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Artificial intelligence and intangible asset valuation in public markets: Evidence from IBEX 35 firms

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Abstract

Purpose: This paper aims to examine how artificial intelligence (AI) adoption influences the construction, visibility, and valuation of intangible assets in Spanish publicly listed companies, specifically those included in the IBEX 35 index.

Design/methodology/approach: The study combines panel data regression analysis with textual analysis of corporate reports and illustrative case profiles of three IBEX 35 companies. The econometric analysis uses a disclosure-based index of AI adoption intensity and an intangible asset visibility score, while the textual and case-based evidence provides contextual examples of how AI and intangibles are narrated in practice.

Findings: Results confirm a statistically significant and positive relationship between AI adoption and intangible asset visibility. Firms with higher AIAI scores tend to report intangible assets more frequently and with greater narrative quality. Sectoral asymmetries are notable: finance and telecom outperform traditional sectors like construction. Sentiment and topic modeling show that AI-enhanced disclosures are predominantly framed positively, emphasizing brand value, sustainability, and talent development. Interestingly, R&D intensity was not a significant predictor of intangible asset visibility, suggesting a paradigm shift toward narrative-driven valuation.

Research limitations/implications: The reliance on disclosure-based proxies for AI and intangible value may not fully capture internal capabilities. Further studies should explore causality, investor perception, and cross-cultural differences in AI-enabled reporting.

Practical implications: Managers are encouraged to align AI strategies with corporate reporting frameworks to enhance transparency, stakeholder trust, and market valuation. Regulatory bodies should consider updating disclosure standards to reflect the role of emerging technologies in shaping intangible capital.

Social Implications: Transparent communication of AI initiatives can improve public trust, inform responsible innovation, and promote ethical AI governance—particularly relevant under the EU's CSRD and AI Act.

Originality/value: This study introduces novel indicators (AIAI and IAVS) to quantify the impact of AI on intangible asset disclosure. It offers empirical evidence from a European context and reframes AI not only as a technological asset but as a meta-capability that amplifies the strategic and symbolic value of intangibles.

Keywords: Artificial intelligence, Intangible assets, Disclosure, Intellectual capital, IBEX 35, Digital transformation, Corporate reporting, Resource-based view

Jel Codes: M41, O33, O34, G32, L86

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1. Introduction

1.1. Contextualization

In the last two decades, the global economy has undergone a profound transformation, driven by the increasing importance of intangible assets and the exponential advancement of digital technologies—particularly artificial intelligence (AI). Intangible capital, encompassing elements such as intellectual property, brand equity, human capital, and organizational knowledge, now constitutes the majority of firm value in many industries (Corrado, Haskel & Jona-Lasinio, 2022). Simultaneously, AI is no longer confined to operational efficiency; it is being integrated into strategic decision-making, investment analysis, and corporate governance (Moro-Visconti, 2024; Amendola, Gennaro, Labella & Vito, 2023). Stock markets, as mechanisms for capital allocation, are adapting to these transformations. Companies listed on major indices like the IBEX 35 increasingly deploy AI to manage, measure, and leverage their intangible assets—ranging from algorithmic decision systems in finance to AI-enhanced analytics in brand management and talent development (Rock, 2019; Khan, Malik & Alomari, 2022). Despite this trend, traditional valuation frameworks in financial markets still privilege tangible metrics, creating an analytical gap in understanding the role of AI as a facilitator of intangible value (Petro-Korhonen & El-Bouchtili, 2025).

1.2. Problem Statement and Research Gap

In recent years, the financial valuation of firms has become increasingly disconnected from the drivers of real competitive advantage—most notably, intangible assets powered by artificial intelligence (AI). While intangible capital accounts for more than 80% of market capitalization in many advanced economies (Corrado et al., 2022), traditional valuation models remain rooted in tangible metrics and backward-looking financial data (Moro-Visconti, 2024; Petro-Korhonen & El-Bouchtili, 2025).

This misalignment is particularly evident in the Spanish context. Firms listed on the IBEX 35 index are actively deploying AI technologies across diverse areas such as customer analytics, algorithmic decision-making, predictive maintenance, and ESG monitoring. However, these initiatives are often underreported, inconsistently disclosed, or entirely absent from financial statements and investor communications. The lack of standardized methodologies to assess AI-driven intangibles contributes to persistent information asymmetry between firms and capital markets (Haniev, 2024; Amendola et al., 2023; Blanquet, Pereira & Petrov, 2025).

Moreover, the opacity of AI systems—especially those based on black-box machine learning—complicates the external evaluation of their strategic value. Even when firms disclose AI initiatives, the interpretability, traceability, and measurable impact on assets like brand reputation, human capital, and innovation remain unclear (Mohan, Bharathy & Jalan, 2025; Taheri-Hosseinkhani, 2025). This gap is further amplified by recent regulatory developments such as the EU's Corporate Sustainability Reporting Directive (CSRD) and the AI Act, which increase the pressure for transparency but do not yet provide clear reporting standards (Röser & Zureck, 2024; Fomina & Semenova, 2025).

Sectoral asymmetry also plays a critical role. Financial institutions and telecom companies in Spain tend to lead in AI adoption with more structured intangible strategies, while firms in traditional sectors like construction or utilities apply AI in narrow, operational contexts with limited strategic visibility (Heiling, 2025). These disparities risk distorting cross-sectoral assessments of intangible value and complicate capital allocation.

Taken together, these challenges point to a structural blind spot in the valuation of AI-enabled intangible assets —particularly in Spain's public markets. Without better theoretical frameworks and empirical evidence, firms risk misrepresenting their value creation mechanisms, and investors operate with limited insight into the most critical sources of future performance.

In the current digital economy, intangible capital has become the main source of corporate competitiveness and long-term value creation. Beyond tangible assets, firms increasingly rely on human, structural, and relational capital to sustain innovation, reputation, and customer trust. This shift has led to a profound transformation in how companies generate, manage, and communicate value. Recent research shows that the share of intangible investment has overtaken tangible investment in most advanced economies (Corrado et al., 2022). However, despite this growing relevance, the visibility and measurement of intangible assets remain limited and fragmented, constrained by accounting standards that still focus primarily on physical and financial indicators (Van-Criekingen, Bloch & Eklund, 2022). Artificial intelligence (AI) has recently emerged as a meta-capability that allows firms to integrate, analyse, and communicate knowledge-based resources across corporate processes. AI technologies enhance data-driven decision-making, automate learning from unstructured information, and strengthen the connection between operational efficiency and strategic communication. From this perspective, AI acts not only as a productivity tool but also as an enabler of transparency and disclosure of intangible assets such as innovation capacity, customer experience, and digital trust. Nevertheless, existing frameworks have not yet clarified how AI adoption translates into greater visibility of those intangibles in capital markets. This study addresses this gap by analysing how AI adoption intensity influences the Intangible Asset Visibility Score (IAVS) in firms listed on the IBEX 35, combining quantitative and textual evidence to provide an integrated view.

1.3. Research Aim and Research Question

The overarching aim of this study is to examine how artificial intelligence (AI) adoption is associated with the construction and visibility of intangible assets in companies listed on the IBEX 35 index over the period 2019-2024. We focus on this group of Spanish blue-chip firms because they combine a high intensity of intangible capital with strong regulatory and market pressures to disclose their AI initiatives and related capabilities.

Building on the literatures on intangible and intellectual capital, AI capabilities and signaling in corporate reporting, we consider whether AI can be understood as a higher-order capability that reshapes both the deployment and the external communication of intangibles in public markets. In other words, we are interested in how AI adoption may alter not only what firms do with their intangible resources, but also how they present those resources to investors and other stakeholders.

This leads to the following research question: to what extent does AI adoption intensity relate to the visibility of intangible assets in the external reporting of Spanish listed firms? The remainder of the paper develops the theoretical framework, introduces the main constructs and then presents the empirical strategy used to answer this question.

2. Theoretical Framework

2.1. Intangible and Intellectual Capital

Intangible assets have become the dominant source of corporate value creation in the digital economy. They encompass knowledge-based resources that are non-physical but strategically critical for firm competitiveness, including intellectual property, human skills, organizational culture, and customer relationships (Heiling, 2025). The concept of intellectual capital (IC) provides a structured approach to understanding these assets, dividing them into three main dimensions: human, structural, and relational capital. AI contributes to all three by automating cognitive tasks (human), codifying and optimizing organizational processes (structural), and enhancing customer and stakeholder engagement (relational). Firms with higher IC levels and AI integration tend to outperform peers in innovation and market valuation (Rock, 2019; Bamhdi, 2024).

