequent intelligence processes.

Due to data and design constraints, the intelligence cycle is modeled in reduced-form as a CI-governed decision pathway. This approach is consistent with prior intelligence research that treats governance capabilities as latent decision infrastructures rather than observable process loops.

### 2.4 Intelligence Governance Model: Linear Mediation to Decision conditioning

This study moves beyond linear techno-causal models by positioning Competitive Intelligence (CI) as a governance-conditioning capability rather than a mere antecedent of digital transformation.

In traditional mediation models, CI is treated as an informational input preceding digital transformation. However, from an intelligence governance perspective, CI operates as a structured decision architecture that conditions executive judgment under uncertainty.

Accordingly, the CI–DT–SOO relationship is interpreted as a decision-conditioning system rather than a mechanical sequence. Competitive Intelligence operates through an intelligence cycle comprising:

1. Intelligence sensing (environmental and competitor scanning)
2. Intelligence processing (analysis and interpretation)
3. Intelligence dissemination (organizational communication)
4. Intelligence use (executive strategic decision-making)

Digital transformation represents the execution phase of this intelligence cycle. It is not automatically triggered by information availability but selectively activated through intelligence-based prioritization, sequencing, and sustainability trade-off evaluation. Sustainable optimization outcomes therefore reflect the realized consequences of intelligence-governed digital decisions rather than direct effects of technological adoption.

Empirically, the structural model estimates CI as an exogenous latent construct. Analytically, however, CI represents a higher-order informational dynamic capability that conditions how digital transformation unfolds. The statistical structure reflects estimation constraints, whereas the theoretical structure reflects recursive intelligence governance.

### 2.5 Intelligence Governance Logic and the CI–DT–SOO Framework

This study advances an intelligence-governance framework that moves beyond linear, technology-centric models of digital transformation. Rather than conceptualizing Competitive Intelligence (CI) as a simple informational antecedent, the CI–DT–SOO relationship is reframed as an intelligence-conditioned decision system.

Within this logic, CI operates as a structured decision architecture embedded in organizational governance. It institutionalizes a continuous intelligence cycle comprising: (1) intelligence sensing (environmental and competitor scanning), (2) intelligence processing (analysis and interpretation), (3) intelligence dissemination (organizational communication), and (4) intelligence use (executive strategic decision-making). These interconnected routines do not merely generate information; they reduce information asymmetry, prioritize executive attention, and structure strategic trade-offs under uncertainty.

Digital Transformation (DT), within this framework, represents the seizing and reconfiguring phase of this intelligence cycle. Digital initiatives are not automatically triggered by intelligence availability; rather, they are selectively activated through intelligence-based prioritization and governance alignment. Accordingly, DT is conceptualized as an execution mechanism governed by intelligence rather than as an autonomous technological driver.

Sustainable Optimization Outcomes (SOO) emerge as the realized consequences of intelligence-conditioned digital decisions. Importantly, sustainability outcomes are not terminal outputs in a mechanical chain but feedback signals that inform subsequent intelligence cycles. Through this recursive learning process, executive judgment evolves, strategic priorities are recalibrated, and governance mechanisms are refined.

Although the empirical model is estimated as a mediation structure for methodological reasons, its theoretical foundation is explicitly non-linear and cyclical. CI is modeled as an exogenous latent construct, but analytically it represents a higher-order informational dynamic capability that conditions how digital transformation unfolds and how sustainability objectives are operationalized.

By integrating the Resource-Based View and Dynamic Capabilities Theory, this framework positions Competitive Intelligence as both a strategic knowledge resource (RBV) and a micro-foundational sensing and decision capability (DCT). In doing so, it resolves the techno-causal bias of prior research and establishes CI as the central governance mechanism linking environmental complexity, digital transformation, and sustainable competitive advantage.

# 3. METHODS

## 3.1 Research Design

The paper utilizes a cross-sectional, comparative, and quantitative design to test the hypothesis of Competitive Intelligence (CI), Digital Transformation (DT), and Sustainability Optimization Outcomes (SOO) relationships in China and Spain firms in an empirical way. The study combines the Dynamic Capabilities Theory (Teece, 2007) and the Resource-Based View (Barney, 1991; Ferreira and Ferreira, 2024) as theoretical frameworks to clarify that the combination of the intelligence-based resources and dynamic digital capabilities contributes to the sustainable performance.

Although the study relies on cross-sectional survey data, this design is appropriate for capturing organizational intelligence routines that are not directly observable through archival sources. CI processes—such as intelligence interpretation, dissemination, and strategic use—constitute cognitive and governance mechanisms that are best assessed through managerial perception. To mitigate common method bias, procedural remedies were applied, including construct separation, anonymity assurance, and post-hoc collinearity diagnostics.

