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The Role of AI in Improving Environmental Sustainability: A Focus on Energy Management

Naiara Uriarte-Gallastegi [1], Germán Arana-Landín [2,*], Beñat Landeta-Manzano [1] and Iker Laskurain-Iturbe [2]

[1] Faculty of Engineering from Bilbao, Department of Business Management, University of the Basque Country, Ingeniero Torres Quevedo Square, 1, 48013 Bilbao, Spain; naiara.uriarte@ehu.eus (N.U.-G.); benat.landeta@ehu.eus (B.L.-M.)
[2] Faculty of Engineering from Gipuzkoa, Department of Business Management, University of the Basque Country, Europa Square 1, 20018 San Sebastian, Spain; iker.laskurain@ehu.eus
* Correspondence: g.arana@ehu.eus; Tel.: +34-943018674

Abstract: This research addresses the increasing importance of understanding how Artificial Intelligence can facilitate the transition of companies to a Circular Economy model. This study focuses on energy management, examining its impact on efficiency and emissions across a multi-case analysis of 18 projects in diverse sectors. The findings indicate that Artificial Intelligence positively influences both variables, with variations across applications and sectors. Notably, Artificial Intelligence significantly enhances energy efficiency in four out of six sectors, achieving over 5% improvement in half of the projects. Regarding emissions, positive effects are observed in 15 out of 18 projects, resulting in over 5% reductions in seven cases. Artificial Intelligence plays a pivotal role in emissions reduction in the Design and Energy sectors, with some projects achieving over 20% reductions. Additionally, this study explores how improved energy efficiency positively affects strategic business variables, such as cost, quality, and delivery time. The impact on emissions contributes to reducing occupational risks, particularly those associated with chemical and biological agents. Although managers are satisfied, measures need to be taken to overcome the lack of employee acceptance. These findings are of great interest to the stakeholders involved in the integration of Artificial Intelligence into companies.

Keywords: Artificial Intelligence; Circular Economy; Industry 4.0; energy management; energy efficiency; emissions; non-energy benefits

Citation: Uriarte-Gallastegi, N.; Arana-Landín, G.; Landeta-Manzano, B.; Laskurain-Iturbe, I. The Role of AI in Improving Environmental Sustainability: A Focus on Energy Management. *Energies* **2024**, *17*, 649. https://doi.org/10.3390/en17030649

Academic Editor: Brian D. Fath

Received: 30 December 2023
Revised: 26 January 2024
Accepted: 26 January 2024
Published: 30 January 2024

1. Introduction

Humanity is currently facing an unprecedented challenge: climate change, an environmental crisis that threatens not only the planet's biological diversity but also the survival and wellbeing of its inhabitants. This global challenge, exacerbated by decades of unsustainable industrial and economic practices, has prompted an urgent call for collective action and innovation in all sectors of society, with sustainable economic practices including areas such as health and clean primary resources [1].

Climate change, driven primarily by greenhouse gas emissions, has generated scientific and political consensus on the need for a profound transformation in the way we produce and consume energy [2]. In this context, energy efficiency measures are considered a first line of action and presented as a financially viable and necessary solution for an energy transition [3]. The "2023 United Nations Climate Change Conference", more commonly known as COP28, has highlighted the need for deepening, rapid, and sustained reductions in greenhouse gas emissions. The agreement reached by the 190 delegations included a 43% reduction by 2030 and a 60% reduction by 2035 compared to 2019 and reaching net zero emissions by 2050, among other measures set out to triple global renewable energy capacity and double the global average annual rate of energy efficiency improvements by 2030 [4].

Businesses, as central players in the global economy, have a crucial role to play in this transformation. Adopting sustainable business practices is not only an ethical responsibility but also an economically smart strategy. Studies have shown that companies that incorporate sustainable practices improve their long-term financial performance and strengthen their resilience to the risks associated with climate change [5].

A key strategy in the pursuit of corporate sustainability is improving energy efficiency. Reducing energy consumption not only lowers operating costs but also contributes significantly to reducing carbon emissions [6]. In parallel, emission reduction has become a priority for companies, not only due to increasing regulation and social pressure but also to anticipate and adapt to an increasingly sustainability-oriented market [7].

In several regions of the world, especially in those countries that are leaders in climate change policies, these strategies are being supported by governmental programs such as the EUs "Horizon Europe", the US "Better Buildings Initiative" [8], China's "National Action Program on Climate Change" [9], Japan's "Strategic Energy and Environmental Innovation Program" [10], and the "Clean Energy Finance and Investment Mobilisation Programme" of the OECD [11]. With financial backing from Australia, Canada, Denmark, Egypt, and Germany, the program proposes to strengthen national conditions for attracting investment and financing in energy efficiency and clean industry. These programs provide financial incentives, technical support, and regulatory frameworks that facilitate the adoption of energy efficiency and clean industry.

These programs provide financial incentives, technical support, and regulatory frameworks that facilitate the adoption of sustainable practices by companies.

In the area of technology, Industry 4.0 (I4.0) has introduced several innovative tools that can play a key role in the transformation towards more sustainable business practices. Among these, Artificial Intelligence (AI) stands out for its ability to optimize processes, reduce resource consumption, and improve decision-making [12].

AI, applied to energy management, has the potential to transform radically the way companies consume and manage energy. By analyzing large volumes of data and Machine Learning (ML), AI can identify consumption patterns, predict future needs, and optimize resource utilization, resulting in greater energy efficiency [13]. Moreover, in the field of emissions reduction, AI can play a crucial role by facilitating the monitoring and management of carbon emissions as well as contributing to the development of more sustainable products and processes [14].

