Article

Cost Effectiveness of the Industrial Internet of Things Adoption in the U.S. Manufacturing SMEs

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ABSTRACT: This research paper explores the financial adoption challenges of the Industrial Internet of Things (IIoT) in industry. Previous studies have mainly concentrated on designing affordable IIoT devices, reducing operational costs, and creating conceptual frameworks to assess the financial impact of IIoT adoption. The objective of this paper is to investigate whether IIoT adoption's financial benefits outweigh the initial costs in small and medium-sized enterprises (SMEs). The data from the Industrial Assessment Centers (IAC) database were analyzed, focusing on 62 U.S. manufacturing SMEs across 10 states and 25 Standard Industrial Classifications (SICs), evaluating projected IIoT implementation costs and anticipated cost savings. Results from the analyses reveal that statistically, the difference between implementation costs and savings is significant at a 95% confidence level. Practically, this indicates that SMEs, despite facing high initial costs, can expect these investments to be counterbalanced by substantial savings. From an engineering perspective, this finding raises awareness among SMEs that, beyond overcoming financial barriers, IIoT technologies serve as a strategic enhancement to operational efficiency and competitive positioning. This study acknowledges the limitations including reliance on estimated projections and a narrow industry focus. Future research should broaden the sample and explore the lifecycle costs of IIoT.

Keywords: Industrial internet of things; Industrial energy efficiency; Small and medium sized manufacturing

1. Introduction

The Internet of Things (IoT) refers to the interconnected network of devices capable of collecting and exchanging data, which has drawn increasing attention from the U.S. industry due to its potential to transform manufacturing processes into smart, efficient, and sustainable operations [1,2]. When applied within industrial settings, this concept is known as the Industrial Internet of Things (IIoT), adopting IoT principles to the industrial sector and focusing on the specific needs of manufacturing facilities and the operational challenges they face [3].

The IIoT is central to the integration of Operational Technology (OT) with Information Technology (IT), leading to enhanced efficiency and sophisticated automation in manufacturing processes [4]. This transformative integration is marked by a network of intelligent devices working collaboratively, revolutionizing automation and data exchange, and facilitating informed decision-making through real-time insights, ultimately elevating operational efficiency [5]. The rapid enhancement of industrial informatization underscores the IIoT as a pivotal component in the future evolution of industrial systems, particularly in improving energy efficiency [6], and supporting the three environmental pillars of sustainable development: resource efficiency, sustainable energy, and transparency [7].

In the United States, the industrial sector, which was responsible for 35% of end-use energy consumption in 2021, is facing an urgent demand for sustainable and energy-efficient innovations given its environmental footprint [8]. Consequently, there is a growing interest in green technologies to reduce such environmental impacts [9,10]. IIoT emerges as a critical solution offering intelligent, efficient, and sustainable operational mechanisms [11]. Despite its potential, IIoT adoption confronts significant barriers. Numerous researchers studied the IIoT adoption barriers in different classifications of industries. For example, Desingh et al. reviewed the barriers to IoT adoption within the context of healthcare systems [12]. Hundal et al. discussed the IIoT adoption challenges, including cost-effectiveness, power requirement, wireless communication range, data latency, data storage, data processing, and data interoperability within the agriculture industry [13].

Through analyzing the existing studies, we classified the IIoT adoption barriers into four categories, following as technological, organizational, educational, and financial barriers. As the IIoT technology continues to revolutionize industries, facilities face significant technological barriers, primarily security concerns, that impede its widespread adoption. Various studies have pinpointed challenges related to security and data sharing, including unauthorized data collection [14], and risks associated with sensitive information being shared, stored by third parties, or logged in unsecured storage [15]. As a result, it becomes necessary for industrial facilities to balance ethical considerations and security measures to ensure the protection of stakeholders' data and privacy [16,17]. Organizational barriers represent another significant challenge to IIoT adoption, often stemming from the novelty of IIoT and the resulting lack of established standards and reference designs, as observed by Kamble et al. in the context of the food retail industry [18].

Closely related to these are educational barriers, where a prevalent issue is the absence of widespread knowledge about new technologies. This lack of awareness inhibits companies from fully understanding both the potential benefits and the inherent risks, such as security threats, of innovations like IIoT. Schrama et al.'s research supports the need for educational initiatives, finding that companies with a keen interest in IIoT but low security awareness are more likely to engage in training programs. In contrast, those already aware of IIoT risks may hesitate to implement these technologies [19].

Financial barriers to adopting the Industrial Internet of Things (IIoT) are another significant concern for many industries. The affordability of technology is a primary barrier, with the initial high cost of implementation often being a deterrent for industrial businesses [20]. In addition, the market for IIoT suppliers and service providers is still maturing, and in some regions, the scarcity of providers can lead to monopolistic pricing, further inflating costs [21,22]. Table 1 summarizes the classifications of these obstacles.

Table 1. IIoT Adoption Barriers.

Classification	Barriers' Examples
Technological	Security and privacy concerns, and data protection [23,24]
	Ensuring Data confidentiality [25].
	Maintaining reliability, safety, and security of data [26,27].
	Trust management issues [28].
	Complexity in big data management [29], including storage, processing, and analysis [30].
	Data heterogeneity and integration challenges [31]
	Complex system architecture [32].
	Device management [33,34].
	Interoperability and standardization [35].
Organizational	Employment disruptions due to new technology implementation [36].
	Employee resistance to change [37].
	Lack of qualified employees to manage and maintain IIoT systems [38].
Educational	Poor IoT education [39].
	Government support and regulations [40].
	Legal and regulatory standards [41].
Financial	Affordability of technology [42].
	High-Implementation costs [43].
	High-Operating costs [44].

This study focuses on the financial barriers to IIoT adoption, and the rest of the paper proceeds as follows, the Literature Review section critically examines the financial barriers to IIoT adoption, exploring existing solutions and assessing the cost-effectiveness analysis of IIoT within SMEs; the Material & Methods section details the study's methodology and describes the dataset used; the Results and Discussion section presents the findings and contextual analysis respectively; the Discussion section critically discuss the observations from this investigation with existing literature; and the Conclusion section summarizes the study's key insights and limitations.

2. Literature Review

Given globalization and market liberalization progress, Small and Medium Enterprises (SMEs) must continuously innovate to keep their competitive advantage. Embracing advanced technologies, such as the Industrial Internet of Things (IIoT), is crucial for these innovations and to stay competitive [45,46]. The IIoT revolutionizes manufacturing by allowing devices within facilities to connect, interact, and exchange data, thereby optimizing operational efficiency and opening new avenues for innovation [47]. Although IIoT offers innovative solutions with the potential to transform manufacturing industries, the transition is not without challenges, with financial barriers being a primary concern for businesses considering its adoption.

The cost-intensive nature of IIoT, necessitated by the need for robust, reliable, and high-performing devices suitable for complex production environments, poses significant financial challenges [48]. These include not only the initial investment in technology and the constraints posed by a limited number of suppliers [49], but also the ongoing operational expenses—such as energy and power management, energy consumption, and costs related to system updates and cybersecurity [50].

