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The mediating role of Artificial Intelligence on the relationship between intangible assets and equity market value: evidence from global context

marwa Rabe Mohamed Ali Elkmash^{1✉}, Sherif El-Halaby^{2✉} & Sherif Nagy Mohamed^{3✉}

While intangible assets (IA) are key drivers of equity market value (EMV) in the knowledge economy, the mediating role of artificial intelligence (AI) in this relationship varies globally. This study investigates the assumption that the value-creating interaction between intangible assets and artificial intelligence is uniform worldwide. The study tests the mediating role of artificial intelligence on the relationship between intangible assets and equity market value, and examines the moderator role of market type (Emerging vs. Developed). Using a longitudinal panel data (2020–2024) of a global sample from the Communication & Information Technology firms, we analyzed data using Generalized Method of Moments (GMM) regression. The results confirm the significant role of AI in the relationship between IA and EMV, and reveal a key difference between the market groups. The impact of IA and EMV on AI adoption is more transparent and more efficient in Developed Markets (DM). Similarly, the analysis reveals two key findings: first, AI has a substantial direct impact on developed-market (DM) firms; second, more critically, the synergistic interaction between AI and IA is significantly enhanced in this context. Consequently, our models explain a larger proportion of the variance in DM firm valuation, offering robust empirical confirmation of the hypothesized valuation gap. This study provides strong evidence that the resource-based view should be understood within the context of market-type frameworks. We identify the “IA-AI valuation gap” and outline specific strategic imperatives: Emerging Market (EM) firms need to focus on developing foundational (IA) before fully integrating deep AI. In contrast, Developed Market (DM) firms should concentrate on using AI to enhance the value of their existing IA. Policymakers should address this gap by strengthening key institutional supports, such as intellectual property protection and digital infrastructure.

¹Department of Accounting, Faculty of Management Sciences, October University for Modern Sciences and Arts, Cairo, Egypt. ²Department of accounting, College of Business Administration, Ajman University, Ajman, United Arab Emirates. ³Department of Accounting, Economics and Business Administration, Innovation University, Cairo, Egypt. ✉email: mrabe@msa.edu.eg; s.elhalby@ajman.ac.ae; Sherief.nagy@iu.edu.eg

Introduction

Traditional accounting primarily uses tangible assets to measure firm performance, thereby ignoring the value of intangible assets (IA), such as intellectual property (IP) (Yallwe & Buscemi, 2014). To support the stakeholders' evaluation process, the firm must produce a practical, comprehensive disclosure of IA (Giacosa et al., 2017). Innovation can be considered a key resource that enables a firm to achieve high, sustainable performance. Investors should know that the legal protection for a patent is not the same as for a trade secret, as well as how the legal and regulatory environment surrounding innovation has evolved and may continue to evolve, to understand the implications of a firm's innovative efforts (Barth and Gee, 2024).

The literature on IA relies on proxies derived from patents or R&D costs. This focus constrains conclusions about the advantages of technological intangibles, such as enhanced product features or lower marketing expenses. Furthermore, it leads to a narrow emphasis on R&D and patent-intensive firms, overlooking IA in a broader range of firms (Chu et al., (2024)). These measurement challenges are persistent, as illustrated by the case of the Tehran Stock Exchange, where accounting standards fail to capture intangible value accurately (Behname et al., 2012). Simpson and Tamayo (2020) discussed the possible channels through which disclosure might affect IA; the next challenge is to measure disclosure and IA. Researchers fight with the (economic) documentation of the real effects of disclosure. The challenge in measuring IA stems from their multidimensional nature and the difficulty of quantifying most of these dimensions.

Over the past two decades, eco-innovation—also known as green, sustainable, or environmental innovation—has attracted increasing attention as an innovation sector. Although innovation is typically discussed in terms of its financial benefits, it is now a key strategy for addressing environmental challenges. To improve a firm's performance in terms of environmental, social, innovative, financial, operational, and market performance, eco-innovative business practices—which include organizational, product, process, and marketing innovations—are also taken into consideration as firm strategies (Hizarci-Payne et al., (2021); Liu (2024); Ding, et al. (2022)).

Modern financial theory is based on the link between equity market value (EMV) and IA. However, as artificial intelligence (AI) emerges as a mediator variable, this relationship is undergoing radical alteration. This study critically compares the AI-mediated role in emerging and developed countries, analyzing how they link and modify the value chain from IA to EMV. The AI has a dual role: as an input AI that modifies the way other intangibles create value, and as an outcome of intangible asset investments. Institutional asymmetries—differing market efficiency, regulatory frameworks, and AI adoption readiness—are also a source of variation that can either amplify or constrain AI's mediating role—a crucial knowledge gap in understanding how technological disruption reinterprets intangible value creation through contextual details.

This study tests whether the mediating role of AI in the relationship between IA and EMV varies significantly between emerging and developed countries, driven by institutional asymmetries. In emerging markets (EM), AI investments primarily enhance firm value by building foundational digital capabilities and improving the efficiency of existing IA. For example, Naeem et al. (2024) found that AI serves as a tool for organizational transformation, improving human, structural, and relational capital, which, in turn, boosts innovation and efficiency and leads to a more favorable market perception. Conversely, in developed markets (DM) with more efficient capital markets, IA are often already priced in, and AI's role shifts. Here, it functions

as advanced financial infrastructure—through algorithmic trading and complex risk models—to enhance market efficiency and accessibility (Yu & Padgett, 2013). However, this can also introduce new systemic risks, challenging the view of AI as a force advantage (Parana, 2024).

AI investments in EM are shown to improve firm value by enhancing IA (Naeem et al., 2024). AI enables automation, predictive modeling, and risk management, which are crucial to the development of financial markets in EM, thereby enhancing efficiency and accessibility (Ochuba et al., 2024). In China, IA are recognized at the EMV, and AI can enhance firm valuation by improving the recognition of IA (Yu & Padgett, 2013). However, in DM, IA are often incorporated into asset pricing models, and AI enhances the efficiency of these models (Yu & Padgett, 2013). AI's infrastructural role in DM includes algorithmic trading and governance, which can increase complexity and systemic risks, challenging the notion of AI as a stabilizing force (Parana, 2024).

On one hand, AI's role is more transformative, focusing on building IA and improving market accessibility in EM (Naeem et al., 2024; Ochuba et al., 2024). On the other hand, in DM, AI's role is more about enhancing existing financial infrastructures and integrating IA into market valuations (Yu & Padgett, 2013; Parana, 2024).

While AI is relevant across emerging and DM, its impact on IA and EMV depends on region-specific economic and technological conditions. In EM, AI is a transformative tool for building IA, whereas in DM, it enhances existing financial infrastructures and market efficiencies. Huyen, Mong Le et al. (2020) argue that firms can acquire a sustainable competitive advantage by owning scarce, valuable, unique, and non-replaceable resources, and by implementing a strategy of IA that competitors cannot easily replicate. This is the theory of the resource-based view (RBV). The academic literature views IA as non-monetary resources. These assets depict how firms activate value-creation processes and are rapidly becoming important inputs for investment decisions. The unique perspective is grounded in a revised view of dynamic capability theory (Salvi et al., 2020).

This study investigates these challenges by bridging the gap between IA and EMV, with a specific focus on the mediating role of AI in emerging versus DM. The structure of this study is divided into five sections. Section 2 reviews the relevant literature and develops the research hypotheses. Section 3 outlines the methodology employed in the study. Section 4 presents and analyzes the empirical findings, providing a detailed account. Section 5 concludes by discussing the implications of the results and suggesting directions for future research.

Literature review and hypotheses formulation

Hedge et al. (2018) discussed the importance of IA for economic growth and firm performance. They argue that academics, especially over the last two decades, have started to study the country-, market-, and firm-level determinants of firm IA. The protection of IA applies to financial reporting to the extent that it supports investors' understanding of how the firm's future cash flows are affected by its intangible asset activities (Barth & Gee, 2024).

