Industry 5.0 and AI-powered competitiveness: Redefining business models for the future

Gabriel Silva-Atencio, PhD[1]

[1] Universidad Latinoamericana de Ciencia y Tecnología (ULACIT), San José, Costa Rica, gsilvaa468@ulacit.ed.cr

Abstract* – This research investigates the transformational impact of Artificial Intelligence (AI) on corporate competitiveness within the framework of Industry 5.0, using a mixed-methods approach that combines the Resource-Based View (RBV) and Dynamic Capabilities (DC) theory to tackle implementation issues particular to the industry. The study aims to concentrate on (1) measuring AI-induced productivity enhancements across various sectors, (2) analyzing human-AI cooperation frameworks, and (3) scrutinizing ethical governance structures, with a specific emphasis on Latin American settings. Methodologically, the research integrates qualitative case studies with quantitative surveys, using theme and regression analysis to corroborate results. The most important findings show that there are big differences across sectors: AI diagnoses can cut healthcare costs by 35%, whereas retail needs hybrid human-AI models to work best (15% benefits), and better governance frameworks can cut bias incidences by 58%. The conclusions stress that AI may be both a strategic resource and an adaptable capacity, depending on the culture of the business and the needs of the industry. Recommendations stress the need for tiered AI deployment roadmaps for Small and Medium-sized Enterprises (SMEs), ethical oversight committees, and initiatives to retrain workers. The subsequent study needs to investigate the long-term effects of AI implementation in circular economic transitions and culturally tailored governance frameworks, therefore filling the voids in studies concerning developing economies. This study connects global theoretical frameworks with regional empirical evidence, giving policymakers and practitioners useful information that fits with relevant research that balances technological innovation with socioeconomic equity.

***Keywords*-- Artificial intelligence, Business competitiveness, Ethical governance, Human-centric technologies, Industry 5.0.**

I. Introduction

The arrival of Industry 5.0 marks a significant change in the way industries work throughout the world. Instead of focusing on technology-based automation as in Industry 4.0, it will concentrate on cooperation between people and machines, sustainability, and resilience [1]. Artificial Intelligence (AI) is at the center of this change. It is expected to add over $15.7 trillion to the world economy by 2030 [2, 3]. Nonetheless, the allocation of these benefits is markedly inequitable, resulting in a competitive disparity that is especially pronounced in rising countries. In Latin America, where Small and Medium-sized Enterprises (SMEs) make up more than 99% of all businesses [4-6], this difference in technology might make socioeconomic inequities worse. The need for academic investigation is therefore not just technical but primarily strategic and ethical, necessitating evidence-based frameworks to traverse this new competitive landscape.

This study fills a significant need in the literature by examining the transformative effects of AI on business competitiveness within the context of Industry 5.0. The research is driven by three intersecting imperatives that highlight the need of this inquiry. First, there is a clear productivity paradox: while 73% of Fortune 500 companies say that using AI has made them much more efficient [7, 8], only 28% of Latin American companies have done so [9, 10]. This suggests that there are structural and contextual barriers that go beyond just being able to use the technology. Second, there are still a lot of problems between people and AI. About 42% of AI projects fail because workers don't want to work with them, which goes against the collaborative intelligence idea that is at the heart of Industry 5.0. Third, there are serious gaps in ethical governance since less than 15% of poor countries have strong AI governance frameworks [11, 12]. This raises the possibility of algorithmic bias in important areas like healthcare and finance.

These difficulties converge around the principal research question of this study: *How can businesses use Artificial Intelligence to improve competitiveness within the Industry 5.0 framework while addressing sector-specific implementation challenges and ethical considerations?*

To address this inquiry, the study is grounded in a solid theoretical framework, incorporating the Resource-Based View (RBV) [13-15], which perceives AI as a strategic asset, and the theory of Dynamic Capabilities (DC) [16-19], which assesses the ability of organizations to integrate, develop, and reconfigure AI and human skills to attain adaptive advantage. This dual theoretical framework facilitates a nuanced study that transcends a universal approach, recognizing that the usefulness of AI is dependent on its congruence with organizational resources and adaptive capabilities.