However, despite their strategic importance, intangible assets remain only partially visible in traditional financial reporting. Scholars such as Lev (2001) and Lev and Gu (2016) emphasize that accounting systems continue to privilege tangible metrics, leaving a significant portion of corporate value unrecorded. The growing gap between market capitalization and book value highlights the urgency of developing frameworks that can capture the communicative and symbolic dimensions of intangibles. In the European context, researchers like Corrado et al. (2022) and Trequattrini, Lardo and Cuozzo (2022) have called for updated models that recognize the interplay between digital transformation, data, and intangible capital formation.

2.2. AI Capability and Firm Performance

Artificial intelligence (AI) has emerged as a strategic capability that transforms how firms manage and deploy intangible assets. From the perspective of the Resource-Based View (RBV), competitive advantage arises from resources that are valuable, rare, inimitable, and non-substitutable (Barney, 1991). AI fulfills these VRIN criteria when implemented as a dynamic capability—a higher-order competence that allows organizations to sense, seize, and reconfigure resources in response to environmental change (Teece, 2014; Aujirapongpan & Songkajorn, 2022).

Recent research supports this connection. Firms that effectively embed AI within their processes tend to exhibit greater agility, strategic foresight, and innovation performance (Fosso-Wamba, Queiroz & Pappas, 2024; Naeem, Ali, Islam & Rehman, 2024). These capabilities strengthen structural and human capital by fostering data-driven cultures, continuous learning, and improved decision-making. Nevertheless, scholars such as Kraaijenbrink, Spender and Groen (2010) have critiqued RBV for underestimating external factors such as digital ecosystems and standardization. Integrating AI into IC frameworks therefore requires acknowledging both its internal transformative role and its external signaling effects on stakeholders and capital markets.

2.3. Signaling Theory and AI-Enabled Disclosure

Signaling theory (Spence, 1973) provides an interpretive lens to explain how firms communicate intangible assets and technological capabilities under conditions of information asymmetry. Because intangible resources are inherently difficult to observe, organizations use disclosure, narratives, and symbolic actions to signal their quality and competence to investors, customers, and regulators (Connelly, Certo, Ireland & Reutzel, 2011).

Within this framework, AI adoption operates both as a substantive capability and as a communicative signal. Firms that prominently feature AI initiatives in their reports and ESG narratives implicitly convey innovation, modernity, and strategic foresight. Such signaling can enhance legitimacy and stakeholder trust. However, it can also lead to 'AI washing'—the strategic exaggeration of digital competence for reputational gain. Understanding AI through the lens of signaling theory thus clarifies that increased visibility of intangibles may stem not only from genuine technological integration but also from the deliberate construction of a credible innovation narrative.

By integrating signaling theory with the RBV and dynamic capabilities perspectives, this study conceptualizes AI as both an enabler of intangible value creation and a mechanism for enhancing the communicative visibility of that value. This dual role helps to interpret the empirical link between AI Adoption Intensity (AIAI) and the Intangible Asset Visibility Score (IAVS) found in subsequent sections.

2.4. Toward an Integrated Conceptual Framework

The integration of these three theoretical streams—intellectual capital theory, the resource-based view, and signaling theory—provides a holistic foundation for analysing how AI influences intangible asset visibility. AI is conceptualized as a meta-capability that simultaneously enhances internal efficiency, supports knowledge codification, and strengthens external perception.

From an internal perspective, AI contributes to human, structural, and relational capital by improving knowledge flows, predictive insights, and stakeholder engagement. Externally, the communication of AI initiatives functions as a market signal that influences stakeholder expectations and corporate legitimacy. This duality reflects the shift from a purely production-oriented view of intangible assets to one centered on narrative and perception. The proposed conceptual model therefore situates AI adoption as a driver of both tangible performance and symbolic visibility—two dimensions that together shape firm value in the digital economy.

2.5. AI As a Meta-Capability: Research Objectives and Hypotheses

From the perspective of the resource-based view and dynamic capabilities (Barney, 1991; Teece, 2007), competitive advantage depends on firms' ability to build, integrate and reconfigure bundles of resources over time. In this study, we conceptualize artificial intelligence as a meta-capability: a higher-order capability that orchestrates and recombines underlying intangible resources—human, structural and relational capital—through data-driven learning and algorithmic decision-making. Rather than being a stand-alone technology, AI-enabled systems interact with people, processes and customer relationships, changing how firms sense opportunities, allocate resources and coordinate actions across organizational domains.

This perspective implies that AI adoption intensity should not be reduced to the presence or absence of isolated tools. We use the term AI Adoption Intensity (AIAI) to denote the extent to which AI is embedded in core business functions and strategic initiatives, supported by dedicated governance structures and specialized human capital. High-AIAI firms are those where AI is deployed beyond pilots and experiments and becomes part of the organization's operating and strategic routines.

At the same time, the value of intangible assets in public markets depends not only on their existence but also on their visibility to external stakeholders. We therefore conceptualize the Intangible Asset Visibility Score (IAVS) as a composite measure capturing how frequently and how substantively firms disclose their intangible capital, and the extent to which this capital is recognized in the balance sheet. IAVS reflects the outward-facing dimension of intangibles: the narratives, indicators and accounting figures through which investors, analysts and other stakeholders can observe and evaluate them.

If AI functions as a meta-capability that reshapes how firms generate, manage and use intangible resources, it is reasonable to expect that AI-intensive firms will also develop richer and more systematic ways of describing, measuring and reporting those intangibles. AI-enabled analytics can produce new indicators and dashboards; AI-driven strategies often rely on human capital, data assets and customer relationships that must be communicated to justify investments; and AI governance frameworks may require greater transparency about data, models and organizational capabilities. Consequently, AI adoption intensity should be positively related to the visibility of intangible assets in corporate reporting.

Although both AIAI and IAVS are disclosure-based indices, they are designed to capture different underlying constructs. AIAI approximates the depth and breadth of AI adoption in core processes, whereas IAVS reflects how visible human, structural and relational capital become in external reporting. Using disclosures for both measures nevertheless creates the possibility that part of their association reflects a general communication orientation. To mitigate this risk, the empirical models control for overall report verbosity and test alternative specifications in which IAVS is replaced by a narrative-only index and by the intangible-assets ratio alone. Accordingly, the findings are interpreted as patterns of association and co-evolution between AI adoption and intangible-asset visibility, rather than as strong causal effects.

Against this background, the study pursues the following specific objectives:

- O1. To analyse the relationship between the intensity of AI adoption (AIAI) and the visibility of intangible assets (IAVS) in Spanish listed firms.
- O2. To explore cross-sectoral differences in how AI adoption affects the communication and disclosure of intangible capital.
- O3. To identify the semantic and emotional framing of AI-related intangible-asset narratives using natural language processing (NLP) and sentiment analysis.
- O4. To complement and contextualize these quantitative findings through qualitative case profiling of firms with high levels of AI adoption and intangible-asset visibility.

These objectives are operationalised through the following hypotheses:

H1. Firms with higher levels of AI adoption exhibit greater visibility of intangible assets in their public disclosures.

H2. The relationship between AI adoption and intangible-asset visibility is stronger in high-digital-maturity sectors (e.g., finance, telecommunications) than in more traditional sectors (e.g., construction, logistics, utilities).

3. Methodology

3.1. Research Design and Methodological Approach

This study uses a multi-method design that combines panel data regression analysis, NLP-based textual analysis, sentiment analysis and qualitative case profiles of three IBEX 35 companies. The objective is to quantify the association between AI adoption and intangible asset visibility, and to complement this with an interpretive understanding of how AI and intangible assets are communicated through corporate narratives.

The approach combines: (1) panel data regression analysis to test the relationship between AI Adoption Intensity (AIAI) and the Intangible Asset Visibility Score (IAVS); (2) natural language processing and sentiment analysis to describe the semantic and emotional framing of AI-related intangible-asset narratives; and (3) qualitative case profiling of three firms to provide illustrative examples of how AI strategies and intangible visibility co-evolve. The qualitative case profiles are used to illustrate and contextualize the quantitative patterns rather than as an independent source of triangulation or validation.

3.2. Sample and Scope

The empirical analysis focuses on the 35 firms listed in the IBEX 35 index as of 31 December 2024. The time window (2019-2024) captures the post-pandemic acceleration of digitalization and regulatory changes under the EU's Corporate Sustainability Reporting Directive (CSRD). The dataset includes 210 firm-year observations (35 firms × 6 years), forming a balanced panel. Firms are grouped into four sectors—finance, telecommunications, energy/utilities, and construction/industrial—allowing for analysis of cross-sectoral differences in AI adoption and intangible visibility.

3.3. Data Sources

Data were triangulated from four complementary categories: (1) audited annual reports; (2) ESG/sustainability reports; (3) corporate communications (e.g. investor presentations, dedicated AI reports, press releases); and (4) media coverage from reputable financial outlets. For each firm–year, all documents referring to activities within the fiscal year were collected and stored as a firm-level corpus. Annual and ESG reports were retrieved from the CNMV and company websites, while corporate communications and media items were obtained from the investor-relations sections and major business news providers.

