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The influence of artificial intelligence on business operational efficiency: a systematic review

Jose Antonio Rojas Guillen [1]; Wini Ebelin Quispe Bautista [2]
[1]Universidad Tecnológica del Perú, Perú, *c27875@utp.edu.pe*
[2]Universidad Continental, Perú, *71265716@continental.edu.pe*

Abstract – This article analyzes the impact of artificial intelligence on business operational efficiency through a systematic literature review based on the PICOC methodology. A total of 219 records were collected in Scopus, of which 44 met the inclusion criteria after applying the PRISMA statement. The results identified factors limiting operational efficiency, such as lack of automation, human error and resistance to change. AI emerged as a key driver for improving productivity, automating processes and optimizing decisions, with the greatest impact in sectors such as manufacturing, logistics and finance. Companies that adopt AI show greater flexibility, cost reduction and resource optimization compared to those that do not. It is concluded that AI transforms operational efficiency, with more marked effects in sectors where automation is crucial, highlighting it as a strategic tool to improve business performance.

Keywords-- Operational efficiency, artificial intelligence, organizational productivity, performance, businesses.

I. INTRODUCTION

Today, artificial intelligence (AI) is increasingly being used to support a wide variety of business activities, including improving services, developing products, evolving business models and promoting innovation. This technological advancement offers a vast array of opportunities for all industries and sectors. However, its implementation is still at a nascent stage [1][2][3][4].

Companies starting to integrate AI into their operations often face challenges and make mistakes due to the lack of established parameters and standards. This situation is understandable, given that the adoption of any novel technology can entail a significant learning curve and the risk of initial failures. Added to this is the volatile nature of the market, which does not follow fixed patterns and continually adapts to changing circumstances. This volatility can have a considerable impact on the operational efficiency of companies, as the market context directly influences how AI solutions are implemented and optimized [1][5].

The question arises: is it feasible for artificial intelligence (AI) to improve operational efficiency in businesses? Although not all the ways in which AI can contribute to business efficiency have been delineated, preliminary studies provide some promising indications. In particular, in the manufacturing sector, one of the main concerns is the maintenance of production-critical machinery. Anticipating failures and errors that may affect daily operability has always been a critical challenge. In this context, intelligent systems have proven to be particularly useful in supporting decision-making processes by applying the concept of predictive maintenance. These systems make it possible to anticipate problems before they occur, which in turn helps to maintain operational continuity and reduce downtime [6][5]. In addition, AI can optimize lean maintenance, a strategy that increases the operational efficiency of companies' technical infrastructure by ensuring that equipment performs optimally and is repaired or replaced just in time [6].

Also in the agricultural sector, exploratory studies have shown some good results in the use of artificial intelligence (AI) to boost business performance. These studies indicate that AI can improve various aspects of agricultural production, such as crop management and resource optimization. However, these initial results also point out that the adoption of AI in agriculture is highly dependent on the size of the company, as well as social factors and market competition. Larger companies tend to have an easier time implementing advanced technologies due to their greater financial and technical resources, while smaller companies may face significant barriers. In addition, social acceptance of the technology and competitive pressure also play important roles in AI adoption [2].

Likewise, in service companies, where success is largely based on the quality of customer relations, it has been shown that the use of artificial intelligence (AI) makes it possible to homogenize standards and optimize forms of interaction. AI not only contributes to establishing consistent and efficient procedures, but also improves qualitative aspects, such as the feelings generated during interactions. This, in turn, translates into improved well-being for both customers and employees. Through AI, it is possible to analyze behavioral patterns and extract meaningful data from conversations, which facilitates strategic decision making. For example, AI can monitor and evaluate brand reputation, as well as measure customer satisfaction more accurately. This ability to analyze and adapt enables service companies not only to maintain high levels of customer service quality, but also to continuously improve based on the feedback and data collected. In short, the implementation of AI in this sector promises significant progress in customer relationship management and business success [7].

Despite these promising findings, the studies are still exploratory and suggest the need for more in-depth and detailed research. Further study is needed to better understand the scope and limitations of AI in the agricultural sector, as well as to develop effective strategies to enable its wider and more efficient implementation [2][8]. As companies continue to explore and adopt AI technologies, it is likely that new applications and benefits will be discovered that have not yet been fully contemplated. However, it is crucial to continue to research and document these advances to establish clear parameters and standards to guide their effective implementation. This research will be conducted in several stages. First, a comprehensive review of the existing literature on the use of AI in various industrial sectors will be conducted. Then, gaps and discrepancies in current studies will be identified to highlight areas that require further research.

Finally, recommendations based on the findings will be proposed to guide future implementations of AI in the business environment. To this end, the main objective of this research is to analyze and synthesize the existing evidence on the impact of artificial intelligence on the operational efficiency of enterprises. Through this systematic review, we seek to provide a clear understanding of how AI can contribute to improve efficiency, identify the challenges associated with its implementation and offer guidelines for a more effective adoption of this technology in the business environment.

II. METHODOLOGY

A. Review Question

The main review question for this study was: how does the use of artificial intelligence influence the improvement of operational efficiency in companies?

The review question was elaborated according to the criteria established in the PICOC search strategy, which is based on the formulation of questions that precisely identify the five key components of the information to be retrieved as shown in Table I.

TABLE I
PICOC QUESTION - COMPONENTS

Acronym	Component	Description
P	Problem	*Operational efficiency in companies*
I	Intervention	*Impact of artificial intelligence*
C	Comparison	*Comparison between companies that use AI and those that do not use AI.*
O	Result (*Outcome*)	*Improved operating efficiency*
C	Context	*Companies from different sectors and industries.*
	R.Q.	How does the use of artificial intelligence influence the improvement of operational efficiency in companies?

