Received: 03 Jan. 2026 | **Revised:** 08 Apr. 2026 | **Accepted:** 12 Apr. 2026 | **e-ISSN:** 3085-7813

Alumni.in

ARTICLE

ARTIFICIAL INTELLIGENCE-ENABLED COMPETITIVE INTELLIGENCE AS A STRATEGIC CAPABILITY: ECONOMIC VALUE CREATION ACROSS FIRMS

INTELIGÊNCIA COMPETITIVA HABILITADA POR INTELIGÊNCIA ARTIFICIAL COMO CAPACIDADE ESTRATÉGICA: CRIAÇÃO DE VALOR ECONÔMICO NAS EMPRESAS

[1*] **Yujie Liu**: Kyrgyz State University named after Ishenaly Arabaev, Bishkek, Kyrgyz Republic. ORCID: https://orcid.org/0009-0004-3242-9562

[2] **Li Liu**: Kyrgyz State University named after Ishenaly Arabaev, Bishkek, 720026, Kyrgyz Republic. ORCID: https://orcid.org/0009-0004-8941-5911

[3] **Kalybek Abdykadyrov**: Kyrgyz State University named after Ishenaly Arabaev, Bishkek, 720026, Kyrgyz Republic. ORCID: https://orcid.org/0000-0001-9235-2537

Corresponding Author:
Yujie Liu
E-mail: 15093180982@163.com

How to cite this article:

Liu, Y., Liu, L., & Abdykadyrov, K. (2026). Artificial Intelligence Enabled Competitive Intelligence as a Strategic Capability: Economic Value Creation Across Firms. *Journal of Sustainable Competitive Intelligence*, *16*, e0644. https://doi.org/10.37497/eagleSustainable.v16i.644

ABSTRACT

Purpose: This study examines how artificial intelligence enabled competitive intelligence (AIECI) creates economic value for firms. Rather than treating artificial intelligence as a standalone automation tool, the paper conceptualizes it as a strategic intelligence infrastructure that strengthens how firms sense market shifts, interpret signals, and orchestrate competitive responses.

Methodology/approach: The study adopts a qualitative comparative multiple case design based on recent public archival evidence. Four theoretically sampled cases Walmart, Unilever, Sprinklr, and DoubleVerify were selected because they publicly document the use of AI in market sensing, customer intelligence, campaign optimization, and decision support. The empirical corpus includes annual reports, 10-K filings, earnings releases, and official corporate materials published mainly between 2024 and 2026, complemented by recent peer-reviewed literature. The analysis proceeded through within-case coding and cross-case pattern matching across five dimensions: intelligence source, AI mechanism, decision domain, economic implication, and boundary condition.

Originality/Relevance: The paper contributes by positioning competitive intelligence, rather than AI alone, as the strategic mechanism through which value is created. It clarifies the sequence through which AI inputs are transformed into competitive intelligence capability, intelligence-informed decisions, and economic outcomes.

Key findings: Across the four cases, AIECI generated value through four recurring pathways: revenue acceleration, efficiency and cost relief, improved allocation quality, and strategic speed under uncertainty. However, these benefits were contingent on complementary conditions, particularly data quality, governance, managerial interpretation, and the integration of intelligence outputs into operating decisions.

Theoretical/methodological contributions: The study develops a process view of AIECI built on sensing, interpretation, and orchestration. It also demonstrates how recent archival case evidence can be used rigorously to analyze an emerging strategic phenomenon without reducing the study to a purely descriptive literature review.

Keywords: Artificial intelligence. Competitive intelligence. Strategic capability. Firm performance. Market sensing. Economic value.

DOI: https://doi.org/10.37497/eagleSustainable.v16i.644

Open access

RESUMO

Objetivo: Este estudo examina como a inteligência competitiva habilitada por inteligência artificial (AIECI) cria valor econômico para as empresas. Em vez de tratar a inteligência artificial como uma ferramenta isolada de automação, o artigo a conceitua como uma infraestrutura estratégica de inteligência que fortalece a capacidade das empresas de identificar mudanças de mercado, interpretar sinais e orquestrar respostas competitivas.

Metodologia/abordagem: O estudo adota um desenho qualitativo comparativo de múltiplos casos baseados em evidências arquivísticas públicas recentes. Quatro casos teoricamente selecionados Walmart, Unilever, Sprinklr e DoubleVerify foram escolhidos por documentarem publicamente o uso de IA em monitoramento de mercado, inteligência do consumidor, otimização de campanhas e suporte à decisão. O corpus empírico inclui relatórios anuais, documentos 10-K, releases de resultados e materiais corporativos oficiais publicados principalmente entre 2024 e 2026, complementados por literatura científica recente revisada por pares. A análise foi conduzida por meio de codificação intra-caso e comparação cruzada de padrões em cinco dimensões: fonte de inteligência, mecanismo de IA, domínio decisório, implicação econômica e condição de contorno.

Originalidade/Relevância: O artigo contribui ao posicionar a inteligência competitiva, e não apenas a IA isoladamente, como o mecanismo estratégico por meio do qual o valor é criado. O estudo esclarece a sequência pela qual entradas de IA são transformadas em capacidade de inteligência competitiva, decisões orientadas por inteligência e resultados econômicos.

Principais resultados: Nos quatro casos analisados, a AIECI gerou valor por meio de quatro caminhos recorrentes: aceleração de receitas, eficiência e redução de custos, melhoria da qualidade de alocação e velocidade estratégica sob incerteza. Entretanto, esses benefícios dependeram de condições complementares, especialmente qualidade dos dados, governança, interpretação gerencial e integração dos outputs de inteligência às decisões operacionais.

Contribuições teóricas/metodológicas: O estudo desenvolve uma visão processual da AIECI baseada em sensing, interpretação e orquestração. Também demonstra como evidências recentes de casos arquivísticos podem ser utilizadas de forma rigorosa para analisar um fenômeno estratégico emergente sem reduzir o estudo a uma revisão de literatura meramente descritiva.

Palavras-chave: Inteligência artificial. Inteligência competitiva. Capacidade estratégica. Desempenho empresarial. Market sensing. Valor econômico.

1. INTRODUCTION

Artificial intelligence has moved beyond its earlier role as a purely technical or automation-oriented tool and has become a strategic resource that shapes how firms sense markets, interpret signals, and respond to competitive change. In contemporary digital markets, firms operate in environments marked by rapidly shifting customer preferences, fragmented media channels, unstable supply conditions, and continuously expanding digital footprints. Under such conditions, the key managerial challenge is no longer the simple collection of data, but the ability to transform dispersed and fast-moving signals into timely, decision-relevant intelligence. This is why competitive intelligence has become an increasingly important lens through which the strategic value of artificial intelligence can be understood (Saheb et al., 2024; Sahut & Laroche, 2025).

This issue has only become even more significant due to the fact that competition has become more and more computational. Companies are currently operating in a place where prices are dynamically adjusted, campaigns are optimised in real-time, consumer discourse is tracked continuously and market reactions occur at a very rapid pace. Periodic reporting and decision making based on intuition are inadequate in such situations. Companies that still consider competitive intelligence as a rare analytical task run the risk of basing their assumptions on consumer behavior, channel performance, and competitor intentions on outdated assumptions. In this regard, AI-powered competitive intelligence cannot be regarded as a non-essential efficiency driver, but a strategic necessity to stay economically viable in digitally mediated markets (Saheb et al., 2024; Sahut & Laroche, 2025).