Numerous studies have been conducted that have examined the potential applications of AI in these areas. These studies usually identify impact, which is mostly derived from cited literature or anecdotal evidence and is rarely measured or quantified. Therefore, a comprehensive and systemic assessment of the actual impact of AI, as well as best practices for its implementation, is still needed [15]. There is a notable gap in our knowledge at the business level about AIs real and quantifiable contribution to energy efficiency and emissions reduction. Nevertheless, this knowledge gap is more noticeable when we introduce into the equation strategic dependent variables for companies, such as product cost, product quality, lead-time, risks, and satisfaction of managers, employees, and customers [13]. However, it is critical to understand the derivative in relation to these variables from the point of view of decision-making on the consequences of AI, energy efficiency, and emission reduction at the industrial operational level. Energy allocations and environmental regulations directly influence energy efficiency, thus seeking improvements in these aspects and contributing to the country moving towards a low-carbon energy transition [16].

This study aims to address this gap at the micro-level and through real-life cases deployed in large industrial corporations with AI developed by highly innovative companies. This study explores whether this technology can aid the business and social shift towards a more circular model. Its focus is on enhancing energy management efficiency and reducing emissions, ultimately aiming to achieve the decarbonization of companies. In addition, it is shown how key variables for business management are affected in this adoption process so that managers can then effectively apply AI to drive the transition to a more sustainable model.

To achieve these objectives, this paper is structured in six sections. After this introduction, the Section 2 presents a review of the relevant academic literature on the subject. The Section 3 describes the methodology used in this research. Then, in the Section 4, the results obtained are presented. Finally, Section 5 discusses the findings and Section 6 presents the conclusions of this research, as well as the limitations identified and possible areas for future research.

2. Literature Review

The impact of I4.0 and digital technologies (DTs) on the Circular Economy (CE) is a complex and multifaceted issue. These technologies can improve circulation processes, contributing to sustainability by achieving economic, social, and environmental benefits [17], mainly when integrated with the principles of reuse, remanufacturing, and recycling [18,19]. However, a more nuanced understanding is needed, as certain technologies, such as sensors, RFID, and AI, turned out to be the most relevant, while others had a negative or no effect [20]. Although, on the other hand, if we take AI, for example, academic literature has highlighted the importance of combining AI with other technologies (IoT, Big Data (BD), robotics, among others) in areas such as economics, quality, design, energy management, and safety in an industrial environment and applied in various sectors [21].

The use of AI enables the adoption of practices that take advantage of data availability and can also maximize the use of available resources, minimize emissions, and contribute to energy management [22]. Precisely, AI has a significant impact on the energy efficiency of companies, particularly in the manufacturing sector [23,24]. AI, in combination with other I4.0Ts, can improve efficiency in an average range of 1525% in the processes in which it is implemented [12]. Liu and Liu [25] found that AI, particularly in the form of industrial robots, could improve energy efficiency and reduce energy intensity in manufacturing firms. The literature highlights the relevance of AI for energy optimization, business internationalization, and resource efficiency, with AI applications such as predictive maintenance and production planning contributing to increased energy efficiency [26]. This effect is more pronounced in labor and technology-intensive sectors [27], demonstrating how the IoT and ML can be used to create autonomous energy management systems, improving energy efficiency in smart environments. In the current industrial context, such applications in many small and medium-sized enterprises can help achieve a shift towards more sustainable and circular business practices that promote more efficient and intelligent use of energy resources [28]. However, the effectiveness of AI in reducing energy intensity varies across industries, with a greater impact observed in capital-intensive sectors [29].

In addition, important barriers to AI implementation, such as the digitization process and semantic interoperability, both crucial to achieving CE, need to be considered [30].

On the other hand, the implementation of AI technologies to monitor energy parameters could reduce each country's greenhouse gas emissions by 70% [31] and, in turn, improve productivity [32]. In line with these findings, the World Economic Forum stated that AI-based systems, thanks to the growing amount of data and increasingly advanced algorithms, could contribute to a 4% reduction in global emissions by 2030 [33].

In this regard, several studies have explored the impact of AI on the intentionality of carbon emissions, particularly in the context of China and especially in large cities with advanced technology and infrastructure [34]. Chen et al. [35] found that AI significantly reduces carbon intensity, with the latter emphasizing the role of AI in optimizing industrial structure and fostering green technology innovation. To achieve these results, the need to innovate in emission-intensive sectors such as waste management or public transport to make them energy efficient, smart, sustainable, and cost-effective is highlighted [32]. The complexity of the relationship between AI and carbon emissions intensity highlights the importance for regulators and policymakers to consider the impact of AI technologies on the energy system as a fundamental systemic element for decreasing greenhouse gas emissions [36].

These studies highlight the potential of AI to improve energy efficiency and mitigate corporate carbon emissions, but also the need for more research to understand the complexities of this relationship and to design industry-specific strategies. There are hardly any articles quantifying the real influence of AI on the transformation of energy and emissions management to achieve an EC model with the goal of decarbonizing companies. Consequently, this research questions (RQ) are formulated as follows:

− RQ 1: To what extent can AI contribute to the improvement of energy efficiency?
− RQ 2: To what extent can AI contribute to the reduction of emissions?

Based on these questions, at the beginning of this research, in the field phase, unanticipated evidence was collected, evaluated, and assessed as being of great interest to academia but also to business managers. Specifically, some data and information were found that pointed to the influence of AI on energy efficiency and emissions, with an impact on some strategic business variables.