As shown in Table I, component (P) described the research problem, in this case, operational efficiency in companies. Component (I) referred to the proposals or solutions developed to solve the problem, that is, artificial intelligence impact. Component (C) pointed to the comparison between companies that use AI and those that do not use AI. Component (O) considered the improvement in operational efficiency. Finally, component (C) or "context" defined the boundaries of the problem, including companies from different sectors and industries.

The following questions are presented here for each PICOC element:

P = Problem: What are the main factors affecting operational efficiency in firms?

What challenges do firms face in maintaining and improving their operational efficiency?

I = Intervention: How does the implementation of artificial intelligence impact operational efficiency in enterprises?

What artificial intelligence-based solutions have proven to be most effective in improving operational efficiency in enterprises?

C = Comparison: What differences in operational efficiency exist between companies that use artificial intelligence and those that do not?

How do the operational practices of firms that adopt artificial intelligence compare with those of firms that do not?

O = Outcome: What specific improvements in operational efficiency can be observed following the implementation of artificial intelligence in companies?

Which operational efficiency metrics show the greatest improvement following the implementation of artificial intelligence in companies?

C = Context: How does the impact of artificial intelligence on operational efficiency vary across firms in different sectors and industries?

To what extent does the impact of artificial intelligence on operational efficiency vary between small, medium and large companies in different industries?

B. Search strategy

A set of keywords relevant to each component of the PICOC question was selected, as described in Table II. These keywords, organized in a search equation, were used to perform a systematic literature search in one database: Scopus (see Table III). These were selected because they are the main databases of bibliographic references and citations of peer-reviewed periodicals and include publications in high-impact journals from the world's leading universities, institutions and scientific publishers.

Although the review question identified the comparison component (C), it was decided not to include it in the literature search equation, since its inclusion generated significant biases in the results. It was considered that omitting the comparison did not affect the inclusion or exclusion criteria, because the objective of the study is different. The main focus is to delimit and analyze the improvement of operational efficiency with the use of artificial intelligence (AI), emphasizing its limitations and success factors.

TABLE II
SELECTED KEYWORDS

	Problem (p)	Intervention (i)	Comparison (c)	Results (o)	Context (c)
Key words	Operational efficiency	Artificial intelligence	Manual processes	Operating Efficiency	industrial company
	Business performance	AI-driven efficiency	Traditional company	Performance	companies
	Corporate efficiency	AI technology adoption		Operational gains	Businesses
	Organizational productivity	AI implementation			

TABLE III
SEARCH EQUATIONS USED TO SEARCH FOR SCIENTIFIC LITERATURE IN THE SELECTED DATABASES

Scopus
(TITLE-ABS-KEY ("Operational efficiency" OR "Business performance" OR "Corporate efficiency" OR "Organizational productivity") AND TITLE-ABS-KEY ("Artificial intelligence" OR "AI-driven efficiency" OR "AI technology adoption" OR "AI implementation") AND TITLE-ABS-KEY ("Operating Efficiency" OR "Performance" OR "Operational gains") AND TITLE-ABS-KEY ("industrial company" OR "companies" OR "Businesses"))

The studies retrieved as a result of the application of this search equation were reviewed and selected according to the following criteria presented in Table IV:

TABLE IV
INCLUSION AND EXCLUSION CRITERIA FOR THE RELEVANT SCIENTIFIC LITERATURE SEARCH

Inclusion criteria	Exclusion criteria
C.I.1 Studies focused on operational efficiency with the use of AI. C.I.2 Original articles, full-text paper published in journals indexed to Scopus. C.I.3 Studies published in English.	C.E.1 Population-focused studies of non-profit organizations or government entities. C.E.2 Studies published as editorial, retracted, book. C.E.3 Studies that synthesize or review the state of knowledge on the subject (Review-type documents).

C. *Search process and article selection*

The application of the search equations indicated in Table II made it possible to retrieve a total of 219 scientific publications from the Scopus databases (n=219). These results were subjected to a screening procedure following the guidelines of the PRISMA statement presented in Fig. 1.

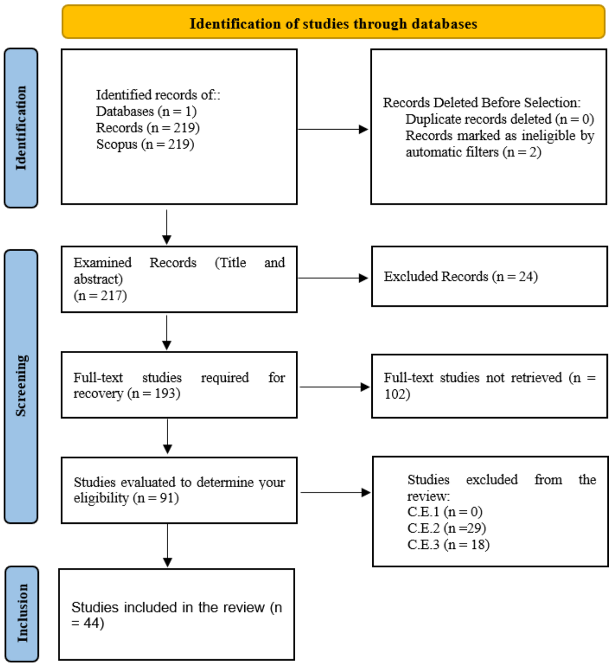

Fig. 1 Statement PRISMA.

The flow diagram above (Fig. 1) summarizes the steps and process of publication selection, which are described below:

Before proceeding with the screening, 2 records were automatically excluded by applying filters available in the databases, specifically in terms of language.