IA is enhancing firms' ability to create novelty in ideas, products, and services. The capabilities of IA come from factors, such as licenses, copyrights, patents, IP, R&D, and software. In the literature, there is disagreement regarding the relationship between IA and EMV. For instance, studies have shown that IA contribute more to the creation of value, efficiency, and financial performance of firms (Kamath, 2008; Pal & Soriya, 2012; Powell, 2003; Tan et al., 2007) than it does to profitability and firm return

(Jordao & de Almeida, 2017). Furthermore, Hussinki et al. (2017) discovered that firms that employ knowledge management techniques and have high levels of IA are likely to perform better.

The relationship between IA and EMV. The relationship between IA and EMV is a complex topic, as evidenced by previous empirical studies across different markets and periods. IA, such as IP, brand value, and goodwill, have been shown to significantly influence a firm's market value. However, the extent and nature of this influence can vary depending on the country context, industry, and specific characteristics of the firms involved.

Traditional IA are positively associated with the firm's market value. Recently, the investment effect in environmental IA has been evident as instrumental for both firms' financial performance and the environment (Khalil et al., (2024)). The average net profits per employee, goodwill, and other IA all have a positive impact on the EMV. This is because firms with highly knowledgeable staff will have an advantage when it comes to IA, be able to create a large number of patents and copyrights, and have an excellent reputation, which is a component of goodwill for oriental firms and would encourage customers and investors to spend more money (Ni et al., 2021).

An empirical study of NASDAQ and NYSE firms found that both reported and unreported IA influence EMV, emphasizing the need for transparent accounting practices (Cosmulese et al., 2021). Research on chemical firms in Indonesia indicates that while IA positively affects market value, firm size can moderate this relationship, suggesting that larger firms may not always benefit equally from IA (Hutauruk, 2024). Similarly, IA have been found to significantly impact EMV, as demonstrated in the EURO STOXX 50, where they play a crucial role in valuation, highlighting their growing importance in today's economy (Petrusova et al., 2024). Moreover, the disclosure of IA positively correlates with EMV, although investors often prioritize profitability over intangible disclosures (Dancakova et al., 2022). Khan and Iqbal (2022) argue that firms with higher IA, such as R&D expenditures, demonstrated increased EMVs, emphasizing the role of innovation in enhancing firm competitiveness (Zarowin, 2016).

Compared to domestic patents in emerging countries, reverse innovation patents—which include IP developed in an emerging nation but patented in a developed nation—are more accurate indicators of innovation value (Hou, Li (2023)). By creating product-market value, advertising a firm's capabilities, and serving as an equivalent to the private value of an invention, reverse innovation patents increase a firm's value. The short- and long-term market worth of firms is positively correlated with reverse innovation patents. This effect is more pronounced for firms with high levels of managerial skill and innovation (Hou, Li (2023)).

Li and Wang (2014) investigated the impact of IA (R&D expenditure) on the financial performance of listed IT firms in Hong Kong. According to the report, the firm's financial performance benefits from both sales training and R&D spending. The amount of IA and a firm's market value were shown to be significantly correlated when the relationship between market value, dividend policy, solvency ratio, intangible value, and firm performance in Indonesia during the financial crisis from 2006 to 2011 was examined.

IA, such as patents developed in an emerging country but patented in a developed country, are better indicators of intangible asset value than domestic patents in EM. According to Hou, Li (2023), patents create high EMV, communicate firms' skills, and act as a proxy for the private worth of IA, all of which

increase EMV. Based on previous studies, we can formulate the following hypothesis.

H1. The impact of IA on EMV differs significantly between EMV and DM.

The relationship between AI and IA. The relationship of AI and IA is a complex and evolving area of study, particularly as businesses increasingly rely on AI technologies to enhance their operations and value propositions. While AI has the potential to transform the valuation and management of IA significant challenges remain, particularly in quantifying these assets and integrating them into existing accounting frameworks.

AI applications can enhance the analysis of IA, such as brand value and customer relationships, by processing large datasets to identify patterns and trends. However, the subjective nature of many IAs complicates AI's predictive capabilities, as these assets often rely on qualitative factors that are difficult to quantify (Gil et al., 2024). The rise of AI-driven platforms has created new IA, such as algorithmic systems and data, which are crucial for financial valuation in venture capital contexts (Kampmann, 2024). The lack of standardized valuation frameworks for IA impedes the integration of AI into financial reporting, potentially leading to inconsistencies and inaccuracies in financial statements (Bamhdi, 2024).

Although AI has transformative potential for managing IA, current valuation and reporting frameworks are insufficient. According to Corrado et al. (2021), to comprehend AI's effect on productivity, investments in both intangible (software and databases) and tangible (hardware) assets must be included. Because some assets are assessed while others are not, traditional productivity evaluations may not fully capture AI's potential. Economic complexity is not much influenced by investments in computers and equipment (tangible assets) or software (an IA) (Uribe, 2025).

Ding et al. (2022) explored the use of IA capabilities for innovation by examining variations in regional environmental information disclosure and differences in industry exposure to such disclosures to address measurement challenges. They investigate the pathways through which environmental information disclosure impacts firms' green innovation, a topic often overlooked in current literature. The study examines two potential ways in which environmental disclosure may mitigate financial constraints and/or improve corporate social responsibility, thereby affecting green patenting efforts.

In recent years, there has been a consistent rise in R&D investments in AI-based systems and solutions across the manufacturing, professional, and scientific sectors, as well as in education. These datasets improve forecasting methods when paired with AI. AI also has a significant impact on R&D in industries, such as chemicals and pharmacy by enabling the discovery of new industrial materials. Through innovations, such as "virtual factories," which enhance the manufacturing chain through simulations, the machinery and equipment industry is also transformed (Uribe, 2025).

Based on previous studies, we can formulate the following hypothesis.

H2. The impact of IA on AI differs significantly between EM and DM.

The relationship between AI and EMV. The integration of AI and EMV has significantly transformed stock prediction and management, enhanced financial transparency, and reduced risks. AI technologies, such as machine learning and natural language processing, have improved the accuracy of stock price forecasts

and trading strategies, thereby influencing market valuations. Several key aspects characterize this evolution.

Since 2020, AI-focused stocks and exchange-traded funds (ETFs) have outperformed the broader market, driven by rising adoption and investor sentiment favoring technology-centric portfolios (Li, 2024). AI technologies enhance trading efficiency by analyzing vast datasets, leading to more accurate predictions and optimized returns (Prabhakaran, 2024). Major financial institutions—including Goldman Sachs and Morgan Stanley—are increasingly using AI for trading and market analysis, enhancing operational efficiency and decision-making processes (Turmanidze, 2024).

While AI presents substantial benefits in EMV, challenges, such as data quality, algorithmic biases, and ethical concerns remain critical considerations for its implementation in financial markets. Predicting equity market behavior is challenging due to the nonlinear relationship between transaction data and the uncontrollable factors driving market fluctuations. Deep learning is a machine learning technique that has been effectively applied across fields and is particularly well-suited for nonlinear approximation. AI has attracted significant interest across a variety of research domains. Recent developments in machine learning and deep learning have enhanced computer capabilities in speech recognition, natural language processing, image recognition and classification, and social network filtering. The outcomes are sometimes better than those of human specialists (Chen et al., 2018).

Hizarci-Payne et al. (2021) argue that although innovation is usually addressed in economic terms, it has become a key approach to addressing environmental issues. In line with these developments, eco-innovation, as a subfield of innovation, has received increasing attention for its intangible asset capabilities, sustainable innovation, and environmental innovation. Liu (2024) discussed the specific drivers of corporate green innovation adoption. He provides a deeper understanding of the underlying factors that determine green innovation. ESG performance positively affects green innovation, which in turn contributes to sustainable development. All these factors can be considered as IA, capabilities, or output.

Ferreira et al. (2021) argue that the rapidly expanding field of AI still holds many unexplored possibilities. Financial portfolio optimization, predicting future prices or trends in financial assets, and sentiment analysis of news or social media comments on the assets or enterprises are three broad uses of AI in finance. Several studies have proposed integrating methods from other domains, even though each domain has distinct features.