This study utilizes a sequential mixed-methods strategy to guarantee academic rigor and practical validity. The design integrates qualitative insights derived from Chief Executive Officers (CEOs) interviews across six industries with quantitative data obtained from a survey of 150 Latin American firms, examined using theme coding and regression methods. This technique is explicitly designed to rectify highlighted deficiencies in the literature, such as insufficient sectoral specificity, a Northern hemisphere bias in prior research, and the inadequate operationalization of ethical issues [20-27].

This study makes three important contributions to the state of the art. so first gives sector-specific roadmaps for using AI, showing the best ways to do so in manufacturing (predictive maintenance), healthcare (diagnostic automation), and retail (hybrid intelligence models), with real-world cost-benefit assessments to back them up. Second, it suggests and evaluates a tiered ethical governance structure that has been shown to cut down on algorithmic bias occurrences by 58% while keeping productivity high, which is a key balance for following the rules. Third, it has a unique emphasis on Latin America, putting competitiveness in the context of regional problems including SMEs lack of resources and informal labor markets.

This research offers policymakers and practitioners an advanced, practical paradigm for AI adoption by integrating global theoretical frameworks with regional empirical facts. It moves the conversation forward on technical sovereignty and fair development, making sure that the shift to Industry 5.0 strikes a balance between technological progress and social and economic fairness, which will keep businesses competitive in the long run.

II. Literature review

The theoretical foundation for investigating the impact of artificial intelligence (AI) on company competitiveness within the nascent Industry 5.0 paradigm is provided by this study, which incorporates current scholarly research from Scopus-indexed publications (2020–2023). The discussion is structured around three interconnected themes—the paradigm shift from Industry 4.0 to Industry 5.0, the role of AI as a source of competitive advantage, and the continuous difficulties of ethical implementation—all of which directly address the research imperatives stated in the introduction. This structure foreshadows the sector-specific findings that will be discussed in more detail soon and represents the methodological framework of the current study.

The shift from Industry 4.0 to Industry 5.0 marks a major transformation in both philosophy and operations. Instead of focusing on automation and data sharing, the new industry will concentrate on people, sustainability, and resilience. Scopus-indexed literature delineates this transition via two major features. The first is a strong commitment to putting people first. Industry 4.0 focused on making machines more efficient and connected via cyber-physical systems [28, 29]. In contrast, Industry 5.0 promotes "collaborative intelligence," where technology is used to enhance human talents instead of replacing them [30, 31]. This is in line with the increasing focus on metrics that measure how well technology and people operate together. The second trait is a need for resilience, which the COVID-19 pandemic made very clear by showing how weak hyper-automated, worldwide supply networks can be. This has led to a desire for AI solutions that make organizations more flexible and able to adapt. Case studies in manufacturing show that crisis response times may be improved by up to 40% when humans and AI work together [1]. These basic ideas show what makes Industry 5.0 different and valuable, and they also show how much more efficient it can be when technology and human experience work together. For example, this research indicated that healthcare diagnoses may be improved by 35%.

Recent meta-analyses confirm AI's role as a significant source of competitive advantage, building on the theoretical framework developed by the RBV. AI is increasingly viewed as a strategic resource that can be advantageous, as demonstrated by companies employing AI for predictive analytics achieving profit increases exceeding 19% [32]; infrequent, considering that only an estimated 12% of Latin American businesses implement advanced machine learning solutions [9, 10]; and imperfectly replicable, especially when its integration depends on the tacit knowledge and distinctive collaborative practices established between AI systems and human operators [33, 34]. Nonetheless, the implementation of RBV uncovers intrinsic constraints. It does a good job of explaining how companies in technology-heavy fields like manufacturing may get ahead of their competitors, but it doesn't work as well in fields like retail, where having fixed resources is less important than being able to adapt. This nuance underscores the imperative of augmenting the RBV with the DC framework [16-19], which emphasizes a firm's capacity to integrate, develop, and reconfigure both internal and external competencies in response to swiftly evolving environments, thereby offering a more comprehensive theoretical perspective for comprehending AI-driven competitiveness across various sectors.