Addressing the financial barriers to IIoT adoption requires an examination of methods outlined in existing research, which reveal strategies for mitigating these financial challenges. One approach to reducing operational costs is the application of predictive methods. Data prediction, particularly through machine learning, identifies inefficiencies for immediate correction and optimizing workflows. For example, Sharma and Obaidat describe an affordable smart farming system that uses IoT and machine learning to provide real-time agricultural insights, although it does not fully account for the implementation costs [20]. Although this paper highlights the need for cost-effective solutions through real-time monitoring and predictive analysis, it lacks a detailed breakdown of the implementation costs associated with establishing or maintaining the IoT infrastructure.

Another aspect of cost reduction is the design of low-cost IIoT devices. The IoT-Q-Band, proposed by Singh et al., presents the IoT-Q-Band, which achieves cost-effectiveness through a minimalist design and repurposing smartphone components. However, this emphasis on cost-saving raises questions about long-term durability and electronic waste [51]. On a broader scale, Ciuffoletti proposes a holistic framework for cost evaluation that emphasizes community involvement and the use of established technologies for cost reduction. Despite its comprehensive approach, this framework does not account for ongoing operational and maintenance expenses, highlighting an area for further research [52].

Research has extensively explored strategies for creating cost-effective IoT devices, focusing on reducing operational costs and simplifying components. Despite these innovations, the high costs associated with IIoT technologies remain a significant barrier to their adoption in manufacturing [53]. The hesitancy is exacerbated by uncertainties surrounding the financial returns and profitability of such investments [54]. This study seeks to contribute to the field by conducting a detailed cost-effectiveness analysis of IIoT adoption, aiming to clarify the economic value proposition for manufacturing facilities.

Related research has been undertaken to provide a conceptual framework for cost-effective analysis of IIOT adoption. Lee & Lee applied NPV and real options methods to evaluate investment opportunities, noting the advantages of flexibility in investment decisions but also the complexity and dependency on uncertain projections [55]. Mitake et al. offered a life cycle cost evaluation method, which, while useful for Return of Investment (RoI) calculations, relies heavily on interview data and is subject to regional cost variability [56]. Prajapati et al. developed an IoT-embedded supply chain model for the textile industry, showing substantial cost implications from IoT integration but basing their findings on simulated data [57]. Similarly, Rose et al., utilized advanced benefit-cost analysis for low-cost flood sensors, with their primary limitation being the benefit estimation which was addressed through sensitivity analysis [58].

Altogether, existing research on the cost-effectiveness of IIoT systems within the industrial sector has concentrated on three main activities: designing low-cost IIoT devices to reduce implementation costs, strategizing to lower operational expenses, and developing conceptual frameworks for analyzing the cost implications of IIoT adoption. Despite these efforts, a significant gap persists in the form of a methodologically robust, evidence-based examination of actual IIoT adoption costs and savings in the industry. Previous research highlights the potential of IIoT technologies to significantly enhance productivity and efficiency, yet facilities remain hesitant to adopt these technologies due to uncertainties around cost savings not sufficiently offsetting the initial costs. This study aims to address this hesitancy by analyzing a comprehensive database that records projected IIoT implementation costs and the anticipated cost savings from its adoption. Our goal is to determine whether the hesitancy stems from concerns that cost savings do not effectively counterbalance implementation costs. Should the evidence suggest that the savings indeed outweigh these costs, our findings will spotlight further opportunities for embracing IIoT systems, thereby contributing a new, evidence-based methodology to the discourse on IIoT adoption in the industry.

While existing studies provide valuable insights into cost-effective strategies and assessment frameworks for the IIoT, there remains a significant gap in empirical research that quantifies the implementation costs and savings for U.S. manufacturing SMEs. This paper identifies this gap and offers a detailed empirical analysis to evaluate the cost-effectiveness of IIoT investments for these enterprises, both as an initial investment and in terms of their long-term financial impact.

3. Materials and Methods

3.1. Research Hypothesis

Addressing the significant gap in empirical research, this paper investigates the cost-effectiveness of IIoT adoption within various U.S. manufacturing classifications. It uses inferential statistical methods, particularly hypothesis testing, to assess if projected savings outweigh implementation costs, thereby supporting or refuting cost-saving assumptions [59]. This approach enables the derivation of generalized predictions about the financial benefits of IIoT technologies from sample data [60]. The adoption of this method could influence the broader acceptance of IIoT in manufacturing by showcasing potential cost efficiencies and guiding strategic resource allocation and may catalyze broader IIoT acceptance by underscoring potential efficiencies. Therefore, the data was collected to assess whether the projected cost savings (PSAVED) and implementation costs (IMPCOST) are statistically different from each other. The following hypothesizes were tested to explore these relationships:

- Null Hypothesis (H0): There is no significant difference between the cost savings and the implementation cost: H0: μ PSAVED = μ IMPCOST;
- Alternative Hypothesis (H1): There is a significant difference, specifically, that the cost savings are greater than the implementation cost: H1: μ PSAVED > μ IMPCOST.

3.2. Data Collection

The data collected in this study is based on the publicly available Industrial Assessment Centers (IACs) database, which compiles comprehensive energy assessments for SMEs throughout the United States. The database records the projected implementation costs and cost savings of IoT devices derived from detailed energy audits. The IACs have calculated the implementation cost and cost savings based on the attributed energy assessment of each SME [61]. This database has been featured in several research papers. For example, Qiu et al. used this database for its relevant data on energy efficiency adoption decisions by such manufacturing facilities when recommended by IACs [62]. Abadie et al. leveraged this data to analyze decisions regarding energy efficiency investments [63].

The IACs, supported by the U.S. Department of Energy's Office of Manufacturing and Energy Supply Chains, provide recommendations to enhance energy efficiency, reduce waste, and improve productivity, which includes the adoption of IIoT technologies. The IACs operate under the Office of Manufacturing and Energy Supply Chains (MESC), a department within the U.S. Department of Energy (U.S. DoE) [64]. The primary objective of the IACs, supported by MESC, is to enhance energy efficiency in small and medium-sized manufacturing plants across the United States [65]. The IACs' recommendations aim to improve productivity, reduce waste, and save energy [66].

This study investigates the recommendation assessments of IIoT technologies which is classified as productivity enhancement in Section 4. To achieve this, the IAC database, containing 20,911 assessments conducted from 1981 to 2023, was utilized [67]. Although the dataset spans a broad timeframe, recommendations for IIoT adoption have been emerging since 2019 [68]. This temporal distinction allows the analysis to concentrate on recent economic trends and practices for IIoT recommendations. The research delves into variables pertinent to IIoT recommendation. Table 2 provides definitions of the variables extracted from the IAC Database.

Table 2. Key Variables Extracted from the IAC Database [69].