During the initial screening stage, the 217 selected articles were evaluated by reviewing their titles and abstracts. At this stage, 24 records that did not meet the inclusion and exclusion criteria were excluded, leaving a total of 193 studies remaining.

The final step in the screening process consisted of evaluating the full studies for eligibility. Initially, we attempted to obtain the full papers of the 193 studies selected for a comprehensive review but were unable to retrieve 102 of them. The studies retrieved in their entirety (n=91) were evaluated according to the prespecified criteria. Of these, 47 studies did not meet at least one of the aforementioned criteria, resulting in the final selection of 44 studies for inclusion in the Systematic Literature Review (SLR).

III. RESULTS

Multiple studies have been compiled and analyzed to provide a more comprehensive view of the impact of AI on the operational efficiency of companies. Systematic reviews typically analyze, synthesize and compare previous studies, providing a clearer understanding of key trends and conclusions. From the studies reviewed, an outline of specific points is presented in Fig. 2 as a synthesis of the information reviewed:

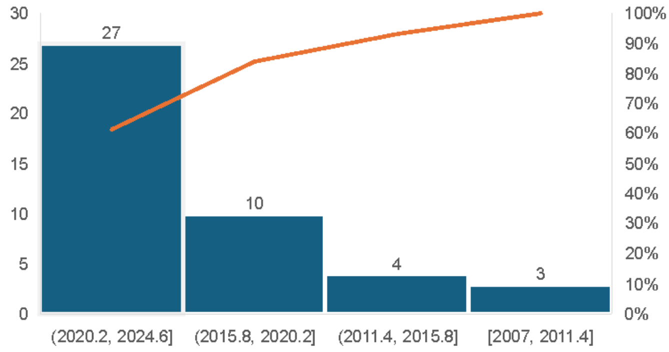

Fig. 2 Results of analysis of year and publication in journals
Note. Each bar represents the range of years (indicated on the X-axis) with the total number of items on the Y-axis.

The first bar (2020.2, 2024.6) shows 27 events, meaning that the most recent period has the most records. The second interval (2015.8, 2020.2) has 10 events, a significantly smaller number. The next bars (2011.4, 2015.8 and 2007, 2011.4) show 4 and 3 events, respectively, indicating a progressive reduction in the number of events as one moves back in time. The line across the graph shows the cumulative frequency, which indicates the total percentage accumulated by the categories as they are summed. This line starts at 0% and reaches 100% when the last group of data is reached. The line shows that about 80% of the total events are concentrated in the first two periods (2020.2-2024.6 and 2015.8-2020.2), which follow the Pareto principle.

Table V also shows the absolute frequency of publications.

TABLE V
ABSOLUTE FREQUENCY OF PUBLICATION OF ARTICLES AND CONFERENCE PAPERS IN THE YEARS UNDER ANALYSIS

		Document Type		Total
		Article	Conference paper	
Year	2007	0	1	1
	2008	0	1	1
	2011	1	0	1
	2012	0	1	1
	2013	1	1	2
	2014	1	0	1
	2017	1	1	2
	2018	1	1	2
	2019	0	3	3
	2020	2	1	3
	2021	2	0	2
	2022	9	2	11
	2023	6	1	7
	2024	7	0	7
Total		31	13	44

Over the period 2007-2024, a total of 44 documents have been produced. Of these, 31 are articles and 13 are conference papers. The majority of the papers are articles (31), while conference papers make up a smaller proportion (13). Between 2007 and 2019, the number of papers published per year is relatively low, with most years having only 1 or 2 publications. Exceptions include 2019 with a total of 4 papers. From 2020 onwards, there is a notable increase in the number of publications, especially in 2022, which is the year with the highest number of papers (11 in total). 2022 stands out as the most productive year with 9 papers and 2 conference presentations. In 2023 and 2024, the rate of publications remains high with 7 papers in 2023 (6 articles and 1 paper) and 7 papers in 2024 (all articles, no papers). No publications are observed in the years 2009 and 2010, thus concluding that a significant increase in the number of published papers is observed from 2020 onwards. The maximum peak is in 2022 with 11 papers. This indicates a greater research or academic activity in recent years, due to more active research projects or a renewed interest in the production of academic papers. Since 2020, the number of conference papers is relatively low, with publication of articles being more common.

Likewise, the most cited article as presented in Fig. 3, "Design and development of logistics workflow systems for demand management with RFID" (81 citations), describes the development and design of logistics workflow systems using RFID technology to optimize demand management.

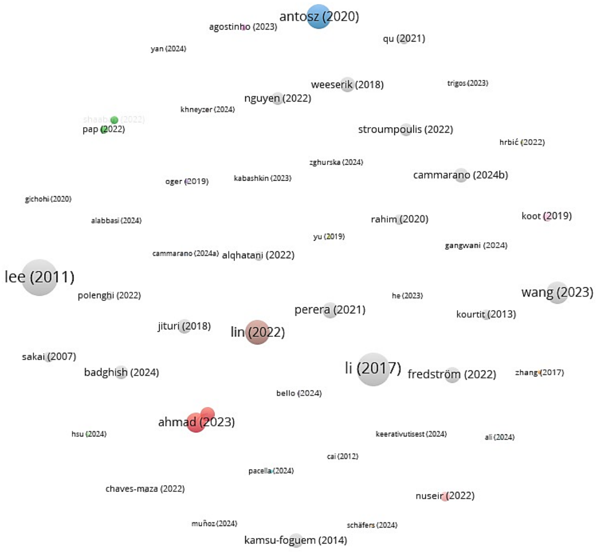

Fig. 3 Most Cited Author

Fig. 4 below shows the context of application of various strategies, technologies and innovations in two major areas: the physical and industrial sphere and the business and marketing sphere [9]. In the first, practical applications in global companies, the management of critical assets in industrial environments and the implementation of forecasting and occupational health systems are highlighted [10][11][12]. In the second, aspects related to the adoption of artificial intelligence in the agricultural sector [13][14], the analysis of market perception of emerging technologies and the role of communication in innovation and collaboration are addressed [15][16][17]. This outline provides a clear vision of the possible areas of study and application, establishing a framework for exploring solutions in different environments.