Additional research involves dynamic system control in the financial market, network analysis, investor behavior analysis, and financial asset clustering, which connects calibrated option volatility to changes in equity market futures prices.

Based on previous studies, we can formulate the following hypothesis.

H3. The impact of AI on EMV differs significantly between EM and DM.

The mediating role of AI on the relationship between IA and EMV. The relationship between IA and EMV can be significantly influenced by the mediating role of AI. Studies indicate that AI investments enhance firm value by leveraging IA, such as intellectual capital and financial technologies. This synthesis highlights the mechanisms through which AI mediates these relationships.

AI investments positively impact firm value by enhancing intellectual capital—human, structural, and relational capital—and by integrating AI, thereby improving organizational

knowledge and innovation, thereby increasing market perception and equity value (Naeem et al., 2024). A balanced strategy that incorporates AI across operational layers is essential for maximizing market value and mitigating potential risks (Visconti, 2024). Conversely, while AI shows promise in enhancing EMV through IA, challenges, such as algorithmic bias and regulatory issues, may hinder its effectiveness. Thus, caution is required to realize AI's promise in this setting fully.

The RBV argues that sustainable competitive advantage stems from rare, valuable resources. Intangibles (including AI) epitomize such resources, but their value extraction depends on complementary capabilities. Developed-market firms typically possess stronger absorptive capacity and ecosystem synergies to leverage IA/AI. In EM, infrastructure gaps and talent shortages may dilute returns on intangibles (Zhao et al., (2022)). The RBV predicts that IA/AI will lead to greater stock premiums in mature markets, as evidenced by pooled regressions and marginal-effect comparisons.

Based on previous studies, we can formulate the following hypothesis.

H4. The Mediating Role of AI on the Relationship between IA and EMV differs significantly between EM and DM.

Study methodology

This study investigates how the mediating role of AI differs in the relationship between IA and EMV across institutional contexts, comparing a sample of EM (Brazil, India, Egypt) with DM (USA, Germany, UK). The operationalization of variables is as follows: Equity Market Value is proxied by Tobin's Q; Intangible Assets are captured by investments in R&D, IP, and software; and AI adoption is measured using the TF-IDF text analysis methodology, following Millidge (2021).

Study design. This study employs a quantitative, longitudinal panel design to examine how AI differentially mediates the relationship between IA and EMV across emerging and DM. The analysis uses secondary financial and market data (2020–2024) from a global sample of publicly listed firms in the Communication and Information Technology (CIT) Sector.

The core analytical framework involves pooled cross-sectional time-series regression analysis and the generalized method of moments (GMM). To account for unobserved time-invariant firm heterogeneity and mitigate omitted variable bias, firm size effects are incorporated into the models. Crucially, to explicitly test the hypothesized differences between market types (emerging vs. developed), interaction terms between the key independent variables IA and AI and a market-type dummy variable are included in the regression specifications. This allows for direct statistical testing of whether the two market classifications differ significantly (H1, H2, and H3). For hypothesis H4, a triple interaction term (IA, AI, and Market Type) is employed to test the differential joint impact. Standard errors are clustered at the firm level to address autocorrelation and heteroskedasticity, ensuring robust statistical inference. This study followed the study by Li et al. (2024). He confirmed that this methodological approach provides a rigorous basis for isolating the relationships of interest while controlling for confounding factors inherent in firm-level financial data.

We select all listed CIT firms in countries classified as “EM” (EM) or “DM” (DM) over the study period. Major financial databases, such as stock exchanges, were combined with specialized databases for IA and AI indices. Use a recognized standard index provider classification to assign firms to EM or DM groups in the final sample. This section details were introduced as follows:

Table 1 Selection Criteria of the Study Sample.

Group	Country	Selection Criteria
Developed	Japan, UK, USA, Germany, Australia	Classification of ECD membership and World Bank “High-Income” status (GNI per capita ≥ \$13,845) maintained for at least 10 years.
Emerging	India, Brazil, Egypt, Vietnam, Mexico	Classification of World Bank “Upper-Middle Income” (GNI per capita \$4466–\$13,845) and membership in the MSCI EM Index.

Empirical model specification: (Panel Regression Framework).

The study in this section presents the statistical models used to test the study hypotheses:

Model One: *H1. The impact of IA on EMV differs significantly between EM and DM.*

$$EMV_{it} = \beta_0 + \beta_1 * IA_{it} + \beta_2 * MKT_TYPE_{it} + \beta_3 * (IA_{it} * MKT_TYPE_{it}) + \beta_3, 4, 5, 6, 7, 8 * CONTROLS_{it} + \epsilon_{it} \tag{1}$$

Where: I = Firm, t = Year

Model Two (AI Value Impact Differs): *H2. The impact of AI on IA differs significantly between EM and EM.*

$$EMV_{it} = \beta_0 + \beta_1 * AI_{it} + \beta_2 * MKT_TYPE_{i} + \beta_3 * (AI_{it} * MKT_TYPE_{i}) + \beta_3, 4, 5, 6, 7, 8 * CONTROLS_{it} + \epsilon_{it} \tag{2}$$

Model Three (IA Impact on AI Differs): *H3. The impact of AI on EMV differs significantly between EM and DM.*

$$AI_{it} = \beta_0 + \beta_1 * IA_{it} + \beta_2 * MKT_TYPE_{i} + \beta_3 * (IA_{it} * MKT_TYPE_{i}) + \beta_3, 4, 5, 6, 7, 8 * CONTROLS_{it} + \epsilon_{it} \tag{3}$$

Model Four (Combined IA & AI Impact Differs): *H4. The mediating role of AI on the relationship between IA and EMV differs significantly between EM and DM.*

$$EMV_{it} = \beta_0 + \beta_1 * IA_{it} + \beta_2 * AI_{it} + \beta_3 * MKT_TYPE_{i} + \beta_4 * (IA_{it} * MKT_TYPE_{i}) + \beta_5 * (AI_{it} * MKT_TYPE_{i}) + \beta_6 * (IA_{it} * AI_{it}) + \beta_7 * (IA_{it} * AI_{it} * MKT_TYPE_{i}) + \beta_3, 4, 5, 6, 7, 8 * CONTROLS_{it} + \epsilon_{it} \tag{4}$$

We can use estimation methods to compare results; we also use Arellano-Bond GMM if dynamic panel bias is a concern. Use lagged values (t-1) of IA and AI to mitigate reverse causality. We were handling missing data and checking for outliers and inconsistencies. All derived variables (Tobin’s Q, IA proxies, AI proxies, and control ratios). Standardize variables if necessary for interpretation.

Data collection. We select two groups of listed firms in EM and DM for the 5-year study.

Study sample. The CIT sector is particularly well-suited for examining AI’s mediating role in the relationship between IA and market value across emerging and developed economies. The rationale for selecting this sector is outlined in the following points:

1. Theoretical relevance. Dominance of IA CIT firms derive 70–90% of their value from intangibles (patents, software, data, human capital, R&D, licenses), aligning perfectly with the IA construct. AI as core business infrastructure is not

peripheral but embedded in CIT operations, including network optimization, predictive maintenance, and natural language processing. This ensures AI mediation is observable and measurable. Market value sensitivity to IA CIT firms exhibit higher Tobin’s Q volatility tied to IA/AI announcements (Corrado et al., (2022)).

2. Methodological advantages. In the CIT sector advantage, intangible asset costs are prominently disclosed. Efficient markets rapidly price IA/AI shocks. For cross-country comparison, CIT firms in emerging and DM share similar business models, global supply chains, standardized accounting practices (e.g., IFRS adoption), and controls to address sectoral heterogeneity. Exogenous factors rather than firm-specific ones often drive endogeneity in AI adoption in CIT.
3. Empirical validation: is strengthened by the high concentration of AI adopters in the CIT sector: 83% of CIT firms deploy AI, compared to 35% in manufacturing (McKinsey, 2023). This provides a larger sample size for robust SEM and multi-group analysis.