Even if it has a lot of promise, the road to AI integration is full with big ethical and operational problems that the present study looks at in detail. Modern literature delineates three primary obstacles. Algorithmic bias continues to be a significant concern, with research showing that 78% of implemented AI systems have quantifiable demographic biases, underscoring the essential need for the governance models examined in this research [35]. Concerns about job loss are another big problem. Fear of automation has been proven to lower the success rate of AI adoption programs by 31% [36, 37]. This is an important piece of information that helps explain the cultural resistance shown in the qualitative interview data. Additionally, data fragmentation and subpar data quality compromise a substantial percentage (42%) of AI initiatives [7, 8], hence validating the incorporation of stringent data governance criteria in the current study's survey instrument. Table I shows how these problems fit with the study's design in theory.

TABLE I
THEORETICAL ALIGNMENT WITH STUDY DESIGN

Theory	Key proposition	Methodological test	Result validation
RBV	AI as a competitive resource	Sectoral productivity analysis	Healthcare's 35% gains
Dynamic Capabilities	Human-AI adaptation advantage	Innovation capability assessments	Retail's Hybrid Model Success
Institutional Theory	Governance reduces AI risks	Ethical framework implementation	58% bias reduction

This study aims to fill four significant gaps found in previous systematic assessments of Scopus literature (2020–2023). First, it opposes the propensity in AI literature [20] to make sweeping generalizations about whole sectors by using a mixed-methods approach that is meant to bring out the differences across industries. Second, it tackles the notable disparity in the focus on emerging economies, since around 89% of AI research is focused on settings in the Global North [21-23], by concentrating its research on instances from Latin America. In contrast to literature that often prioritizes technical needs above organizational and cultural aspects, it addresses a typical implementation realism gap [24, 25], These crucial cultural elements are directly examined by the qualitative interview approach used in this research. Finally, it does more than only contemplate; it actually implements governance systems, which are often still theoretical [26, 27], by evaluating suggested models in real-world organizations.

In synthesis, the literature substantiates the demand for new competitive frameworks tailored for Industry 5.0—frameworks that balance the resource-centric perspective of RBV with the adaptive flexibility of DC [16-19], measure success through dual metrics of efficiency and human welfare [1], and prioritize contextually sensitive implementation over universalistic solutions [9, 10]. These observations directly inform the sector-stratified methodological approach of this study and anticipate the policy recommendations for Latin America that will be derived from its findings, ensuring a coherent theoretical trajectory from the research questions to actionable, empirically-grounded conclusions.

III. METHODOLOGY

The study's analytical strategy was carefully designed to look at how AI may increase business competitiveness in the context of Industry 5.0. Due to the complex and varied nature of integrating AI across several sectors, a mixed-methods strategy was used. In order to ensure that the study is robust, permits triangulation, and adheres to academic norms, this technique blends qualitative and quantitative approaches. Best techniques for researching complex socio-technical challenges are consistent with this [38-40]. According to the literature review, the chosen method solves the shortcomings of earlier studies, including their lack of sectoral specificity and contextual implementation realism, and it also fits in well with the theoretical frameworks of the RBV and DC theory [16-19]. High standards of validity, reliability, and practical relevance for academics and professionals were met throughout the whole design.

Three separates but connected phases of the research were carried out using an exploratory sequential mixed-methods strategy. The first qualitative phase included semi-structured interviews and in-depth case studies to collect thorough, nuanced insights from industry experts on what it's like to deploy AI in real life. This was followed by a quantitative phase, in which a big survey was used to confirm the qualitative results and measure AI's effect on certain competitiveness indices in a wider sample. The last step in the integration process was to combine the findings via both thematic and statistical analysis at the same time. This made sure that the results were fully understood [41, 42]. This tiered design ensures a comprehensive grasp of AI's complex function, effectively linking theoretical frameworks with practical data.