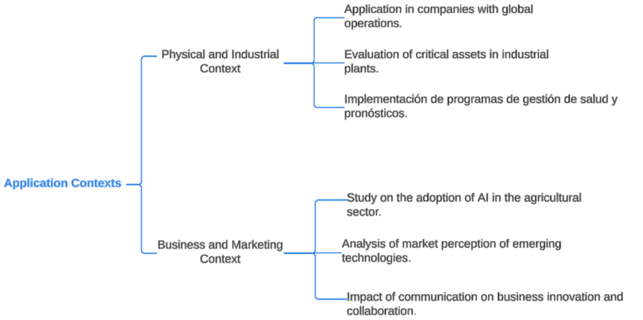

Fig. 4 Outline of particular points on application context

Fig. 5 shows the methods and techniques used, summarizing the main approaches applied in data and sentiment analysis to evaluate perceptions and efficiency in different contexts. It highlights the use of the Vader algorithm to measure emotional responses in large volumes of online observations [15], as well as its effectiveness in market perception. In addition, advanced techniques such as efficiency analysis through DEA (Data Envelopment Analysis) [11][18], data mining applied in the industry and statistical models such as regression and structural equations [19], which allow the identification of complex relationships between variables [20][21], are presented. This outline provides an overview of the tools used in data-driven studies.

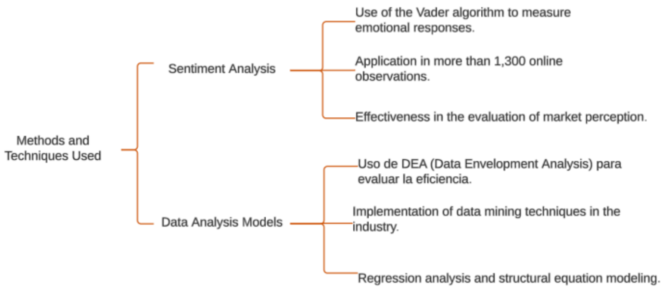

Fig. 5 Outline of particular points on methods and techniques used

Fig. 6 includes the measurements and metrics that organize the tools used to evaluate efficiency and results in different business contexts. The Efficiency Indicators include metrics such as RPN (Risk Priority Number) for asset evaluation [10], OEE (Overall Equipment Effectiveness) to measure maintenance effectiveness [22], and others related to performance, such as ROI and technical efficiency. In Performance Evaluation, methodologies such as the comparison of composite scores in sentiment analysis [23], the measurement of effectiveness in the adoption of technologies [24], and the analysis of the relationship between digital capabilities and business performance stand out [13].

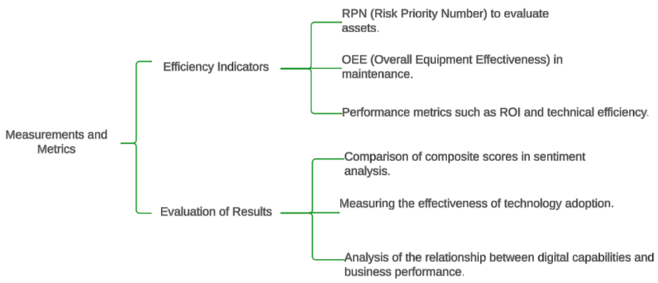

Fig. 6 Outline of particular points on measurements and metrics

Fig. 7 presents a hierarchical scheme that organizes the conclusions and recommendations into two main categories: Proposed Solutions and Successful Technology Adoption. In the Proposed Solutions, the implementation of ontological models to prioritize assets [10], the improvement of artificial intelligence (AI) communication to optimize performance [13], and the development of resilient planning frameworks in logistics stand out [25]. Furthermore, the application of advanced data mining techniques to improve business performance can be crucial for optimizing operational strategies [26]. On the other hand, in the Successful Adoption of Technologies, the identification of emerging practices in the use of AI [13], the importance of human capital and its training in the implementation process [12], and the need for a strategic approach to operational risk management are highlighted [27]. Additionally, fostering a deep understanding of AI's impact on business models and technology innovation is key to enhancing adoption success [28]. This outline suggests a comprehensive approach to address both technological optimization and operational strategy in the context of artificial intelligence.

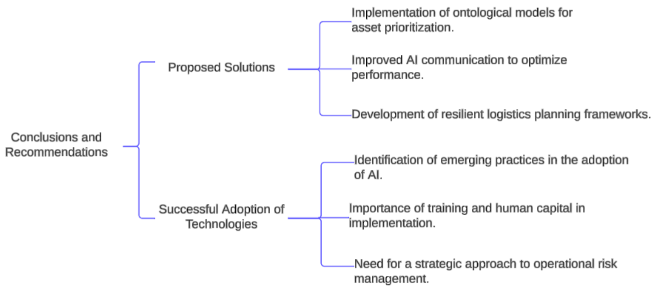

Fig. 7 Outline of particular points on conclusions and recommendations

A. *P = Problem*

The authors point out that one of the key issues is the complexity of decision making that companies face when trying to manage multiple attributes in their operations. Often, companies are constrained by the lack of comprehensive tools that allow them to optimize their processes efficiently, leading to decisions that do not always maximize productivity or minimize costs [10]. This challenge is also addressed by decision support systems, which aim to provide businesses with more efficient ways to meet their objectives and improve operational processes [29]. Additionally, advanced modeling techniques can be employed to predict and enhance business success, guiding companies towards better decision-making strategies [30].