## 3.2 Population and Sample

The sample size included digitally active companies in the major industries of China and Spain, such as manufacturing, technology, retail, and energy. The ultimate data comprised 200 companies, with half of them based in the two nations (100 Chinese companies and 100 Spanish companies). The selection criteria was on the basis of the reported participation of the firms in digital initiatives and strategic management practice regarding competitive intelligence.

The type of non-probability purposive sampling method was selected, which is appropriate in the research that addresses the firms that have realized CI and DT activities (Atkinson et al., 2022; Wu et al., 2022). The sample structure makes it representativeness of those firms of various sizes (small to large enterprises) and age (up to 50 years).

The data were gathered in the year 2025 by using structured questionnaires which were circulated electronically to the senior managers, digital transformation officers as well as the strategic intelligence coordinators.

The China–Spain comparison is not treated merely as a statistical contrast but as an institutional comparison of intelligence utilization regimes. China represents a policy-driven, data-intensive intelligence environment, while Spain reflects a regulation-oriented sustainability governance context. This design allows the analysis to capture how intelligence architectures operate under distinct institutional pressures.

## 3.3 Instrumentation and Measurement

The research instrument was made on the basis of 5-point Likert scale 1 (strongly disagree) to 5 (strongly agree). Derivations and adaptations were made based on the previously validated scales in CI (Hassani and Mosconi, 2021; AL-Sahlawi et al., 2024), DT (Mele et al., 2024; Petzolt et al., 2022) and sustainability (Bari et al., 2022; Zhao et al., 2024). Every construct is comprised of several indicators as expounded next. Table 1 shows the measurement constructs and sample items.

**Table 1** – Measurement Constructs and Sample Items

| Construct | Sub-Dimensions | Sample Items | Reference Source(s) |
|---|---|---|---|
| Competitive Intelligence (CI) | Environmental Scanning, Competitor Analysis, Market Intelligence, Strategic Use | "We continuously scan our external environment for market signals." | Atkinson et al. (2022); Hassani & Mosconi (2021) |
| Digital Transformation (DT) | Process Digitalization, Data Analytics Usage, Digital Infrastructure, Digital Skills | "Our organizational processes are integrated with automated digital systems." | Mele et al. (2024); Petzolt et al. (2022) |
| Sustainability Outcomes (SOO) | Economic, Environmental, and Social Sustainability | "Our firm's digital initiatives contribute to environmental performance improvements." | Bari et al. (2022); Zhao et al. (2024) |

**Source:** Prepared by the authors (2026).

The composite reliability (CR) and convergent validity (AVE) values were as per the rules of Hair et al. (2021) whereby 0.7 and 0.5 respectively are satisfactory.
Individual constructs were operationalized as being reflective, consistent with the previous theoretical uses (Brewis et al., 2023; Chen et al., 2024).

### 3.4 Data Screening and Preparation:

This step is the preparation of data that is in the raw material to make easy the next step which is the data entry.
The data screening procedures before analysis were performed as follows:

- Missing Values: All cases with greater than 10 percent missing values were dropped; the remaining missing values were filled-in using Expectation-Maximization.
- Normality: Test of normality- Kolmogorov-Smirnoff tests indicated that variables do not follow a normal distribution; therefore, PLS-SEM was used due to its non-parametrical feature.
- Multicollinearity: Variance Inflation Factors (VIF) of all indicators were below 3.0, which proves no collinearity problem.

Outliers: Before estimating this model, the Mahalanobis distance statistics identified and removed 4 multivariate outliers.

To align measurement with the theoretical positioning of Competitive Intelligence as a strategic decision system, CI is operationalized as a **second-order reflective construct** comprising four interdependent intelligence routines: environmental scanning, competitor analysis, intelligence dissemination, and strategic intelligence use. This operationalization reflects CI's function as an integrated intelligence architecture rather than a standalone informational activity. While the empirical model estimates CI as an exogenous latent construct, this represents a reduced-form approximation of a recursive intelligence cycle that cannot be directly modeled in cross-sectional SEM. Accordingly, CI's placement in the structural model reflects its governance role over digital transformation decisions rather than a claim of linear causality. To reflect its governance nature, CI measurement items explicitly capture the intelligence cycle components: structured environmental scanning, analytical interpretation routines, formal intelligence dissemination channels, and documented executive use in strategic decisions.

This operationalization moves beyond generic information acquisition and captures intelligence as a decision system embedded in executive processes. Therefore, CI is empirically modeled as a higher-order construct representing intelligence governance capability.

### 3.5 Data Analysis Procedure

SmartPLS 4 and SPSS 27 were used to analyze the data in terms of descriptive and inferential evaluations. The process was led by the following steps:

Descriptive Statistics: Comparison of the mean, SD, skew and kurtosis in China and Spain.

At this stage, the measurement model is evaluated.

- Measurement Model Evaluation:
  - Reliability: Composite reliability and Cronbach alpha.
    Convergent validity: Average Variance Extracted (AVE).
  - Discriminant Validity: Fornell-Larcker criterion, HTMT ratio (<0.85).