Energy efficiency provides a broad set of benefits in multiple areas (e.g., cost, quality, lead-time, risks, and satisfaction) beyond mere energy savings, known as non-energy benefits (NEB) [37]. Therefore, considering "energy" in a broader spectrum within the industry and assessing the implications of energy efficiency on relevant strategic variables can be crucial for business sustainability [12,38].

The literature has highlighted the potential benefits of I4.0Ts, such as AI, the Internet of Things (IoT), Cyber-Physical Systems, and Industrial Robots, to improve the performance of manufacturing industries. However, they forget about the NEBs. Katic et al. [39] and Nota et al. [40] both emphasize the importance of understanding the impact of Energy Efficiency Measures (EEMs) on production resources and the potential for reducing energy consumption in manufacturing processes using I4.0Ts. Medojevic et al. [41] further support this, highlighting the correlation between I4.0 concepts and manufacturing energy and environmental management systems. Ghobakhloo et al. [42] expand on this by explaining how I4.0 contributes to energy sustainability, particularly through the digitalization of the energy demand sector and the introduction of smarter and more sustainable products.

However, despite the many benefits attributed to energy efficiency, the pace of NEB-related improvements has slowed down in recent times [43], which has contributed to an "energy efficiency gap" [32]. This fact applies equally to the case of emissions that, although closely linked to energy consumption, have not been the subject of research in academia, although energy efficiency and emissions may have profound implications for strategic variables and may be of great interest to key industrial decision-makers [44].

In agreement with the proposal presented by Hassan and Trianni [13], these researchers propose a framework to evaluate the contribution of I4.0Ts to the increase of operational performance in energy efficiency initiatives. Hassan and Trianni [13] argue that technologies such as AI and IoT positively influence the operational performance of energy efficiency measures, generating improvements in Overall Equipment Effectiveness (OEE), productivity, and reduced operating costs. The promotion of sustainable development (SD) globally involves adopting undertakings and production processes focused on environmental sustainability [45].

Thus, according to the literature review conducted on the subject, the following questions can be posed, with the aim of providing proven evidence of the influence of energy efficiency and emissions through AI on some strategic business variables:

− RQ 3: To what extent can AI contribute through energy efficiency improvements on cost, quality, lead time, risk, and satisfaction variables?
− RQ 4: To what extent can AI contribute through the reduction of generated emissions in the variables of cost, quality, lead-time, risks, and satisfaction?

Table 1 below presents a review of the main academic articles and studies on the influence of AI on carbon emissions and energy efficiency in industry. It shows the knowledge gap they detected, the objectives they pursued, the methodology they used, the main contributions they made, and the main limitations, weaknesses, or unresolved aspects of their research.

Table 1. Main academic contributions on the role of AI in the transformation of energy and emissions management to achieve a CE model.

Ref.	Knowledge Gap	Methodology	Main Contributions	Main Limitations
[13]	The adoption of EEMs in industry and I4.0Ts	Systematic Literature Review (SLR), N = 25, Scopus and WoS (2022–2023). Semi-struct. Interviews.	AI helps to close the loop in water management (improving OEE, productivity, and costs).	Cover a broader range of I4.0 cross-cutting technologies
[23]	Influence of I4.0Ts on CE.	Multiple case studies, N = 27, (2018–2021).	AI ↓ material, energy use, waste, and emissions.	Findings may not be generalizable to other contexts. Limit quantitative analysis
[24]	Integrate I4.0 and CE into the supply chain network.	SLR, N = 90, Scopus and WoS (2011–2020)	I4.0Ts help to transform waste into new products in a circle.	The model overlooks social responsibility.
[25]	Impact of AI on the carbon footprint.	Panel data, 13 industries in China (2005–2016). STIRPAT model method.	AI has an inhibitory effect on carbon. Robots can contribute to GDP growth.	Limited data sources. Other technologies can distort the data.
[27]	A holistic perspective integrates I4.0Ts in the energy sector.	SLR, N = 581, WoS and Scopus (2017–2022).	AI intelligent algorithms enable prediction and trading.	I4.0Ts must be developed jointly to avoid obstacles.
[37]	Measuring and monetizing non-energy benefits and sustainability performance	Survey, N = 31, face-to-face interviews, qualitative and statistical analysis.	Firms' limited non-energy benefits to profitability in energy-efficiency investments and investment decisions.	Ambiguous understanding of potential non-energy benefits among respondents.
[38]	Incorporating AI into companies' existing information systems for integrated energy management.	Survey, N = 217 SMEs BISNODE GVIN database, Slovenia. Cluster analysis.	EEMs influence production resources, irrespective of energy intensity. There is a varied perception of resource importance and management efficiency.	Limited Sample Size. Self-reported data. Limited Slovenian manufacturing sector. EEM adoption is not discussed in detail.
[39]	Impact of EEMs on shop-floor operations and the operational performance of industrial organizations.	Theory building.	The preliminary conceptual framework combines EEM adoption, production resources, and operational performance for a structured assessment.	Limited generalizability. Current research offers incomplete advice. Difficulty in comprehensively assessing EEMs.
[40]	Application of the OEE indicator, its relationship to I4.0, and its contribution to value co-creation in the industry	SLR, N = 128, Elsevier, Emerald, IEEE, Springer and Taylor and Francis (2015–2020). PRISMA method.	Integrating OEE with I4.0Ts improves accuracy, enables real-time production monitoring and control, and involves stakeholders.	Limited data sources. Only articles with more than 20 citations were considered.
[42]	I.0 technology trends and industry digitization enhance energy sustainability.	Nominal Group Technique, N = 8 experts, Matrice d'Impacts Croisées Multiplication Appliquée aun Classement analysés (MICMAC).	Demonstrates how I4.0 contributes to energy sustainability. I4.0 promotes energy sustainability, including the digitalization of energy.	Primarily focusing on European experts limits the generalizability. Need of further research to address these gaps.
[43]	The impact of AI on sustainable entrepreneurship	SLR, N = 482, Scopus (1994–2022). PRISMA method.	AI and ML stand out in SD.	A lack of legislation does not promote sustainable business.