Another factor mentioned by these authors is the lack of automation and reliance on manual processes. Companies that do not have advanced technologies rely on outdated operational processes, which increases the likelihood of human error and makes operations slower and more costly [12]. This lack of automation can be mitigated by adopting advanced technologies, such as RFID for logistics workflow management, which can significantly enhance operational efficiency [31]. Furthermore, the integration of big data and AI technologies can enable better data processing and decision-making, helping organizations overcome the challenges of managing large volumes of data and reduce the risk of human error [32]. Overall, the authors stress that inefficient resource management, inability to process large volumes of data, and organizational resistance to technological change are major barriers to operational efficiency [33].

B. *AI as a Driver of Operational Efficiency*

The studies reviewed address key issues about the ability of AI to improve business operational efficiency. For example, one of the titles on "An ontological modelling of multi-attribute", suggests that artificial intelligence can be used to model decisions based on multiple attributes [10]. This indicates that AI has the ability to help companies make faster and more accurate decisions, optimizing their processes. The fact that an ontological model is used implies that AI not only improves traditional workflows, but also redefines the way companies understand and prioritize decisions. By taking multiple variables into account, AI could help eliminate operational inefficiencies, automate processes and increase accuracy in tasks that previously relied on human judgment [13]. Additionally, AI's ability to process large datasets and make informed decisions is also reflected in models used for financial data mining, which further support more efficient business operations [34]. Furthermore, AI technologies can be leveraged to improve risk management and business performance by helping businesses navigate operational risks with greater precision and agility [35].

C. *I = Intervention*

The implementation of artificial intelligence has a transformative impact on the operational efficiency of companies, as seen in the article “What is the market value of artificial intelligence?”. The authors highlight that AI brings tangible value by enabling automation of routine processes, which reduces operational burden and improves accuracy in everyday tasks. A good example of this is Robotic Process Automation (RPA), which is used to reduce human intervention in repetitive tasks, thus minimizing errors and speeding up response times [12].

In addition, AI enables companies to implement predictive solutions that optimize business decisions by anticipating market trends, supply chain issues or future operational needs. These predictive tools, based on machine learning algorithms and big data analysis, improve planning and prevent bottlenecks in operations [33].

On the other hand, other studies indicate that AI also plays a crucial role in managing complex decisions, helping companies to balance multiple criteria and improve their ability to prioritize key decisions more efficiently [10].

D. C = Comparison

When you compare companies that use AI with those that do not, you see clear evidence of differences in operational efficiency. Companies that implement AI are more agile and able to react quickly to market fluctuations, in part because AI allows them to analyze large volumes of data much faster than traditional methods [33]. These companies achieve greater optimization of resources, as they can accurately forecast product demand and adjust their inventories and production accordingly, resulting in less waste and greater operational efficiency [15].

In contrast, companies that do not use AI rely on manual processes or decisions based on intuition, making them less flexible and more prone to errors. In addition, companies without AI often struggle to handle data growth and operational complexity, limiting their ability to improve efficiency [13]. Companies without AI miss key opportunities to optimize their processes, as they lack the tools to handle multiple variables simultaneously [12].

E. Economic Impact and Market Value of AI

The literature explores how the implementation of AI in companies can generate tangible value. This type of study is crucial because operational efficiency not only improves the internal processes of organizations but can also influence the economic value of firms. By adopting AI, companies reduce operating costs, improve the quality of their products or services, and generate new sources of revenue by offering innovative technology-based solutions [1][36][37][38]

Therefore, from a market value perspective, AI not only optimizes what exists, but also transforms a company's positioning in the digital economy, making it more competitive and agile in the face of technological change [33][13].

F. O = Outcome

The results following the implementation of AI in companies are significant, according to the studies analyzed companies experience a drastic reduction in operating costs by automating tasks that previously required intensive labor. This automation not only saves costs, but also frees employees to focus on more strategic activities that bring greater value to the company [10].

Another key improvement is increased productivity. AI enables companies to complete operational processes in much shorter times by eliminating bottlenecks and reducing cycle times. In addition, decision-making accuracy improves substantially, as AI algorithms are able to analyze complex data in real time and provide fact-based recommendations [23].

Among the operational efficiency metrics that show the greatest improvement are production cycle time, error reduction in critical processes, and better use of resources. The use of AI improves consistency in results by eliminating variability caused by human error [15][33].

G. C = Context

The impact of AI on operational efficiency varies significantly depending on the sector and size of the company. In sectors such as manufacturing and logistics, AI has a particularly strong impact, as automation and supply chain optimization are critical aspects of operational efficiency in these sectors [39]. For example, in manufacturing, AI is used to perform predictive maintenance, which reduces unplanned downtime and increases equipment lifetime [40].

In the financial sector, AI is used for risk analysis and automation of administrative processes, which improves both efficiency and accuracy in decision making [33]. However, in more traditional or skill-intensive industries, AI adoption is slower and the benefits are not yet as pronounced.

A key finding in the analysis of the impact of AI on operational efficiency is the influence of firms' level of technological readiness. The successful adoption of AI-based solutions by SMEs is highly dependent on factors such as available digital infrastructure, staff training and institutional support. According to the TOE (Technology-Organization-Environment) framework, organizations with greater technological maturity achieve more significant improvements in their operational performance after incorporating these tools, while those with limited capabilities face barriers that make it difficult to take full advantage of their benefits. This shows that the impact of AI is not uniform, but varies according to the degree of technological readiness, which underlines the need for differentiated strategies for its implementation in different business contexts [13].