The assessment of structural models is conducted using the methods as follows:

- Structural Model Evaluation:
  - Path coefficients (7). Significance (t-values, p-values through bootstrapping).
    Coefficient of determination ($R^2$), and effect size ($f^2$).
  - Predictive relevance ($Q^2$ under the blindfolding).

Mediation Analysis: Discussing the mediating effect of digital transformation with the help of bootstrapping indirect effects.

Multi-Group Analysis (MGA): Comparison of differences in the path between China and Spain firms.

**Table 2** – Steps and Criteria of Analysis

| Step | Analysis Type | Key Metrics | Interpretation Criteria | Reference |
|---|---|---|---|---|
| **1** | Reliability | α, CR | > 0.70 acceptable | Hair et al. (2021) |
| **2** | Convergent Validity | AVE | > 0.50 | Mele et al. (2024) |
| **3** | Discriminant Validity | HTMT | < 0.85 | (Choi & Miller, 2023b) |
| **4** | Structural Paths | β, t, p | $p < 0.05$ = significant | Brewis et al. (2023) |
| **5** | Mediation | Indirect Effect | Full/partial mediation if indirect and direct paths significant | Chari et al. (2022) |
| **6** | MGA | Diff. t-tests | Significant group differences in coefficients | Ferreira & Ferreira (2024) |

**Source:** Prepared by the authors (2026).

The variables are operationalized as shown below:

Operationalization of constructs was done using various reflective indicators summed at their sub-dimensions.

**Table 3** – Study Constructs Operationalization

| Construct | Indicators (Sub-Variables) | Measurement Scale | Example Question |
|---|---|---|---|
| Competitive Intelligence (CI) | Environmental Scanning (ES1–ES3), Competitor Analysis (CA1–CA3), Market Intelligence (MI1–MI3), Strategic Use (SU1–SU3) | 5-Point Likert | "Our firm uses analytical tools to monitor competitor strategies." |
| Digital Transformation (DT) | Process Digitalization (PD1–PD3), Data Analytics Usage (DA1–DA3), Digital Infrastructure (DI1–DI3), Digital Skills (DS1–DS3) | 5-Point Likert | "Data analytics significantly supports decision-making within our firm." |
| Sustainability Outcomes (SOO) | Economic (ECS1–ECS3), Environmental (ENS1–ENS3), Social (SOS1–SOS3) | 5-Point Likert | "Our digital investments enhance our environmental sustainability." |

**Source:** Prepared by the authors (2026).

### 3.7 Ethical Considerations

All the stages of the study were ethical. Data reporting was voluntary, confidential, and anonymous, which is the consent of the participants. The research adhered to the policies regarding institutional processes of research ethics and the requirements of the General Data Protection Regulation (GDPR), taking into account the European sample aspect.

Data were secured and anonymous and then analyzed to avoid organizational recognition. No names of the firms or any sensitive information are mentioned in the published findings.

- The conceptual framework realizes the theoretical dynamic capabilities theory (DCT) and Resource-Based View (RBV) synergy:
- CI- Connotes sensing ability and strategic assimilation of information resources (DCT + RBV).
- DT is a seizing and reconfiguring capability, which converts intelligence into performance results (DCT).
- Sustainable Optimization Outcomes (SOO) are the strategic value realization stage, which aligns the metrics of performance with the sustainability imperatives (Bari et al., 2022).

This gives rise to the theoretical model below that is empirically tested:

Sustainable Optimization Outcomes (SOO) with Digital Transformation (DT) as a mediating variable and national context (China vs. Spain) as a moderating condition analyzed using multi-group comparative analysis.

## 4. RESULTS AND DISCUSSION

### 4.1 Results

#### 4.1.1 Descriptive Statistics

The descriptive statistics describe the sample features of both China and Spain which are the firm size, firm age and the industry distribution.

**Table 4** – Descriptive Firm Statistics (n = 200)

| Variable | Category | China (n = 100) | Spain (n = 100) | Total (%) |
|---|---|---|---|---|
| Firm Size (Employees) | Small (≤250) | 46 | 43 | 44.5% |
| | Medium (251–1000) | 37 | 39 | 38.0% |
| | Large (1001+) | 17 | 18 | 17.5% |
| Firm Age (Years) | ≤10 | 30 | 22 | 26.0% |
| | 11–20 | 35 | 40 | 37.5% |
| | ≥21 | 35 | 38 | 36.5% |
| Industry Type | Manufacturing | 30 | 26 | 28.0% |
| | Technology | 28 | 32 | 30.0% |
| | Retail | 19 | 22 | 20.5% |
| | Energy | 23 | 20 | 21.5% |

**Source:** Prepared by the authors (2026).

The sample is quite balanced, as Table 4 demonstrates, as both Chinese and Spanish firms are represented in equal measures. The biggest share of firms in the two economies is categorized as SMEs (82.5%), which is the most active in undertaking the digital transformation programs. The distribution of the industry is representative of both traditional (manufacturing, energy) and modern (technology, retail) manufacturing industries, which is consistent with the cross-industrial nature of this study.