Even though recent studies have come to associate the concept of artificial intelligence with better firm-level performance, such as profitability, operating efficiency, innovation, and strategic adaptability, much of this debate continues to view the interplay between AI and performance too directly. Companies are not able to generate economic value merely because they implement algorithms or analytics systems. Instead, value is created when AI enhances the quality, speed, and usability of intelligence regarding markets, competitors, customers, and operating conditions, and when the intelligence is used to make decisions that affect revenues, costs, resource use, and strategic responsiveness. This is why competitive intelligence offers a more accurate way of understanding the role of AI in the economic results at the firm level (Haftor et al., 2024; Xiao & Zhang, 2025).

Such a difference is particularly critical due to the fact that economic implications are not homogenous. The impacts of AI-powered intelligence can manifest themselves in various ways, such as quality of revenues, cost-effectiveness, and increased precision of spending, accelerated learning processes, enhanced resilience, and more pertinent innovation decisions. These results are not exchangeable, neither do they develop at the same rate. Others can be seen in the short run but others can be seen in the long run due to better adaptation and more disciplined strategic action. By emphasizing economic implications over a single aggregate performance measure, such as the short-term accounting impacts, can thus enable a more subtle interpretation of the reasons why firms persist in investing in AI-enabled intelligence systems despite the uneven accounting impacts (Haftor et al., 2024; Xiao & Zhang, 2025).

To address this issue, the present study examines artificial intelligence-enabled competitive intelligence (AIECI) through a comparative archival multiple-case design. It concentrates on four companies that have apparent and reported AI-enabled intelligence routines: Walmart, Unilever, Sprinklr, and DoubleVerify. These examples were chosen since they are various points in the value chain and various methods of converting intelligence into economic value. Walmart exemplifies AI-assisted intelligence in large-scale retailing; Unilever exemplifies the application of AI in consumer sensing, marketing and in decision processes related to procurement; Sprinklr is an exemplar of a platform-based model commercializing AI-supported customer and market intelligence; and DoubleVerify is an example of how AI can be utilized to verify, optimize and increase the efficiency of media-spend. Combined, these examples allow looking at AIECI as an internal organizational capability and monetizable intelligence service, as opposed to viewing the phenomenon in a single industry context (Walmart Inc., 2025; Unilever, 2025; Sprinklr, 2026; DoubleVerify Holdings, Inc., 2026).

The study addresses three research questions. First, how does artificial intelligence-enabled competitive intelligence generate economic value for firms? Second, which types of economic outcomes are most visible in recent public case evidence? Third, which organizational and governance conditions enable or constrain value capture? In answering these questions, the paper makes four contributions. First, it positions AIECI as the central strategic capability linking AI infrastructure to firm-level economic outcomes. Second, it develops a process explanation based on sensing, interpretation, and orchestration. Third, it identifies four recurring economic pathways associated with AIECI: revenue acceleration, efficiency and cost relief, improved allocation quality, and strategic speed under uncertainty. Fourth, it demonstrates how recent and cross-validated archival evidence can be used to study an emerging strategic phenomenon with analytical rigor. The remainder of the paper is organized into the theoretical framework, methodology, results and discussion, and final considerations.

1.1 Analytical model of the study

Artificial intelligence is considered the technological base, competitive intelligence the strategic process, and economic performance the organizational outcome in this research. More specifically, the study adopts the following explanatory sequence: AI inputs, competitive intelligence capability, strategic decisions, economic implications**.** This framing clarifies that firms do not create value from AI in isolation. Instead, value emerges when AI enhances the firm’s ability to sense relevant signals, interpret them in a decision-relevant form, and orchestrate coordinated action across recurring business decisions.

2. THEORETICAL FRAMEWORK

The literature on artificial intelligence, market sensing, dynamic capabilities, and digital strategy suggests that economic outcomes do not arise from technology alone. They arise when technology enhances the firm's ability to detect relevant environmental change, interpret its competitive significance, and reorganize action more quickly and effectively than rivals. From this perspective, artificial intelligence-enabled competitive intelligence (AIECI) should be understood as a strategic capability that links data-intensive environments with decision quality and economic value creation.

2.1 Competitive Intelligence Enabled by Artificial Intelligence as a Strategic Capability

The classical routines of competitive intelligence have traditionally been linked with competitor, buyer, technology and regulatory scanning, yet the classical methods have been restricted by the slowness of information flow and human information processing. Digitalization enhanced the amount and types of available signals, but contributed to the issue of signal overload as well. Consequently, such strategic issue was not about access but rather about filtration, interpretation and actionability. AI alters this formula by allowing companies to process big volumes of unstructured and semi-structured data, such as conversations with customers, social media content, product reviews, search histories, images, support communications, vendor data and internal transaction history. AI has been thus discussed in the marketing and strategy literature both as a device of automation and as a supplementary capability to managerial thought. By incorporating AI into market sensing processes, firms are able to sense weak signals sooner, recognize pattern changes that human intelligence officers might fail to notice and have a smaller gap between information surfacing and response. (Verma et al., 2021; Labib, 2024).

This paper defines AIECI as a more advanced ability that is made up of three complementary activities. The first is sensing. In this case, AI expands the scale and scope of the data collection through constant collection and organization of the signals concerning customers, competitors, campaigns, prices, channels, and supply conditions. Interpretation is the second one. Models, recommendation systems, classification engines and predictive analytics do not summarize data; they rank pertinence, find anomalies, approximate probable results and uncover relationships that allow inferences on the part of the manager. The third is orchestration. Intelligence becomes economically significant when organizations transform insight in to co-ordinated decisions regarding prices, assortment, and allocation of media, content production, procurement, innovation, service recovery or channel design. AIECI would not, in that regard, be similar to an AI tool. It is the application of AI to competitive knowing and competitive acting by an organization. (Dias & Lages, 2021; Hossain et al., 2022).

The dynamic capabilities approach is particularly applicable in explaining the potential creation of advantage with respect to AIECI. Dynamic capabilities scholarship is focused on seizing, sensing and reconfiguring in the face of change. AI enhances sensing through expanding the extent and time-responsiveness of the environmental perception. It facilitates the taking of by enhancing the assessment of the opportunities and threats by forecasting and optimization. It helps in reconfiguration in pointing out where resources, processes, or priorities need to change. This logic can be based on recent empirical studies. The empirical findings of AI focus in public companies are related to increased net profitability, enhanced net operating efficiency, and increased profitability of the investment related to marketing. The development of AI potential and data-driven culture is also a labor that implies that the increase in performance is contingent on the presence of analytics in organizational processes and not in technical departments. Research into SMEs and manufacturing companies also suggests that AI implementation is likely to add to the competitive edge and performance under conditions of absorptive capacity, customer agility, organizational agility, or market analytics capacity. All these results suggest that AI will be of the greatest value when it turns into a market-facing and decision-making capability. (Krakowski et al., 2023; Cimino et al., 2025).

The other implication of the capability perspective is the capability to AIECI to be self-reinforcing. The more firms adopt AI to feel and understand markets, the more labeled information, feedbacks, and organizational learning they create, and with which to enhance the system even more. This mechanism can be rather beneficial to platform firms, as all the interactions with clients can be used to improve further models. Repeated use can also be useful to operating firms in improving the forecast quality, content learning, or anomaly detection. Nevertheless, self-reinforcement is not necessarily inevitable. It relies on how well firms are able to capture, curate and govern feedback loops. Scale may either increase noise instead of learning without those routines. AIECI economic ramifications are thus highly correlated to the capability of the firm to convert recurrent intelligence application to cumulative capability. (Gao et al., 2025; Raina et al., 2026).