In this sense, technological readiness is consolidated as a determining factor to obtain positive results with the incorporation of AI. This readiness goes beyond having digital infrastructure; it also includes the ability to manage change, the development of digital competencies in personnel and the existence of a strategic vision aligned with digital transformation. Companies with greater technological maturity not only adopt Industry 4.0 technologies more easily, but also manage to translate their potential into concrete efficiency improvements. Elements such as access to specialized talent and investment in training are decisive for this transformation to be reflected in tangible operational benefits [24].

IV. Discussion of Results

The results of the present study confirm that artificial intelligence generates a positive impact on the operational efficiency of companies, which is in line with the reference [1]. These improvements are attributable to process automation, reduction of human error and the ability to manage complex data. However, challenges such as the learning curve and the absence of standardized parameters, also noted in reference [2] and [4], represent significant initial barriers. In line with reference [10], this analysis also highlights that AI tools enable companies to optimize their decision making and redefine operational strategies, thus increasing their competitiveness in a dynamic environment [12].

The study reaffirms that the adoption of AI can be a transformative tool for companies, especially in sectors such as manufacturing, where predictive maintenance has proven to be crucial to improve efficiency, as mentioned in reference [6] [41] and [5]. In the service sector, AI not only homogenizes standards, but also personalizes interactions with customers, generating qualitative and quantitative advantages [7]. However, sectors such as agriculture still face significant barriers due to limitations in infrastructure, social acceptance and lack of resources, challenges that require priority attention to close technological gaps.

Although a homogeneous adoption of AI across companies was expected, marked differences were observed according to size and sector. Large manufacturing companies, for example, showed substantial improvements due to their ability to integrate advanced technologies. In contrast, SMEs and traditional sectors, such as agriculture, have experienced limited progress, probably due to technological and cultural resource constraints. This result underscores the importance of a differentiated approach when designing AI implementation strategies [13].

The findings depend on the context of the companies analyzed, especially in terms of technological resources and adaptability. The sample may also not fully capture the diversity of sectors, as some, such as agriculture and certain SMEs, have unique characteristics that affect AI implementation [42]. In addition, the lack of a uniform regulatory framework and market volatility complicate comparison across cases [43].

Further research into AI applications in sectors with lower levels of adoption is recommended, exploring scalable and adaptable models for small businesses and rural areas [44]. While this study confirms the positive impact of AI on operational efficiency, it is critical to provide practical guidelines for companies looking to integrate this technology into their operations.

First, organizations should assess their level of technological readiness, considering available digital infrastructure, staff competencies and strategic alignment with digital transformation. Having a clear understanding of internal capabilities enables realistic expectations to be set and appropriate AI tools to be selected. Secondly, it is recommended to identify operational areas with high volumes of manual tasks, repetitive processes or frequent decision-making needs, as they are often more suitable for optimization using AI. The adoption process should start with small-scale pilot projects, allowing for impact measurement and adjustments before full implementation.

In addition, staff training plays a key role in reducing resistance to change and ensuring effective adoption. Companies should invest in developing digital skills and strengthening data literacy to maximize the benefits of AI integration. Finally, establishing measurable metrics; such as reduced processing times, reduced errors and lower operational costs; allows progress to be monitored and encourages continuous improvement. By following these strategic steps, companies can move from exploratory AI adoption to sustained operational transformation.

V. Conclusion

The research confirms that artificial intelligence (AI) positively impacts business operational efficiency, aligning with the main objective of analyzing how its implementation optimizes processes, reduces errors and improves decision making in various sectors. The results obtained reflect that, although the improvements are significant, the impact varies according to the business context: sectors such as manufacturing and services have successfully adopted AI technologies, while areas such as agriculture and SMEs face economic, technological and cultural barriers that limit their implementation. This shows that operational efficiency depends not only on technological capabilities, but also on organizational, sectoral and contextual factors.

The contribution of this Systematic Literature Review (SLR) to the existing study lies in providing a comprehensive perspective on AI applications in various economic sectors, synthesizing previous findings and highlighting areas with high potential for development. The SLR has identified not only the key benefits of AI, such as automation and resource optimization, but also the current limitations and challenges, such as the lack of regulatory standards and the associated learning curve. This analysis broadens the understanding of the impact of AI in specific contexts, providing a solid foundation for future research that seeks to address technology gaps and promote inclusive implementation strategies.

VI. Limitations and Study Forward

Although this study offers a deep insight into the impact of AI on the operational efficiency of companies, it has several limitations that deserve to be highlighted. One of the main ones is the variability in the results obtained depending on the sector and size of the organizations. This diversity of effects underscores the urgent need to develop more differentiated approaches to AI adoption studies, adapted to the particular contexts of each sector and type of firm. Thus, future studies should consider variables such as technological infrastructure, innovation capacity and specific organizational barriers.

A critical limitation is the absence of a uniform regulatory framework for AI implementation. This lack of standardization generates significant disparities in the adoption and use of technology, which could create a competitiveness gap between companies operating under disparate regulations and technological capabilities. In this sense, it is essential to create international regulatory frameworks to guide the implementation of AI, ensuring its ethical and effective use, and to promote a level playing field for all companies, regardless of their size or sector.

Going forward, the importance of conducting longitudinal studies that measure the effects of AI adoption over time is highlighted. This approach would capture the progressive transformations in companies as they move forward in their digitization process, providing a more accurate perspective on the long-term benefits and challenges. In addition, it is essential to address sectoral and business size differences, providing customized solutions that enable small and medium-sized enterprises (SMEs) to overcome the technological and cultural barriers inherent in the adoption of these technologies.