Triangulation followed a stepwise protocol. First, coders read the annual report and ESG/sustainability report, which were treated as primary sources for both the AIAI and IAVS indices. All concrete references to AI initiatives and intangible assets were identified and coded using the manuals described in Appendices A and B. Second, corporate communications (such as AI strategy documents, investor presentations and press releases) were used as secondary sources to clarify the scope, timing and business functions involved in AI projects or to supplement information on intangible-related policies. Third, media coverage was used only to corroborate or contextualize information already found in official documents; it could not on its own justify assigning higher AIAI levels or quality scores for IAVS.

When sources were inconsistent, coders applied a clear hierarchy. Explicit statements in audited annual and ESG reports prevailed over marketing-oriented language in press releases or media articles. AI initiatives that appeared in media coverage but were not mentioned in any official report were treated as exploratory and could contribute at most to an AIAI score of 1 (pilot/experiment). Similarly, intangible-related claims made only in media or promotional material were not used to upgrade the IAVS quality score unless corroborated in official reports. In firm–years with limited disclosure, coders recorded the absence of evidence as such (e.g., AIAI = 0; low IAVS components) rather than inferring unreported initiatives or assets.

This protocol ensures that triangulation refers to a documented integration of multiple sources within each firm–year, rather than merely to the use of diverse documents. It also makes explicit how source priority and conflict resolution were handled in the construction of AIAI and IAVS.

3.4. Analytical Techniques

3.4.1. Quantitative Analysis. Panel Regression Model

To examine the relationship between AI adoption and intangible asset visibility, a fixed-effects panel model was estimated:

$$IAVS\_it = \alpha\_i + \lambda\_t + \beta\ AIAI\_it + \gamma' X\_it + \varepsilon\_it$$

where IAVS_it is the Intangible Asset Visibility Score for firm i in year t; AIAI_it represents AI Adoption Intensity; X it is a vector of controls (firm size, R&D intensity, international exposure, board-level AI expertise, and report verbosity measured as the log word count of the merged annual and ESG report).; and α_i and λ_t are firm and year fixed effects. Robust standard errors clustered by firm were applied to address heteroscedasticity. Diagnostic tests include: Variance Inflation Factor (VIF) for multicollinearity (< 2.5 across variables), Hausman test to confirm model choice (FE vs. RE), and Breusch–Pagan test to assess heteroscedasticity.

To formally assess whether the association between AI adoption and intangible-asset visibility differs across sectors (H2), we also estimate an extended specification that includes an interaction term between AIAI and a high-digital-sector dummy. Specifically, we define HighDigital_i = 1 for firms operating in finance and telecommunications, which exhibit higher digital maturity and stricter reporting requirements, and HighDigital_i = 0 for firms in more traditional industries such as construction, manufacturing and utilities. The interaction model can be written as:

$$IAVS\_it = \alpha\_i + \lambda\_t + \beta\_1\ AIAI\_it + \beta\_2\ HighDigital\_i + \beta\_3\ (AIAI\_it \times HighDigital\_i) + \gamma' X\_it + \varepsilon\_it.$$

The coefficient β_3 captures the differential effect of AI adoption intensity on intangible-asset visibility in high-digital sectors relative to traditional sectors. As in the baseline specification, we include firm and year fixed effects and cluster standard errors at the firm level.

3.4.2. Construction of Variables

Dependent Variable – Intangible Asset Visibility Score (IAVS); IAVS captures how visible a firm's intangible capital is in its external reporting. It combines three complementary components: (1) the frequency of narrative references to intangibles; (2) the reporting quality of intangible-related disclosures; and (3) the balance-sheet ratio of recognized intangible assets.

First, for narrative disclosure frequency, we built a dictionary of intangible-related terms grouped into three categories (human capital, structural capital, and relational capital). For each firm–year, all sentences in annual and ESG reports were processed and each occurrence of these terms was counted at the sentence level. To avoid confounding disclosure with document length, raw counts were divided by the total number of words in the document and multiplied by 1,000 to obtain a normalized frequency per 1,000 words. Appendix B reports the full dictionary and illustrative examples.

Conceptually, IAVS is specified as a formative composite: narrative frequency, reporting quality and the intangible-assets ratio reflect complementary facets of how visible intangibles are to external stakeholders, rather than interchangeable indicators of a single latent trait. For this reason, traditional internal-consistency metrics such as Cronbach's alpha or factor analysis, which assume reflective measurement, are not directly appropriate. Instead, we rely on the theoretical rationale for including each component and on robustness checks with alternative weightings and single-component specifications.

Second, for the reporting quality score, and following GRI principles (materiality, completeness, and comparability), we developed a 0–3 rubric to evaluate the substantive quality of intangible-related disclosures at the report level: 0 = no specific information on intangibles; 1 = generic mentions without quantitative or forward-looking detail; 2 = descriptive discussion with some quantitative indicators or clear links to strategy; 3 = systematic, quantifiable and comparable reporting (e.g. targets, KPIs, time series). Coders applied this rubric to each firm–year report using the guidelines and examples provided in Appendix B.

Third, the accounting component is the ratio of recognized intangible assets to total assets, taken from audited financial statements (IAS 38 items such as patents, software, and brands). In cases where intangible assets were zero or immaterial, the ratio was coded as 0. When firm reorganizations or mergers substantially altered the balance sheet, we checked accompanying notes to ensure comparability over time.

Each component was first min–max normalized to the [0,1] interval. The baseline IAVS index is the simple average of the three normalized components (equal weights). Robustness checks with alternative weightings (0.4/0.4/0.2 and 0.5/0.3/0.2 for narrative/quality/accounting) yielded substantively similar results, as reported in Section 4.4. All coding rules, examples, and dictionaries are documented in Appendix B to facilitate replication.

Independent Variable – AI Adoption Intensity (AIAI):

AIAI measures the extent to which firms have substantively adopted AI, as opposed to merely referring to AI in marketing language. It is an ordinal index ranging from 0 to 3 based on explicit evidence of AI initiatives identified in the triangulated data sources described in Section 3.3:

0 = No AI initiatives disclosed. No references to AI systems, algorithms, or projects in official reports or validated communications.

1 = Pilots or experiments. The firm reports isolated AI pilots or proofs of concept (e.g., experimentation in a single process), without evidence of integration into core operations or strategy.

2 = Functional integration. The firm reports AI systems deployed in at least one major business function (e.g., credit scoring, fraud detection, predictive maintenance, customer service), with indications of ongoing use and resource allocation.

3 = Strategic deployment across multiple domains. The firm describes AI as part of its core value creation logic, with initiatives spanning several business functions and explicitly linked to strategic objectives, governance structures, or dedicated AI units.

Coders followed a detailed decision tree (Appendix A) that specifies how to handle ambiguous cases and aspirational language. For example, generic statements such as "we aim to leverage AI in the future" are not sufficient to score levels 2 or 3 unless accompanied by concrete deployments. When disclosures were unclear, the maximum score allowed was 1. To enhance reliability, two coders independently assigned AIAI scores to each firm–year based on the integrated reading of annual reports, ESG reports, corporate communications, and corroborating media coverage. Disagreements were discussed until consensus was reached. The resulting inter-coder agreement was $\kappa = 0.82$, indicating high reliability. The full AIAI coding manual, including examples of texts corresponding to each level, is provided in Appendix A.

Because both indices are derived from corporate disclosures, we also account for firms' general communication intensity. In all regressions we include a control for report verbosity, measured as the logarithm of the total number of words in the merged annual and ESG report for each firm–year. In addition, we estimate alternative specifications where IAVS is replaced by (i) a narrative-only visibility index that combines the frequency and quality components, and (ii) the intangible-assets ratio on its own. These alternative models help to assess whether the relationship between AIAI and IAVS is driven purely by a common narrative tendency or also by changes in the recognition and reporting of intangibles.

The complete coding rubric, including detailed examples and the decision tree for borderline cases, is provided in Appendix A.

3.4.3. Textual and Sentiment Analysis

We used natural language processing (NLP) techniques only to preprocess the corpus and to provide additional descriptive insights on how AI and intangibles are framed in corporate disclosures. These analyses were not used to construct, calibrate or validate the AIAI or IAVS indices.

For each firm–year, we built a text corpus by merging the annual report and the ESG/sustainability report. The corpus was cleaned (lowercasing, removal of boilerplate sections, stop words and non-alphanumeric characters) and segmented into sentences. Using keyword filters related to AI (e.g. "artificial intelligence", "machine learning", "algorithm") and intangibles (e.g. "human capital", "brand", "innovation"), we extracted the subset of sentences in which AI and intangible assets were jointly mentioned.