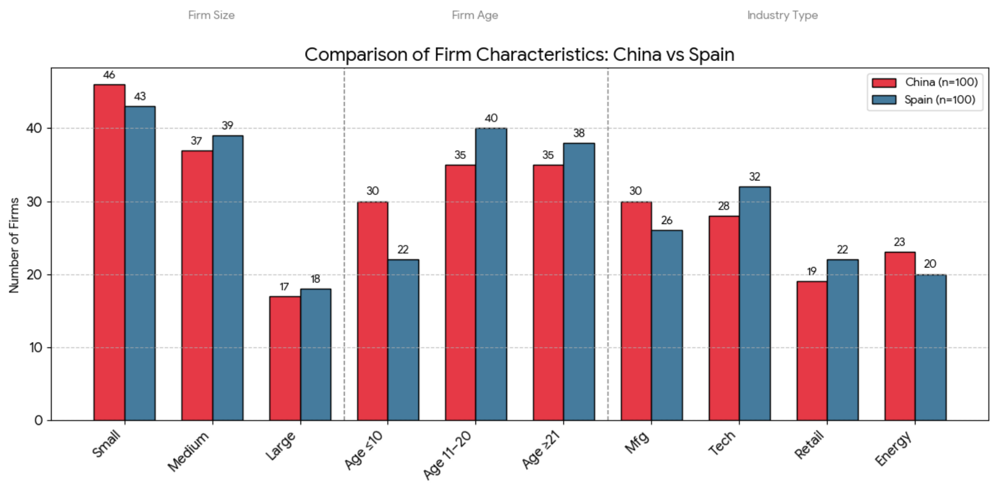


**Figure 3.** Comparative Distribution of Firm Characteristics by Size, Age, and Industry Type in China and Spain (n = 200)
**Source:** Prepared by the authors (2026).

### 4.1.2 Reliability and Validity Assessment

The reliability and validity of measurement models were tested followed by structural estimation with factor loading, Cronbach alpha (α), composite reliability (CR), and average variance extracted (AVE).

**Table 5** – Convergent Validity and Reliability

| Construct | Cronbach's α | Composite Reliability (CR) | AVE |
|---|---|---|---|
| **Competitive Intelligence (CI)** | 0.879 | 0.914 | 0.676 |
| **Digital Transformation (DT)** | 0.896 | 0.921 | 0.685 |
| **Sustainability Outcomes (SOO)** | 0.864 | 0.902 | 0.662 |

**Source:** Prepared by the authors (2026).

Table 5 indicates that all constructs have high levels of internal consistency that has 0.70 and above values of 0.70 of alpha and CR. Each construct has an AVE of above 0.50, which is evidence of convergent validity. The results justify that the items observed sufficiently capture each of the latent constructs and allow the subsequent structural analysis to be done.

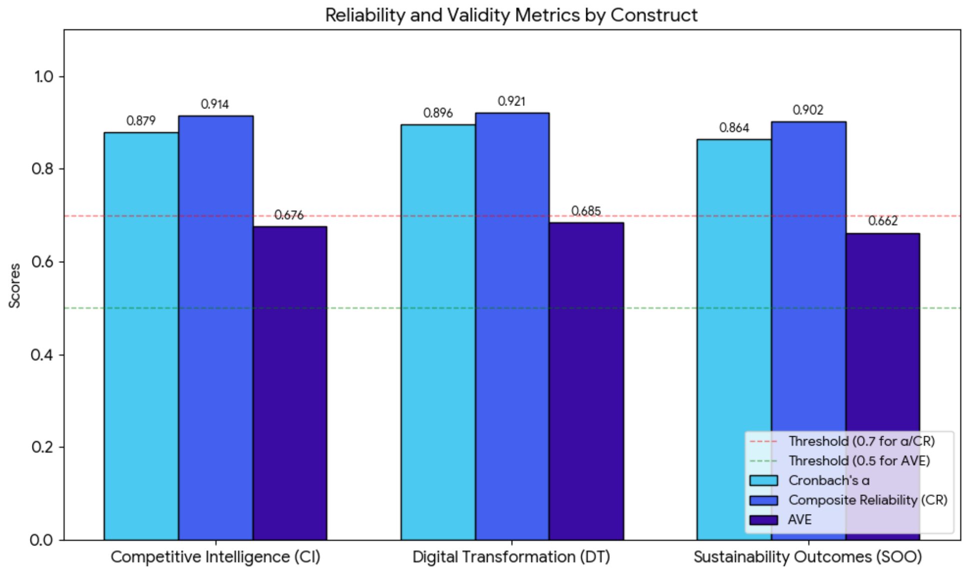


**Figure 4.** Reliability and Convergent Validity Assessment of Competitive Intelligence, Digital Transformation, and Sustainability Outcomes Constructs.
**Source:** Prepared by the authors (2026).