References

[1] A. Fredström, V. Parida, J. Wincent, D. Sjödin, and P. Oghazi, “What is the Market Value of Artificial Intelligence and Machine Learning? The Role of Innovativeness and Collaboration for Performance,” *Technological Forecasting and Social Change*, vol. 180, no. 121716, July 2022.

[2] V. Keerativutisest, W. Chaiyasoonthorn, B. Khalid, B. Ślusarczyk, and S. Chaveesuk, “Determinants of ai-based applications adoption in the agricultural sector – multi-group analysis,” *Agricultural Engineering*, vol. 72, pp. 750-764, 2024.

[3] Z. Wang, S. Lin, Y. Chen, O. Lyulyov, and T. Pimonenko, “Digitalization Effect on Business Performance: Role of Business

Model Innovation," *Sustainability (Switzerland)*, vol. 15, no. 9020, June 2023.

[4] M. Nuseir, and G. Refae, "The role of artificial intelligence, marketing strategies, and organizational capabilities in organizational performance: The moderating role of organizational behavior," *Uncertain Supply Chain Management*, vol. 10, pp. 1457-1466, 2022.

[5] C. Agostinho, Z. Dikopoulou, E. Lavasa, K. Perakis, S. Pitsios, R. Branco, S. Reji, J. Hetterich, E. Biliri, F. Lampathaki, S. Rodríguez Del Rey, and V. Gkolemis, "Explainability as the key ingredient for AI adoption in Industry 5.0 settings," *Frontiers in Artificial Intelligence*, vol. 6, no. 1264372, 2023.

[6] K. Antosz, Ł. Paśko, and A. Gola, "The use of artificial intelligence methods to assess the effectiveness of lean maintenance concept implementation in manufacturing enterprises," *Applied Sciences (Switzerland)*, vol. 10, no. 7922, pp. 1-24, November 2020.

[7] M. Pacella, P. Vasco, G. Papadia, and V. Giliberti, "An Assessment of Digitalization Techniques in Contact Centers and Their Impact on Agent Performance and Well-Being," *Sustainability (Switzerland)*, vol. 16, no. 714, January 2024.

[8] A. Cammarano, V., Varriale, F., Michelino, and M. Caputo, "A Framework for Investigating the Adoption of Key Technologies: Presentation of the Methodology and Explorative Analysis of Emerging Practices," *IEEE Transactions on Engineering Management*, vol. 71, pp. 3843-3866, 2024.

[9] O. Zghurska, O. Vynogradova, O. Yerankin, O. Korchynska, N. Ovsiienko, and A. Aisulu, "Media planning as a necessary condition for increasing the efficiency of business structures' digital marketing activities," Financial and Credit Activity: Problems of Theory and Practice, vol. 1, pp. 578-590, February 2024.

[10] A. Polenghi, I. Roda, M. Macchi, and A. Pozzetti, "An ontological modelling of multi-attribute criticality analysis to guide Prognostics and Health Management program development," *Autonomous Intelligent Systems*, vol. 2, no. 2, December 2022.

[11] S. Yu, and C. Song, "Research on Performance Evaluation of Real Estate Enterprises Based on DEA," *Journal of Physics: Conference Series*, vol. 1325, no. 12063, July 2019.

[12] Y. He, "Path and Mechanism of Industrial Internet Industry Promoting the Transformation and Upgrading of Small and Medium-sized Enterprises with Artificial Intelligence," *Mobile Information Systems*, vol. 2023, no. 3620662, 2023.

[13] S. Badghish, and Y. Soomro, "Artificial Intelligence Adoption by SMEs to Achieve Sustainable Business Performance: Application of Technology–Organization–Environment Framework," *Sustainability (Switzerland)*, vol. 16, no. 1864, March 2024.

[14] A. Stroumpoulis, E. Kopanaki, and S. Varelas, "Role of artificial intelligence and big data analytics in smart tourism: a resource-based view approach," *WIT Transactions on Ecology and the Environment*, vol. 256, pp. 99-108, May 2022.

[15] O. Alghamdi, and G. Agag, "Boosting Innovation Performance through Big Data Analytics Powered by Artificial Intelligence Use: An Empirical Exploration of the Role of Strategic Agility and Market Turbulence," *Sustainability (Switzerland)*, vol. 15, no. 14296, October 2023.

[16] S. Qu, H. Shi, H. Zhao, L. Yu, and Y. Yu, "Research on enterprise business model and technology innovation based on artificial intelligence," *Eurasip Journal on Wireless Communications and Networking*, vol. 2021, no. 145, December 2021.

[17] F. Trigos, and C. Aldana, "A Transdisciplinary Approach for Predicting and Tuning to Optimise Initial Business Performance Steady State in a Changing and Connected Environment," *Advances in Transdisciplinary Engineering*, vol. 41, pp. 541-550, July 2023.

[18] Z. Li, J. Crook, and G. Andreeva, "Dynamic prediction of financial distress using Malmquist DEA," *Expert Systems with Applications*, vol. 80, pp. 94-106, September 2017.

[19] A. Shaaban, M. Khafagy, M. Elmasry, H. El-Beih, and M. Ibrahim, "Knowledge discovery in manufacturing datasets using data mining techniques to improve business performance," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 26, pp. 1736-1746, June 2022.

[20] A. Perera, N. Jayamaha, N. Grigg, M. Tunnicliffe, and A. Singh, "The application of machine learning to consolidate critical success factors of lean six sigma," *IEEE Access*, vol. 9, no. 9511473, pp. 112411-112424, 2021.