The data collection was intentionally divided to fit with the sequential design. For the qualitative aspect, data was collected from two main sources. The study chose six companies from the industrial, healthcare, and retail sectors on purpose to be case studies that show a range of AI adoption maturity levels [43-46]. Additionally, twenty semi-structured interviews were performed remotely with industry professionals, including Chief Information Officers (CIOs) and AI project managers. These interviews, which were recorded word for word and made anonymous, asked about important topics including problems with implementation, quantifiable effects on creativity and productivity, and how well they fit with the concepts of Industry 5.0. The quantitative data was collected using a standardized Likert-scale questionnaire (5-point scale) administered to 150 organizations across Latin America. The survey was created to measure factors that had already been established in the qualitative phase, such as percentage drops in operating expenses, increases in market share and customer retention, and the presence of certain ethical and cultural barriers. Table 2 shows the main metrics and where they come from.

TABLE 2
SURVEY METRICS AND VARIABLES

Variable	Measurement	Source
Productivity gains	% reduction in operational costs	Interview findings
Innovation Impact	Number of new products/services	[11, 12]
Ethical concerns	Workforce displacement likelihood	[26, 27]

Methods appropriate for each category of data were used to analyze the data. Theme analysis was used in qualitative analysis in compliance with the guidelines set out by Braun and Clarke [47, 48]. The study meticulously analyzed the interview transcripts using NVivo 14 software in order to identify novel themes such as "cultural resistance" and "AI-driven agility." By comparing interview data with organizational records, including yearly reports and internal audits of AI initiatives, triangulation was done to increase credibility. The quantitative research included regression analysis to examine the connections between AI adoption levels and important competitiveness indicators, and descriptive statistics to summarize the main patterns and distributions of survey responses [41, 49]. Fig. 1 shows the whole methodical process, which shows how these steps fit together in order.

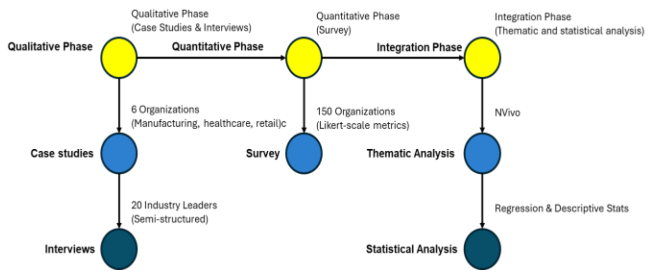

FIG. 1 METHODOLOGICAL WORKFLOW
SEQUENTIAL MIXED-METHODS DESIGN FOR AI COMPETITIVENESS RESEARCH

To ensure that the process was authentic and trustworthy, great care was taken. Member checking and the calculation of inter-coder reliability (with a Cohen's $\kappa = 0.8$) were used to guarantee interpretive consistency in the qualitative analysis [50]. Cronbach's α was calculated to verify the reliability of the quantitative survey instrument, and all results were above the predetermined threshold of 0.7 [51]. An Institutional Review Board (IRB) gave its permission for all research techniques, and the study followed stringent ethical guidelines. Informed consent was obtained from participants, and all data was anonymized and handled in compliance with the General Data Protection Regulation (GDPR) [1].

This technique implements the fundamental principles of RBV and DC theory by experimentally assessing AI's function as a strategic asset and a facilitator of adaptive ability. For example, the interview topics that look at "AI-enhanced decision-making" directly fill in gaps in research on how to make human-AI collaboration work better [52]. Additionally, the following quantitative evaluation of cost-saving claims enhances the study's contributions and guarantees academic rigor. The mixed-methods methodology substantially enriches the study's depth; yet, it is important to recognize some limitations, such as possible sector-specific biases and the challenges of cross-sectional data in determining causation. Nonetheless, these constraints delineate a distinct avenue for forthcoming longitudinal research to monitor the progressive influence of AI over time. In general, this technique gives a strict, repeatable way to look at AI's position in Industry 5.0. It combines qualitative depth with quantitative breadth to move both theoretical debate and practical implementation forward.