Table 1. *Cont.*

Ref.	Knowledge Gap	Methodology	Main Contributions	Main Limitations
[44]	AI for energy efficiency and the impact on productivity.	Statistical regression, N = 30, Panel data (2006–2019).	Smart networks ↑ energy management and ↑ total factor efficiency.	Data from publicly traded energy companies could facilitate a detailed analysis.

Note: ↑ increase, ↓ decrease.

Our research helps fill a vital gap by focusing specifically on the role of AI within the broader spectrum of I4.0Ts to achieve a CE. It provides more specific knowledge on how AI can be effectively applied for decarbonization and sustainable practices in companies. The solid foundation established by existing studies, combined with our specific focus on AI, brings valuable new insights to the field, informing future research and policy.

3. Materials and Methods

This research process was conducted in four phases. The initial phase consisted of a literature review on the relationship between I4.0Ts and CE, more specifically, on the potential of I4.0 to influence positively the transition process of companies towards a circular business model. This analysis detected the growing interest in recent years in exploring the capabilities of AI and its potential to support and drive change. We also noted and were surprised by the scarcity of studies addressing the role of AI in energy and emissions management, being two fundamental interrelated areas in the environmental behavior of companies and their circular performance, strongly linked to climate change and UN Sustainable Development Goals 7, "Affordable and Clean Energy", and 13, "Climate Action" [4]. Because of this initial analysis, we set out to find out what role AI is playing in companies and how they are managing the energy they consume and the emissions they emit directly. However, because of its ambition, this objective required us to assess the possibilities of achieving it, first by accessing the necessary, sufficient, and reliable direct sources of data and information. If we wanted such data and information, we had to look to the source, the company, in action. Nevertheless, access to such data and information and the availability of resources to do so had to be considered because the sources of evidence for such data and information were also different in nature, quantity, and quality. Their collection and subsequent analysis would require resources, and the scope of the investigation therefore had to be determined. Taking all this into account, the case study was considered the most appropriate methodology for approaching this study phenomenon, given that it is a methodology that "investigates a contemporary phenomenon in its real context" [46] and allows the use of multiple sources of evidence, quantitative and/or qualitative, simultaneously [47].

Once the methodological design of this research was defined, the unit of analysis and the selection of cases were defined. This was based on a theoretical and logical, rather than statistical and random, sampling, trying to choose those cases that could offer a greater opportunity for learning [45]. Accessibility to the information required (although in some cases it have been required to keep some of the data collected confidential), an adequate willingness on the part of the people most directly involved with the management of AI projects, and the implementation of AI-based solutions with at least 1 year of experience in full operation were required conditions.

The selected cases correspond to companies participating in the BIND 4.0 program to support technology-based start-ups organized by the Basque Business Development Agency (SPRI) in the Basque Country, Spain. It is a program recognized as "Exceptional Industry Support" in the start-up Ecosystem Stars 2023 awards given by the International Chamber of Commerce and Mind the Bridge in Europe. The program, acknowledged as "Exceptional Industry Support" in the 2023 start-up Ecosystem Stars awards by the International Chamber of Commerce and Mind the Bridge in Europe, facilitates the connection and advancement of open innovation projects for disruptive start-ups, primarily within venture clients, notably large tractor companies. A study was conducted on 18 projects covering a variety of AI applications across sectors such as Health, Energy, Maintenance and Security, Supply and Distribution, Image Processing, and Design, as detailed in Figure 1.