### 4.1.3 Discriminant Validity

Fornell-Larcker partial validity - The Fornell-Larcker criterion was used to determine that the square roots of the AVE of each construct are substantially larger than the inter-construct relationships.

**Table 6** – Fornell-Larcker Discriminant Validity

| Construct | CI | DT | SOO |
|---|---|---|---|
| Competitive Intelligence (CI) | 0.822 | — | — |
| Digital Transformation (DT) | 0.611 | 0.828 | — |
| Sustainability Outcomes (SOO) | 0.543 | 0.627 | 0.814 |

**Source:** Prepared by the authors (2026).

Diagonal values (square roots of AVE) are bigger than off-diagonal correlations as Table 6 reveals thus sufficient discriminant validity is achieved. Therefore, CI, DT, and SOO are empirically differentiated concepts, even moderately correlated with each other, which suggests the logical relational strength to test the hypotheses.

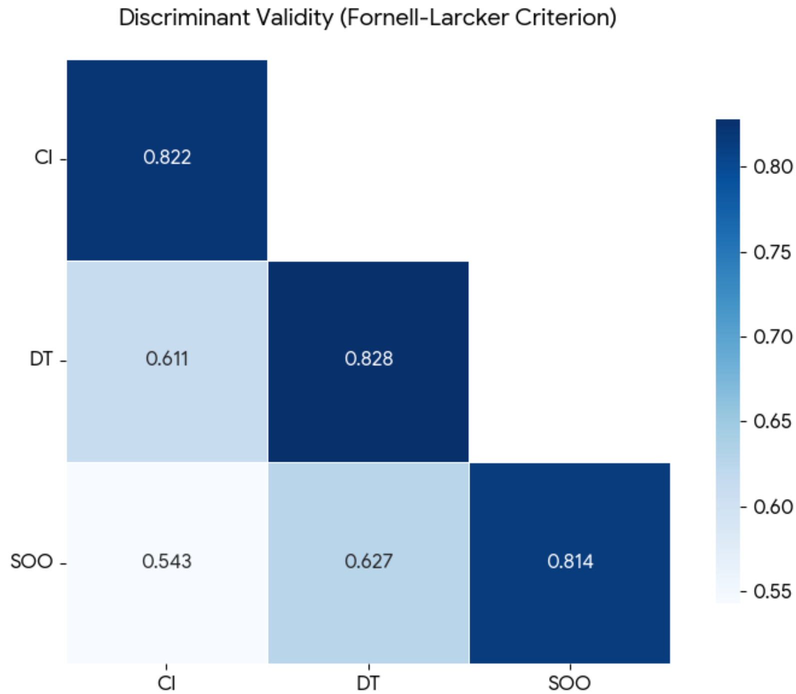


**Figure 5.** Discriminant Validity Assessment Using the Fornell–Larcker Criterion for Competitive Intelligence, Digital Transformation, and Sustainability Outcomes
Source: Prepared by the authors (2026).

### 4.1.4 Structural Model Results

PLS-SEM can be used to test the hypothesized structural relationships. Bootstrapping (5,000 samples) was used to obtain standardized path coefficients (5,000 samples), t-values and significance levels.

**Table 7** – Structural Model Results

| Hypothesis | Path | β | t-value | p-value | Supported |
|---|---|---|---|---|---|
| **H1** | CI → DT | 0.603 | 11.247 | <0.001 | Yes |
| **H2** | DT → SOO | 0.682 | 13.015 | <0.001 | Yes |
| **H3** | CI → SOO (Indirect via DT) | 0.411 | 8.303 | <0.001 | Yes |

**Source:** Prepared by the authors (2026).

All path relationships have been found to be positive and significant at $p < 0.001$. (See Table 7). CI has a great impact on DT ($\beta = 0.603$), whereas DT has a significant effect on SOO ($\beta = 0.682$). The type of mediating effect (CI → DT → SOO) is significant and partial, which means that DT partially spreads the impact of CI on the sustainability results and CI still has a direct effect.