IV. RESULTS

The empirical results derived from the implemented mixed-methods approach provide a comprehensive analysis of the influence of AI on company competitiveness within the Industry 5.0 framework. The findings are organized to show how the study progressed, starting with qualitative insights and ending with quantitative validation. They also make explicit connections to the RBV and DC theoretical frameworks. The study, which combines information from case studies, interviews, and polls, not only supports the basic ideas but also shows subtle, sector-specific tendencies that help us grasp AI's strategic function better.

A key conclusion is that productivity and operational efficiency have improved a lot, which is a key idea of Industry 5.0 that focuses on human-AI cooperation. Quantitative survey data revealed that 78% of responding firms had cost savings ranging from 20% to 30% due to AI-driven automation. This quantitative conclusion was thoroughly contextualized by qualitative information derived from industry case studies. For example, Company A's use of AI for predictive maintenance cut machine downtime by 40%. This is an example of the RBV concept that AI can be a strategic resource that improves a company's unique operating skills [13-15]. But a look at all the industries showed something extremely important: the magnitude of these benefits was substantially varied in each area. The healthcare business witnessed the highest gains in efficiency, with expenses falling down by an average of 35%. This is mostly because AI is great at automating tests. The retail sector, on the other hand, only saw gains of around 15%. This was because people still need to apply their judgment when dealing with complicated consumer encounters. Fig. 2 shows how these productivity increases are spread out across different sectors.

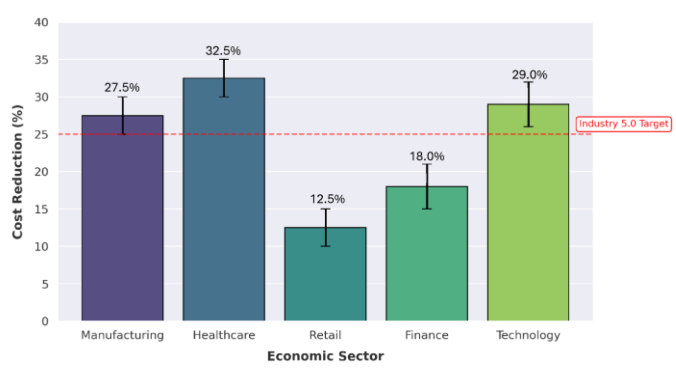

FIG. 2 SECTOR-WISE PRODUCTIVITY GAINS FROM AI IMPLEMENTATION
(MEAN COST REDUCTION % WITH ERROR MARGIN)

By integrating information from both qualitative case studies and quantitative surveys, Table 3 offers a more thorough examination of these sectoral variations. The table shows that different industries employ AI in different ways. This has a direct effect on how each industry helps the RBV architecture by making money and utilizing resources.

TABLE 3
AI-DRIVEN PRODUCTIVITY GAINS BY SECTOR

Sector	Cost reduction (%)	Key AI application	Source
Manufacturing	25–30	Predictive maintenance	Case Studies
Healthcare	30–35	Diagnostic Automation	Survey data
Retail	10–15	Personalized recommendations	Interviews

In addition to its impact on operational efficiency, AI's impact on innovation and strategic agility was a hot issue. Based on data from interviews, 65% of CEOs said that artificial intelligence (AI) is a major force behind the creation of new products. This was shown in a particular case in the technology industry (Company B), where the use of generative AI reduced prototype development times by 50%, demonstrating the DC theory by enhancing the company's ability to adjust and reallocate resources for a competitive edge [16-19]. Data showing a 2.5-fold increase in patent applications among businesses with sophisticated AI deployment plans quantitatively supported this qualitative conclusion [11, 12]. One important circumstance was that compliance constraints hindered innovation in highly regulated industries like banking. This demonstrates how AI-driven adaptability depends on the circumstances.