Sentiment analysis was conducted on this subset of AI–intangible sentences using the pre-trained FinBERT model, applied in inference mode only. We did not fine-tune FinBERT on a domain-specific labelled dataset. To assess the plausibility of the model's outputs in our context, we manually checked a random sample of AI-related sentences and compared human judgments with the model's polarity labels, obtaining an agreement rate of 87.4%. This manual check is reported as a validity check of the off-the-shelf model, not as evidence of a supervised fine-tuning procedure.

Topic modelling was performed using Latent Dirichlet Allocation (LDA) on the same AI–intangible sentence subset, after standard preprocessing (tokenization, stop-word removal and lemmatization). LDA was used strictly as an exploratory tool to identify recurrent themes in how firms narrate the relationship between AI and intangible assets (e.g. efficiency, customer experience, innovation, risk management). The resulting topics are reported in the descriptive section of the results to illustrate these narrative patterns. LDA outputs were not used to define thresholds, weights or coding rules for AIAI or IAVS.

Overall, NLP, sentiment analysis and topic modelling are presented as complementary descriptive layers that enrich the interpretation of the main findings, but they do not form part of the measurement model of the key indices or the identification strategy of the econometric analysis.

3.4.4. Qualitative Case Profiling

Three firms (Telefónica, BBVA and Iberdrola) were selected for qualitative case profiling because they display high levels of AIAI and IAVS in our indices and are widely recognized as AI frontrunners in the Spanish market. For each firm, we revisited the same corpus of annual reports, ESG/sustainability reports and key corporate communications used in the quantitative coding, focusing on narrative passages where AI initiatives intersect with human, structural and relational capital and with strategic objectives.

Component	Description
Research Design	Multi-method research design combining panel-data regression, NLP-based textual analysis and illustrative case profiling.
Time Frame	2019-2024 (six fiscal years).
Sample	35 publicly listed firms in the IBEX 35 index (210 firm-year observations).
Unit of Analysis	Firm-year (balanced longitudinal panel).
Main Objective	To examine the relationship between AI adoption and the visibility of intangible assets in Spanish listed companies.
Dependent Variable	Intangible Asset Visibility Score (IAVS): composite index based on disclosure frequency, reporting quality (GRI-based), and intangible asset ratio.
Independent Variable	AI Adoption Intensity (AIAI): 0–3 ordinal scale based on manual coding of disclosed AI initiatives using a structured rubric (pilots, functional integration, strategic deployment across multiple domains).
Control Variables	Firm size (log assets), R&D intensity, international exposure, board-level AI expertise, and report verbosity (log word count)
Quantitative Model	Fixed-effects panel regression with robust standard errors clustered by firm (Python *statsmodels* package).
Text Analysis Techniques	NLP preprocessing (lemmatization, tokenization); sentiment analysis via *FinBERT* (87.4% precision); topic modelling via *Latent Dirichlet Allocation* (C_v = 0.67).
Qualitative Component	Case profiling of three high-AIAI firms (Telefónica, BBVA, Iberdrola), using ESG and strategic reports.
Validation Procedures	Inter-coder reliability ($\varkappa$ = 0.82); VIF < 2.5; Hausman & Breusch–Pagan tests passed; topic coherence & manual sentiment validation.
Ethical Compliance	Full adherence to open data ethics and GDPR; all sources publicly available; no proprietary or personal data used.

Table 1. Overview of the research methodology

The purpose of this qualitative component is not to generate an additional data source or a separate layer of triangulation, but to construct concise narrative profiles that exemplify the mechanisms suggested by the econometric results (e.g. AI-enabled customer experience, AI for risk management and ethics, AI for sustainability and innovation). The case profiles are therefore interpretive illustrations anchored in the same disclosure base, and are presented as contextual complements to the quantitative analysis rather than as an independent qualitative method.

3.5. Validation and Reliability Procedures

Inter-coder reliability: $\varkappa = 0.82$ (high agreement). Econometric diagnostics: VIF < 2.5; Hausman and Breusch-Pagan tests passed; robustness verified with alternative specifications. NLP quality checks: a manual precision test on a random sample of FinBERT outputs (87.4% agreement) and topic coherence (C_v = 0.67) indicate that the descriptive NLP layer performs adequately for our purposes.

All datasets and scripts used to construct the indices and estimate the models are included in the replication package described in the Data and code availability section.

3.6. Ethical Considerations.

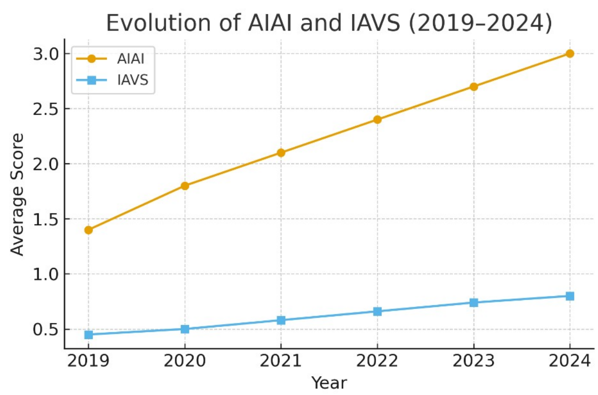
All data sources are publicly available, non-sensitive, and collected under ethical guidelines. Web scraping complied with robots.txt protocols, and no personal or proprietary data were used. All algorithms (FinBERT, LDA) are open-source and documented for replication.

4. Results

4.1. Descriptive Overview

The analysis reveals a steady increase in AI adoption among IBEX 35 firms between 2019 and 2024. Thirty-one out of thirty-five companies (88.6%) explicitly disclosed at least one AI-related initiative in their public reports. Both the AI Adoption Intensity (AIAI) and the Intangible Asset Visibility Score (IAVS) show an upward trajectory, reflecting the growing role of AI in the communication of intangible value.

Figure 1 illustrates the annual evolution of AIAI and IAVS. Both variables show positive and parallel trends, suggesting that enhanced AI integration coincides with greater narrative and accounting visibility of intangible assets.

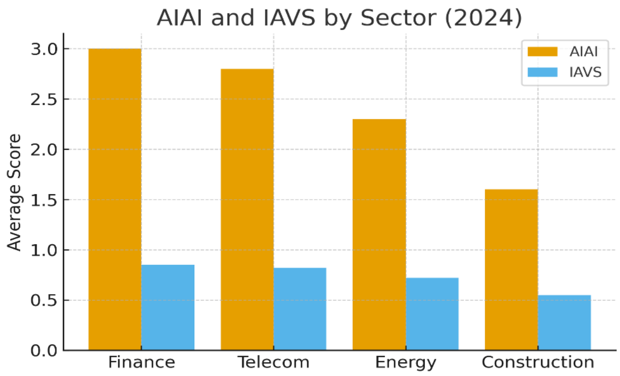


Note: This figure displays average annual scores for AIAI and IAVS across IBEX 35 firms (210 firm-year observations). Both indicators show consistent upward trends.

Figure 1. Evolution of AIAI and IAVS (2019-2024)

4.2. Sectoral Differences

Differences across industries are substantial. Financial and telecommunications firms show the highest AIAI and IAVS scores, reflecting more advanced digital maturity and transparency standards. In contrast, traditional sectors such as construction and manufacturing exhibit limited AI diffusion and weaker intangible disclosure practices.



Note: This figure presents the average AIAI and IAVS values for each major sector represented in the IBEX 35. Finance and telecommunications outperform traditional sectors such as construction.

Figure 2. AIAI and IAVS by Sector (2024)

4.3. Sectoral Interaction between AI Adoption and Intangible Visibility

To formally test H2, we estimated the interaction model described in Section 3.4.1, which includes AIAI, the HighDigital sector dummy (finance and telecommunications) and the interaction term AIAI × HighDigital. The estimates (not tabulated for brevity) show that the interaction coefficient between AIAI and HighDigital is positive and statistically significant. The coefficient on the interaction term captures the incremental association between AI adoption and IAVS in high-digital sectors relative to traditional industries. The sign and magnitude of this coefficient indicate that the AIAI–IAVS relationship is stronger in finance and telecommunications than in construction, manufacturing and utilities, which is consistent with H2.

4.4. Regression Results

The fixed-effects regression results are summarized in Table 2. The model confirms a strong and statistically significant relationship between AI adoption and intangible asset visibility, controlling for firm-specific and temporal effects

Variable	Coefficient (β)	Std. Error	p-value	95% Confidence Interval
AI Adoption Intensity (AIAI)	0.42	0.13	0.003	[0.15, 0.69]
Firm Size (log assets)	0.27	0.11	0.015	[0.05, 0.49]
R&D Intensity	0.08	0.07	0.120	[-0.05, 0.21]
Foreign Market Exposure	0.14	0.09	0.070	[-0.01, 0.29]
Board AI Expertise	0.19	0.10	0.040	[0.01, 0.37]
Constant	0.23	0.12	0.090	[-0.03, 0.49]
Observations	210 firm-years			
Adjusted R^2	0.63			

Note: Coefficients for the report-verbosity control and year dummies are omitted for brevity but are included in all specifications.