Variable	Definition
SIC	Standard Industrial Classification Code.
STATE	Abbreviation of the State where the energy assessment has been performed.
PSAVED	Annual Projected Cost Savings refer to the financial benefits a facility's manager could anticipate from adopting IIoT technologies. In simpler terms, these savings have a positive effect on the facility's budget by decreasing expenses compared to scenarios without this technology.
IMPCOST	The Projected Implementation Cost includes either the capital component (i.e., equipment and IIoT materials) or labor costs. This expenditure represents a negative impact on the facility's budget during the installation phase.

To gain a comprehensive understanding of the IIoT recommendation, this study details the procedure of energy assessments as performed by IACs. The energy assessment begins with a questionnaire requesting basic information about the facility and its energy usage. The IAC team then examines the facility's energy consumption patterns, including spikes, and conducts an exhaustive assessment tour to gather more data. Meetings with facility staff are held to review findings and discuss potential recommendations. The results are documented in a report and submitted for review. After 60 days, the report is dispatched to the facility staff. A follow-up survey is conducted 6 to 9 months later to ensure the effectiveness of the recommended changes [70]. The IAC program is among many initiatives aiming to mitigate the adverse impacts of industrialization on the environment by reducing energy consumption and enhancing energy efficiency in manufacturing facilities. Figure 1 illustrates the energy assessment process undertaken by the Industrial Assessment Centers.

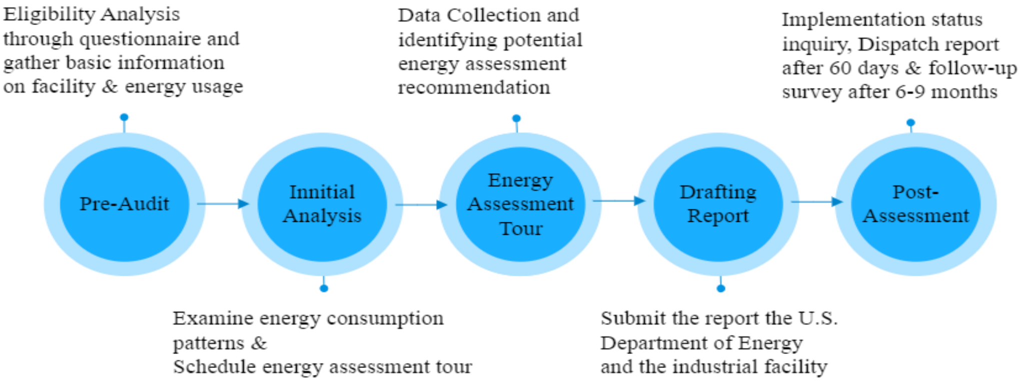

Figure 1. The Process of Energy Assessment is Conducted by the IACs.

Before conducting the statistical analysis, an exploratory data analysis was performed to assess the comprehensiveness of the dataset. This analysis encompassed an examination of the spectrum of identified operational practices related to IIoT for SMEs, the geographic distribution across various U.S. states, and the diversity of Standard Industrial Classification (SIC) codes where the IIoT adoption has been recommended. The following subsections describe these variations to fulfill the scope of this study.

3.3. IIoT-related Energy Assessment Recommendations

The Center for Advanced Energy Systems (CAES) at Rutgers University has created a technical manual book that compiles all recommendations from the IACs [71]. The manual was divided into two main sections: energy management and waste minimization/pollution prevention. These sections encompass nine key areas of focus, including combustion systems, thermal systems, electrical power, motor systems, industrial design, operations, building and grounds, ancillary costs, and alternative energy usage [72]. Over time, the manual has undergone regular updates and continuous improvements. In the current manual, version 21.1, the scope has expanded with the inclusion of an additional area: productivity enhancements in section 4 [73]. The Industrial Internet of Things recommendations are subsections of productivity enhancements. This code falls within the 'reduction of downtime' category, a subdivision of direct productivity enhancements. According to the manual, the IIoT recommendation is divided into four levels, which correspond to operational practices as follows:

(a) Level Zero—Install Control Systems for Existing Equipment

The focus of this recommendation is on integrating control mechanisms into existing equipment. IIoT devices could automate the monitoring, inspection, and control of industrial equipment and processes [74]. An example could be the addition of temperature sensors to a traditional HVAC system to collect environmental data, which can be used to automate and optimize the HVAC's operations, improving energy efficiency and system responsiveness [75].

(b) Level One—Add Communication Using IIoT Devices to Existing Control System to Modify Operations

In this recommendation, the key focus is on integrating network components such as IoT gateways, routers, and switches into existing control systems. This integration facilitates the transmission of data from IoT devices to a central system or the cloud, enabling remote monitoring and basic data analytics [76]. The core idea behind this recommendation is to enhance existing control systems with IIoT devices, empowering them to adapt operations in real time based on incoming data. This transformation fosters a more connected and responsive industrial environment [77]. Furthermore, this integration plays a pivotal role in realizing the principles of Industry 4.0, effectively turning machines into interconnected elements within a larger and communicative ecosystem [78].

(c) Level Two—Install Control System Using IIoT Devices with Communication Capabilities to Store Data to the Cloud

This recommendation extends beyond mere communication enhancements of previous integrations, introducing advanced IIoT devices equipped with superior communication functionalities directly linked to cloud platforms. This direct cloud connectivity offers on-demand, flexible computing services [79]. In the cloud, this data can be used for predictive maintenance, optimizing production workflows, and enhancing overall operational efficiency [80].

(d) Level Three—Install or Modify the Control System with Communication and non-local External Information (i.e., Weather Forecast) to Enable Better Decision-making

This strategy emphasizes the integration of external data sources, such as weather forecasts, into the control systems. By incorporating real-world information, industries can make more informed, context-aware decisions that directly impact operational efficiency and responsiveness [81]. It also enables industries to make informed decisions, improving efficiency and responsiveness.

In this study, all levels (i.e., operational practices) shown above were analyzed. Figure 2 shows the frequency distribution of each level of IIoT recommendations obtained from the 62 assessments. Level 0 and level 1 had the most identified assessment recommendations. Therefore, this study provides an analysis of all IIOT recommendations, with the majority of identified recommendations concentrated at levels 0 and 1. To acknowledge the limited number of levels 2 and 3, this research paper suggests future research, with a more balanced representation across all levels, to provide a deeper insight into the full spectrum of IIoT recommendations.