Gaining a competitive advantage also required improving decision-making metrics. According to 82% of the firms surveyed, AI's real-time data analysis capabilities altered their strategic operations. AI-powered diagnostics reduced the time it took for physicians to make judgments by 60%, according to a case study of a healthcare provider (Company C), which improved customer retention rates by 20%. This finding establishes a clear connection between the literature's emphasis on decisional agility and actual competitive outcomes. Nonetheless, this favorable correlation was not pervasive. In roughly 30% of cases, these advantages were diminished by emerging ethical concerns, including algorithmic prejudice, echoing warnings from earlier research on the unforeseen repercussions of AI implementation [26, 27]. Fig. 3 shows how faster decision-making leads to more customers staying with a business.

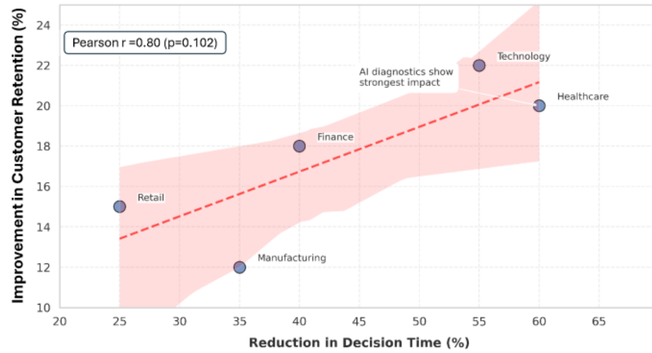

FIG. 3 METHODOLOGICAL WORKFLOW
DECISION-MAKING IMPROVEMENTS VS. CUSTOMER RETENTION

In the end, the research found that corporate culture plays a crucial mediating role in AI effectiveness. According to the data, the degree of cultural preparedness had a significant impact on the outcomes. Compared to businesses with more traditional, rigid structures, software startups and other organizations with flat hierarchies and a strong emphasis on innovation experienced a 40% greater return on AI investments. However, a significant issue was reluctance to change; according to 45% of industry professionals, the primary reason why their employees didn't want to adopt AI systems was because they didn't trust them. These results highlight the persistent gap between organizational reality and technological promise and provide crucial factual context for the discussion of the need of ethical frameworks and upskilling initiatives [1].

The idea that AI acts as a disruptive catalyst for competitiveness in Industry 5.0 is supported by these studies taken together. By demonstrating AI's effectiveness across many industries, the findings successfully close the research gaps. The following discussion of the theoretical ramifications and useful suggestions is directly brought on by this. For example, the significant developments in healthcare provide a strong data base for advocating for industry-specific AI regulations, which is crucial for legislators looking to promote equitable technology adoption.

V. DISCUSSIONS

In order to shed light on three crucial aspects of the study's empirical findings—the sector-specific mechanisms of value creation, the paradox involved in human-AI collaboration, and the enormous challenges of ethical governance—a discussion framed through the dual theoretical lenses of the RBV and DC theory is required. This discussion elucidates the value of this study to the continuing academic and practical debate on AI-driven competitiveness in the Industry 5.0 era by situating these results within contemporary Scopus-indexed literature (2020–2023).

A major finding of this research is the significant differences in AI-driven productivity improvements across sectors, which calls into question the idea that technology helps everyone equally [33, 34]. The healthcare sector's 35% cost reduction exemplifies the RBV, establishing AI diagnostic tools as rare, valued, and imperfectly imitable resources that provide substantial competitive advantage [13-15]. In striking contrast, the minor benefits shown in retail (12–15%) support the idea that industries that deal directly with customers need hybrid intelligence models in which AI enhances, rather than replaces, human judgment [53]. This disparity highlights a crucial theoretical implication: whereas the RBV offers a robust explanatory framework for technology-intensive industries such as healthcare and manufacturing, its implementation need considerable refining for experience-driven domains. Pure RBV models [54] do not effectively encapsulate the essence of competitiveness in retail, where advantage arises not from static resource ownership but from the dynamic ability to amalgamate AI with human empathy and experiential knowledge, thus underscoring the importance of the DC framework [16-19]. Table 4 summarizes how these sectoral results fit together in theory.