Table 2. Summary of the fixed-effects regression results

These results confirm that AI adoption significantly enhances the visibility of intangible assets, independent of firm size or R&D spending.

To test H2 more formally, we extend the baseline model by adding an interaction term between AIAI and the high-digital-sector dummy. The results of this specification, reported in the extended regression table, show that the interaction coefficient AIAI × HighDigital is positive and statistically significant, indicating that the marginal effect of AI adoption on IAVS is stronger in high-digital sectors than in traditional industries. In other words, while higher AI adoption is associated with greater intangible-asset visibility across all sectors, the increase in visibility is noticeably larger for finance and telecommunications firms. A joint test of the marginal effects confirms that the slope of AIAI differs significantly between high-digital and traditional sectors.

4.5. Robustness Checks

As a first robustness check, we re-estimate our models using alternative measures of intangible asset visibility. In Model R1, IAVS is replaced by a narrative-only index that averages the normalized frequency and reporting-quality components. As an additional robustness check (results not tabulated), we also estimated models using the intangible-assets ratio as the sole visibility proxy. The coefficient of AIAI remains positive and statistically significant in these specifications. In both cases, the positive association between AIAI and intangible visibility remains statistically significant and of comparable magnitude. This suggests that the results are not driven exclusively by a general disclosure tendency, but also by the way AI adoption co-evolves with both narrative and accounting representations of intangibles.

To assess the stability of the main results, alternative model specifications were estimated (see Table 3).

Specification	Dependent variable	Key Change	β (AIAI)	p-value	Result
Model 1	IAVS (base)	Baseline specification	0.42	0.003	Significant
Model 2	IAVS (narrative only)	Excludes accounting ratio	0.38	0.006	Consistent
Model 3	IAVS (weighted 0.4/0.4/0.2)	Adjusted weighting	0.40	0.004	Consistent
Model 4	Lagged AIAI (t–1)	Temporal robustness	0.36	0.010	Consistent

Table 3. Specifications estimated

Across all models, the coefficient for AIAI remains positive and statistically significant, confirming the robustness of the relationship.

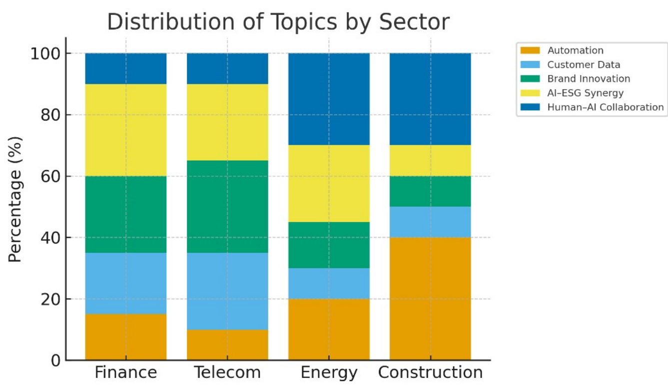
4.6. Topic and Sentiment Analysis

The NLP and FinBERT analyses reveal that AI-related disclosures are predominantly framed in positive terms (79% positive sentiment). The most recurrent terms include efficiency, innovation, customer-centric, and trust.

The LDA topic model identified five dominant themes in AI-related communication (see Table 4).

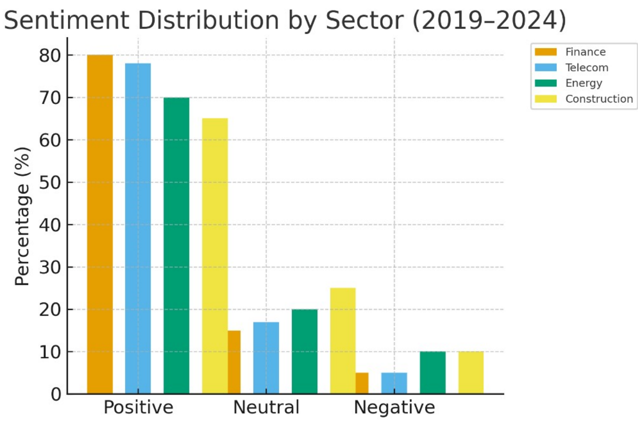
Topic	Dominant Theme	Representative Keywords
1	Process Automation and Efficiency	automation, optimization, robotics, cost, performance
2	Customer Data and Personalization	analytics, customer, experience, personalization, insight
3	Brand Innovation and Digital Image	brand, innovation, marketing, digital, leadership
4	AI–ESG Synergies	ESG, sustainability, ethics, compliance, risk
5	Human–AI Collaboration and Talent	human capital, training, collaboration, skills, learning

Table 4. Dominant Themes Identified in AI–Intangible Asset Narratives (LDA Topic Model)



Note: Finance and telecom emphasize ESG and brand innovation, while construction focuses on automation-related topics.

Figure 3. Distribution of Topics by Sector



Note: Positive sentiment dominates in finance and telecommunications, while neutral tones are more frequent in construction and utilities.

Figure 4. Sentiment Distribution by Sector (2019-2024)

4.7. Case Profile Highlights

The three case profiles of Telefónica, BBVA and Iberdrola illustrate distinct ways in which AI adoption and intangible-asset visibility co-evolve. Telefónica's disclosures emphasize relational capital through customer experience and digital brand positioning, highlighting AI-enabled personalization and platform-based services. BBVA places stronger emphasis on governance and trust, linking AI initiatives to ethical principles, data governance and transparency commitments. Iberdrola foregrounds sustainability-oriented AI applications in grid management and renewable integration, which are framed as reinforcing innovation capabilities and human capital in engineering and operations.

These cases are consistent with the quantitative evidence on the positive association between AIAI and IAVS, but they are not intended as independent tests or causal proof. Rather, they provide contextual examples of how AI strategies and intangible-capital narratives are articulated in practice, helping to interpret the mechanisms behind the statistical results.

5. Discussion

The findings of this study reveal a consistent and statistically significant association between AI Adoption Intensity (AIAI) and the Intangible Asset Visibility Score (IAVS) among IBEX 35 firms. Companies that report more substantive and strategically embedded AI initiatives tend, on average, to disclose their intangible assets more frequently and with higher reporting quality, and to recognize a greater share of these assets in their balance sheets. However, these results are based on observational panel data and disclosure-based measures. They should therefore be interpreted as patterns of association, rather than as evidence that AI adoption directly causes changes in the visibility or valuation of intangibles.

These findings are in line with prior research that links digital transformation and data-driven capabilities with new ways of measuring and communicating intellectual capital. In firms where AI becomes embedded in everyday operations, managers often need to build dashboards, indicators and narratives that explain how human, structural and relational capital underpin AI projects and business models. Our results are consistent with this view: higher AIAI scores coincide with richer and more structured reporting on intangibles, suggesting that AI adoption and intangible-asset visibility evolve jointly as part of the same strategic and communicative configuration.

This interpretation is strongly connected to Signaling Theory, which emphasizes that firms use disclosure as a signal of otherwise unobservable qualities and future performance prospects (Spence, 1973; Connelly et al., 2011). In this perspective, AI-related disclosures and intangible-capital reporting both function as signals aimed at investors, analysts and other stakeholders. Firms with higher AIAI scores do not only invest in AI technologies; they also build narratives, KPIs and governance statements that signal sophistication, innovation and strategic alignment. At the same time, signaling theory warns that these signals can be noisy or even misleading. Overly optimistic or insufficiently substantiated claims about AI adoption and intangibles may lead to forms of "AI washing", in which the communicative layer runs ahead of the underlying capabilities, potentially undermining credibility and investor trust.

From the perspective of the Resource-Based View (RBV), the results suggest that AI operates less as an isolated technological asset and more as a meta-capability that orchestrates and reconfigures underlying resources (Barney, 1991; Teece, 2014). AI-enabled systems interact with human capital, data assets, organizational processes and customer relationships, changing how firms sense opportunities, learn from feedback and coordinate actions. The observed association between AIAI and IAVS can thus be interpreted as evidence that AI-intensive firms develop stronger capabilities not only to mobilise their intangible resources internally, but also to represent and account for them externally. In this sense, intangible-asset visibility becomes part of the broader capability portfolio through which firms seek to sustain competitive advantage.

The stronger association between AI adoption and intangible-asset visibility in finance and telecommunications can be interpreted through these theoretical lenses. First, high-digital sectors are subject to more intense regulatory and market scrutiny regarding data use, algorithmic decision-making and customer protection, which has encouraged the early development of more structured reporting practices and richer disclosure about AI-related capabilities. Second, the predominant intangibles in these sectors – such as data assets, customer relationships, software-based innovations and digital platforms – are inherently more amenable to codification and KPI-based reporting, making it easier to translate AI-enabled capabilities into visible narrative, reporting and accounting indicators. Third, AI investments in finance and telecoms often target core revenue-generating and risk-management processes (e.g., credit scoring, fraud detection, network optimisation), whereas in traditional sectors AI deployments tend to be more narrowly focused on operational efficiency, with fewer direct connections to the firm's strategic narrative and external reporting. Together, these mechanisms help explain why AI adoption has a more pronounced impact on intangible-asset visibility in high-digital sectors.