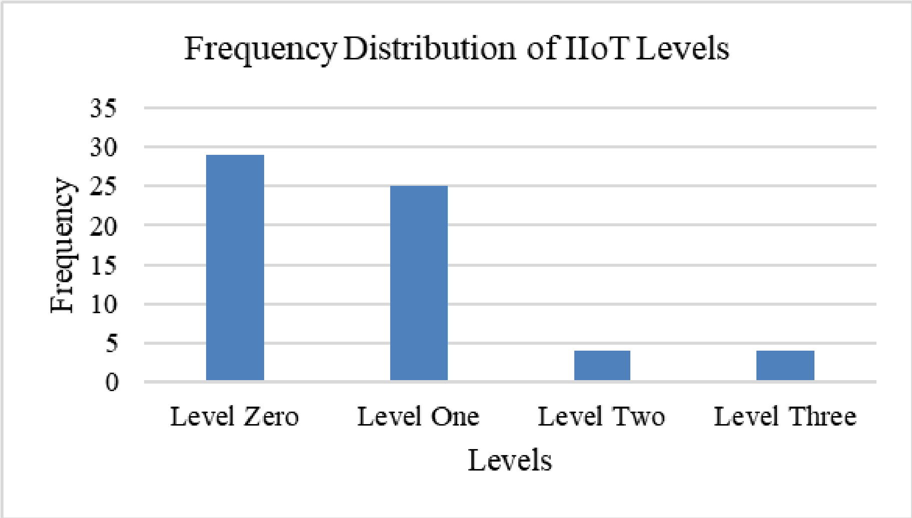

Figure 2. Frequency Distribution of IIoT Energy Assessment Recommendations based on IAC's Level.

3.4. Geographical Variation of IIoT-related Energy Assessment Recommendations

The locations of the assessments where IIoT adoption has been recommended by IACs are visualized in Figure 3. The colors of the states indicate the frequency of recommendations where IIoT adoption is identified, and the numbers indicate the relative quantity of assessments in each region.

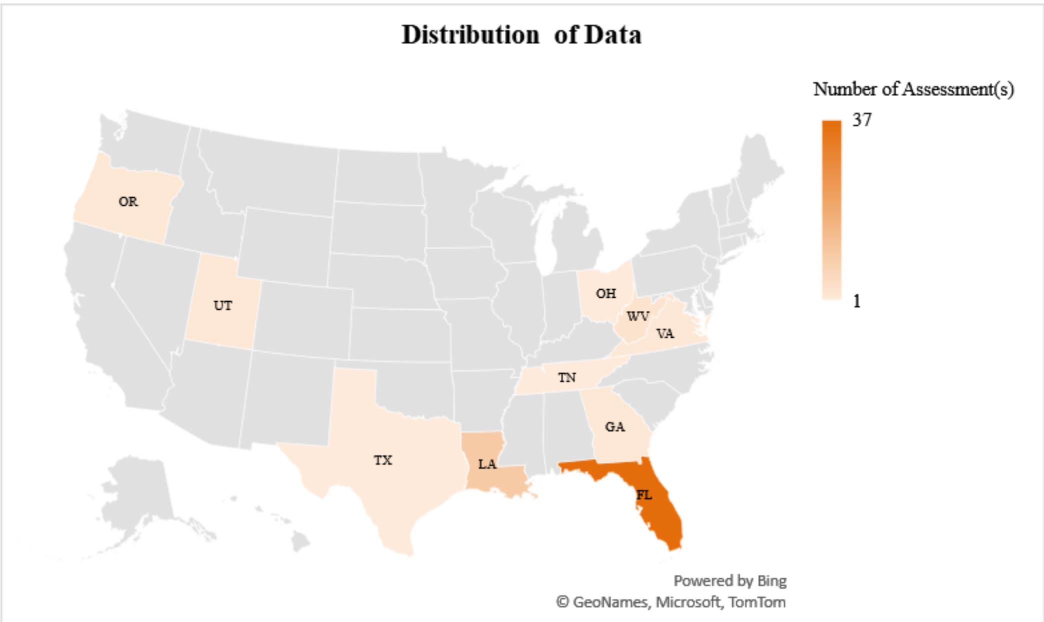

Figure 3. Geographical Variation of IIoT Energy Assessment Recommendations.

3.5. Data Distribution in Terms of SIC Variable

The IIoT technology holds potential for use in industries that require the collection and analysis of data from machines and devices. Figure 4 displays the Standard Industrial Classification (SIC) codes of the industries where IIoT technology has been recommended.

Based on the IAC Database, the IIoT energy assessment recommendations were identified within 25 SICs. The sewerage systems (SIC 4952) were the most prevalent SIC where the IACs identified there are potential cost savings through adopting the IIoT technology. Industrial IoT sensors can be instrumental in monitoring wastewater flow, aiding in the early detection of potential issues such as blockages or leaks [82]. This was followed by SIC 2051 (bread, cake, and related products) with 6 out of 62 recommendations (approximately 10%) and SIC 3841 (surgical and medical instruments) with 5 out of 62 recommendations (about 8%).

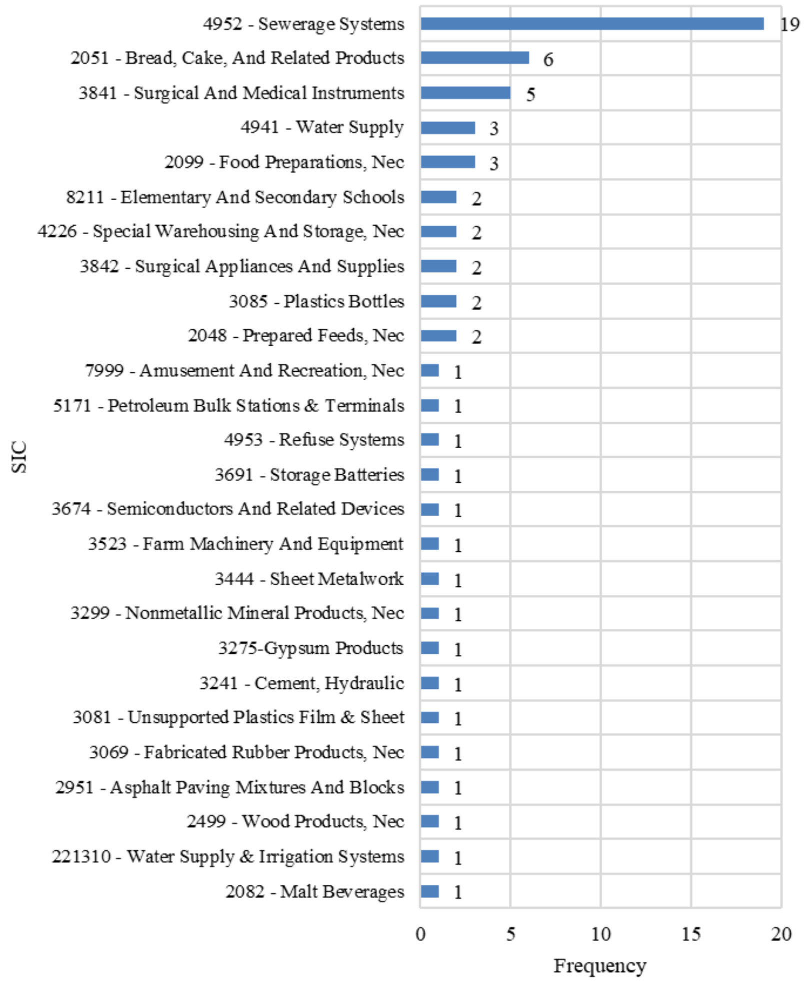

Figure 4. SIC Variation of IIoT Energy Assessment Recommendation.