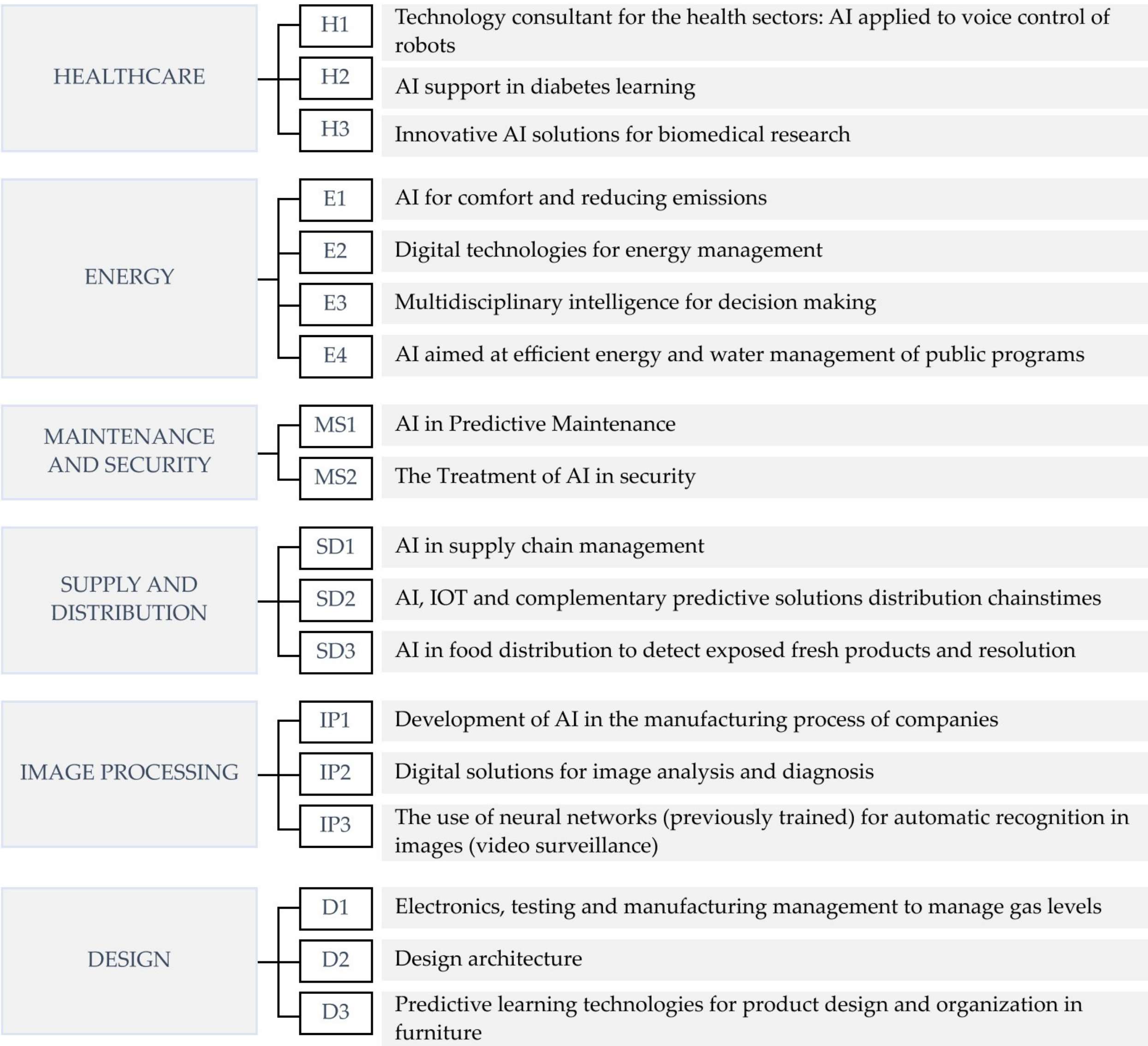

Figure 1. AI projects conducted in 6 sectors of business activity.

This study aimed for a balance between the number of cases analyzed and the depth and breadth of the analysis, prioritizing a cross-case (comparative) analysis based on the information provided by start-ups and venture clients. This approach sought to maintain constructive validity and reliability without compromising the evidence chain [46]. While considering a larger number of cases would enhance certainty, it could sacrifice depth and breadth. Notably, there is no consensus on the ideal number of cases [46,48]. Following Eisenhardt's [49], the target was set at three cases, reaching theoretical saturation in all except the "Energy" and "Maintenance and Safety" sectors. An additional case was conducted in the "Energy" sector due to its unique nature. However, constraints prevented further cases in the "Maintenance and Safety" sector. Despite not meeting the target number, the two cases in this sector offered valuable insights into high-interest AI applications, emphasizing the significance of the findings.

Subsequently, the third phase of this research, the field phase, began with the collection of evidence. To ensure conclusive findings, the data collection phase employed the concept of triangulation [50,51]. This involved utilizing various methods and sources for evidence, both quantitative and qualitative, gathered from start-ups and venture clients. Documentation, including reports and internal studies, archives containing presentation files, image and sound files, in-depth interviews, and direct observation through visits to venture client facilities, were conducted.

Once the characterization of the cases investigated was completed, the last and fourth phases were carried out. The individual analysis of the cases and the cross-case analysis were carried out following the methodological indications of Miles et al. [51]. It consisted of examining, categorizing, and tabulating the evidence collected, trying to identify common patterns of behavior between the cases and the sectors, and determining the connection between the data and this research questions at the company and sector level. The results of the cross-case analysis are summarized in Section 4, “Results”. This section shows the degree of influence of the AI with respect to energy efficiency and emissions generated from the venture clients (per case and per sector) as a five-point Likert type item ranging: 0, no influence; 1, low influence (less than 1%); 2, medium influence (1% or more and less than 5%); 3, high influence (5% or more and less than 20%); and 4, very high influence (20% or more). These are numerical values calculated based on empirical evidence collected in the field phase, shared with the main actors in the cases, and contrasted with those of two external academic evaluators. In no case were data or information about a negative influence collected.

On the other hand, the main results in aggregate form on how the influence of AI on these energy efficiency and emissions generated affects key performance indicators related to cost, quality, lead-time, risks, and company satisfaction are presented. In this case, it was agreed to also employ a five-point Likert-type scale, with ‘0’ as the central value, with ‘−2’ representing a generalized negative impact and ‘2’ representing a generalized positive impact. Given the exploratory nature of our purpose and the complex nature of the phenomenon, it was agreed to perform the cross-case analysis at a general, non-sectoral level in order to produce a sufficient number of replications in the search for a common behavioral pattern [51,52]. Each new case provides us with an independent test of the hypothesized relationships by comparing the expected pattern of behavior followed by the dependent variables as a function of the independent variables with the actual pattern [53].