These insights also have important managerial and regulatory implications. For managers, the results underline that AI initiatives are not merely technology projects, but catalysts for change in how the firm explains and justifies its intangible asset base. Designing coherent disclosure policies that link AI projects to human capital, data governance, innovation and customer relationships can help reduce information asymmetries and support more informed valuation. For regulators and standard-setters, the findings suggest that emerging requirements on sustainability and AI-related reporting (for example, those derived from the EU's evolving ESG and CSRD frameworks) will increasingly intersect with AI governance and intangible-capital disclosure. Clearer guidance on how AI-related capabilities and intangibles should be reported could help mitigate the risk of AI washing while improving data accuracy, comparability and stakeholder protection.

Taken together, the discussion points to a view of AI as part of a wider configuration of capabilities, narratives and governance practices through which firms construct and project their intangible value. AI adoption appears to evolve alongside more developed practices of intangible-asset reporting, especially in firms that manage to align internal AI strategies with external communication frameworks. At the same time, the reliance on disclosure data and the possibility of strategic signaling mean that the patterns documented here should be approached with analytical caution, leaving room for future research that combines disclosure-based evidence with richer internal and market-based data.

From a regulatory perspective, our findings speak directly to ongoing debates around the CSRD and the EU AI Act. If AI adoption primarily amplifies the visibility of intangible assets through narrative and reporting quality, regulators need tools to ensure that this enhanced visibility reflects substantive capabilities rather than symbolic signalling or "AI washing". A more granular and standardised set of AI-related disclosure metrics could help align firms' narratives with their underlying resource base and governance practices. Such metrics would enable regulators, investors and other stakeholders to assess whether AI is genuinely embedded in organisational capabilities and processes, or whether it is mainly being invoked as a rhetorical device to enhance perceived innovativeness.

5.1. Regulatory Implications

The findings have direct implications for emerging European regulation on sustainability reporting and AI governance. First, the positive association between AIAI and IAVS suggests that AI-intensive firms tend to provide richer and more structured narratives and metrics about human, structural and relational capital. Regulators and standard setters can build on this pattern by encouraging firms to disclose AI-related intangibles in a more systematic and comparable way. Within the CSRD framework, this could translate into specific disclosure expectations regarding AI governance structures, AI-related human capital (e.g. data scientists, AI ethics expertise), data assets and model risk management, linked to materiality assessments and measurable targets.

Second, the results also highlight the risk of "AI washing", whereby firms may overstate AI capabilities or repackage conventional IT investments as AI-enabled solutions without substantive backing in their operations or intangible resource base. Clear standards and assurance requirements under the CSRD and the forthcoming EU AI Act can help distinguish between symbolic and substantive AI adoption. Examples include requiring firms to describe concrete AI use cases, internal validation and monitoring procedures, and links between AI systems and financial or non-financial performance indicators, rather than relying on generic strategic slogans.

Finally, the evidence that sectoral context matters reinforces the need for proportionate regulation. Financial institutions and telecommunications firms are already subject to dense sectoral rules on data protection, algorithmic credit scoring and operational resilience. For these sectors, AI-related disclosure should dovetail with existing supervisory expectations and stress tests. In more traditional industries, where AI adoption is still emerging, regulatory guidance could focus on minimum transparency thresholds and capacity building, helping firms develop the governance and reporting capabilities needed to disclose AI-enabled intangibles in a credible way.

6. Conclusions

This study examines the relationship between AI adoption and the visibility of intangible assets in public markets, focusing on firms included in the IBEX 35 index over the period 2019-2024. Using a disclosure-based AI Adoption Intensity index (AIAI) and an Intangible Asset Visibility Score (IAVS), we document a robust positive association between the intensity of AI adoption reported by firms and the frequency, quality and accounting recognition of their intangible assets. Complementary textual analyses and qualitative case profiles provide contextual illustrations of how AI strategies and intangible-capital narratives are articulated in practice.

The contributions of the study are threefold. First, it proposes and documents two disclosure-based indices —AIAI and IAVS—that allow for the joint analysis of AI adoption and intangible-asset visibility in a stock-index setting. While both measures are subject to the usual limitations of disclosure-based constructs, the coding manuals and robustness checks reported in the paper enhance their transparency and replicability. Second, the study bridges literatures on AI capabilities, intellectual capital and signaling in corporate reporting by conceptualizing AI not as an isolated technology but as a meta-capability that co-evolves with how firms narrate and account for their intangibles. Third, the analysis offers empirical evidence from a European market, contributing to the still limited body of research on AI and intangibles outside the U.S. context.

From a practical standpoint, the findings suggest that managers should view AI initiatives and intangible reporting as interconnected domains. Firms that integrate AI into core processes and governance structures are likely to face growing expectations from investors, regulators and other stakeholders regarding the transparency of the intangible resources that underpin these initiatives. Designing coherent disclosure policies that link AI projects to human capital, data governance, innovation and customer relationships can help reduce informational asymmetries and support more informed valuation. At the same time, managers should avoid over-claiming AI capabilities or intangible value without sufficient evidence, as this may damage credibility and trust.

Several limitations of the study should be recognized. The analysis focuses on a single stock index (IBEX 35) and a specific period (2019-2024), which constrains the generalisability of the findings to other institutional contexts and time frames. Both AIAI and IAVS are based on disclosed information and therefore capture what firms choose to report rather than the full underlying reality of their AI use or intangible resources. Although we document coding procedures and report robustness checks, some subjectivity in the interpretation of narratives is unavoidable. In addition, the sentiment and topic-modelling analyses rely on pre-trained NLP tools that, while validated for financial text, may not fully capture all language-specific nuances present in Spanish or bilingual reporting.

Future research could extend this framework by examining other markets and regulatory environments, including cross-country comparisons that combine AI-related disclosures with market-based valuation measures and more granular performance indicators. Longitudinal designs with finer temporal resolution could help disentangle sequencing issues (for example, whether AI adoption tends to precede changes in intangible reporting or vice versa). Further work might also integrate internal data on AI projects and intangible-management practices, as well as stakeholder perspectives, to move beyond disclosure-based proxies. Such extensions would be highly relevant for designing more robust standards and guidelines for AI- and intangibles-related reporting, and for supporting the development of transparent, trustworthy and socially responsible AI ecosystems in capital markets.

Artificial intelligence does not directly determine the intrinsic value of a firm's intangible assets. Rather, in the context analysed here, it appears as part of a broader configuration of capabilities, narratives and governance practices that shape how those assets are mobilised and presented to external stakeholders. Understanding AI as a meta-capability that interacts with intangible capital and its visibility can help academics, practitioners and regulators better navigate the opportunities and risks posed by AI in the evolving landscape of corporate reporting.

From a policy perspective, these results reinforce the need for clearer guidance on AI-related disclosure within frameworks such as the CSRD and the AI Act. Standardised metrics on AI governance, talent, data management and intangible-capital outcomes would help regulators and stakeholders distinguish substantive AI capabilities from symbolic narratives, reducing the risk of AI washing while supporting a more accurate valuation of AI-enabled intangible assets.

Data and Code Availability

The coding manuals for AIAI and IAVS are provided in Appendices A and B. An anonymized replication package including the firm–year panel dataset used in the regressions and the main text-processing and estimation scripts is available from the authors upon reasonable request for academic purposes.

Sex-Based Differences Statement

The study did not analyze data disaggregated by sex or gender, as these variables were not part of the research scope. Consequently, no conclusions can be made regarding potential differences between male and female subjects.

The authors declare that no AI tools were used in the writing, translation, or generation of texts, figures, or tables in this manuscript. The authors assume full responsibility for the intellectual content.