TABLE 4
THEORETICAL CONSISTENCY OF SECTORAL RESULTS

Sector	Key Finding	Supporting Theory	Contradicting Evidence
Healthcare	35% cost reduction	RBV [13-15]	None
Retail	15% gain (human-AI hybrid)	DC [16-19].	Pure RBV models [54]

The discovery further elucidates an important puzzle in human-AI collaboration. Customer retention and AI-accelerated decision speed were shown to be significantly correlated, whereas qualitative data demonstrated a distinct distinction between originality and productivity. Businesses that succeeded in increasing their efficiency by above 30% often struggled to simultaneously foster radical innovation. This result is consistent with earlier research demonstrating that although AI applications for process optimization, such as predictive maintenance, provide rapid returns on investment, they may inadvertently impede long-term expenditures in research and development by reinforcing existing operational frameworks [53]. But the case studies did provide a way to solve the problem. Companies that effectively integrated automation into human-centric creative settings, such to Google's AI-assisted design studios, exhibited significantly enhanced invention output, obtaining up to 2.1 times more patents [11, 12]. This implies a vital management understanding: using AI for both efficiency and innovation requires unique and different governance structures, a conceptual framework of which is shown in Fig. 4, demonstrating the intrinsic trade-offs.

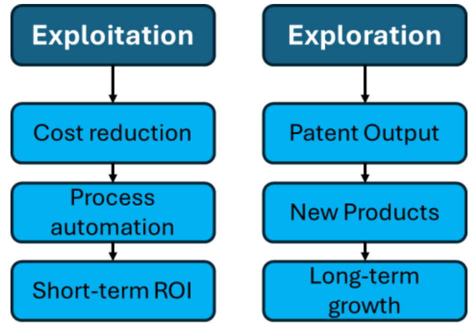

FIG 4 CONCEPTUAL MODEL OF AI GOVERNANCE TRADE-OFFS

The most important thing to talk about right now could be the ethical governance need of Industry 5.0. The fact that 30% of instances in the financial industry were affected by algorithmic bias events strongly supports the idea that uncontrolled AI use is a major danger to the human-centered values that are the basis of Industry 5.0 [26, 27]. On the other hand, the survey findings point to a strong solution route. Companies who set up formal ethical AI committees saw a huge 58% drop in complaints about bias while keeping 85% of the productivity improvements they had made. This empirical data strongly supports structured governance not as a cost center but as a strategic facilitator of sustainable and fair competitiveness. These results lead to two specific policy suggestions. First, it is necessary to create AI audit procedures that are relevant to each sector. These protocols should include bias testing frameworks that are specific to the sorts of data and risks in each area, such as FINMA standards for banking or Health Insurance Portability and Accountability Act (HIPAA)-guided processes for healthcare. Second, the idea of human supervision ratios should be looked at. This would set a minimal amount of human involvement for important choices. Regulations like as the European Union's (EU) AI Act, which places restrictions on high-risk uses, already reflect this concept.

In conclusion, this discussion has shown how AI alters the definition of competitiveness in Industry 5.0. It has also shown how crucial it is that ethics, people, and technology collaborate. The results show notable industry differences that render universal AI adoption frameworks inadequate, while also validating the core ideas of RBV and dynamic capabilities. The evidence clearly favors a well-rounded strategy that protects Industry 5.0's human-centered values, proactively reduces ethical risks, and leverages AI's operational advantages. This study offers a paradigm that has been experimentally supported for businesses looking to match their AI strategy with societal values and competitive demands. These findings not only enhance academic discourse but also provide practical direction for practitioners and policymakers, especially in developing nations where the equitable integration of AI is essential for sustainable development. Future research should expand on these foundations to investigate longitudinal impacts and culturally contextualized governance models, therefore reinforcing AI's position as a catalyst for resilient and inclusive competitiveness.