As a mechanism that is best revealed through competitive intelligence, the latter is well placed at the junction point between external sensing and internal decision-making. Intelligence uses have unique strategic characteristics, though there are numerous areas in which a firm can apply AI. They educate about how the managers read consumers, interpret rivals, identify campaign waste, predict demand, compare sourcing choices, or time strategy. They also transverse functional silos. The intelligence architecture can be used to affect product development, advertising, supply planning, pricing, customer experience, and corporate resource allocation. That is why AIECI can be perceived as a cross-functional capability the value of which is conditional upon the integration of an organization. The greater the number of intelligence outputs that flow into the economic decision making the greater the performance effect would be. (Costa Climent et al., 2024; Haftor et al., 2024).

2.2 Economic Implication of AIECI to Firms

There are four major economic implications associated with AIECI. The former is acceleration of revenue. Companies able to identify emerging preferences, conversion frictions, media inefficiencies, or moves of their competitors sooner are more able to adjust propositions more quickly and generate quality sales. AI-based market sensing aids this by assisting in micro-segmentation, content resonance, channel effectiveness, and new demand trend detection in near real time. In advertising and commercial application, this intelligence may increase efficiency of conversion, economics of customer acquisition and increase the rate of success of campaigns or product introduction. The effects of revenue can be both direct, where campaigns would be optimized dynamically, and indirect, where better insights would result in more successful innovations decisions and brand relevance. (Mu & Zhang, 2025; Sahut & Laroche, 2025).

The second one is efficiency and cost compression. The AI-based intelligence can assist companies in detecting waste and duplication, leakage, and process friction in marketing, procurement, service, and operations. An earlier-signaling retailer or manufacturer can reduce distortion of stock, or better target promotions, or can negotiate better with suppliers. The media-performance company with access to invalid traffic or poor quality placements will be able to minimize wasteful ad expenditures. The synthesis of complaints and unsolicited feedback into a customer-intelligence platform can help reduce the time of diagnosis, decrease the service costs, and decrease the manual burden of analysis. The effects of this tend to manifest themselves initially as an increase in productivity, as opposed to top-line growth, but are economically significant since they enhance the quality of expenditure and the pace at which some corrective action can be taken. (Moderno et al., 2024; Kassa & Worku, 2025).

The third group is better capital and budget allocation. Competitive intelligence, informs on where to focus, where to withdraw and how to focus limited management time. AI enhances the accuracy of such decisions by transforming noisy data into ranked options and forecasts in terms of probabilities. This is relevant to campaign funding, channel combination, assortment planning, supplier selection and even sequence of innovation projects. In turbulent conditions, fast reallocation can be no less significant than the absolute degree of investment. Better allocation is a unique economic advantage: it does not always increase revenue in the short run, but it cushions margins and enhances better utilization of the available resources. The recent literature on the use of AI in marketing, algorithmic pricing, and the data-driven organizational culture substantiates the concept of the AI influencing performance not only due to automation but also due to the economic benefits of managerial choice. (Babina et al., 2024; Xiao & Zhang, 2025).

The fourth one is strategic speed when there is uncertainty. The economic cost of interpretation delays is great in most industries. Any slowness in the responsiveness of firms within the changing pattern of consumer discourse, media fraud, competitive pricing, or supply can result in a loss that is not reflected in the conventional productivity indicators. AIECI minimizes this lag by decreasing the period between the signal detection, analysis and action. This effect of speed is cost-effective since it forms the strategic responsiveness value of options. Rapid experimentation, faster reallocation, discovering issues earlier, and reduced learning cycles all increase a broad range of opportunities that a firm can capture as well as reducing the cost associated with being wrong too long. There is some public evidence of AI-intensive companies that speed-to-insight and speed-to-execution are being considered as key business productivity and growth initiatives. (Elshaer et al., 2025; Ma et al., 2025).

2.3 Boundary Conditions, Boundary Risks, and Delayed Returns

As much as the economic promise of AIECI is high, value capture is not universal and automatic. Data quality is one of the boundaries. AI systems magnify inputs, however, they magnify mistakes, bias, duplication and blind spots. In case the data base upon which the intelligence is being elaborated is either partial or structurally inclined, the intelligence production may hence deceive decision makers on false grounds. Interpretive capacity is a second boundary condition. Managers should know which of their outputs are actionable, which are probabilistic and which need to be judged based on the context. Spurious precision is produced as a result of over-automated systems, whereas underutilized systems produce an inventory of insights into which action never enters. The third boundary is organizational integration. Intelligence cannot have value when it is confined in analytics teams or vendors without any visible connection to decision rights, incentives and operating rhythms.

Another set of constraints is comprised of trust, legitimacy and regulation. Pricing and targeting made by AI can be more efficient, yet it is likely to result in the loss of consumer trust, a sense of fairness, or regulatory attention. Likewise, companies that become more reliant on opaque third-party designs can also win temporary benefits in productivity but undermine autonomy of learning on a long-run basis. Recent studies also indicate that effects of AI investment might be non-linear or delayed: initiative investment can be subject to adjustment costs before parity sets in, and benefits will not be realized until complementary capabilities are developed. These findings are essential to a competitive intelligence framing since they suggest that governance and organizational structure are as important in the economic impacts of AI as model correctness. Based on this, this paper will consider AIECI as a social-technical capability, not a plug-and-play technology, whose performance impacts are contingent on complementary assets. Taken together, the preceding discussion leads to a clear theoretical expectation: the economic value of AIECI will be stronger when AI-supported intelligence is embedded in recurring decision routines, supported by governance, and aligned with managerial interpretation and organizational integration. Conversely, value capture will remain limited when intelligence outputs are weakly trusted, poorly connected to decision rights, or isolated from operating processes. In this sense, AIECI should be understood not as a standalone technological asset, but as a socio-technical capability whose outcomes depend on complementary organizational conditions.

3. METHOD

This study employs a qualitative comparative multiple-case design based on recent public archival evidence. The design is appropriate because the phenomenon under investigation is contemporary, strategically significant, and difficult to isolate through single-variable analysis. The research questions are explanatory rather than merely descriptive, as they seek to understand how artificial intelligence-enabled competitive intelligence generates economic value and under which organizational conditions that value is more or less likely to be captured (Raisch & Krakowski, 2025; Haftor et al., 2024).

The fact that the archival cases are chosen in place of the interview-based fieldwork is also analytically convenient. When it comes to modern AI environments, companies tend to make announcements, since investors, analysts, customers and regulators expect to see more transparency in approach to technology. This generates an accountable structure of how businesses themselves articulate the economic reason of AI. Although such disclosures are selective, they are not arbitrary. They disclose what companies believe is strategic salient enough to share, what types of claims of value they believe to be credible, and what types of economic categories are repeated in the kind of industries. By examining these documents comparatively and not descriptively, the study will be able to progress beyond a self-isolated corporate assertion to a broader way of explaining how the AI-enabled intelligence is set-up and monetized. (Mu & Zhang, 2025; Wamba et al., 2024).