List of Acronyms

AI – Artificial Intelligence

AIAI – AI Adoption Intensity

CSRD – Corporate Sustainability Reporting Directive

ESG – Environmental, Social and Governance

FE – Fixed Effects (panel model specification)

GRI – Global Reporting Initiative

IC – Intellectual Capital

IAVS – Intangible Asset Visibility Score

IBEX 35 – Benchmark stock index of the 35 largest listed companies in Spain

LDA – Latent Dirichlet Allocation (topic modelling technique)

ML – Machine Learning

NLP – Natural Language Processing

RBV – Resource-Based View

VRIN – Valuable, Rare, Inimitable, and Non-substitutable (attributes of strategic resources)

Declaration of conflicting interests

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References

Amendola, C., Gennaro, A., Labella, S., & Vito, P. (2023). The evolution of intellectual capital disclosure driven by European regulatory change: Evidence from the Italian stock market. *Journal of Intellectual Capital,* 24(5), 1136-1163. https://doi.org/10.1108/JIC-10-2022-0195

Aujirapongpan, S., & Songkajorn, Y. (2022). Organizational strategic intuition for high performance: The role of knowledge-based dynamic capabilities and digital transformation. *Journal of Open Innovation: Technology, Market, and Complexity,* 8(3), 117. https://doi.org/10.3390/joitmc8030117

Bamhdi, A.M. (2024). Analysis of intangible assets reporting standards and automation in KSA within an Islamic context–a case study. *Journal of Islamic Accounting and Business Research.* https://doi.org/10.1108/jiabr-08-2023-0273

Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management,* 17(1), 99–120. https://doi.org/10.1177/014920639101700108

Blanquet, L.B., Pereira, M.A., & Petrov, S. (2025). An interpretable ML framework for company valuation. *Decision Analytics Journal,* 16. https://doi.org/10.1016/j.dajour.2025.100611

Connelly, B.L., Certo, S.T., Ireland, R.D., & Reutzel, C.R. (2011). Signaling theory: A review and assessment. *Journal of Management,* 37(1), 39-67. https://doi.org/10.1177/0149206310388419

Corrado, C., Haskel, J., & Jona-Lasinio, C. (2022). Intangible capital and modern economies. *Journal of Economic Perspectives,* 36(3), 3-28. https://doi.org/10.1257/jep.36.3.3

Fomina, O., & Semenova, S. (2025). Intellectual Capital Valuation under EU Digital Strategy. Scientia Fructuosa, 160(2), 60-77. Available at: https://journals.knute.edu.ua/scientia-fructuosa/article/view/2257

Fosso-Wamba, S., Queiroz, M.M., & Pappas, I.O. (2024). Artificial intelligence capability and firm performance: A sustainable development perspective by the mediating role of data-driven culture. *Information Systems Frontiers,* 26, 2189-2203. https://doi.org/10.1007/s10796-023-10460-z

Haniev, A. (2024). Intangible Assets and US Stock Returns: An analysis using the Index Method, Panel Regression, and Machine Learning. *Journal of Applied Economic Research,* 23(3), 833-854. Available at: https://journalaer.ru/fileadmin/user_upload/site_15934/2024/11_KHaniev.pdf

Heiling, J. (2025). Digital transformation and the accounting for intangible assets in the public sector. *Journal of Public Budgeting, Accounting & Financial Management*. https://doi.org/10.1108/jpbafm-09-2024-0177

Khan, H.U., Malik, M.Z., & Alomari, M.K.B. (2022). Transforming the capabilities of artificial intelligence in GCC financial sector: A systematic literature review. *Wireless Communications and Mobile Computing,* 2022, 8725767. https://doi.org/10.1155/2022/8725767

Kraaijenbrink, J., Spender, J.C., & Groen, A.J. (2010). The Resource-Based View: A review and assessment of its critiques. *Journal of Management,* 36(1), 349-372. https://doi.org/10.1177/0149206309350775

Lev, B. (2001). *Intangibles: Management, measurement, and reporting.* Brookings Institution Press.

Lev, B., & Gu, F. (2016). *The end of accounting and the path forward for investors and managers.* Wiley. https://doi.org/10.1002/9781119270041.fmatter

Mohan, S.K., Bharathy, G., & Jalan, A. (2025). Enterprise Data Valuation: A Targeted Literature Review. *Journal of Economic Surveys,* 40(1), 73-92. https://doi.org/10.1111/joes.12705

Moro-Visconti, R. (2024). The Valuation of Artificial Intelligence-Driven Know-How and Patents. In *Artificial Intelligence Valuation.* Palgrave Macmillan . https://doi.org/10.1007/978-3-031-53622-9_2

Naeem, M., Ali, S., Islam, M., & Rehman, A. (2024). Does Intellectual Capital mediate AI Investment and Firm Value? *NICE Journal,* 17(3). Available at: https://nicerjss.com/index.php/JFME/article/view/483

Petro-Korhonen, S., & El Bouchtili, S. (2025). *AI-Driven Valuation Techniques in Cross-Border Mergers and Acquisitions: Enhancing Accuracy in Emerging Markets.* Theseus Repository. Available at: https://www.theseus.fi/handle/10024/888692

Rock, D.I. (2019). *Essays on information technology, intangible capital, and the economics of artificial intelligence.* MIT DSpace. Available at: https://dspace.mit.edu/handle/1721.1/123582

Röser, A.M., & Zureck, A. (2024). *A critical analysis of ESG reporting using AI in American and European PE firms.* SSRN. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4887834

Spence, M. (1973). Job Market Signaling, *The Quarterly Journal of Economics,* 87(3), 355-374. https://doi.org/10.2307/1882010

Taheri-Hosseinkhani, R. (2025). Does intellectual capital mediate AI investment and firm value? *NICE Journal of Financial Management and Economics*, 17(3). https://nicerjss.com/index.php/JFME/article/view/483

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal,* 28(13), 1319–1350. https://doi.org/10.1002/smj.640

Teece, D. J. (2014). *A dynamic capabilities-based entrepreneurial theory of the multinational enterprise.* SSRN. https://ssrn.com/abstract=5065346

Trequattrini, R., Lardo, A., & Cuozzo, B. (2022). Intangible assets and digital transformation. *Meditari Accountancy Research,* 30(4), 989-1006 . https://doi.org/10.1108/medar-03-2021-1216

Van-Criekingen, K., Bloch, C.W., & Eklund, C.M. (2022). Measuring intangible assets: A review of the state of the art. *Journal of Economic Surveys,* 36(5), 1539-1558. https://doi.org/10.1111/joes.12475

Appendix A. AI Adoption Intensity (AIAI) Coding Manual

A.1. Purpose and Overview

This appendix documents the coding rules used to construct the AI Adoption Intensity (AIAI) index. AIAI is an ordinal 0–3 scale that captures the extent to which firms have substantively adopted AI, based on their external disclosures. The objective is to distinguish between (i) the mere use of AI-related language and (ii) concrete, sustained deployment of AI systems across business functions.

A.2. Data Sources and General Coding Principles

Coders drew on the triangulated set of sources described in Section 3.3 of the main text: annual reports, ESG/sustainability reports, corporate communications (e.g., investor presentations, AI-related press releases), and corroborating media coverage. The following general principles guided the coding:

- **Priority of official sources.** Audited annual and ESG reports are treated as primary sources. Corporate communications and media items are used to clarify or corroborate, but cannot override explicit statements in official reports.
- **Evidence over rhetoric.** Generic, forward-looking statements (e.g., "we aim to leverage AI", "we want to become an AI-driven company") are not sufficient to justify higher levels of AIAI unless accompanied by concrete descriptions of deployed systems or projects.

- **Conservatism in ambiguous cases.** When the available evidence is unclear or contradictory, coders assign the lowest plausible score consistent with the text (upper bound = 1 in highly ambiguous cases).
- **Firm–year unit.** AIAI is coded at the firm–year level. All available documents referring to activities within the fiscal year are considered jointly.

A.3. AIAI Scale and Decision Rules

The AIAI scale ranges from 0 to 3 and is defined as follows:

- **Level 0 – No AI initiatives disclosed**

  Definition: No references to AI systems, algorithms, machine learning, or closely related technologies in the firm's official documents for the year.

  Typical evidence:

  - The term "artificial intelligence", "AI", "machine learning", "deep learning" or equivalent does not appear in the annual or ESG report.
  - Media coverage, if any, refers only to generic statements by external parties with no concrete projects attributed to the firm.

  Examples of texts coded as 0:

  - Reports focused exclusively on traditional IT investments (e.g., ERP upgrades, cybersecurity) without mentioning AI, algorithms, or predictive models.

- **Level 1 – Pilots or experiments**

  Definition: The firm reports isolated AI pilots or proofs of concept in a limited part of the business, with no evidence of integration into core operations or strategy.

  Typical evidence:

  - References to "pilot projects", "experiments", or "testing AI tools" in a single business process.
  - Mentions of collaborating with a technology partner or startup to explore AI applications without confirmed deployment.

  Examples of texts coded as 1:

  - "During the year we launched a pilot project to explore the use of AI-based chatbots in our customer service centre."
  - "We are experimenting with machine learning to analyse a small subset of our customer data."

- **Level 2 – Functional integration**

  Definition: The firm reports AI systems deployed in at least one major business function, with indications of ongoing use and dedicated resources. AI is presented as a tool embedded in specific processes rather than purely experimental.

  Typical evidence:

  - Description of AI models used in credit scoring, fraud detection, predictive maintenance, pricing, or recommendation systems.
  - Statements about efficiency, accuracy, or risk management improvements attributable to AI systems.
  - References to specialized teams or roles (e.g., data scientists, AI engineers) working on these applications.