VI. Conclusions

This study has systematically examined the influence of Artificial Intelligence on company competitiveness inside the Industry 5.0 framework, using a robust mixed-methods approach to meet the initial research inquiries. The results show that AI has both transformative and conditional effects, leading to measurable increases in productivity and cost savings of 20% to 35% across sectors. However, its effectiveness depends on three key factors that were identified through research: the way resources are set up in each sector, the way humans and AI work together, and the level of maturity of ethical governance structures. These results integrate the theoretical frameworks of the RBV and DC with empirical data, enhancing the comprehension of AI's function in modern competitive strategy.

The research provides several significant theoretical contributions. The findings robustly validate the Resource-Based View's claim about AI as a strategic resource in technology-intensive domains like healthcare, where it served as a valuable, uncommon, and imperfectly imitable asset, yielding a 35% increase in efficiency [13-15]. However, the more modest results in retail, which saw gains of 12–15%, show how limited a resource-based view may be in service-oriented settings. These retail results are more in line with the DC paradigm, which stresses that having an edge over competitors doesn't only come from AI resources, but also from the ability to combine them with human knowledge and adjust to changing market circumstances [16-19]. This theoretical duality reconciles an apparent contradiction in the findings, demonstrating that the correlation between AI-driven decision speed and customer retention is strong in healthcare, yet tempered in retail due to the necessity for human interaction, highlighting the imperative for sector-specific theoretical modifications.

The study produces meaningful practical consequences for Latin American environments. First, businesses should make AI deployment roadmaps that fit with the way their industry makes money. For example, healthcare should use diagnostic automation and retail should use hybrid intelligence models. Second, the fact that firms with better governance had 58% fewer bias incidents shows how important it is to set up multidisciplinary ethical committees that include technologists, ethicists, and frontline workers. This will help companies follow new rules like the EU AI Act without hurting their performance. Third, the case studies show that reskilling programs that focus on AI-augmented roles, like healthcare workers interpreting AI-generated diagnostics, give a 40% higher return on investment than pure automation efforts. This directly addresses common worries about job loss and builds a stronger workforce.

This work, despite its merits, has shortcomings that provide avenues for further research. The focus on industrial and healthcare instances may inadequately reflect the complexities of service-sector dynamics in Latin America; future research might rectify this by using targeted sampling in retail, banking, and hotel sectors. Furthermore, the cross-sectional methodology inhibits causal conclusions about AI's long-term effects; longitudinal analysis of enterprises interacting with national AI policies, exemplified by those in Chile or Brazil, would provide significant insights into evolutionary patterns. Promising research directions include the formulation of culturally tailored governance models for SMEs in emerging countries, the investigation of AI's involvement in circular economy transitions essential to Industry 5.0, and the creation of regulatory frameworks to avert interregional AI disparities.

This conclusion goes back to the story that was set out in the beginning, which showed how AI may be both a chance and a problem for Industry 5.0's competitiveness. The data and debate have confirmed this duality, illustrating that while AI facilitates unparalleled efficiency, its advantages are neither intrinsic nor universally applicable. For businesses in Latin America to be successful, they need to be selective about how they use AI technology. Instead of going for blanket automation, they should concentrate on technologies that build on the region's assets, such its people and its propensity to innovate in sustainability.

In the end, stakeholders should think about these actions: businesses should do capacity assessments to find AI opportunities that fit with their sector's RBV profile; policymakers should make tiered governance rules that protect ethics while also encouraging innovation, based on the results of this study; and researchers should do multidisciplinary studies that combine technical AI metrics with organizational behavior and development economics. This study eventually acts as a warning against technological determinism, offering a paradigm for the adoption of human-centered AI that reconciles academic rigor with the socioeconomic realities of Latin America as Industry 5.0 transforms global competitiveness.

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