4. Results

This study empirically examines the cost-effectiveness of IIoT adoption across different U.S. manufacturing sectors by employing hypothesis testing to compare projected implementation costs with annual savings. The research aims to determine if the anticipated cost savings significantly differ from the actual implementation costs, potentially influencing the wider adoption of IIoT through demonstrated economic benefits.

Before performing the data analysis, the descriptive statistics for both IMPCOST and PSAVED were analyzed using JMP Pro software version 17.0.0. JMP Pro is predictive analytics software developed by the JMP business unit of the SAS Institute [83]. Results obtained from JMP Pro are presented in Table 3.

Given the results obtained from the JMP Pro software, it was found that both variables had skewness to the right, indicating that the values are not symmetrically distributed around the mean. A positive skew indicates a longer right tail with values clustered to the left of the mean [84]. It also highlighted uncertainties in accurately estimating the average cost savings and implementation costs.

Table 3. Descriptive Statistics of IMPCOST and PSAVED.

Variable	IMPCOST ($)	PSAVED ($)
Mean	22,054.565	58,087.661
Std Dev	78,186.799	87,275.319
Std Err Mean	9929.7335	11,083.977
Upper 95% Mean	41,910.294	80,251.442
Lower 95% Mean	2198.835	35,923.88
N	62	62
Skewness	5.174	1.985
Kurtosis	26.477	2.908
N Missing	0	0

Furthermore, the substantial standard deviations observed for both IMPCOST and PSAVED point to a considerable spread of values, further confirming the significant variability within the data set. The standard error of the mean and the upper and lower bounds of the 95% confidence interval for both variables provide additional evidence of this variability, indicating the range within which the true population mean is likely to fall. With an equal number of observations (N = 62) for both variables, the analysis rests on a balanced and comparable dataset. Figure 5 and Figure 6 visually represent the skewness, underscoring the non-normal distribution of the data. The histograms use seven brackets to illustrate the distribution of data. The histogram of cost savings reveals a concentration of 40 observations in the lower savings bracket ($451 to $47,959), indicating that most projected savings are modest. Correspondingly, the histogram for implementation costs exhibits a right skew, with the majority of observations, 58 in total, residing in the lowest cost bracket ($0 to $70,000), which indicates that lower implementation costs are more frequently observed.

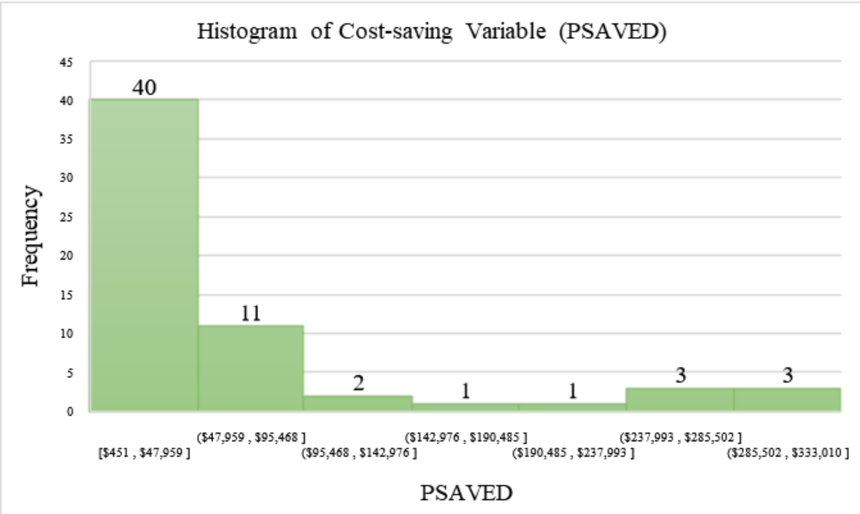

Figure 5. Histogram of PSAVED variable (Projected Cost Savings through IIoT adoption).

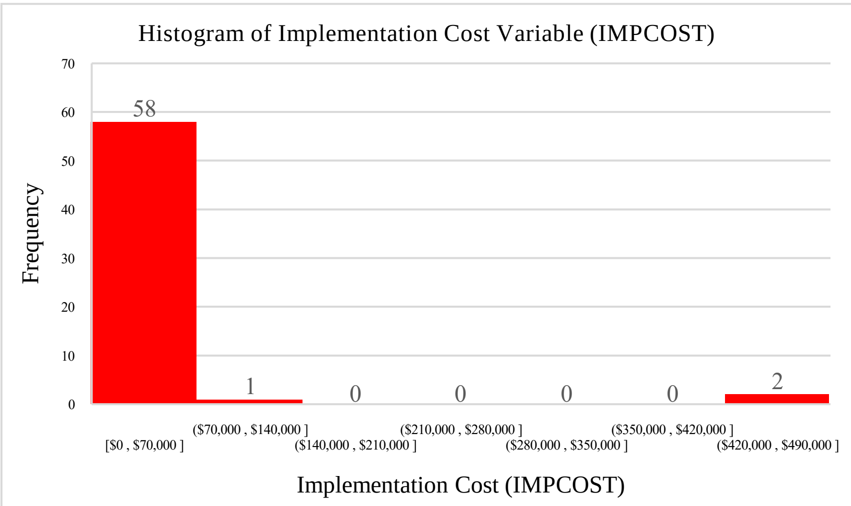

Figure 6. Histogram of IMPCOST variable (Projected Implemented Cost through IIoT adoption).

Since both variables are not normally distributed, the non-parametric Mann-Whitney U test was employed to compare their distributions. The Mann-Whitney U test evaluates whether two independent samples come from the same distribution by comparing their ranks [85]. The samples were entered into the Mann-Whitney U function to test the one-tailed hypothesis. Python Programming language was executed to perform the tests (https://gist.github.com/f-ghafari/8ea9a917015a6bb905aef3b2208875eb). The outcomes from the Mann-Whitney U test are as follows:

- U1: 999.5
- U2: 2844.5
- U statistic: 999.5
- *p*-value: <0.0001
- z-score: −4.610
- Critical U: 999.50

Results from hypothesis testing show a *p*-value of less than 0.001. As this is below the 5% significance level, the null hypothesis was subsequently rejected. This indicates a statistically significant difference, with the projected implementation cost being lower than the projected cost savings from IIoT. From a practical standpoint, the results imply that IIoT adoption is not only operationally beneficial for SMEs, but it also suggests financial prudence, potentially leading to significant cost-trade-off.