The sample facilitates robust statistical modeling, including Structural Equation Modeling (SEM) and multi-group analysis, by ensuring an adequate number of observations. Countries within the sample are systematically classified as either “Developed” or “Emerging” economies to enable cross-group comparisons. This classification is based on objective, widely recognized criteria. Developed economies (e.g., USA, Germany, UK, Japan, and Australia) are defined by their long-standing OECD membership and sustained “High-Income” status as per World Bank benchmarks. Conversely, EM (e.g., Brazil, India, Egypt, Vietnam, and Mexico) are identified by their “Upper-Middle Income” classification and inclusion in the MSCI EM Index. While this dichotomous grouping provides a valid and practical framework for analysis, it is acknowledged that economic classifications are dynamic. Some economies categorized as emerging may be in transition toward developed status. Nonetheless, the applied criteria ensure a conceptually sound and empirically grounded distinction between the two groups (World Bank, 2025). The final study sample, detailed in Table 1, is constructed according to these explicit selection criteria.

To address Heterogeneity, we incorporated key macroeconomic and institutional variables into our regression models to account for cross-country differences. We will employ panel data models with country-fixed effects or firm-fixed effects. This technique effectively controls for all time-invariant, unobserved heterogeneity between countries, isolating the effect of our variables of interest within each country over time. We will conduct a robustness check by dividing the ‘EM’ group into more homogeneous sub-groups (Brazil, India, and Egypt) and re-running the analysis.

Data collection. Data were collected from financial reports of firms listed on stock exchanges in emerging and developed countries, focusing specifically on the CIT sector due to its reliance on IA. The CIT sector was selected as it grew approximately 16.3% in FY 2022/2023, making it the fastest-growing AI sector.

The study covers the last five years and includes all listed CIT firms from selected exchanges, resulting in a balanced sample of 940 observations equally divided between emerging (470) and developed (470) markets.

Variable measurement. Tobin's Q serves as our measure of EMV (the dependent variable). It gauges a firm's valuation by comparing its EMV to equity book value. A Q ratio of 1 indicates equilibrium, where EMV equals equity book value.

$$\text{Tobin's Q} = (\text{Equity Market Value}) / (\text{Equity Book Value})$$

Regarding IA (independent variable), we assume that firms with IA can innovate, with R&D intensity measured by R&D expenditure/total revenue. Software is measured by capitalized software costs/total assets and trademark/total assets. Then we can measure IA using the financial data of IA (Lev & Sougiannis, 1996), and we can develop this model:

$$IA_{it} = \sum(R\&D_{it}/TR_{it} + \text{Software}_{it}/TA_{it} + TM_{it}/TA_{it})$$

We measure AI using the method described by Millidge (2021), which relies on Term Frequency-Inverse Document Frequency (TF-IDF) to quantify a word's importance in a document relative to a corpus. TF: Frequency of a term in a document. $TF(t, d) = \text{count of } t \text{ in } d / \text{total terms in } d$. IDF: Downscales terms appearing frequently across documents. $IDF(t, D) = \log(\text{Total documents in } D / \text{Documents containing } t)$.

$$TF - IDF_{it} = TF(t, d)_{it} \times IDF(t, D)_{it}$$

The terms that are defined as AI keywords or terms, such as "AI," "machine learning, deep learning, neural network, natural language processing, algorithmic decision-making, AI model, computer vision, and autonomous systems" (Millidge, 2021). We posit that, in the context of market value research, the information disclosed to shareholders is itself a meaningful object of study. The annual report is the primary channel through which management signals strategy and capability to the market. Therefore, our measure directly captures the aspect of AI activity intended to influence investor perceptions, a key mechanism in the relationship we are testing. We took the following actions:

- Using NLP techniques to distinguish between substantive discussions of AI (e.g., in MD&A, R&D sections) and boilerplate mentions (e.g., in risk factors).
- Triangulation with IA data, we collected data on AI-related IA, and we used a validated keyword search strategy to identify the AI role in IA. A significant positive correlation between our 'AI Disclosure Intensity' score and the IA patents provides strong empirical evidence for the validity of our text-based measure.
- Made manual content analysis of a random sample of high-scoring and low-scoring reports to provide qualitative evidence that high TF-IDF scores correlate with meaningful discussions of AI strategy and implementation.
- Include additional control variables in our regression models to account for other factors that might influence disclosure habits, such as firm size, profitability (ROA), and R&D intensity. This helps isolate the unique effect of AI disclosure.

We can show variable measures in Table 2.

Study model. This study develops a novel analytical framework to quantify firm AI exposure through textual analysis of 10-K/20-F filings and evaluates its impact on firm valuation. The model employs TF-IDF to systematically assess the prominence of AI-

related keywords in annual reports, creating a standardized disclosure index that captures the strategic emphasis on AI capabilities. This textual metric is then integrated with financial variables in a multivariate regression framework, using Tobin's Q as the primary valuation benchmark to assess how market perceptions correlate with AI disclosure intensity. By bridging computational linguistics with financial econometrics, the model addresses critical gaps in measuring intangible technological assets while controlling for industry dynamics, firm size, and R&D investment. The approach enables longitudinal tracking of AI adoption trends and their valuation implications across market sectors, offering empirical insights into how voluntary disclosure of strategic technologies influences investor pricing decisions. Then, we can show the conceptual model, as shown in Fig. 1.

Results and discussion

The connection between IA, EMV, and AI was tested using OLS regression after descriptive statistics, VIF, and correlation analyses. Researchers used correlation matrices to examine relationships among variables; panel regression models were specified to test the impact of variables and their coefficients. The results were as follows:

Descriptive analysis. The results of the descriptive analysis were estimated for 940 observations, including means, standard deviations, and min/max for all variables, separately for EM and DM sub-samples. Table 3 shows the descriptive results.

The results of Table 3 show that the mean of Tobin's Q in EM was 5.48 vs. DM 9.85, with a maximum value of 46.99 vs. 72.45 in both EM and DM. The mean log size in EM was 9.966, vs. 4.32 in DM, and the maximum value was 452.35 in both EM and DM. The mean of ROA in EM was 0.15 vs. DM 0.18, with a maximum value of 0.45 vs. 0.79 in both EM and DM. The mean of Log IA in EM was 32.84 vs. DM 35.94, with a maximum value of 115.17 vs. 201.65 in both EM and DM. The mean of AI in EM was 2.618 vs. DM 3.519, with a maximum value of 415.04 vs. 524.54 in both EM and DM.

These results highlight significant differences between EM and DM. EM firms exhibit substantially lower market valuations (mean Tobin's Q: 5.48 vs. 9.85) and profitability (mean ROA: 0.15 vs. 0.18) compared to DM firms, reinforcing the typical premium associated with DM. Surprisingly, EM firms appear drastically larger on average (mean log size: 9.966 vs. 4.32) and exhibit an extreme maximum size (452.35 vs. 93.50), suggesting the EM sample is with national currencies. Developed market firms hold significantly more IA on average (mean Log IA: 35.94 vs. 32.84) and achieve much higher maximum levels (max Log IA: 201.65 vs. 115.17). While DM shows a higher average level of AI activity (mean AI: 3.519 vs. 2.618), it also contains the firm with the highest AI intensity (max AI: 415.04 vs. 524.54). This suggests AI adoption might be more widespread but potentially shallower in DM.

Multi-collinearity analysis results. The test for multicollinearity was performed in Table 4 to determine whether multicollinearity exists in the data. The results show no multicollinearity, with an average VIF of 1.950 or lower.

The multicollinearity analysis, as presented in Table 4, shows that the VIF results indicate no significant multicollinearity among the independent variables in the model. All individual VIF values are well below the commonly accepted threshold of 5 (or 10), with the highest VIF of 1.950 for LRit and an average VIF also low. This suggests that the independent variables are not excessively correlated with each other, ensuring that the

Table 2 List of variables.