Case selection followed a theoretical sampling logic. The cases were selected using four criteria: (1) explicit public disclosure of AI deployment, (2) visible use of AI for market sensing, customer intelligence, campaign optimization, or strategic decision support, (3) observable economic claims, indicators, or managerial statements linked to such routines, and (4) documentation across more than one public source. Based on these criteria, Walmart, Unilever, Sprinklr, and DoubleVerify were selected. Walmart and Unilever represent incumbent operating firms that embed AI-enabled intelligence within internal decision processes, whereas Sprinklr and DoubleVerify represent platform-based firms that commercialize intelligence capabilities for client organizations (Walmart Inc., 2025; Unilever, 2025; Sprinklr, 2025; DoubleVerify Holdings, Inc., 2025)

There are three data layers incorporated in the empirical corpus. The former is comprised of company archival publications that were released in majority in 2024-2026, such as annual reports, 10-Ks, quarterly or full-year results releases, official pages covering AI-related initiatives. The second one includes peer-reviewed articles published between 2021 and 2026 regarding AI capability, AI in marketing use, dynamic capabilities, organizational agility, algorithmic pricing, market sensing and change in business models. These articles were applied to frame mechanisms instead of substituting the empirical cases. The third layer is cross-case memoing which was done as part of analysis where the case observations were matched with theoretical categories. Since the research is anchored on the public disclosures, it does not purport to have causal attribution of AI and all the performance changes. Rather, it examines publicized patterns of utilization, the economic reasoning planned, and noticeable results that coexist with AI-facilitated intelligence habits.

(Walmart Inc., 2025; Unilever, 2025; Sprinklr, 2026; DoubleVerify Holdings, Inc., 2026).

Data analysis proceeded in two stages. In the first stage, each case was coded along five dimensions: intelligence source, AI mechanism, decision domain, economic implication, and boundary condition. In the second stage, cross-case pattern matching was used to identify recurring mechanisms across industries and business models. The goal was analytical rather than statistical generalization. To strengthen rigor, claims were retained only when supported by recent official or peer-reviewed sources, and performance indicators were interpreted conservatively as contextual signals rather than proof of one-to-one AI effects.

Table 1 presents the research design and the conditions of selection of the case.

Table 1 - Research design and case selection

Case	**Selection logic**	**Primary intelligence domain**	**Illustrative AI use**	**Expected economic relevance**
Walmart	Large incumbent retailer with explicit AI investment narrative and observable operating metrics.	Retail demand, e-commerce, pricing, and operations intelligence.	AI-enhanced shopping, operational efficiency, merchandising and price support.	Revenue growth, e-commerce contribution, productivity, faster response.
Unilever	Global consumer-goods firm integrating AI with social, marketing, and procurement routines.	Consumer discourse, brand demand, supplier and sourcing intelligence.	Social listening, AI-assisted content creation, procurement workflow support.	Growth quality, faster campaign response, sourcing efficiency.
Sprinklr	Platform firm commercializing AI-supported customer and consumer intelligence.	Real-time customer feedback, listening, and experience intelligence.	Unifying direct and indirect feedback into real-time insights.	Subscription revenue, scalable insight monetization, operating leverage.
DoubleVerify	Adtech firm monetizing AI-based media verification and optimization.	Media quality, ad performance, and spend-efficiency intelligence.	AI models for campaign optimization, waste reduction, and verification.	Return on ad spend, reduced waste, margin protection, operational efficiency.

Figure 1. AIECI Conceptual Framework

Source: Elaborated by the authors based on the comparative case analysis and recent public archival evidence.

Figure 1 is the synthesis of the explanatory framework of the study. Multi-source signal capture of customers, competitors, channels, media, operations, and suppliers are the initial stages of AIECI. AI might thereupon assist interpretation by means of classification, prediction, anomaly detection and optimization. The resulting intelligence is economically consequential in the event that it is planned into decisions repetitive in nature particularly decisions regarding revenue generation, allocation of spending, procurement, pricing, service, and innovation. The moderating variables of each stage are governance, data quality, trust, and integrative routines. The framework implies that the benefit is not in the possession of AI but an organizational transformation of AI-based intelligence into greater commercial and strategic actions, which are disciplined.

4. RESULTS AND DISCUSSION

The comparative evidence indicates that artificial intelligence creates economic value in these cases not by replacing managerial judgment, but by strengthening competitive intelligence routines. Across Walmart, Unilever, Sprinklr, and DoubleVerify, AI repeatedly appears as an interpretive layer that helps firms collect, prioritize, and act on fragmented market signals. The findings therefore support the central argument of this paper: economic value does not arise from AI alone, but from AI-enabled competitive intelligence embedded in recurring strategic and operating decisions (Mishra et al., 2022; Mu & Zhang, 2025).

4.1 Within-Case Evidence

Walmart uses the examples of AIECI on a large-scale with an operating firm. Recent revelations make AI remain under a large investment agenda that also includes e-commerce, automation, supply chain, and customer experience. Competitive intelligence in this instance is integrated into a broad retail decision milieu in which the company must continuously read the demands, price perception, channel behavior and operational variation. This is enhanced by AI, which enhances a shopping experience, aids operational efficiency, and guides price and merchandising decisions in the environment of high traffic volumes of transactions. In the Walmart 2025 reporting, one can also see the economic background where these capabilities are implemented: the increase in revenues, the growing role of e-commerce, and the clear focus on the quantifiable benefits of AI and automation. Notably, the case recommends that the economics of intelligence are not limited in the functions of a retailer. They include assortment visibility, pricing assistance, labor and process efficiency and how quick the management can react to fast moving customer behavior. (Walmart Inc., 2025; Mu & Zhang, 2025).

A different but complementary logic is demonstrated in Unilever. Unilever professes to make use of AI as a key platform in a social-first, consumer-linked growth model, as opposed to AI as a back-end optimization system. The company claims to be listening to consumer demand, responding more quickly, better content creation, as well as simplifying the process of supplier onboarding and sourcing activity, using AI and data. In terms of competitive intelligence, AI will allow the company to incorporate signals in the social platforms, market discourse, and procurement environments into making decisions on brand communication, product relevance, and internal productivity. The economic implication is two-fold. To begin with, the quality of growth can be improved through a better market understanding that would match contents and innovation to the emerging demand. Second, AI can make internal functions like procurement shorter and more efficient through better supplier comparison. The case is hence crucial since it proves that AIECI is not merely outward thinking; it also generates value by establishing inward focusing coordination and productivity. (Unilever, 2025; Sahut & Laroche, 2025).

The platformification of AIECI is Sprinklr. Its products are aimed at transforming customer feedback, social listening and digital interactions to actionable intelligence on client firms. According to publicly available descriptions of Sprinklr Insights, real-time consumer intelligence is created by unifying direct and indirect, solicited and unsolicited feedback between channels. Economic model of the firm in this instance is determined by its capability to commercialize the intelligence per se. The more intelligible and systematized, summarized and exposed its insights, the more useful the site is to customers who wish to get more responsive, service-catchy and improved campaign and experience choices. The latest financial statements indicate an increase in revenue and enhanced operating income of Sprinklr that although it cannot be attributed to any particular product, is typical of a business model where scalable intelligence services can create and capture value. The situation exposes the ways in which AIECI can transform into a product line that generates income itself as opposed to merely being an internal management potential (Sprinklr, 2025; Sprinklr, 2026; Beyari & Hashem, 2025).

A fourth trend identified by DoubleVerify is the verified and optimized digital media economics. The company applies AI to assist the advertisers and publishers to evaluate media quality, cut invalid traffic and waste, manage to deliver a campaign, and enhance the results, including the return on ad spend. It's Scibids AI Disclosures and products, as well as the Scibids AI, showcase the efficiency of algorithmic models that measure lift reduction and efficiency. It is a form of competitive intelligence that is very economical: media environment knowledge, positioning success, conversion processes, and spending utility. The importance of real-time intelligence is immediate due to the nature of the digital advertising that is opaque and fast to respond to. Having more insight on what is working and what is being squandered enables clients to redistribute spend in a shorter period of time and preserve margins. The growth and high adjusted EBITDA margin by DoubleVerify, therefore, demonstrates how intelligence on external market execution can be, in turn, monetized.