4. Results

When assessing the main influences of AI in relation to energy management, the results show that AI has a high or very high positive influence on energy efficiency in 9 of the 18 cases. This indicates that more than 5% efficiency improvements have been achieved in half of the projects. Only in three projects was sufficient evidence found to prove any influence of AI, specifically on energy efficiency. These are projects in three completely different sectors (Supply and Distribution, Image Processing, and Design). In contrast, in the other projects in these sectors, evidence was found to corroborate the influence of AI on the energy management performance of companies.

In the case of emissions, in 15 of the 18 projects it is evident that there have been positive influences, allowing in 7 of these cases reductions of more than 5% (see Figure 2). As in the case of energy efficiency, only three projects in three sectors (Maintenance and Security, Supply and Distribution, and Image Processing) are considered to have no improvement due to AI implementation. The rest of the projects in these sectors show positive results. However, in the Health sector, two projects were found in which the influence of AI was relatively low. Nevertheless, this contrasts with the third project analyzed in the sector, where a very high influence was observed.

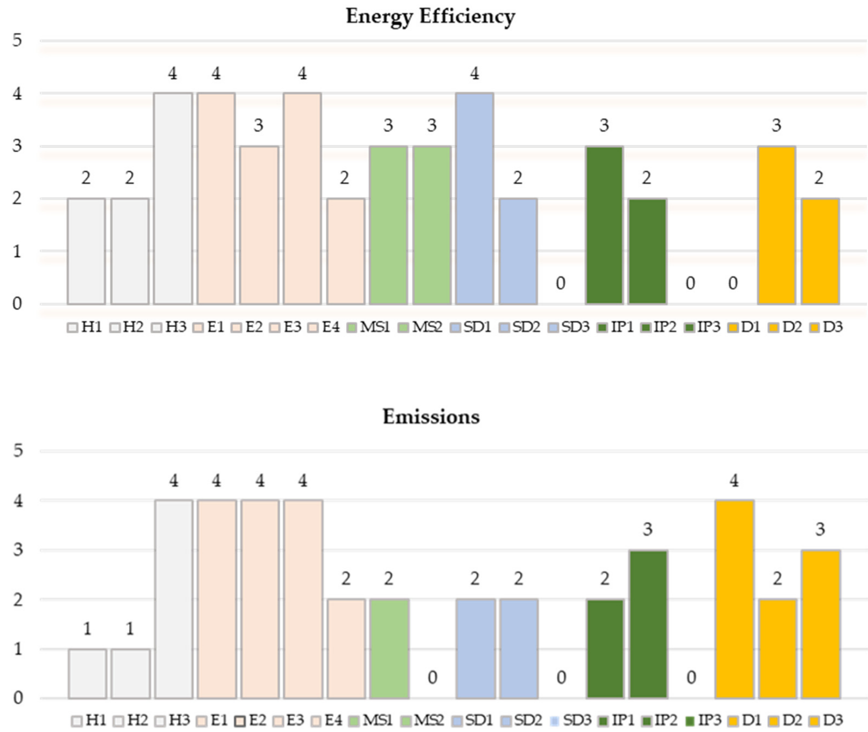

Figure 2. Influence of AI on energy efficiency and emissions generated in the cases conducted.

At the sectoral level, AI has a medium, high, or very high influence on energy efficiency in 4 of the 6 sectors analyzed (see Figure 3). In the Image Processing and Design sectors, there is only a moderately low positive influence. In other words, in the sectors of Health, Energy, Maintenance and Security, and Supply and Distribution it is necessary to consider the influence of AI on energy efficiency. This could be because AI has proven to be a useful tool to improve the energy efficiency of clean energy production processes. In this sense, it is worth noting that the Energy and Maintenance and Security sectors are those in which AI has a high or very high influence on energy efficiency. Specifically, it should be noted that in 2 of the 4 companies in the energy sector, the improvements obtained in terms of efficiency were higher than 20%.

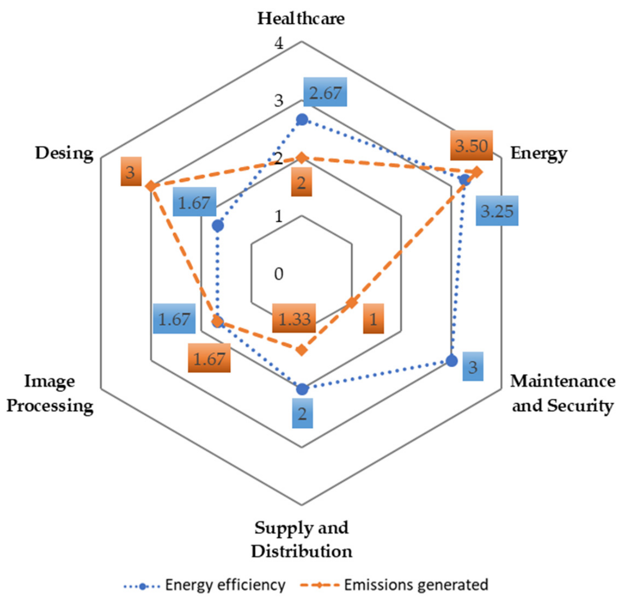

Figure 3. Influence of AI on energy efficiency and emissions generated in the sectors conducted.

On the other hand, a high influence of AI in relation to emissions is evident in 2 of the 6 sectors: Energy and Design (see Figure 3). This could be attributed to the fact that AI has proven to be a valuable tool for improving emissions monitoring and applying ML models to measure key performance indicators. Significant reductions of more than 20% of the emissions generated have been corroborated in 3 of the 4 projects analyzed in the energy sector.