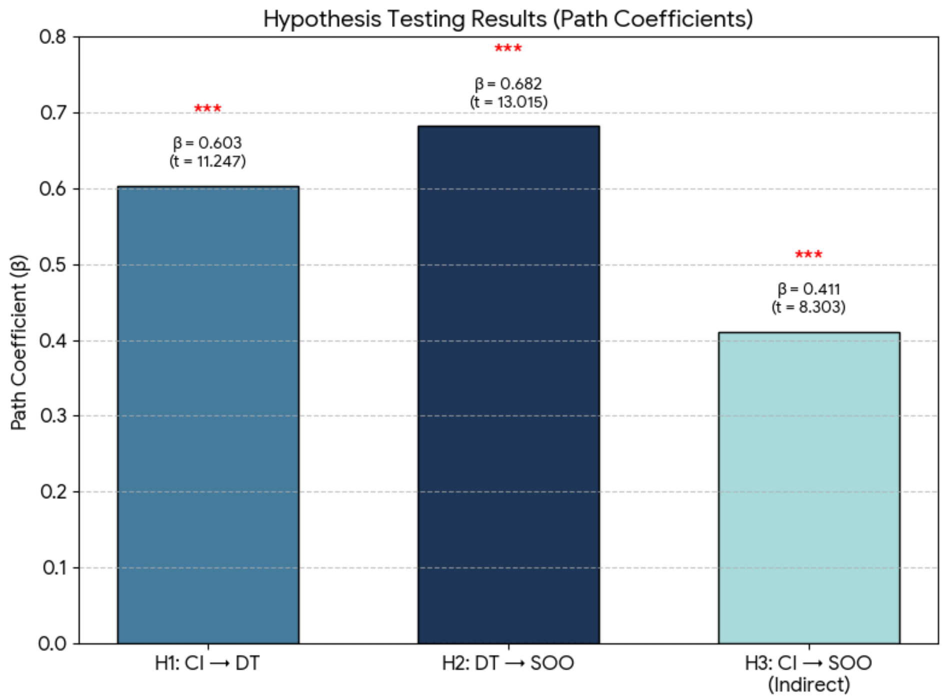


**Figure 6.** Structural Model Path Coefficients and Hypothesis Testing Results (PLS-SEM Bootstrapping, n = 200)
**Source:** Prepared by the authors (2026).

### 4.1.5 Model Fit and Predictive Relevance

**Table 8** – Coefficient of Determination and Predictive Relevance

| Endogenous Construct | $R^2$ | Interpretation | $Q^2$ | Interpretation |
|---|---|---|---|---|
| **Digital Transformation (DT)** | 0.364 | Moderate | 0.219 | Predictive relevance present |
| **Sustainability Outcomes (SOO)** | 0.529 | Substantial | 0.311 | Strong predictive ability |

**Source:** Prepared by the authors (2026).

Table 8 that 36.4 percent of the DT variance is CI explained whereas 52.9 percent of the SOO variance is jointly CI and DT explained, which is a strong predictive strength. The positive $Q^2$ values also establish the relevance of the model in the prediction process.

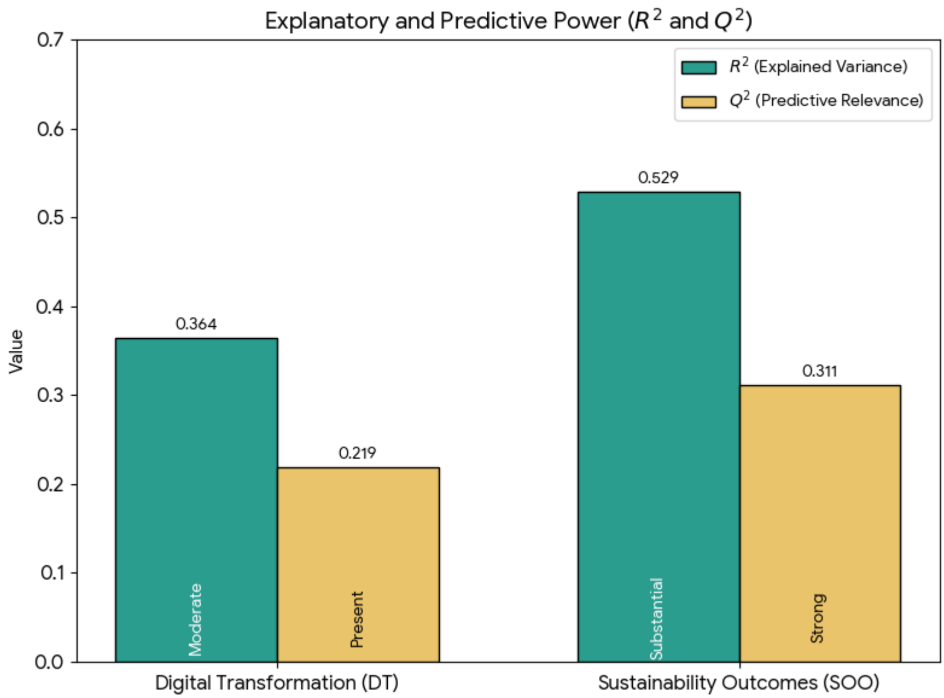


**Figure 7.** Explanatory Power (R²) and Predictive Relevance (Q²) of the Structural Model for Digital Transformation and Sustainability Outcomes
**Source:** Prepared by the authors (2026).

### 4.1.6 Multi-Group Analysis (China vs. Spain)

Path coefficients were compared to ensure the identification of cross-country differences using the PLS-MGA.