Another eye-catching trend in Walmart and Unilever is that the intelligence processes associated with AI are integrated into the larger change-related narratives instead of implemented as independent projects. This is important in the sense that it implies that the firms forming the complex heritage would capture value more when AI is connected with an operating model rather than being limited to a pilot. Consumer-goods companies and retailers operate under the environmental constant flux of variation in consumer demand, channel fragmentation, and execution complexity. In this kind of situation, solitary wisdom cannot do much unless it is combined with repetitive beats of merchandising, media, sourcing, and supply co-ordination. The archival evidence thus suggests the opinion that organizational embedding is critical to the economics of AIECI in large incumbents (Walmart Inc., 2025; Unilever, 2025; Gao et al., 2025).

Another insight, which is the addition to the two platform cases, is that AIECI can be monetized by using the business models that are based on the intelligence as a service business model. Sprinklr and DoubleVerify do not merely apply AI internally to reduce costs, but it is a layer of intelligence they sell to client firms to learn how audiences, experience break downs and media work. They have a value proposition of minimizing decision uncertainty among other people. This indicates that this is not a one-off event in relation to the economic connotations of AIECI. AI-powered intelligence can even be formatted as a product, which companies bundle, scale and monetize as subscription, platform, or performance-based revenue services. Strategically, this extends the applicability of competitive intelligence as an internal support activity to a marketable strength (Sprinklr, 2026; DoubleVerify Holdings, Inc., 2026; Costa Climent et al., 2024).

4.2 Cross-Case Patterns

Cross case comparison shows that there is a similar architecture regardless of the range of sectors. To begin with, all the four cases are based on intelligence aggregation. Walmart incorporates both commerce and operation signals. Unilever integrates the social, consumer, and procurement information. Sprinklr compiles feedback and experience indications across various touchpoints. The media-performance and verification signals are grouped together by DoubleVerify. In both instances AI is employed in order to decrease fragmentation. This is important since incoherent information leads to slow inconsistent and politicized decisions. In contrast, the unified intelligence architectures allow the establishment of a common base of information based on which quicker allocation decisions can be made. Immediate economic gain is not the improved knowledge per se but it is the reduction in the cost of coordination. (Hossain et al., 2022; Haftor et al., 2024).

Second, the cases indicate that interpretation is the economic pivot of AIECI. The collection of data by itself does not create an advantage. The point is the transformation of the big data streams into the prioritized signals which could be used to take managerial action. The fact that Sprinklr promises real-time consumer intelligence and DoubleVerify focuses on the waste reduction and the improvement of media results makes this point obvious. The same logic within operating companies can be seen in Unilever social listening (with the help of AI) and operational and customer-related applications in Walmart. The leverage of AI is in interpretation since it reduces the time and effort required to transform raw signal into decision-relevant information. The gains which are associated are in form of speed, productivity or accuracy as opposed to the pure automation savings. (Raisch & Krakowski, 2025; Gao et al., 2025).

Third, orchestration discriminates the stronger and the weaker economic logic. The examples indicate that value capture increases with the allocation of intelligence in repetitive managerial decisions having distinct economic benefits. In the case of Walmart, they are e-commerce, operations, and price or merchandising support. In the case of Unilever, they are content development, demand insight, and sourcing. In the case of Sprinklr, these are enterprise decisions regarding customer experience and feedback management. In the case of DoubleVerify, they are live media allocation and verification. That is, AIECI can be economically significant when it controls the direction of money flow, the direction of effort flow, and the speed of the adjustment process. This is an argument supporting the notion that AI is not to be perceived as a model that is implemented somewhere on the stack but as a component of a decision system within an organization. (Mu & Zhang, 2025; Wamba et al., 2024).

Fourth, the cross-case evidence indicates that AIECI has direct and indirect economic impacts. Direct impacts can be the decrease in waste, lesser manual work, enhancement of performance of campaigns, or expedited sourcing decisions. The indirect impacts are enhanced innovation relevance, greater brand responsiveness, high learning, and a wide range of options in the event of uncertainty. This difference is critical since multiple corporate disclosures highlight the productivity prior to its displaying clear profit impacts. The literature also indicates that the returns to AI can be postponed and are mediated by the complementary capabilities. The cases thus justify a stratified perspective of economic implications: some of them manifest themselves quite soon in the cost or efficiency measures, and others get collected in the better organizational adaptation. (Xiao & Zhang, 2025; Sahut & Laroche, 2025).

Another way the findings of the study soften the general assumption that increased information will lead to improved decisions is by showing that increased data does not necessarily translate into improved decisions. The useful gesture was, in all four examples, not merely the hoarding of more signals but the building of filters which filter out the strategically significant and only the available. Only after being made comparable, ranked and linked to a decision window, do consumer conversations, media events, transaction records or supplier data become intelligence. This is a distinction that should be considered by firms that design AI investments. The lack of data abundance is less important than the capacity to transform abundance into selective attention to provide economic value. That way, AIECI is more of an attention-allocation system, than an analytics system. (Dias & Lages, 2021; Raisch & Krakowski, 2025).

4.3 Boundary Conditions and Interpretation

The cases also shed light on the AIECI limitations. First, there is plenty of intelligence, which leads to a false impression of managerial certainty. AI is able to prioritize signals and make probable predictions, yet there is still a need to investigate strategic judgment due to the fact that competitive settings are predetermined by interpretation, politics, and context. Second, it has a problem of governance. With the growing sphere of algorithmic pricing and AI-based targeting, companies are exposed to the dangers of fairness, trust, explainability, and regulation. These are not fringes. They have a direct impact on economic performance as they determine the pace of adoption, reputational exposure and monetization model sustainability. Third, reliance on outside suppliers may be cost-doubled. Social media tools like Sprinklr or DoubleVerify generate value to the clients and high reliance on the vendors can eventually restrict a learning process of client firms as well as raise the switching or coordination costs. (Machucho & Ortiz, 2025; Raina et al., 2026).

One last cross-case trend is that of complementarity. The best indicators of economic value are where AI has been integrated with managerial practices, data management, and organizational connectivity. This is in line with recent empirical studies that have demonstrated that the AI capability is not enough; rather, data-driven culture, absorptive capacity, agility, and market analytics capability interpose or magnify results. The implication has a theoretical significance. The competitive intelligence that is augmented with AI is not to be discussed as an independent technological asset. It must be considered as a complementary system where data, models managerial interpretation, process design and decision rights are jointly produced as sources of economic performance. (Cimino et al., 2025; Wamba et al., 2024).

Lastly, the paper suggests that comparison of intelligence structure may form the basis of future competition as opposed to single algorithms. With the proliferation of generative and predictive AI, access can become less differentiating than the ability of organizations to feed them with relevant signals, regulate their outputs and embed them into action. Companies that are able to match external sensing, internal data, managerial judgment, and resource reallocation would create more lasting economic advantages compared with companies that view AI as a symbolic innovation project. This reframing can be of great value in both scholarship and practice since it changes the question to one of who has the best model? To who is most intelligent to action system? The summary of cross-case evidence of economic implications is included in Table 2.

Table 2 - Cross-case evidence on economic implications

Mechanism	**Direct economic effect**	**Indirect economic effect**	**Illustrative boundary condition**
Signal aggregation across multiple data sources	Lower search and coordination costs; faster detection of shifts.	Shared informational base across functions and reduced decision latency.	Data quality and integration discipline.
AI-supported interpretation and prioritization	Reduced manual analysis time; better campaign and spend optimization.	Improved managerial attention and faster learning cycles.	Managerial ability to contextualize model outputs.
Orchestration into recurring operating decisions	Better pricing, media allocation, sourcing, and service actions.	Improved resource allocation and stronger adaptation under uncertainty.	Clear decision rights and process embedding.
Commercialization of intelligence as a product	Subscription growth, verification revenue, and scalable service monetization.	Client lock-in, data network effects, and platform leverage.	Vendor dependence, trust, and switching costs.