Variable Type	Variable	Symbol	Calculations	Source of Data
Independent Variable	IA	IA_{it}	$\sum (R\&D_{it}/TR_{it} + Software_{it}/TA_{it} + TM_{it}/TA_{it})$	Financial statements
	R&D/Revenue		$(R\&D_{it}/TR_{it})$	Financial statements
	Capitalize software	$Software_{it}$	$software/TA_{it}$	Financial statements
	Trademark	TM_{it}	TM_{it}/TA_{it}	Financial statements
Dependent Variable	EMV	Tobin's Q	$(EMV)/(Equity\ Book\ Value)$	Financial statements
Mediating	AI	AI	$TF(t,d)_{it} \times IDF(t,D)_{it}$	Disclosure Reports
Control Variables	Firm Size	$SIZE_{it}$	Log Total Assets	Financial statements
	Financial leverage	LEV_{it}	Total Liabilities/Total Assets	Financial statements
	Return on Assets	ROA_{it}	Net income/Total Assets	Financial statements
	Earnings Per Share	EPS_{it}	Earnings Per Share	Financial statements
	Liquidity Ratio	LR_{it}	Total Current Assets/Total Assets	Financial statements
	Country Group (Moderator)	CG	0 = Emerging (MSCI EM), 1 = Developed (OECD)	World Bank, MSCI

Source: Done by authors.

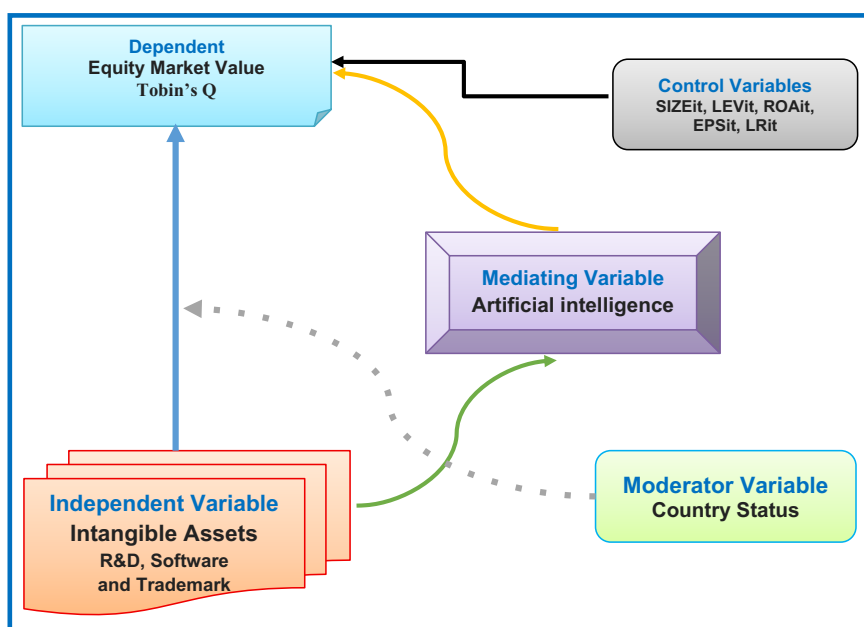


Fig. 1 presents the study conceptual framework. Source: Done by authors.

regression coefficients are reliable and their individual effects can be interpreted without significant distortion from multicollinearity.

Person correlation results. The results of the Pearson correlation test were examined in panel B in Table 5 to find the significant relationship between EMV and IA.

As shown in Table 5, there is a positive relationship between IA and EMV in the EM, with a Pearson correlation of 0.212, compared to 0.246 in DE at the 1% significance level. There is a positive relationship between AI and EMV in EM, with a Pearson correlation of 0.203, compared with 0.500 in DE at the 1% significance level. The correlation results presented in Table 5 reveal varying relationships between Tobin's Q and the independent variables across emerging, developed, and total sample contexts. The firm size (SIZEit), leverage (LEVit), AI (AIit), and IA (IAit) consistently exhibit statistically significant positive correlations with Tobin's Q across both emerging and DMts, indicating their general importance to firm valuation. However, profitability indicators, such as ROAit and EPSit exhibit

stronger, more significant positive correlations with Tobin's Q in established countries than in emerging countries, where the correlations are weak or non-significant. These findings demonstrate that, while some factors have a universal influence on business value, the market's assessment of profitability and other financial measures can vary greatly depending on the country's economic growth stage.

Hypothesis tests. To test the hypothesized relationships, we employed regression analysis with EMV as the dependent variable. Our analysis proceeded in two stages. First, we conducted simple regressions to examine the individual relationship between each category of IA and market value. Second, we specified a multiple regression model to assess the collective impact of all intangible asset variables, along with relevant control variables, on firm valuation. Results were as follows:

Results for the relationship between IA and EMV. The regression results for the first hypothesis are shown in Table 6.

Table 3 Descriptive analysis results.

	N		Mean		Std. Deviation		Variance		Minimum		Maximum	
	Emerging	Developed	Emerging	Developed	Emerging	Developed	Emerging	Developed	Emerging	Developed	Emerging	Developed
Tobin Q	470	470	5.488	9.850	48.809	8.8867	2382.33	78.974	1.04	1.21	46.993	72.45
SIZEit	470	470	9.966	4.329	28.133	19.152	791.471	366.83	1.91	2.10	452.35	93.50
LEVit	470	470	0.14392	0.4963	0.112915	0.23312	0.127502	0.54347	0.073	0.145	0.71386	0.9957
ROAit	470	470	0.1513	0.1873	0.49816	0.2622	0.248171	0.6875	0.00	0.00	0.45235	0.7978
EPSit	470	470	14.328	32.31	97.835	23.421	9571.73	548.5	0.00	0.00	842.66	96.94
LRit	470	470	0.132	0.2490	0.67510	0.23439	0.455771	0.5494	0.020	0.010	0.64670	98.61
Alit	470	470	2.618	3.519	19.696	5.3640	387.971	28.773	0.030	0.056	415.04	524.54
IAit	470	470	32.843	35.94	19.388	36.920	375.920	1363.1	0.103	0.240	115.04	201.65

Source: authors' calculations (Numbers by natural log).

Table 4 VIF results.

Model	Std. Error	t	Sig.	Collinearity Statistics	
				Tolerance	VIF
1 (Constant)	1.620	0.877	0.380		
SIZE it	0.044	12.630	0.000	0.808	1.237
LEVit	0.015	5.498	0.000	0.620	1.612
ROAit	0.033	-0.172	0.863	0.548	1.823
EPSit	0.014	-1.938	0.053	0.897	1.114
LRit	0.026	-1.145	0.253	0.513	1.950
Alit	0.165	6.070	0.000	0.975	1.025
IAit	0.035	5.373	0.000	0.713	1.403
Country	2.190	-4.737	0.000	0.770	1.299

Source: authors' calculations.

Table 5 correlation results.

		Tobin's Q		
		Emerging	Developed	Total Sample
Tobin's Q	Pearson	1	1	1
	Correlation			
	Sig. (2-tailed)			
	N	470	470	940
SIZEit	Pearson	0.561**	0.208**	0.465**
	Correlation			
	Sig. (2-tailed)	0.000	0.000	0.000
	N	470	470	940
LEVit	Pearson	0.213**	0.170**	0.220**
	Correlation			
	Sig. (2-tailed)	0.000	0.000	0.000
	N	470	470	940
ROAit	Pearson	0.058	0.203**	0.070*
	Correlation			
	Sig. (2-tailed)	0.213	0.000	0.033
	N	470	470	940
EPSit	Pearson	0.027	0.134**	0.016
	Correlation			
	Sig. (2-tailed)	0.953	0.004	0.629
	N	470	470	938
LRit	Pearson	0.066	0.116*	0.074*
	Correlation			
	Sig. (2-tailed)	0.156	0.011	0.023
	N	470	470	940
Alit	Pearson	0.203**	0.500**	0.210**
	Correlation			
	Sig. (2-tailed)	0.000	0.000	0.000
	N	470	470	940
IAit	Pearson	0.212**	0.246**	0.260**
	Correlation			
	Sig. (2-tailed)	0.000	0.000	0.000
	N	470	470	940

Source: authors' calculations.