5. Discussion

This research paper provided a new perspective of cost-effective analysis of IIoT technologies in industry, indicating a statistically significant difference at a 95% confidence level between the implementation costs and savings of IIoT adoption in SMEs. This study aligns with the theoretical propositions suggesting that IIoT investments offer potential financial flexibility [55]. However, the empirical evidence extends this narrative by quantifying the extent to which projected cost savings can offset the initial high costs of implementation, a question that has remained largely theoretical in existing studies. Critically comparing the results with Lee and Lee's discussion on the advantages of investment flexibility reveals a crucial insight: while flexibility is inherently valuable, the direct financial return, as evidenced by this study, provides a more compelling justification for SMEs contemplating IIoT adoption. This distinction underscores the importance of empirical data in supporting theoretical models and decision-making processes.

Furthermore, this research addresses a gap identified by previous studies, which relied on interview data and simulated models to evaluate IIoT's cost implications [56,57]. By utilizing real-world data from the IAC database, this study provides a grounded understanding of the financial dynamics of IIoT adoption, offering a more reliable basis for SMEs to evaluate the cost-benefit ratio of such technological investments.

The practical implications of our findings also resonate with the challenges of high implementation costs [22]. However, our analysis moves beyond identifying the problem to providing a quantifiable analysis that the anticipated benefits of IIoT adoption, across a variety of industrial contexts indicated by the diversity of SIC codes in our sample, significantly outweigh these initial costs. This directly addresses the hesitancy rooted in financial uncertainties that many SMEs face, offering a clear economic rationale for embracing IIoT technologies.

In engineering terms, the implications of our findings extend beyond the immediate financial considerations. Although the high upfront costs of IIoT adoption have been a deterrent, this study highlights that the return on investment, in terms of cost savings, justifies these expenditures. This serves as an important awareness piece for SMEs, suggesting that the initial financial barriers can indeed be overcome. More critically, it positions IIoT technologies not merely as cost centers but as strategic investments capable of enhancing operational efficiency and securing competitive advantages in the marketplace.

6. Conclusions

IIoT is a transformative technology in industrial facilities, crucial for automating and optimizing operations, enhancing efficiency, and facilitating sustainable, informed decision-making through real-time insights. Nevertheless, manufacturing facilities have concerns about its adoption. This study investigated the challenges surrounding the adoption of IIoT, classifying the barriers into technological, organizational, educational, and financial categories.

Despite numerous studies addressing financial barriers, there remains a conspicuous absence of empirical research into the actual cost-effectiveness of IIoT technology within the U.S. industry. Prior research has focused on three primary areas: the design of low-cost IIoT devices to reduce implementation costs, strategies to minimize operational expenses, and the development of conceptual frameworks for analyzing the cost implications of IIoT adoption. Yet, the potential of IIoT technologies to significantly boost productivity and efficiency is overshadowed by the hesitancy of facilities to adopt these technologies, largely due to uncertainties about whether the anticipated cost savings effectively outweigh the initial investment.

To mitigate this hesitancy, our research aimed to provide a methodologically robust, evidence-based examination of actual IIoT adoption costs and savings within the industry. By analyzing a comprehensive database that records projected IIoT implementation costs alongside anticipated cost savings from its adoption, we sought to uncover whether the reluctance to adopt IIoT stems from concerns that the cost savings do not adequately counterbalance the implementation costs. This approach allowed us to explore whether the evidence supports the notion that the financial benefits of IIoT adoption surpass these initial costs, thereby highlighting further opportunities for the industry to embrace IIoT systems.

The publicly available IAC database, which provides energy assessment data throughout the United States, was analyzed. The data covered a variety of 10 states, 25 Standard Industrial Classifications (SICs), and 4 operational practices (levels) IIoT energy assessment recommendations. A descriptive statistical analysis of implementation costs and cost savings was tested for normality. Given that they were not normally distributed, non-parametric hypothesis testing was performed. It was observed that the initial implementation costs were lower than the potential cost savings, with a statistically significant difference at a 95% confidence level. Practically, this empirical evidence challenges the prevailing hesitancy by quantitatively demonstrating the economic viability of IIoT adoption in U.S. manufacturing SMEs.

The IAC database does not allow the determination of which factors the IAC teams considered when estimating implementation costs and cost savings associated with IIoT adoption. Therefore, the outcomes of this study are based on estimated projections rather than actual savings and costs after installation, which imposes certain constraints and suggests avenues for future research. Another limitation is the focus on specific 25 SIC codes and a limited sample size of 62 IIoT energy assessment recommendations, which may affect the generalizability of the findings. Future research could improve these insights by including a larger and more diverse sample. The limited assessments identifying levels 2 and 3 of IIoT integration within the IAC database indicate a lack of comprehensive data on advanced IIoT integration, pointing to further areas for inquiry.

The implications of our study suggest avenues for future research, particularly in extending the analysis beyond initial investment assessments to include lifecycle cost assessments and refining predictive models for more accurate forecasts of IIoT adoption cost savings. Furthermore, the need for a more comprehensive data set on advanced IIoT integration is evident, pointing to further areas for inquiry. Through this study, we contribute a new, evidence-based methodology to the discourse on IIoT adoption in the industry, addressing a notable gap in existing research and paving the way for a broader acceptance and implementation of IIoT technologies in the manufacturing sector.

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Author Contributions

Conceptualization, F.G. and E.S; Methodology, F.G.; Software, F.G.; Validation, F.G., E.S. and C.W.; Formal Analysis, F.G.; Investigation, E.S.; Resources, C.W.; Data Curation, C.W.; Writing – Original Draft Preparation, F.G.; Writing – Review & Editing, C.W.; Visualization, E.S.; Supervision, C.W.; Project Administration, C.W.; Funding Acquisition, C.W. All authors have read and agreed to publish this version of the manuscript.