Source: Elaborated by the authors.

Combined with the supplementary tables and figures, the analysis is reinforced by demonstrating that AIECI possesses a stratified economic logic: some of the advantages are quickly seen in terms of growth or efficiency statistics, whereas others are more gradually felt in terms of better allocation of resources, learning or organizational flexibility. The tabular and visual evidence also help to understand more clearly that the boundary conditions are not an outer thing; they influence the translation of intelligence to captured value and only the conversion to more data. Table 3 presents the most important conditions of the boundaries and managerial protections.

Table 3- Boundary conditions and managerial safeguards

Boundary condition	How the risk appears	Potential economic leakage	Managerial safeguard
Data fragmentation	Signals arrive in incompatible formats or unequal quality across functions and partners.	False positives, poor comparability and slower decision cycles.	Shared data definitions, integration discipline and governance ownership.
Opaque or weakly trusted AI use	Managers cannot explain why outputs are recommended or how models were trained.	Compliance costs, brand risk and delayed organizational adoption.	Human review routines, auditability and explicit accountability for use.
Workflow misfit	Insights remain in dashboards instead of entering pricing, marketing, sourcing or service routines.	Low conversion of intelligence into measurable action.	Embed outputs in recurring operating processes and decision rights.
Metric myopia	Short-term productivity metrics dominate while learning and strategic adaptation are under-measured.	Premature abandonment of useful systems or overinvestment in superficial wins.	Balanced performance metrics that track both immediate gains and capability accumulation.

Source: Elaborated by the authors from the capability coding scheme.

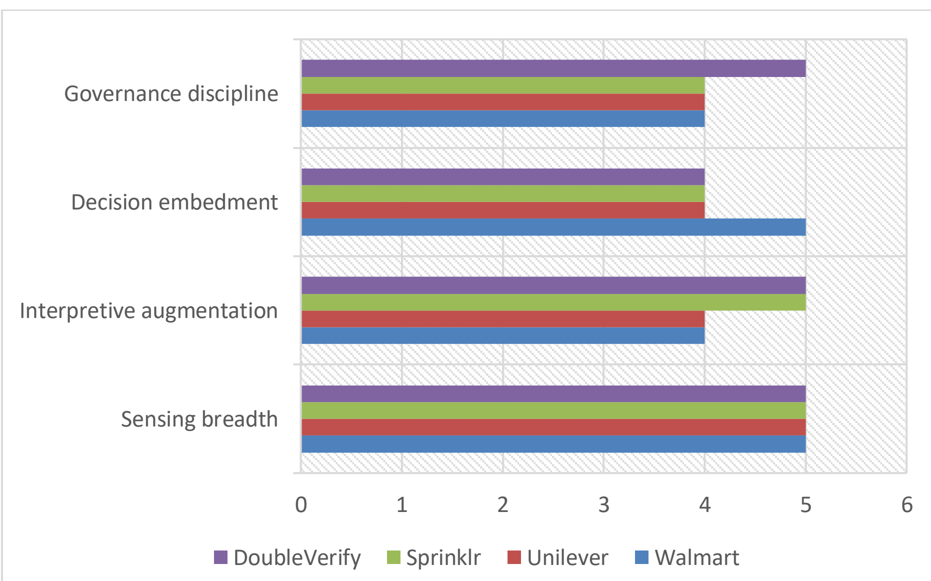

Figure 2. AIECI Capability Architecture across Cases
Source: Elaborated by the authors with reference to the within-case evidence and the comparative discussion.

Figure 2 visualizes the capability architecture across cases and points to the fact that the platform firms evaluate higher on interpretive augmentation and governance discipline, whereas Walmart is outstanding in terms of decision embedding. This trend underpins the claim that capturing value varies depending on the operationalization of intelligence, and not just based on the magnitude of data that a company possesses. Table 4 provides the direct and indirect economic impacts of each case.

Table 4 - Direct and indirect economic implications of AIECI

Economic pathway	Observable manifestation	Representative cases	Type of implication
Revenue acceleration	Faster campaign refinement, better targeting and improved offer relevance.	Walmart, Unilever, Sprinklr.	Direct commercial effect.
Efficiency and cost relief	Reduced waste, lower manual effort, cleaner media spend and smoother workflow execution.	Walmart, Unilever, DoubleVerify.	Direct operating effect.
Allocation quality	Sharper prioritization of channels, suppliers and response options under uncertainty.	All four cases.	Indirect strategic effect with medium-term payoff.
Learning and adaptation	Better feedback loops, stronger experimentation and wider option sets for future action.	Sprinklr, Unilever, Walmart.	Indirect capability-building effect.

Source: Elaborated by the authors from the cross-case coding matrix.

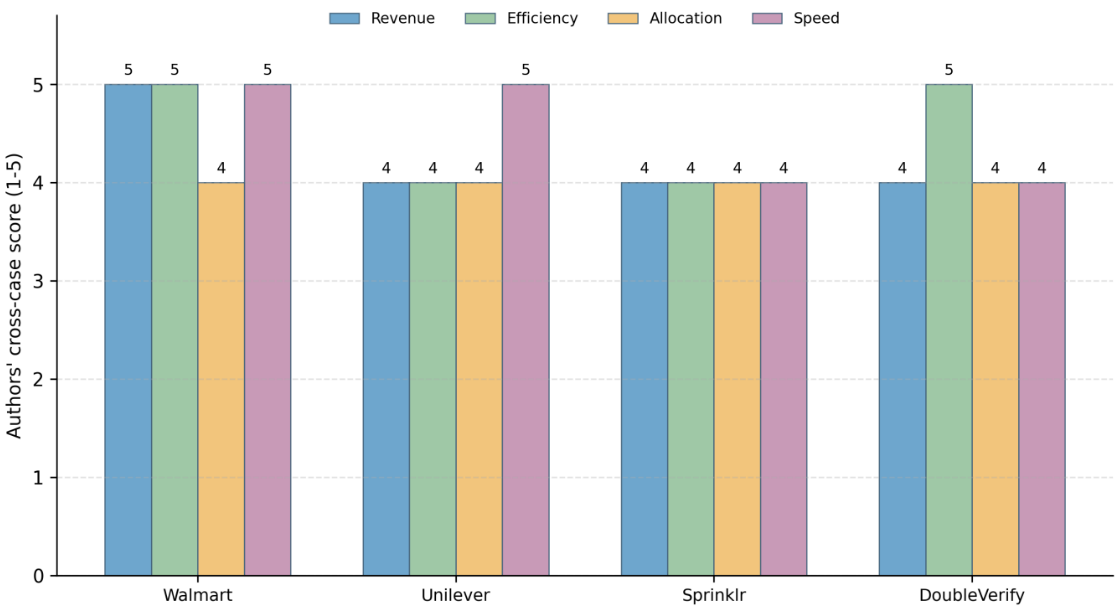

Figure 3. Economic Pathway Intensity by Case

Figure 3 translates the qualitative coding to a bare comparative scorecard across the four economic pathways. The figure strengthens the point that there is no single case that prevails across all dimensions rather, the firms will be different in terms of the channels through which the intelligence will be translated into value. Table 5 is a summary of the cross-case capability architecture.