In relation to the third and fourth research questions, see Figure 4, the relationship between the influence of AI on energy efficiency and emissions and strategic business variables (cost, quality, lead-time, risks, and satisfaction) was contrasted. Although in some cases the influence of AI on energy efficiency is reported to be related to quality and cost improvement, it is not fully shared. However, it is strongly linked to reductions in lead-times, mainly in the Design, Supply and Distribution sectors.

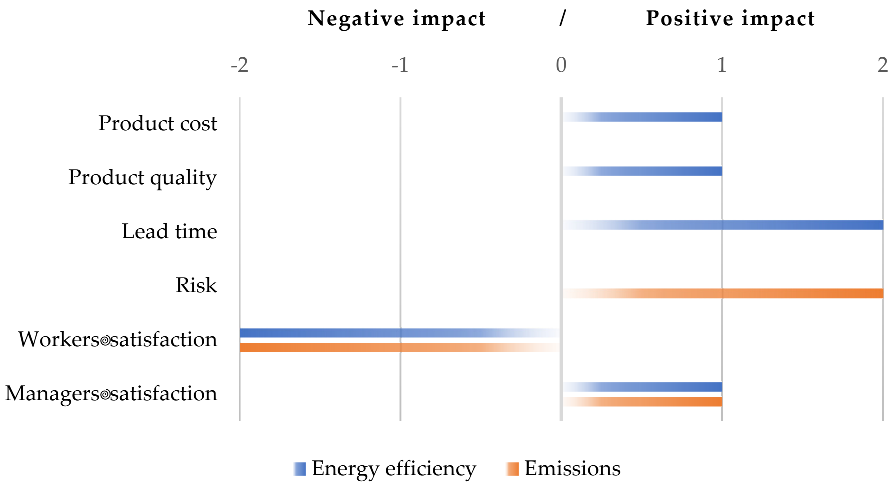

Figure 4. Influence of energy efficiency and emissions through AI on some business strategic variables. Note: There is no clear evidence of the influence of emissions on the dependent variables of product cost and lead-time, but they do improve the product and the company's image, although not across the board, which is why the net valuation takes the central value of zero.

However, the link between this influence and satisfaction is noteworthy. Some customers and managers are satisfied, but this is not widespread. Employees are generally dissatisfied. They feel that this influence affects them negatively because it creates a sense of insecurity associated with changing ways of working to achieve these efficiencies, a perception that some of their work is not necessary, and a fear of possible job cuts.

Except for the case of a small influence on product and company image, no evidence has been found regarding the influence of AI on emissions and variations in quality, cost, or lead-time. However, impacts on occupational risks are reported in more than half of the cases. Generally, improvements are linked to a reduction of chemical and biological occupational hazards. However, employees are not satisfied and consider that AI affects them negatively. They do not feel safe because they lose some process control.

5. Discussion

The evidence of the influence of AI has been very varied, but, in general, this research has empirically confirmed the contribution of AI in improving energy efficiency and emissions generated, in line with Ghobakhloo et al. [42], Entezari et al. [54], or Khan et al. [55]. The extent of its effects varies significantly depending on the application and sector, as already noted by Chauhan et al. [56], which is a result of the wide variety of current AI applications.

In the analysis of the cases, the improvement of these indicators in the application of AI has not been a priority. The main objective of the companies is to improve their economic indicators, leaving environmental and social indicators in the background. This is in line with the trend in business and academia, which has focused primarily on economic competitiveness. The control of energy consumption and emissions and the use of ML models are aspects that are considered a priority in the industrial sector [57,58]. This implies a delay in the consideration of environmental and social aspects [38].

When assessing the main influences of AI in relation to energy management, the results show that AI has a high or very high positive influence on energy efficiency. This is consistent with findings in the literature [42].

In the Health, Energy, Maintenance and Security, and Supply and Distribution sectors, it is necessary to consider the influence of AI on energy efficiency. This could be because AI has proven to be a useful tool to improve the energy efficiency of clean energy production processes. In this sense, it is worth noting that the Energy and Maintenance and Security sectors are those in which AI has a high or very high influence on energy efficiency. In the case of the Energy sector, there is evidence proven by several studies [59,60], but none have been found for the Maintenance and Security sector, where energy efficiency or emissions may not have been a central issue so far.

On the other hand, in some cases, the influence of AI on energy efficiency is reported to be related to quality and cost improvement, but it is not fully shared, which contrasts with Hasan and Triani [13]. Although the authors apply the framework, they develop it in three different sectors. However, it does seem to be strongly linked to the reduction of lead times, mainly in the design, supply, and distribution sectors.

On the human aspect, some customers and managers are satisfied, but this is not widespread, as AI may intensify the issue of digital skill gaps [61]. In this respect, Ghobakhloo et al. [62] talk about the benefits of management digitalization competency as one of the factors influencing the implementation of AI. On the other hand, employees are generally dissatisfied, which can make it difficult to implement AI [61]. Employees feel that AI influence affects them negatively because it creates a sense of insecurity associated with changing ways of working to achieve these efficiencies, a perception that some of their work is not necessary, and a fear of possible job cuts. This confirms the findings of previous studies such as those of Leesakul et al. [63], Malik et al. [64], or Palos- Sánchez et al. [65].