* The correlation coefficient is statistically significant at the 5% level (p 0.05).

** The correlation coefficient is statistically significant at the 1% level (p 0.01).

H1. The impact of IA on EMV differs significantly between EM and DM.

Table 6 presents the regression results for the first hypothesis, disaggregated by emerging and developed countries, revealing distinct impacts of the IA on the equity market value show a highly significant positive relationship in emerging markets, also firm size (SIZEit), and leverage (LEVit) all show a highly significant positive relationship ($p < 0.001$), indicating their strong contribution to the dependent variable (EMV). At the same time,

Table 6 Results for the relationship between IA and EMV.

	Unstandardized Coefficients				Coefficients		Sig.	
	B		Std. Error		Beta		Emerging	Developed
	Emerging	Developed	Emerging	Developed	Emerging	Developed		
(Constant)	-3.096	0.381	2.299	0.648			0.179	0.557
IAit	3.118	0.070	0.458	0.011	0.250	0.290	0.000	0.000
SIZEit	0.894	0.109	0.065	0.027	0.515	0.235	0.000	0.000
LEVit	0.079	0.062	0.020	0.022	0.184	0.161	0.000	0.005
ROAit	0.068	0.073	0.050	0.018	0.069	0.215	0.080	0.000
EPSit	0.007	0.017	0.019	0.022	0.014	0.044	0.723	0.451
LRit	-0.005	-0.003	0.037	0.023	-0.007	-0.009	0.898	0.881
R	0.429	0.627						
R Square	0.184	0.393						
Adjusted R Square	0.174	0.385						
F Change	17.423	49.911						
Sig. F Change	0.000	0.000						

Source: authors' calculations.

Table 7 Results for the relationship between AI and IA.

	Unstandardized Coefficients				Coefficients		Sig.	
	B		Std. Error		Beta		Emerging	Developed
	Emerging	Developed	Emerging	Developed	Emerging	Developed		
(Constant)	0.260	1.284	0.214	0.409			0.225	0.002
IAit	1.015	2.005	0.043	0.107	0.749	0.833	0.000	0.000
SIZEit	-0.009	0.072	0.006	0.017	-0.050	0.256	0.122	0.000
LEVit	0.001	0.010	0.002	0.014	0.027	0.041	0.483	0.489
ROAit	0.002	0.005	0.005	0.011	0.017	0.026	0.706	0.631
EPSit	0.005	0.019	0.002	0.014	0.096	0.083	0.004	0.178
LRit	-0.001	0.022	0.003	0.014	-0.010	0.095	0.815	0.128
R	0.332	0.743						
R Square	0.110	0.552						
Adjusted R-Square	0.099	0.546						
F Change	9.54	95.10						
Sig. F Change	0.000	0.000						

Source: authors' calculations.

ROAit, EPSit, and LRit are not statistically significant. In contrast, for DM, IA (IAit) have a highly significant positive impact on EMV, as well as on firm size (SIZEit) and leverage (LEVit), with LEVit also exhibiting a highly significant positive impact ($p < 0.001$ and $p < 0.005$ for LEVit). However, ROAit additionally shows a significant positive relationship ($p < 0.001$), and EPSit and LRit remain insignificant. The overall model fit, as indicated by the R Square and Adjusted R Square, is notably higher for developed countries (0.393 and 0.385, respectively) compared to emerging countries (0.184 and 0.174, respectively), suggesting that the model explains a greater proportion of the variance in the dependent variable in DM. The highly significant F Change for both groups (0.000) confirms the overall statistical significance of the models. There is a significant positive impact of IA on EMV in both DM and EM. However, the results show DM is higher than EM.

Results for the relationship between AI and IA. The regression results for the second hypothesis are shown in Table 7

H2. The impact of IA on AI differs significantly between EM and DM.

Table 7 presents the regression results for the second hypothesis, showing the impact of IA on the AI adoption

variable across emerging and DM. For EM, only IA (IAit) have a highly significant positive impact on AI ($B = 1.015$, $Sig = 0.000$), while firm size, leverage, ROA, EPS, and LRit are not statistically significant. In contrast, for developed countries, IA (IAit) have a highly significant positive impact on AI. Firm size (SIZEit) and leverage (LEVit) demonstrate a highly significant positive impact ($B = 2.005$, 0.072 , and 0.010 , respectively, all with $Sig = 0.000$), indicating a broader set of significant drivers. The model's explanatory power, as indicated by the R-squared and adjusted R-squared, is substantially higher for developed countries (0.552 and 0.546, respectively) than for emerging countries (0.110 and 0.099, respectively), suggesting that the model explains a greater share of the variance in AI adoption in DM. The highly significant F Change for both groups (0.000) confirms the overall statistical significance of the models. Then there is a significant positive impact for IA on AI in both DM and EM. However, the results show DM is higher than EM.

Results for the relationship between AI and EMV. The regression results for the third hypothesis are shown in Table 8.

H3. The impact of AI on EMV differs significantly between EM and DM.

Table 8 Results for the relationship between AI and EMV.

	Unstandardized Coefficients				Coefficients		Sig.	
	B		Std. Error		Beta			
	Emerging	Developed	Emerging	Developed	Emerging	Developed	Emerging	Developed
(Constant)	-0.563	1.978	2.251	0.497			0.803	0.000
AIit	1.831	2.766	0.341	0.068	0.199	0.462	0.000	0.000
SIZEit	0.931	0.061	0.065	0.025	0.536	0.131	0.000	0.016
LEVit	0.071	0.046	0.020	0.020	0.165	0.120	0.000	0.025
ROAit	0.083	0.060	0.051	0.016	0.084	0.177	0.105	0.000
EPSit	0.007	0.014	0.019	0.021	0.015	0.037	0.701	0.493
LRit	-0.001	-0.035	0.037	0.021	-0.002	-0.093	0.973	0.091
R	0.546	0.609						
R Square	0.299	0.371						
Adjusted R Square	0.290	0.363						
F Change	32.85	45.57						
Sig. F Change	0.000	0.000						

Source: authors' calculations.

Table 9 Results for the mediating role of AI on the relationship between IA and EMV.

	Unstandardized Coefficients				Coefficients		Sig.	
	B		Std. Error		Beta			
	Emerging	Developed	Emerging	Developed	Emerging	Developed	Emerging	Developed
(Constant)	-0.635	-1.375	0.566	2.253			0.015	0.542
IAit	0.074	5.008	0.009	0.595	0.307	0.358	0.000	0.000
AIit	0.775	6.376	0.064	0.387	0.469	0.696	0.000	0.000
SIZEit	0.059	0.991	0.023	0.063	0.128	0.509	0.000	0.000
LEVit	0.054	0.054	0.019	0.019	0.142	0.112	0.000	0.005
ROAit	0.070	0.006	0.015	0.049	0.206	0.005	0.524	0.905
EPSit	-0.030	-0.045	0.019	0.019	-0.079	-0.080	0.234	0.017
LRit	-0.021	-0.060	0.020	0.036	-0.055	-0.074	0.292	0.096
R	0.623	0.734						
R Square	0.388	0.539						
Adjusted R Square	0.379	0.532						
F Change	41.894	77.311						
Sig. F Change	0.000	0.000						

Source: authors' calculations.

Table 8 presents the regression results for the third hypothesis, where we measure the impact of AI on EMV, revealing distinct patterns across emerging and DM. In emerging markets, AI AIit shows a highly significant positive impact on EMV, and firm size (SIZEit) shows a highly significant positive impact (Sig = 0.000). At the same time, ROAit is marginally significant (Sig = 0.105). Leverage (LEVit), EPSit, and LRit are not statistically significant. In contrast, for developed countries, AIit shows a highly significant positive impact on EMV. Also, firm size (SIZEit), leverage (LEVit), and ROAit all exhibit a highly significant positive impact (Sig = 0.000 or 0.025), indicating a broader set of significant drivers for the dependent variable EMV. The model's explanatory power, as indicated by the R-squared and adjusted R-squared, is higher for developed countries (0.371 and 0.363, respectively) than for emerging countries (0.299 and 0.290, respectively), suggesting that the model explains a greater proportion of the variance in EMV in developed economies. The highly significant F Change for both groups (0.000) confirms the overall statistical significance of the models. Then there is a significant positive impact of AI on EMV in both DM and EM. However, the results show DM is higher than EM.