[21] A. Alqhatani, M. Ashraf, J. Ferzund, A. Shaf, H. Abosaq, S. Rahman, M. Irfan, and S. Alqhtani, "360° Retail Business Analytics by Adopting Hybrid Machine Learning and a Business Intelligence Approach," *Sustainability (Switzerland)*, vol. 14, no. 11942, October 2022.

[22] V. Nguyen, C. Wang, F. Yang, and T. Vo. "Efficiency Evaluation of Cyber Security Based on EBM-DEA Model," *Eurasia Proceedings of Science, Technology, Engineering and Mathematics*, vol. 17, pp. 38-44, July 2022.

[23] J. Pap, C. Mako, M. Illessy, Z. Dedaj, S. Ardabili, B. Torok, and A. Mosavi, "Correlation Analysis of Factors Affecting Firm Performance and Employees Wellbeing: Application of Advanced Machine Learning Analysis," *Algorithms*, vol. 15, no. 300, September 2022.

[24] R. Hrbić, and T. Grebenar, "Assessment of Readiness of Croatian Companies to Introduce I4.0 Technologies," *Journal of Risk and Financial Management*, vol. 15, no. 558, December 2022.

[25] M. Koot, "Towards a framework for smart resilient logistics," *Proceedings - IEEE International Enterprise Distributed Object Computing Workshop, EDOCW*, vol. 2019, no. 8907340, pp. 202-207, October 2019.

[26] T. Palpanas, and J. Sairamesh, "Knowledge mining for the business analyst," Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 5181, pp. 770-778, September 2008.

[27] R. Oger, M. Lauras, F. Benaben, and B. Montreuil, "Strategic Supply Chain Planning and Risk Management: Experiment of a Decision Support System Gathering Business Departments Around a Common Vision," *Proceedings of the 2019 International Conference on Industrial Engineering and Systems Management, IESM. 2019*, no. 8948116, September 2019.

[28] B. Gichohi, "Leveraging on big data and advanced technologies to enhance domestic revenue mobilization," *Statistical Journal of the IAOS*, vol. 36, pp. S111-S119, 2020.

[29] S. Jituri, B. Fleck, and R. Ahmad, "Lean or ERP - A Decision Support System to Satisfy Business Objectives," *Procedia CIRP*, vol. 70, pp. 422-427, May 2018.

[30] D. Gangwani, and X. Zhu, "Modeling and prediction of business success: a survey," *Artificial Intelligence Review*, vol. 57, no. 44, February 2024.

[31] C. Lee, W. Ho, G. Ho, and H. Lau, "Design and development of logistics workflow systems for demand management with RFID," *Expert Systems with Applications*, vol. 38, pp. 5428-5437, May 2011.

[32] H. Ahmad, R. Hanandeh, F. Alazzawi, A. Al-Daradkah, A. Eldmrat, Y. Ghaith, and S. Darawsheh, "The effects of big data, artificial intelligence, and business intelligence on e-learning and business performance: Evidence from Jordanian telecommunication firms," *International Journal of Data and Network Science*, vol. 7, pp. 35-40, 2023.

[33] B. Weeserik, and M. Spruit, "Improving Operational Risk Management using Business Performance Management technologies," *Sustainability (Switzerland)*, vol. 10, no. 640, February 2018.

[34] F. Cai, N. Lekhac, and M. Kechadi, "An integrated model for financial data mining," Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 7694, pp. 306-317, December 2012.

[35] H. Rahim, S. Ibrahim, S. Kamaruddin, N. Ghani, and I. Musirin, "Exploration on digital marketing as business strategy model among malaysian entrepreneurs via neurocomputing," *IAES International Journal of Artificial Intelligence*, vol. 9, pp. 18-24, 2020.

[36] I. Kabashkin, and V. Perekrestov, "Concept of Aviation Technical Support as a Service," *Transport and Telecommunication*, vol. 24, pp. 471-482, November 2023.

[37] H. Sakai, and S. Masuyama, "Extraction of cause information from newspaper articles concerning business performance," *IFIP International Federation for Information Processing*, vol. 247, pp. 205-212, 2007.

[38] M. Chaves-Maza, and E. Fedriani, "Defining entrepreneurial success to improve guidance services: a study with a comprehensive database from Andalusia," *Journal of Innovation and Entrepreneurship*, vol. 11, no. 22, December 2022.

[39] H. Lin, J. Lin, and F. Wang, "An innovative machine learning model for supply chain management," *Journal of Innovation and Knowledge*, vol. 7, no. 100276, October 2022.

[40] K. Bello, M. Kanakana-Katumba, R. Maladzhi, and C. Omoyi, "Recent Advances in Smart Manufacturing: A Case Study of Small, Medium, and Micro Enterprises (SMME)," *Nigerian Journal of Technological Development*, vol. 21, pp. 29-41, March 2024.

[41] M. Mesgarpour, D. Landa-Silva, and I. Dickinson, "Overview of Telematics-Based Prognostics and Health Management Systems for

Commercial Vehicles," *Communications in Computer and Information Science*, vol. 395, pp. 123-130, October 2013.
[42] K. Kourtit, P. Nijkamp, and E. Leeuwen, "New Entrepreneurship in Urban Diasporas in our Modern World," *Journal of Urban Management*, vol. 2, pp. 25-47, 2013.
[43] M. Zhang, and J. Wen, "Profitability analysis of KINGLONG nearly 5 years," *Journal of Physics: Conference Series*, vol. 887, no. 12001, July 2017.
[44] B. Kamsu-Foguem, and Y. Mathieu, "Software architecture knowledge for intelligent light maintenance," *Advances in Engineering Software*, vol. 67, pp. 125-135, 2014.