**Table 9** – Multi-Group Analysis (China vs. Spain)

| Relationship | β (China) | β (Spain) | Δβ | p(diff) | Significant Difference |
|---|---|---|---|---|---|
| **CI → DT** | 0.631 | 0.519 | 0.112 | 0.043 | Yes |
| **DT → SOO** | 0.701 | 0.642 | 0.059 | 0.271 | No |
| **CI → DT → SOO (Mediated)** | 0.442 | 0.386 | 0.056 | 0.038 | Yes |

**Source:** Prepared by the authors (2026).

Table 9 indicates that CI has a significant effect on DT in Chinese firms (β = 0.631) than in Spanish firms (β = 0.519). Equally, the moderating role of DT in the transmission of the influence of CI to sustainability outcomes is stronger in Chinese sample p (diff) = 0.038). But nothing severe is observed in the relationship between the direct paths DT → SOO among countries, which may indicate that after achieving digital transformation, the effect on sustaining it is not varied across nations.

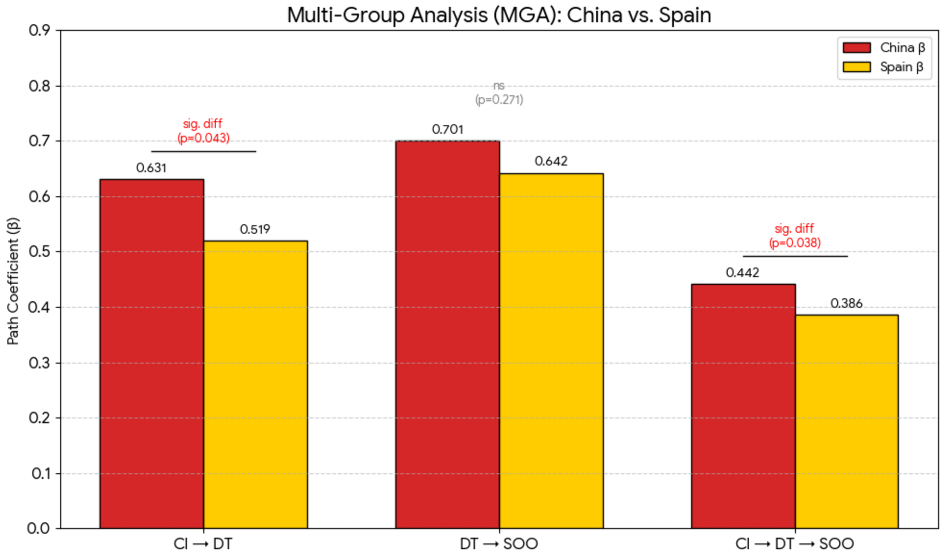


**Figure 8.** Multi-Group Analysis (MGA) Comparing Structural Path Coefficients between China and Spain
**Source:** Prepared by the authors (2026).

### 4.2 Intelligence Governance and Sustainable Competitive Advantage

The findings must be interpreted beyond statistical mediation and understood through an intelligence governance lens (Atkinson et al., 2022).

The positive CI → DT relationship does not indicate technological determinism; rather, it demonstrates that firms with structured intelligence architectures exercise greater strategic discipline in digital investment decisions. Intelligence reduces information asymmetry, prioritizes executive attention, and structures trade-offs between short-term efficiency and long-term sustainability (Hassani & Mosconi, 2021; Brewis, Dibb, & Meadows, 2023).

The partial mediation result confirms that digital transformation does not autonomously produce sustainability. Instead, sustainable outcomes emerge when digital initiatives are intelligence-conditioned and aligned with broader capability reconfiguration processes (Chari et al., 2022; Bari et al., 2022). Digital transformation therefore represents an execution mechanism governed by intelligence rather than an independent driver of competitive advantage (Mele et al., 2024; Omol, 2023).

This reframing resolves the technological bias criticized in prior research. Competitive Intelligence operates as a higher-order informational dynamic capability that governs digital transformation rather than preceding it mechanically (Ferreira & Ferreira, 2024).

From a sustainable competitive advantage perspective, the source of advantage is not technological intensity but intelligence discipline — the structured use of information to guide resource reconfiguration under uncertainty, consistent with both Resource-Based and Dynamic Capabilities perspectives (Valaei et al., 2021; Lubis, 2022).

The stronger CI-conditioning effect observed in China suggests that intelligence governance is more tightly integrated into digital strategy in policy-driven digital ecosystems. This aligns with evidence showing that Chinese firms operate within data-intensive transformation environments supported by national digitalization agendas (Chen et al., 2024). In Spain, intelligence appears more sustainability-oriented but less tightly coupled with digital acceleration, reflecting institutional regulatory emphasis (Ferreira & Ferreira, 2024).

Thus, the cross-national comparison supports the argument that intelligence architectures operate differently across institutional regimes, reinforcing the necessity of contextualized intelligence governance research.