Results for the mediating role of AI on the relationship between IA and EMV. The regression results for the fourth hypothesis are shown in Table 9.

H4. The Mediating Role of AI on the relationship between IA and EMV differs significantly between EM and DM.

Table 9 presents the regression results for the fourth hypothesis, disaggregated by emerging and DM, revealing distinct patterns in the impact of AIit and IAit on the EMV. For emerging markets, AIit and IAit show a highly significant positive impact; firm size (SIZEit) and ROAit also show a highly significant positive impact (Sig = 0.000), while EPSit exhibits a significant negative impact (Sig = 0.000). Leverage (LEVit) and LRit are not statistically significant. In contrast, for DM, AIit and IAit show a highly significant positive impact on EMV; firm size (SIZEit) also shows a highly significant positive impact (Sig = 0.000 or 0.026); and ROAit demonstrates a highly significant positive impact (Sig = 0.000 or 0.026). However, EPSit shows a significant negative impact (Sig = 0.005). The model's explanatory power, as indicated by the R-squared and adjusted R-squared, is higher in developed countries (0.539 and 0.532, respectively) than in emerging countries (0.388 and 0.371, respectively), suggesting that the model explains a greater proportion of the variance in the

Table 10 The significant differences test.

		Levene's Test for Variances		T-test for Equality of Means				
		F	Sig.	T	Df	Sig. (2-tailed)	Mean Difference	Std. Error Difference
Tobin's Q	Equal variances assumed	17.23	0.000	-1.899	938	0.000	-4.34553	2.28854
	Equal variances not assumed.			-1.899	500.1	0.000	-4.34553	2.28854
AI _{it}	Equal variances assumed	11.090	0.000	-1.713	938	0.000	-2.27387	1.38404
	Equal variances not assumed.			-1.713	925.2	0.000	-2.27387	1.38404
Iait	Equal variances assumed.	276.37	0.000	-13.72	938	0.000	-26.6814	1.9435
	Equal variances not assumed.			-13.72	730.8	0.000	-26.6814	1.9435

Source: authors' calculations.

Table 11 GMM Results.

Variable	Coefficient	Std. err.	z-	P >	[95% Conf. Lower]	[95% Conf. upper]
L1.Y	0.4512924	0.05825	7.75	0.00	0.3371194	0.5654653
SIZEit	0.7379927	0.07985	9.24	0.00	0.5814828	0.8945025
LEVit	-0.0229595	0.03064	-0.75	0.45	-0.0830195	0.0371006
ROAit	0.1682939	0.06853	2.46	0.01	0.0339725	0.3026152
EPSit	0.0127936	0.02422	0.53	0.59	-0.0346784	0.0602655
LRit	-0.0872216	0.04633	-1.88	0.06	-0.1780272	0.0035839
AIit	3.029029	0.41289	7.34	0.00	2.219762	3.838296
IAit	0.3704403	0.08453	4.38	0.00	0.2047496	0.5361311
Country	100.034	91.484	1.09	0.02	79.2733	279.3413
Year	0.1242617	1.1043	0.11	0.91	-2.040156	2.28868
Firm	-0.6093446	0.76935	-0.79	0.42	-2.117251	0.8985613
_cons	-258.7785	2238.7	-0.12	0.90	-4646.623	4129.066

Source: authors' calculations.

dependent variable EMV in developed economies. The highly significant F Change for both groups (0.000) confirms the overall statistical significance of the models. There is a significant positive impact of IA and AI on EMV in both DM and EM. However, the results show DM is higher than EM.

Robust tests. This section employs more advanced econometric techniques to deepen the analysis. Such as the independent-samples t-test, which determines whether the means of two groups are statistically different, assuming the data meet certain conditions; Levene's test, which explicitly assesses whether the variances of two (or more) groups are equal; and the GMM estimator. GMM is particularly well-suited for this context, as it provides consistent and efficient parameter estimates while effectively addressing potential endogeneity concerns, such as simultaneity bias or unobserved heterogeneity, and accounting for dynamic relationships within the panel data. This approach allows us to move beyond simple mean comparisons and rigorously model the underlying economic relationships driving the observed differences.

The significant differences test. Researchers conducted statistical tests to assess significant differences between EM and DM across key financial and strategic metrics. The results of this test are shown in Table 10.

Based on Table 11, the results indicate highly statistically significant differences between the emerging and developed countries being compared for all tested variables (AI, IA, EMV). Levene's Test (all Sig. = 0.000) strongly rejects the null hypothesis of equal variances for each comparison. Consequently, the t-test results, not assuming equal variances, are the

appropriate ones to interpret. For each variable, this t-test shows a highly significant difference in means (Sig. = 0.000), with negative mean differences indicating that the EM mean is consistently lower than the DM mean. The magnitude of these differences, relative to their standard errors (Std. Error Difference), further underscores the strength of these findings.

GMM test. GMM is employed in this study to analyze AI's mediating role between IA and equity value across emerging and developed countries, as it directly addresses the core methodological challenges. Its ability to handle endogeneity ensures reliable causal inference across complex relationships among IA, AI, and EMV. Furthermore, GMM's consistency provides robustness against data limitations in emerging markets and heteroskedasticity differences between country groups. Crucially, as the most efficient estimator using only the information in the specified moment conditions, GMM maximizes statistical power for testing the mediation model without imposing extraneous assumptions, making it the optimal choice for rigorous cross-country comparison. Table 11 shows the GMM results.

The GMM results presented in Table 11 indicate that several variables significantly influence the dependent variable. The lagged dependent variable shows a highly significant positive coefficient (0.451, $p = 0.000$), which means strong persistence in the dependent variable. Among the independent variables, SIZEit (0.738, $p = 0.000$), ROAit (0.168, $p = 0.014$), AIit (3.029, $p = 0.000$), IAit (0.370, $p = 0.000$), and Country (100.034, $p = 0.027$) all exhibit statistically significant positive coefficients, indicating their positive influence on the EMV. Conversely, LRit (-0.087, $p = 0.060$) shows a marginally significant negative relationship. Variables LEVit, EPSit, Year, and Firm, along with the constant, do not appear to have a statistically significant

Table 12 Results and their consistency with the hypotheses.

Hypothesis	Results	Decision	Agreed or disagreed with previous studies
H1. The impact of IA on EMV differs significantly between EM and DM.	For emerging markets, IA show a highly significant positive impact on the dependent variable EMV ($R^2 = 0.184$). For DM, IA exhibit a highly significant positive impact on the dependent variable EMV ($R^2 = 0.393$).	Accepted	Agreed with Khalil et al., (2024) Hutauruk, 2024 Petrusova et al., 2024 Dancakova et al., 2022
H2. The impact of IA on AI differs significantly between EM and DM.	For emerging markets, IA have a highly significant positive impact on AI ($R^2 = 0.110$). For DM, IA have a highly significant positive impact on AI ($R^2 = 0.552$).	Accepted	Agreed with Gil et al., 2024 Bamhdi, 2024 Kampmann, 2024 Uribe, 2025
H3. The impact of AI on EMV differs significantly between EM and DM.	For emerging markets, AI shows a highly significant positive impact on EMV ($R^2 = 0.299$). In DM, AI also shows a highly significant positive impact on EMV ($R^2 = 0.371$).	Accepted	Agreed with Li, 2024 Turmanidze, 2024 Prabhakaran, 2024 Ferreira et al. (2021)
H4. The Mediating Role of AI on the Impact of IA on EMV differs significantly between emerging and developed markets.	For emerging markets, AI and IA show a highly significant positive impact on EMV ($R^2 = 0.388$). Before entering AI was ($R^2 = 0.184$). For DM, AI and IA also demonstrate highly significant positive impacts ($R^2 = 0.539$). Before entering AI was ($R^2 = 0.393$).	Accepted	

impact on the dependent variable in this model. The substantial positive coefficients for ALit and Country suggest they are strong drivers of the EMV.