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Ethics Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Magomedov I, Bagov A, Zolkin A. Internet of things: Future business. *Eur. Proc. Soc. Behav. Sci.* **2020**, doi:10.15405/epsbs.2020.10.03.62.
2. Ma S, Ding W, Liu Y, Ren S, Yang H. Digital twin and big data-driven sustainable smart manufacturing based on information management systems for energy-intensive industries. *Appl. Energy* **2022**, *326*, 119986.
3. Khan WZ, Rehman M, Zangoti HM, Afzal MK, Armi N, Salah K. Industrial internet of things: Recent advances, enabling technologies and open challenges. *Comput. Electr. Eng.* **2020**, *81*, 106522.
4. Hsiao CH, Lee WP. OPIIoT: Design and Implementation of an Open Communication Protocol Platform for Industrial Internet of Things. *IoT* **2021**, *16*, doi:10.1016/j.iot.2021.100441.
5. Sisinni E, Saifullah A, Han S, Jennehag U, Gidlund M. Industrial internet of things: Challenges, opportunities, and directions. *IEEE T. Ind. Inform.* **2018**, *14*, 4724–4734.
6. Wang K, Wang Y, Sun Y, Guo S, Wu J. Green industrial Internet of Things architecture: An energy-efficient perspective. *IEEE Commun. Mag.* **2016**, *54*, 48–54.
7. Beier G, Niehoff S, Xue B. More sustainability in industry through industrial internet of things? *Appl. Sci.* **2018**, *8*, 219.
8. Use of energy explained Available online: https://www.eia.gov/energyexplained/use-of-energy/industry.php (accessed on 2 May 2023).
9. Tsai S-B, Xue Y-Z, Chen Q, Zhou J. Discussing and Evaluating the Green Environmental Performance of Manufacturers. *Res. Adv. Ind. Eng.* **2015**, 59–75, doi:10.1007/978-3-319-17825-7_4.
10. Petrescu MG, Neacșa A, Laudacescu E, Tănase M. Energy in the Era of Industry 5.0—Opportunities and Risks. In *Industry 5.0: Creative and Innovative Organizations*; Springer: New York, NY, USA, 2023; pp. 71–90.
11. Khalid R, Javaid N, Rahim MH, Aslam S, Sher A. Fuzzy energy management controller and scheduler for smart homes. *Sustain. Comput. Inform. Syst.* **2019**, *21*, 103–118.
12. Desingh V. Internet of Things adoption barriers in the Indian healthcare supply chain: An ISM-fuzzy MICMAC approach. *Int. J. Health Plann. Manag.* **2022**, *37*, 318–351.
13. Hundal GS, Laux CM, Buckmaster D, Sutton MJ, Langemeier M. Exploring Barriers to the Adoption of Internet of Things-Based Precision Agriculture Practices. *Agriculture* **2023**, *13*, 163.
14. Ranchordas S, Kaplan B. MHealth for Alzheimer's Disease: Regulation, Consent, and Privacy Concerns. In *Beyond IP: The Future of Privacy (Fordham University Press, 2017), accepted but book not published*; SSRN: Rochester, NY, USA, 2016.
15. He D, Naveed M, Gunter CA, Nahrstedt K. Security concerns in Android mHealth apps. AMIA *Annu. Symp. Proc*. **2014**, *2014*, 645–654.
16. Lohachab A, Jangra A. Opportunistic internet of things (IoT): Demystifying the effective possibilities of opportunisitc networks towards IoT. In Proceedings of the 2019 6th International Conference on Signal Processing and Integrated Networks (SPIN), Noida, India, 7–8 March 2019; pp. 1100–1105.
17. Miorandi D, Sicari S, De Pellegrini F, Chlamtac I. Internet of things: Vision, applications and research challenges. *Ad. Hoc. Netw.* **2012**, *10*, 1497–1516.
18. Kamble SS, Gunasekaran A, Parekh H, Joshi S. Modeling the internet of things adoption barriers in food retail supply chains. *J. Retail. Consum. Serv.* **2019**, *48*, 154–168.
19. Schrama V, Gañán CH, Aschenbrenner D, de Reuver M, Borgolte K, Fiebig T. Understanding the Knowledge Gap: How Security Awareness Influences the Adoption of Industrial IoT. In Proceedings of the 20th Annual Workshop on the Economics of Information Security (WEIS 2020), Brussels, Belgium, 14–15 December 2020; pp. 1–17.
20. Peter O, Pradhan A, Mbohwa C. Industrial internet of things (IIoT): opportunities, challenges, and requirements in manufacturing businesses in emerging economies. *Procedia Comput. Sci.* **2023**, *217*, 856–865.
21. Tan L, Sun J, Sundarasekar R, Prethi KA. Competition Laws and Regulations For a Digital Industry. *Res. Sq*. **2021**, doi:10.21203/rs.3.rs-924649/v1.
22. Sharma B, Obaidat MS. Comparative analysis of IoT based products, technology and integration of IoT with cloud computing. *IET Netw*. **2020**, *9*, 43–47.
23. Nebbione G, Calzarossa MC. Security of IoT application layer protocols: Challenges and findings. *Future Internet* **2020**, *12*, 55.
24. Moosavi SR, Gia TN, Nigussie E, Rahmani AM, Virtanen S, Tenhunen H, Isoaho J. End-to-end security scheme for mobility enabled healthcare Internet of Things. *Future Gener. Comp. Sy.* **2016**, *64*, 108–124.
25. Yadav EP, Mittal EA, Yadav H. IoT: Challenges and issues in indian perspective. In Proceedings of the 2018 3rd International Conference On Internet of Things: Smart Innovation and Usages (IoT-SIU), Bhimtal, India, 24 February 2018; pp. 1–5.