Table 5 - Cross-case capability architecture

Capability layer	Cross-case pattern	Representative cases	Economic implication
Sensing breadth	All four cases combine multiple external and internal signal streams rather than relying on a single dashboard.	All four cases; strongest breadth in Walmart and DoubleVerify.	Broader sensing reduces blind spots and improves the timeliness of opportunity detection.
Interpretive augmentation	AI is used to rank, classify and prioritize signals, but human validation remains central.	Strong in Sprinklr and DoubleVerify; visible in Walmart and Unilever.	Economic value rises when signal abundance is converted into selective managerial attention.
Decision embedding	The strongest cases connect intelligence outputs to recurring operating decisions.	Most visible in Walmart, Unilever and DoubleVerify.	Embedding improves execution speed and increases the probability of measurable returns.
Governance discipline	Public narratives increasingly stress trusted use, workflow fit and measurement discipline.	Visible across all cases; strongest emphasis in DoubleVerify.	Governance lowers leakage risk and supports scalable appropriation of value.

Source: Elaborated by the authors from the most recent public case disclosures.

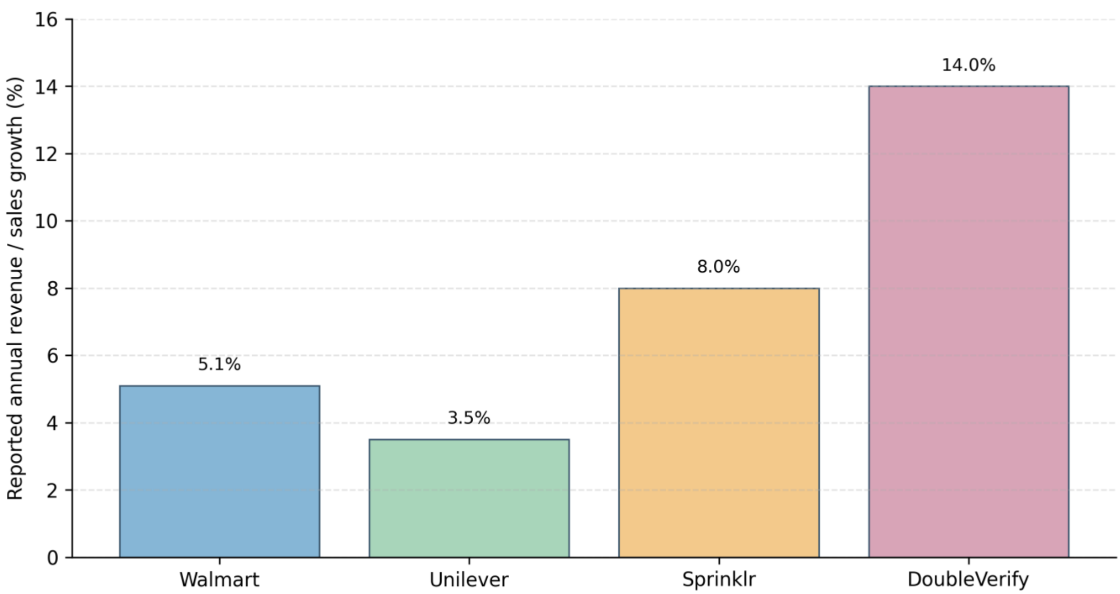

Figure 4. Reported Top-line Growth in the four Cases

Figure 4 makes a comparison of the reported top-line growth values identified in the case evidence. According to the chart, the two platform-based cases had the most acute monetization profile, whereas the existing operating firms had a more consistent yet significant commercial boost associated with AI-supported intelligence processes. Table 6 demonstrates the within-case evidence and pathways of prevalent values.

Table 6 - Within-case evidence and dominant value pathway

Case	Key intelligence inputs	AI-enabled routine	Dominant reported economic signal
Walmart	Retail demand, price signals, fulfilment and inventory data.	Forecasting, recommendation support, operational prioritization and workflow automation.	Revenue growth with stronger e-commerce contribution, productivity gains and faster response cycles.
Unilever	Consumer discourse, campaign feedback, brand and sourcing signals.	Social listening, content support and procurement workflow augmentation.	Growth quality, quicker campaign adaptation and sourcing efficiency.
Sprinklr	Customer feedback, social listening, service and experience signals.	Unification, classification and ranking of real-time customer intelligence.	Subscription growth, scalable insight monetization and operating leverage.
DoubleVerify	Media quality, fraud risk, campaign performance and spend signals.	Verification, optimization and waste-reduction models for media decisions.	Improved spend efficiency, margin protection and stronger return on ad spend.

In order to present a more accurate empirical presentation, the revised analysis supplements the analysis with four additional exhibits. Tables 3 through 6 summarize the within-case data, capability architecture, economic pathways and boundary conditions and Figures 2 to 4 present the relative patterns that arise out of the archival coding.

5. FINAL CONSIDERATIONS

This paper examined how artificial intelligence-enabled competitive intelligence affects the economic performance of firms. Based on a comparative archival analysis of Walmart, Unilever, Sprinklr, and DoubleVerify, the study argues that AI becomes economically meaningful when it strengthens competitive intelligence rather than when it is treated as a standalone automation tool. Across the cases, AIECI generated value by expanding sensing breadth, improving interpretive speed, and strengthening the orchestration of recurring strategic and operating decisions (Haftor et al., 2024; Mu & Zhang, 2025).

The study makes three main contributions. First, it recenters competitive intelligence as the strategic mechanism connecting AI infrastructure to economic outcomes. Second, it develops a process explanation based on sensing, interpretation, and orchestration. Third, it shows that the economic returns of AI are contingent on data quality, governance, managerial interpretation, and organizational integration rather than determined by technology alone (Krakowski et al., 2023; Wamba et al., 2024; Raisch & Krakowski, 2025).

In the case of managers, the paper recommends considering investment in AI as a less focused software choice and rather a restructuring of the intelligence architecture of the firm. The fundamental issues are whether AI enhances the quality of information picked up externally, whether the understanding transfer into repetitive economic choices, and whether the organizational routines are able to consume and take action on it. Companies that merely consider AI a dashboard and do not integrate it with decisions can build up analytics without benefit. Compared to that, more companies that link measurements of intelligence to pricing, media placement, sourcing, service, and innovation choices are likely to be value-seeking. (Sahut & Laroche, 2025; Kassa & Worku, 2025).

The study has limitations. It is based on the evidence of public archives that is selective and fails to show all the details of internal implementation. The cases are not statistically representative and not information-rich and performance changes cannot be linked to AI only. The future study can also be done by these limitations. Future research can be used to test the proposed framework with survey, panel or mixed methods designs; compare results with other industries, where data maturity is different; how governance influences trust and adoption and whether long-run returns vary between firms, which develop internal intelligence and those, which extensively depend on external AI vendors. Despite these limitations, the paper demonstrates that it is possible to create a rigorous empirical research article on AI and the economics of firms with proper theoretical framing and by use of recent archival comparison. (Machucho & Ortiz, 2025; Xiao & Zhang, 2025).