  Examples of texts coded as 2:

  - "Our credit risk models now rely on machine-learning algorithms, which are fully integrated into the loan approval process."

- “We use AI-based predictive maintenance in our network infrastructure to reduce downtime and optimize interventions.”

- **Level 3 – Strategic deployment across multiple domains**

  Definition: The firm describes AI as part of its core value creation logic, with initiatives spanning several business functions and explicitly linked to strategic objectives, governance structures, or dedicated AI units.

  Typical evidence:

  - AI initiatives in multiple areas (e.g., operations, marketing, risk, customer experience), discussed as an integrated portfolio rather than isolated projects.
  - AI embedded in corporate strategy documents, with clear targets or roadmaps.
  - Formal AI governance structures (e.g., AI committees, ethics boards, dedicated AI centres of excellence).

  Examples of texts coded as 3:

  - “AI is a central pillar of our digital transformation strategy, supporting personalized customer journeys, real-time risk management, and operational automation across the group.”
  - “We have established an AI Centre of Excellence to coordinate projects in pricing, logistics, fraud detection, and customer analytics, overseen by an AI governance committee.”

A.4. Handling Ambiguous and Borderline Cases

Coders followed a simple decision tree in ambiguous situations:

1. **Is AI explicitly mentioned with a concrete application?**

   If **no**, assign level 0.

   If **yes**, proceed to step 2.

2. **Is the application clearly limited to a pilot or experiment, without evidence of ongoing deployment?**

   If **yes**, assign level 1.

   If **no**, proceed to step 3.

3. **Is AI clearly embedded in at least one ongoing business function (with evidence of regular use and resources)?**

   If **yes**, assign at least level 2.

   If AI is present in several functions and linked to strategy or governance, consider level 3.

4. **Do disclosures rely mostly on aspirational or marketing language (e.g., “we want to use AI”, “we are exploring AI”), with limited details?**

   If **yes**, cap the score at 1.

   When documents provided mixed signals (e.g., a strategic claim of being “AI-driven” but only one small pilot described), coders privileged the most conservative interpretation consistent with the evidence, typically assigning level 1.

A.5. Coder Training and Inter-Coder Reliability

Two coders were trained using a set of practice cases covering all four AIAI levels. Training included joint reading of company reports, discussion of borderline examples, and calibration of judgments against the coding manual.

For the final coding, both coders independently assigned AIAI scores to each firm–year. Discrepancies were discussed case by case until consensus was reached, using the rules in Sections A.3 and A.4. The initial agreement rate corresponded to $\varkappa = 0.82$, which indicates high inter-coder reliability. The final consensus scores are used in the empirical analysis.

Appendix B. Intangible Asset Visibility Score (IAVS) Coding Manual

B.1. Purpose and overview

This appendix documents the construction of the Intangible Asset Visibility Score (IAVS). IAVS captures how visible a firm's intangible capital is in its external reporting, combining three components: (1) the frequency of narrative references to intangibles, (2) the reporting quality of intangible-related disclosures, and (3) the ratio of recognized intangible assets to total assets.

B.2. Narrative Disclosure Dictionary and Classification

Narrative references to intangibles are identified using a dictionary organised into three categories:

- **Human capital:** skills, training, learning, talent, employees, workforce, competencies, leadership development, reskilling, upskilling, diversity and inclusion, etc.
- **Structural capital:** R&D, innovation, patents, software, data assets, algorithms, organizational processes, IT infrastructure, proprietary platforms, intellectual property, brand guidelines, internal know-how, etc.
- **Relational capital:** brand, reputation, customer relationships, loyalty, customer experience, partnerships, ecosystems, alliances, distribution networks, stakeholder engagement, community relations, etc.

The dictionary includes stems and synonyms in English and Spanish to reflect the actual language used in IBEX 35 reports. Terms referring purely to tangible assets (e.g., "plant, property and equipment") or generic "resources" not clearly linked to intangibles were excluded. Appendix Table B1 (optional if quieres añadir una tabla en Word) lists the main terms used in each category.

B.3. Procedure for Counting and Normalizing Narrative Frequency

For each firm–year, the following steps were followed:

1. **Document selection.** Annual reports and ESG/sustainability reports were merged into a single text corpus, excluding boilerplate sections such as tables of contents and legal disclaimers.
2. **Text preprocessing.** Text was converted to lower case, stop words and non-alphanumeric characters were removed, and simple stemming was applied to align inflected forms with dictionary entries.
3. **Sentence-level scanning.** The corpus was segmented into sentences. Each sentence was scanned for dictionary terms, and each occurrence was counted. When multiple terms appeared in the same sentence, all were counted.
4. **Aggregation.** Counts were aggregated at the firm–year level for all dictionary terms (and, where relevant, by human/structural/relational categories).
5. **Normalization.** To avoid confounding disclosure with document length, total counts were divided by the number of words in the corpus and multiplied by 1,000, producing a normalized frequency per 1,000 words.

The resulting normalized frequencies form the **narrative frequency component** of IAVS. In robustness checks, we also inspected category-specific frequencies (human, structural, relational capital) and obtained similar patterns.

B.4. Reporting Quality Rubric (0-3 Scale)

Reporting quality is evaluated at the report level using a 0–3 scale adapted from GRI principles (materiality, completeness, comparability):

- **Score 0 – No specific information on intangibles**

  The report contains at most generic references to "resources" or "assets" without clear mention of human, structural, or relational capital.

No dedicated sections or indicators related to intangibles are provided.

Example: "Our assets support our long-term growth" with no further detail.

- **Score 1 – Generic, unspecific mentions**

  Intangibles are mentioned in broad terms (e.g., "people are our greatest asset", "innovation is key"), but without quantitative indicators, time series, or clear links to strategy.

  Information is largely qualitative and aspirational.

  Example: "We invest in training our employees" with no data on training hours, budgets, or outcomes.

- **Score 2 – Descriptive discussion with some quantification or strategic linkage**

  The report includes specific descriptions of intangible-related policies or programs, accompanied by at least some quantitative indicators (e.g., training hours per employee, R&D expenditure, customer satisfaction scores) or explicit links to strategic objectives.

  Information begins to be comparable over time, but may still be fragmentary or incomplete.

  Example: "Employees received an average of 22 hours of training per year, aligned with our digital transformation strategy."

- **Score 3 – Systematic, quantifiable and comparable reporting**

  The report provides structured, recurring indicators on key intangibles (e.g., human capital KPIs, R&D intensity, brand metrics, NPS) across multiple years.

  Targets, time series, segmentation (by geography, business unit or employee group), and clear connections to strategy are present.

  The information allows stakeholders to track the evolution of intangible assets over time.

  Example: A dedicated human capital section reporting targets and multi-year series for training, engagement, turnover, and diversity; an innovation section with R&D spending, pipeline metrics, and patent counts.

Coders assign the quality score at the firm–year level after a holistic reading of the report, using these criteria and the examples compiled in an internal coding guide. When in doubt between two adjacent scores, coders choose the lower one unless strong evidence supports the higher score.

B.5. Intangible Assets Ratio (Accounting Component)

The accounting component of IAVS is the ratio of intangible assets to total assets:

Intangible assets ratio=Recognized intangible assetsTotal assets.\text{Intangible assets ratio} = \frac{\text{Recognized intangible assets}}{\text{Total assets}}.Intangible assets ratio=Total assetsRecognized intangible assets.

Recognized intangible assets include items classified under IAS 38 (e.g., patents, software, brands, licences, development costs) as reported in the consolidated balance sheet and notes. Goodwill is treated consistently with the firm's reporting policy; when goodwill is presented separately, we document whether it is included or excluded in robustness checks.

Special cases were handled as follows:

- **Zero or immaterial intangibles.** When recognized intangible assets were zero or negligible, the ratio was set to 0.

- **Major reorganizations and M&A.** When mergers, acquisitions or divestments led to substantial changes in the balance sheet, accompanying notes were reviewed to ensure that the observed movements in the ratio reflected genuine changes in intangible recognition rather than purely mechanical effects.

- **Restatements.** If prior-year figures were restated, the restated values were used for consistency.

For comparability across firms and years, the ratio was min–max normalized to the [0,1] interval before being combined with the other components.

B.6. Aggregation Into the IAVS Index and Robustness

Each of the three components—normalized narrative frequency, reporting quality score, and intangible assets ratio—was transformed to the [0,1] interval using min–max normalization based on the full sample distribution. The baseline IAVS index is the simple average of the three normalized components (equal weights).

To assess robustness, we tested alternative weightings that place more emphasis on narrative components (e.g., 0.4/0.4/0.2 and 0.5/0.3/0.2 for frequency/quality/accounting). These alternative specifications yielded substantively similar results in the regression analysis, as reported in Section 4.4 of the main text.