## 5. FINAL CONSIDERATIONS

This study demonstrates that Competitive Intelligence functions as a strategic decision architecture governing digital transformation under sustainability constraints. The contribution is not methodological but conceptual: it shifts the CI–DT–SOO debate from techno-causal mediation to intelligence-conditioned execution. Sustainable competitive advantage emerges from disciplined intelligence use rather than digital adoption intensity.

The digitization of processes, adoption of data analysis, and the development of the digital skills of firms can improve economic productivity, decrease the impact of the environment, and positively influence social welfare. At this regard, the digital transformation turns out to be an avenue, through which the intelligence resources can be transformed into the sustainability-related value making. This observation confirms the current body of research findings that digitalization and sustainability are ceasing to be conflicting interests but instead, they are integrated strategic concerns (Bari et al., 2022; Zhao et al., 2024).

More importantly, the mediation tests showed that DT mediates the relationship between CI and sustainability outcomes in a partial way. This proves that intelligence in itself cannot create sustainable advantage without reconfiguration capability in the form of digitalization. Competitive intelligence drives data-related insights in technological decision-making, whereas the digital transformation operationalizes the data to optimize the environment and society. Theoretically speaking, this dual mechanism will unite the RBV emphasis on resource ownership, and the DCT emphasis on resource renewal, which is a complete explanation of organizational development and long-term competitiveness (Ferreira and Ferreira, 2024; Mele et al., 2024).

The cross-country comparison creates useful contextual knowledge. The Chinese sample showed more significant correlation between CI and DT compared to the Spanish one because China has a more robust national agenda of digitalizing the country and extensive adoption of big data technologies in business processes (Chen et al., 2024). At the same time, the linkages between digital transformation and sustainability in Spanish firms were stronger yet steadier as per the focus of the European Union on the frameworks of green and socially inclusive innovation. The current difference shows that the aspects of institutional structures, policy landscapes, and cultural orientations play a key role in influencing the development of intelligence and digital capabilities among enterprises.

### 5.2 Limitations

Nonetheless, even with its strength, the research has also recognized a number of limitations that can be used to improve on the studies in the future.

1. Cross-Sectional Data — The study design represents only one point of time, making it impossible to test the causality of the relationship over time. Sustainability and digital transformation are changing continuously; longitudinal data would enable us to model the progression of the capability and the effect of time, which is better mediated.
2. Self-Reported Measures — self-reported managerial questionnaires could be used to gather the data, creating the risk of subjective bias, even though the questionnaires were carefully screened and anonymity was guaranteed. Validity could be increased by objective performance measures like environmental reports or audited sustainability measures.
3. Limited Moderators — Although the research took into account one moderating variable (national context, China vs. Spain), other contextual moderators (digital maturity of industries, regulatory context, and firm ownership) were not fully addressed. It may be that the inclusion of them accounts better for inter-firm variance.
4. Sectoral Differences — The sample was a mix of different industries (manufacturing, technology, retail, and energy) without attempting to separate structural differences. Sector-specific models would also uncover unique intelligence and change patterns used in sectoral digital preparedness.
5. Cultural and Institutional Subtleties - Despite the fact that China and Spain are quite different settings, more inclusion of other economies or regional blocs (e.g., North America, Africa, or even the rest of Europe) may enhance cross-cultural generalizability and theoretical universality.

Identifying such constraints is a way of becoming transparent and open to further research on the CI-DT-Sustainability nexus to learn more.

### 5.3 Future Research Directions

The research experiences and limitations of this study can be extended in the future as follows:

Longitudinal and Panel Studies - It would be beneficial to trace the evolution of dynamic capabilities over a series of years by tracking the firms. Longitudinal structural modeling may demonstrate the presence of a long-term causality between intelligence investment to-day giving sustainability performance to-morrow.

Multi-layer Constructs - Sub-level constructs that can be investigated in the future (individual digital competence or team-level intelligence collaboration) can be used to further explain the role of organizational learning processes on the outcomes of transformation.

State-of-the-Art Techniques of Analysis - Scholars may use artificial intelligence-based analytics (e.g., machine learning prediction models, fuzzy-set qualitative comparative analysis) to investigate the non-linear and configurational relations of CI, DT, and sustainability indicators.

Aggregation of Complementary Theories - The addition of theories, including Institutional Theory, Technology-Organization-Environment (TOE) Model, or Stakeholder Theory might be offering more detailed accounts of external forces and stakeholder interdependencies on strategies of transformation.

Sector- or Size-Specific Analyses -A better practical diversification and policy relevance would be to study CI-enabled change in small businesses or within the government or in a particular industry (e.g. renewable energy, healthcare).

Qualitative and Mixed-Method Studies - The current research is qualitative but the future studies might involve interviews, case analysis, or ethnographic research to get managerial interpretations, internal issues, and cultural factors that influence the formation of CI and DT.

Global Comparative Expansion - By expanding the comparative framework to a global level with more than two countries having different degrees of digital and sustainability maturity would be able to hone cross-national knowledge on how institutional settings mediate the outcomes of digital transformation.

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