Regarding emissions, it is evident that there have been positive influences from AI. A high influence of AI in relation to emissions is evident in the Design and Energy sectors, especially in the last one. This could be attributed to the fact that AI has proven to be a valuable tool for improving emissions monitoring and applying ML models to measure key performance indicators [25], as in the case of smart energy meters. The data collected by these devices can help accurately predict electricity and natural gas consumption to better plan and manage the energy supply system and reduce associated emissions [59]. Concerning the Design sector, there is a lack of prior research either confirming or refuting the impact of AI on emissions. It is perhaps because it lacks any a priori relevance, although the sector does have a delayed impact with the generation of emissions in other phases of the product cycle, and AI has the potential to reduce and even prevent them, as it does in problem-solving tasks [59,66].

The literature highlights that innovation obtained from AI applications is much needed in sectors with high levels of emissions, such as Supply and Distribution or Maintenance and Safety, so that they can be energy efficient, smart, sustainable, and cost-effective [32]. However, except for the case of a small influence on product and company image, no evidence has been found regarding the influence of AI on emissions and variations in quality, cost, or lead-time. There is also no evidence in the literature to provide further clarity on this aspect. Nevertheless, impacts on occupational risks are reported in more than half of the cases. Generally, improvements are linked to a reduction of chemical and biological occupational hazards, which has already been reported in recent studies [67]. However, employees are not satisfied and consider that AI affects them negatively. They do not feel safe because they lose some process control. This novel finding perfectly complements the profile that the worker adopts with respect to AI implementation.

These results confirm the need raised in previous studies on the need to take measures in the AI adoption process to minimize the frustration it generates among workers [59]. Employee empowerment is essential, as failure to address it properly can lead to unsuccessful implementation and cause them to miss the opportunity to strategically align AI with potential sustainability benefits [62]. By empowering employees, the positive implications of AI adoption in general and energy and emissions management in particular will be maximized.

6. Conclusions

Companies must take advantage of the opportunities offered by technological development, considering the threats and opportunities for SD generated by this technological revolution. Despite AI being acknowledged for its impact on economic competitiveness, a notable literature gap exists in understanding its implications for social and environmental aspects within the industrial sector [38]. The primary objective of this study is to scrutinize how the integration of AI shapes circularity in companies by enhancing energy efficiency, reducing emissions, and influencing key strategic variables for economic performance.

Through a multiple case study approach, this research empirically affirms AIs positive impact on energy efficiency and emissions reduction, aligning with Sustainable Development Goals 7, 12, and 13. Case analyses reveal AIs influence varies across sectors and applications, with a predominant focus on economic indicators in AI applications (rather than environmental and social considerations), except in the energy sector, where improved energy efficiency positively affects strategic variables such as product cost, quality, and lead-time.

Concerning emissions, this study identifies the need for AI innovation in emission-intensive sectors for enhanced energy efficiency, sustainability, and cost-effectiveness. Although our findings do not establish a direct link between cost and emissions, they do show a correlation with improved image and risk reduction, particularly in chemical and biological aspects.

On a societal level, despite managers and customers expressing moderate satisfaction, workers articulate significant dissatisfaction, attributing AI to increased job instability and a feeling of insufficient control over processes. Consequently, actions should be taken in the AI adoption process to minimize the frustration experienced by workers. This will enhance the positive implications of AI adoption overall.

In light of the results, a collaborative effort by the public and private sectors, guided by a roadmap, is recommended to formulate policies integrating AI for effective energy and emissions management.

Turning to the limitations of this research, we underscore those derived from the case study methodology. While offering a more detailed and realistic understanding than other methodologies, there are limitations related to the generalisability of the results. These are highly context-dependent, as stated by Yin [46]. Therefore, further research along these lines would be of great interest, aiming to deepen and enhance the level of knowledge, especially considering that companies can accrue higher experience levels over time and work with more information on the obtained results.

Author Contributions: Conceptualization, N.U.-G. and G.A.-L.; methodology, B.L.-M. and G.A.-L.; investigation and resources, N.U.-G., B.L.-M. and I.L.-I.; writing—original draft preparation, N.U.-G., G.A.-L. and B.L.-M.; writing—review and editing, N.U.-G., G.A.-L. and B.L.-M. All authors have read and agreed to the published version of the manuscript.

Funding: The researchers are members of the research team IT169122 of the Basque University System.

Data Availability Statement: The data presented in this study are available upon request from the corresponding author. The data are not publicly available because the original data may be considered sensitive due to the increased risk of identification of sources, and therefore, the express approval of the companies for the purposes requested will be required.

Acknowledgments: The researchers are members of the research team IT169122 of the Basque University System. This research work has had the technical and human support of the Environmental Sustainability and Health Institute (ESHI) of the Technological University Dublin, the Circular Economy University-Company Classroom (Faculty of Engineering Gipuzkoa, UPV/EHU, Provincial Council of Gipuzkoa), the Centre de Documentation et de Recherches Europeennes (Universite de Pau et des pays de l'Adour) and the Euskampus Foundation through the Missions 1.0 and Mission 2.0 programs.

Conflicts of Interest: The funders had no role in the design of the study, the collection, analysis, or interpretation of data, the writing of the manuscript, or the decision to publish the results.

Abbreviations

AI	Artificial intelligence
BD	Big Data
CE	Circular Economy
DTs	Digital technologies
EEMs	Energy Efficiency Measures
I4.0	Industry 4.0
I4.0Ts	Industry 4.0 Technologiess
IoT	Internet of Things
MICMAC	Multiplication Appliquée aun Classement
ML	Machine Learning
OEE	Overall Equipment Effectiveness
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RQ	Research Question
SD	Sustainable Development
SLR	Systematic Literature Review

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