REFERENCES

Abdul Wahab, M. D., & Radmehr, M. (2024). The impact of AI assimilation on firm performance in small and medium-sized enterprises: A moderated multi-mediation model. *Heliyon, 10*(8), e29580. https://doi.org/10.1016/j.heliyon.2024.e29580

Abrokwah-Larbi, K., & Awuku-Larbi, Y. (2024). The impact of artificial intelligence in marketing on the performance of business organisations: Evidence from SMEs in an emerging economy. *Journal of Entrepreneurship in Emerging Economies, 16*(4), 1090–1117. https://doi.org/10.1108/JEEE-07-2022-0207

Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics, 151*, 103745. https://doi.org/10.1016/j.jfineco.2023.103745

Badghish, S., & Soomro, Y. A. (2024). Artificial intelligence adoption by SMEs to achieve sustainable business performance: Application of the technology-organization-environment framework. *Sustainability, 16*(5), 1864. https://doi.org/10.3390/su16051864

Beyari, H., & Hashem, T. (2025). The role of artificial intelligence in personalizing social media marketing strategies for enhanced customer experience. *Behavioral Sciences, 15*(5), 700. https://doi.org/10.3390/bs15050700

Cimino, A., Corvello, V., Troise, C., Thomas, A., & Tani, M. (2025). Artificial intelligence adoption for sustainable growth in SMEs: An extended dynamic capability framework. *Corporate Social Responsibility and Environmental Management, 32*(5), 6120–6138. https://doi.org/10.1002/csr.70019

Costa Climent, R., Haftor, D. M., & Staniewski, M. W. (2024). AI-enabled business models for competitive advantage. *Journal of Innovation & Knowledge, 9*(3), 100532. https://doi.org/10.1016/j.jik.2024.100532

Dias, A. L., & Lages, L. F. (2021). Measuring market-sensing capabilities for new product development success. *Journal of Small Business and Enterprise Development, 28*(7), 1012–1034. https://doi.org/10.1108/JSBED-07-2019-0216

DoubleVerify Holdings, Inc. (2025). *Annual report on Form 10-K for fiscal year 2025* [Annual report].

DoubleVerify Holdings, Inc. (2026). *Fourth quarter and full year 2025 financial results* [Press release].

Elshaer, I. A., Azazz, A. M. S., Alqudah, H., Elsaied, M. A., & Mubarak, M. F. (2025). Artificial intelligence-driven supply chain agility and resilience: Pathways to competitive advantage in the hotel industry. *Logistics, 10*(1), 5. https://doi.org/10.3390/logistics10010005

Gao, Y., Liu, S., & Yang, L. (2025). Artificial intelligence and innovation capability: A dynamic capabilities perspective. *International Review of Economics & Finance, 98*, 103923. https://doi.org/10.1016/j.iref.2025.103923

Haftor, D. M., Costa Climent, R., & Ribeiro-Navarrete, S. (2024). Firms' use of predictive artificial intelligence for economic value creation and appropriation. *International Journal of Information Management, 79*, 102836. https://doi.org/10.1016/j.ijinfomgt.2024.102836

Hossain, M. A., Agnihotri, R., Islam Rushan, M. R., Rahman, M. S., & Sumi, S. F. (2022). Marketing analytics capability, artificial intelligence adoption, and firms' competitive advantage: Evidence from the manufacturing industry. *Industrial Marketing Management, 106*, 240–255. https://doi.org/10.1016/j.indmarman.2022.08.017

Kassa, B. Y., & Worku, A. (2025). The impact of artificial intelligence on organizational performance: The mediating role of employee productivity. *Journal of Open Innovation: Technology, Market, and Complexity, 11*(1), 100474. https://doi.org/10.1016/j.joitmc.2025.100474

Krakowski, S., Luger, J., & Raisch, S. (2023). Artificial intelligence and the changing sources of competitive advantage. *Strategic Management Journal, 44*(6), 1425–1452. https://doi.org/10.1002/smj.3387

Labib, N. (2024). Artificial intelligence in marketing: Exploring current and future trends. *Cogent Business & Management, 11*(1), 2348728. https://doi.org/10.1080/23311975.2024.2348728

Ma, X., Luo, S., & Xi, M. (2025). The impact of regional artificial intelligence development on the resilience of enterprise supply chains. *International Review of Economics & Finance, 102*, 104305. https://doi.org/10.1016/j.iref.2025.104305

Machucho, D. G., & Ortiz, J. (2025). The impacts of artificial intelligence on business innovation: A comprehensive review of applications, organizational challenges, and ethical considerations. *Systems, 13*(4), 264. https://doi.org/10.3390/systems13040264

Mishra, S., Ewing, M. T., & Cooper, H. B. (2022). Artificial intelligence focus and firm performance. *Journal of the Academy of Marketing Science, 50*(6), 1175–1197. https://doi.org/10.1007/s11747-022-00876-5

Moderno, O., Braz, A. C., & Nascimento, P. T. S. (2024). Robotic process automation and artificial intelligence capabilities driving digital strategy: A resource-based view. *Business Process Management Journal, 30*(1), 105–129. https://doi.org/10.1108/BPMJ-08-2022-0409

Mu, J., & Zhang, J. Z. (2025). Artificial intelligence marketing usage and firm performance. *Journal of the Academy of Marketing Science, 53*(4), 1081–1134. https://doi.org/10.1007/s11747-024-01076-z

Raina, K., Sharma, G. D., Taheri, B., Dev, D., & Chavriya, S. (2026). Artificial intelligence-driven management: Bridging innovation, knowledge creation, and sustainable business practices. *Journal of Innovation & Knowledge, 11*, 100860. https://doi.org/10.1016/j.jik.2025.100860

Raisch, S., & Krakowski, S. (2025). Combining human and artificial intelligence: Hybrid problem-solving in organizations. *Academy of Management Review, 50*(2), 441–464. https://doi.org/10.5465/amr.2021.0421

Saheb, T., Sidaoui, K., & Schmarzo, B. (2024). Convergence of artificial intelligence with social media: A bibliometric and qualitative analysis. *Telematics and Informatics Reports, 15*, 100146. https://doi.org/10.1016/j.teler.2024.100146

Sahut, J.-M., & Laroche, M. (2025). Using artificial intelligence (AI) to enhance customer experience and to develop strategic marketing: An integrative synthesis. *Computers in Human Behavior, 170*, 108684. https://doi.org/10.1016/j.chb.2025.108684

Spann, M., Bertini, M., Koenigsberg, O., Zeithammer, R., Aparicio, D., Chen, Y., Fantini, F., Jin, G. Z., Morwitz, V. G., Popkowski Leszczyc, P. T. L., Vitorino, M. A., Williams, G. Y., & Yoo, H. (2025). Algorithmic pricing: Implications for marketing strategy and regulation. *International Journal of Research in Marketing*. Advance online publication. https://doi.org/10.1016/j.ijresmar.2025.05.001

Sprinklr, Inc. (2025). *Annual report for fiscal year 2025* [Annual report].

Sprinklr, Inc. (2026). *Fiscal year 2026 financial results* [Press release].

Unilever. (2025). *Annual report and accounts 2025* [Annual report].

Unilever. (2025). *Social-first, social-led, social at the heart: How social intelligence drives growth at Unilever* [Company webpage].

Verma, S., Sharma, R., Deb, S., & Maitra, D. (2021). Artificial intelligence in marketing: Systematic review and future research direction. *International Journal of Information Management Data Insights, 1*(1), 100002. https://doi.org/10.1016/j.jjimei.2020.100002

Walmart Inc. (2025). *2025 AI business predictions: Transformation with purpose* [Company webpage].

Walmart Inc. (2025). *Annual report for fiscal year 2025* [Annual report].

Wamba, S. F., Queiroz, M. M., Pappas, I. O., & Sullivan, Y. (2024). Artificial intelligence capability and firm performance: A sustainable development perspective by the mediating role of data-driven culture. *Information Systems Frontiers, 26*(6), 2189–2203. https://doi.org/10.1007/s10796-023-10460-z

Xiao, L., & Zhang, Y. (2025). When do the competitive effects of artificial intelligence investment emerge? *Finance Research Letters, 86*, 108402. https://doi.org/10.1016/j.frl.2025.108402