This study provides empirical evidence that the mediating role of AI in the relationship between IA and EMV differs significantly between emerging markets EM and DM. All four hypotheses are strongly supported: H1 confirms IA's impact on EMV is significantly weaker in EMs ($R^2 = 0.184$) than in DMs ($R^2 = 0.393$). This result aligns with Ding et al. (2022), who find that environmental information disclosure as IA promotes green innovation among listed firms. The results of H2 reveal that IA drives AI adoption more strongly in DMs ($R^2 = 0.552$) than in EMs ($R^2 = 0.110$), while H3 demonstrates that AI's effect on EMV is substantially stronger in DMs ($R^2 = 0.371$) than in EMs ($R^2 = 0.299$). Crucially, H4's triple interaction confirms that the joint impact of IA and AI on EMV varies significantly by market type, with DM ($R^2 = 0.539$) firms capturing greater EMV than EM ($R^2 = 0.388$) firms. These results disagree with Hizarci-Payne et al., (2021) findings, which indicate that the effect records a more substantial influence for the association between eco-innovation and firm EMV in developing countries ($r = 0.467$, CI 95% 0.421 to 0.512) in comparison with developed countries ($r = 0.233$, CI 95% 0.165 to 0.299). They argue that this result can be attributed to the fact that eco-innovation is critically relevant to developing nations, primarily because of their vulnerability to environmental challenges and the importance of access to technology for economic development.

These differences stem from structural differences: DM firms possess superior IA endowments (mean log IA 35.94 vs. 32.84) and achieve more effective AI integration, transforming IA into EMV more efficiently. EM firms, despite a larger average size, face valuation discounts (Tobin's Q 5.48 vs. 9.85) and demonstrate shallower AI absorption. Regression models typically explain greater variance in DMs than in EMs, suggesting that EMV drivers are more predictable in developed economies. Profitability measures (ROA/EPS) have greater EMV correlations in DM. Methodologically, the (GMM) technique supported the findings by accounting for endogeneity and heterogeneity. Key controls, such as firm size (SIZEit) and leverage (LEVit), maintained significance across markets, while multicollinearity diagnostics

(max VIF = 1.95) ensured reliable estimates. The persistent significance of the lagged EMV and market-type dummy variables in GMM models further confirms the existence of intrinsic market-type distinctions. Table 12 summarizes the results discussion.

Conclusion

The relationship between IA and EMV is well established but complex. It is influenced by external economic conditions, reporting standards, and variable investor perceptions—challenges that highlight the need for improved accounting practices. Grounded in the RBV, this study addresses a critical gap in this literature. We move beyond establishing the fundamental IA-EMV link to investigate the precise mechanism that connects them. We posit and test a model in which AI serves as the key mediator, translating foundational IA (e.g., R&D and software) into market value. We examine how this entire process is conditioned by country type.

This study investigates the differential mediating role of AI in the relationship between IA and EMV, across EM and DM. It tests four hypotheses concerning significant market-type differences in the impacts of IA on EMV, and the joint effect of IA and AI on EMV. The GMM model is applied to check the relationship between these variables. The GMM model is appropriate for both regression analysis and mediation.

All hypotheses are supported, revealing significant disparities between the groups. The impact of IA on enterprise market value and that of AI is markedly greater in DM than in emerging markets. Similarly, the influence of AI on enterprise market value, along with the synergistic effect of IA and AI, is more potent in DM. Furthermore, the statistical models demonstrate substantially greater explanatory power for DM, explaining significantly more variance than models for emerging markets.

For EM firms, the results suggest that initially prioritizing foundational information architecture (IA) development over AI adoption may yield better expected market value (EMV) returns. In contrast, DM firms should focus on integrating AI with their existing IA to enhance valuation premiums. Policymakers in EMs need to address institutional gaps, such as IP protection and digital infrastructure, to unlock AI-driven value creation. These

findings advance RBV theory by contextualizing how market maturity influences the IA-AI-EMV relationship. For stakeholders and policymakers, the research highlights a practical imperative: to enhance resource productivity, businesses must prioritize technological adoption ahead of manual labor in the digital era.

Our findings offer actionable strategies for executives navigating intangible asset (IA) and AI investments across market contexts. For developed market (DM) firms, results demonstrate that maximizing EMV requires orchestrating IA and AI synergistically: Managers should prioritize integrating AI systems, such as generative AI for R&D or predictive maintenance, with existing IA portfolios, as the triple interaction term confirms this combination drives disproportionate EMV gains in DMs. Conversely, emerging market (EM) firms must first address foundational gaps. Given the significant IA on EMV discount and shallow AI assimilation, managers should reallocate resources from standalone AI projects toward strengthening core IA infrastructure—particularly by formalizing IP and data governance. Policymakers can leverage these results to design market-tailored innovation ecosystems. In emerging economies, governments must address the institutional voids causing IA/AI valuation discounts. This requires modernizing IP frameworks to protect IA, subsidizing AI-complementary infrastructure, and establishing regulatory sandboxes for AI testing—reducing adoption barriers evidenced by weaker IA and AI linkages. For DM, policies should accelerate cross-industry AI diffusion.

This study also has some limitations. The study sample focuses exclusively on CIT firms, limiting applicability to sectors with different IA/AI dynamics, such as manufacturing or services. The temporal scope and unobserved factors present additional constraints. The 5-year panel data (2020–2024) captures pandemic-era anomalies and short-term effects but is insufficient for establishing long-term trends in IA/AI adoption and financial outcomes. Crucially, unobserved variables—such as country-level AI policies, digital infrastructure quality, or geopolitical shocks—could confound the results but remain uncontrolled in the analysis. Although the GMM estimator helps mitigate endogeneity, these limitations warrant caution when extrapolating findings beyond the specific CIT context or the study period.

This study makes a significant contribution to the literature by providing empirical evidence of the differential impact of IA and AI on EMV across both emerging and DM. The findings have critical implications for investors, policymakers, and firm strategists, underscoring the need for tailored approaches that account for each region's unique economic and market conditions. Future research could delve deeper into the qualitative aspects of AI integration and intangible asset management, exploring specific industry-level variations and the long-term sustainability implications of these relationships.

Future research could delve deeper into the qualitative aspects of AI integration and intangible asset management, exploring specific industry-level variations and the long-term sustainability implications of these relationships. In addition, future studies could incorporate qualitative dimensions of IA (e.g., organizational culture) and explore nonlinear relationships between AI and EMV. Longitudinal tracking could also reveal if EMs converge toward DM patterns as digital ecosystems evolve. Nonetheless, this study establishes a critical foundation for understanding market-specific pathways to value creation in the AI-driven knowledge economy.

Data availability

Data is provided within the manuscript files.

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Author contributions

Conceptualization : Marwa Rabe, Sherif Nagy. Data curation: Sherif Nagy Formal analysis : Marwa Rabe, Sherif Nagy. Funding acquisition : Marwa Rabe, Sherif El-Halaby Investigation : Marwa Rabe, Sherif Nagy. Methodology: Marwa Rabe, Sherif Nagy. Project administration : Marwa Rabe, Sherif El-Halaby. Resources : Marwa Rabe, Sherif Nagy. Software: Marwa Rabe, Sherif Nagy. Supervision: Marwa Rabe, Sherif Nagy. Validation: Marwa Rabe, Sherif Nagy. Visualization: Marwa Rabe, Sherif Nagy. Writing – original draft: Marwa Rabe, Sherif Nagy. Writing – reviewing & editing: Sherif El-Halaby.

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Ethical approval

Ethical approval was not required as the study did not involve human participants, human data, or biological material; it was based on secondary data.

Informed consent

The study does not involve human participants, human data, or biological material; it was based on secondary data.

Additional information

Correspondence and requests for materials should be addressed to marwa Rabe Mohamed Ali Elkmash, Sherif El-Halaby or Sherif Nagy Mohamed.

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