26. Moore SJ, Nugent CD, Zhang S, Cleland I. IoT reliability: A review leading to 5 key research directions. *CCF Trans. Pervasive Comput. Interact.* **2020**, *2*, 147–163.
27. Ma Y, Wu C, Ping K, Chen H, Jiang C. Internet of Things applications in public safety management: A survey. *Library Hi Tech* **2020**, *38*, 133–144.
28. Yan Z, Zhang P, Vasilakos AV. A survey on trust management for Internet of Things. *J. Netw. Comput. Appl.* **2014**, *42*, 120–134.
29. Khan M, Wu X, Xu X, Dou W. Big data challenges and opportunities in the hype of Industry 4.0. In Proceedings of the 2017 IEEE International Conference on Communications (ICC), Paris, France, 21–25 May 2017; pp. 1–6.
30. Zhong RY, Newman ST, Huang GQ, Lan S. Big Data for supply chain management in the service and manufacturing sectors: Challenges, opportunities, and future perspectives. *Comput. Ind. Eng.* **2016**, *101*, 572–591.
31. Noaman M, Khan MS, Abrar MF, Ali S, Alvi A, Saleem MA. Challenges in integration of heterogeneous internet of things. *Sci. Program.* **2022**, *2022*, 1–14.
32. Chen S, Xu H, Liu D, Hu B, Wang H. A vision of IoT: Applications, challenges, and opportunities with china perspective. *IEEE IoTJ* **2014**, *1*, 349–359.
33. Hussain MI. Internet of Things: challenges and research opportunities. *CSI Trans. ICT* **2017**, *5*, 87–95.
34. Borgia E. The Internet of Things vision: Key features, applications and open issues. *Comput. Commun.* **2014**, *54*, 1–31.
35. Konduru VR, Bharamagoudra MR. Challenges and solutions of interoperability on IoT: How far have we come in resolving the IoT interoperability issues. In Proceedings of the 2017 International Conference On Smart Technologies For Smart Nation (SmartTechCon), Bengaluru, India, 17–19 August 2017; pp. 572–576.
36. Frey CB, Osborne MA. The future of employment: How susceptible are jobs to computerisation? *Technol. Forecast. Soc. Change* **2017**, *114*, 254–280.
37. Sievers F, Reil H, Rimbeck M, Stumpf-Wollersheim J, Leyer M. Empowering employees in industrial organizations with IoT in their daily operations. *Comput. Ind.* **2021**, *129*, 103445.
38. Benešová A, Hirman M, Steiner F, Tupa J. Determination of changes in process management within industry 4.0. *Procedia Manuf.* **2019**, *38*, 1691–1696.
39. Mohammadian HD, Mohammadian FD, Assante D. IoT-education policies on national and international level regarding best practices in German SMEs. In Proceedings of the 2020 IEEE Global Engineering Education Conference (EDUCON), Porto, Portugal, 27–30 April 2020; pp. 1848–1857.
40. Crawford D, Sherman J. Gaps in United States federal government IoT security and privacy policies. *J. Cyber Policy* **2018**, *3*, 187–200.
41. AboBakr A, Azer MA. IoT ethics challenges and legal issues. In Proceedings of the 2017 12th International Conference on Computer Engineering and Systems (ICCES), Cairo, Egypt, 19–20 December 2017; pp. 233–237.
42. Bi S, Wang C, Zhang J, Huang W, Wu B, Gong Y, et al. A survey on artificial intelligence aided Internet-of-Things technologies in emerging smart libraries. *Sensors* **2022**, *22*, 2991.
43. Ramesha M, DankanGowda V, Jeevan K, Sathisha B. Implementation of IoT Based Wireless Electronic Stethoscope. In Proceedings of the 2020 Third International Conference on Multimedia Processing, Communication & Information Technology (MPCIT), Karnataka, India, 11–12 December 2020; pp. 103–106.
44. Wanasinghe TR, Gosine RG, James LA, Mann GK, De Silva O, Warrian PJ. The internet of things in the oil and gas industry: A systematic review. *IEEE IoTJ* **2020**, *7*, 8654–8673.
45. Tatić K, Džafić Z, Haračić M, Haračić M. The use of business intelligence (BI) in small and medium-sized enterprises (SMEs) in Bosnia and Herzegovina. *Econ. Rev. J. Econo. Bus.* **2018**, *16*, 23–37.
46. Safar L, Sopko J, Bednar S, Poklemba R. Concept of SME business model for industry 4.0 environment. *Tem J.* **2018**, *7*, 626.
47. Sharma N, Solanki VK, Davim JP. Basics of the internet of things (IoT) and its future. In *Handbook of IoT and Big Data*; CRC Press: Boca Raton, FL, USA, 2019; pp. 165–186.
48. Stukach O. Analysis of Barriers to the Development of Industrial Internet of Things Technology and Ways to Overcome Them. *IOP Conf. Ser.: Mater. Sci. Eng.* **2019**, *1019*, 012079.
49. Vuković M, Jorg O, Hosseinifard M, Fantoni G. Low-Cost Digitalization Solution through Scalable IIoT Prototypes. *Appl. Sci.* **2022**, *12*, 8571.
50. Dange A, Ranjan P, Mesbah H, Chokshi R. Digitalization using IIoT and cloud technology in oil and gas upstream-merits and challenges. In Proceedings of the International Petroleum Technology Conference, Beijing, China, 22 March 2019; p. D011S002R005.
51. Singh V, Chandna H, Kumar A, Kumar S, Upadhyay N, Utkarsh K. IoT-Q-Band: A low cost internet of things based wearable band to detect and track absconding COVID-19 quarantine subjects. *EAI Endorsed Trans. IoT* **2020**, *6*, doi:10.4108/eai.13-7-2018.163997.
52. Ciuffoletti A. Low-cost IoT: A holistic approach. *J. Sens. Actuator Netw.* **2018**, *7*, 19.
53. Martens C.D.P.; da Silva LF, Silva DF, Martens ML. Challenges in the implementation of internet of things projects and actions to overcome them. *Technovation* **2022**, *118*, 102427.

54. Ritzén S, Sandström GÖ. Barriers to the Circular Economy–integration of perspectives and domains. *Procedia Cirp* **2017**, *64*, 7–12.
55. Lee I, Lee K. The Internet of Things (IoT): Applications, investments, and challenges for enterprises. *Bus. Horiz.* **2015**, *58*, 431–440.
56. Mitake Y, Tsutsui Y, Alfarihi S, Sholihah MA, Shimomura Y. A life cycle cost analysis method accelerating IoT implementation in SMEs. *Procedia CIRP* **2021**, *104*, 1424–1429.
57. Prajapati D, Chan FT, Chelladurai H, Lakshay L, Pratap S. An Internet of Things embedded sustainable supply chain management of B2B e-commerce. *Sustainability* **2022**, *14*, 5066.
58. Rose A, Wei D, Machado J, Spencer K. Benefit–Cost Analysis of Low-Cost Flood Inundation Sensors. *Nat. Hazards Rev.* **2023**, *24*, 05022011.
59. Walpole RE, Myers RH, Myers SL, Ye K. *Probability and Statistics for Engineers and Scientists*; Macmillan: New York, NY, USA, 1993; Volume 5.
60. Hill R, Berry S, Hill R, Berry S. Data, Analysis and Statistics. In *Guide to Industrial Analytics: Solving Data Science Problems for Manufacturing and the Internet of Things*; Springer: New York, NY, USA, 2021; pp. 21–51.
61. Martin M, Tonn B, Schmoyer R, Overly J, Schexnayder S, Johnson D. *Industrial Assessment Center Program Impact Evaluation. ORNL/CON-473*; Oak Ridge National Laboratory: Oak Ridge, TN, USA, 1999; pp. 15–25.
62. Qiu Y, Wang YD, Wang J. Implied discount rate and payback threshold of energy efficiency investment in the industrial sector. *Appl. Econ.* **2015**, *47*, 2218–2233.
63. Abadie LM, Ortiz RA, Galarraga I. Determinants of energy efficiency investments in the US. *Energy Policy* **2012**, *45*, 551–566.
64. About the Office of Manufacturing and Energy Supply Chains. Available online: https://www.energy.gov/mesc/office-manufacturing-and-energy-supply-chains (accessed on 18 July 2023).
65. Industrial Assessment Centers (IACs). Available online: https://www.energy.gov/mesc/industrial-assessment-centers-iacs (accessed on 18 July 2023).
66. Chaudhari S, Gupta D, Gopalakrishnan B. Using IAC Database for Longitudinal Study of Small to Medium Sized Automotive Industry Suppliers' Energy Intensity Changes. *SAE Int. J. Mater. Manuf.* **2013**, *6*, 427–435.
67. IAC Download Data. Available online: https://iac.university/download (accessed on 9 October 2023).
68. Search IAC Recommendations. Available online: https://iac.university/searchRecommendations?arcCode=4.66&implemented=&center=&state=&yearThen=lt&year=2024&savingsThen=lt&savings=&costThen=lt&cost=&SIC=&NAICS= (accessed on 9 October 2023).
69. Muller M. *IAC Assessment Database Manual*; US Department of Energy: Washington, DA, USA, 2011; Volume 32.
70. Selim OM, Abousabae M, Hasan A, Amano RS. Analysis of Energy Savings and CO_2 Emission Reduction Contribution for Industrial Facilities in USA. *J. Energy Resour. Technol.* **2020**, *143*, doi:10.1115/1.4048983.
71. Muller MR, Kasten DJ. Industrial Assessment Center Assessment Recommendation Code (ARC), New Brunswick, NJ, United States 2007. Available online: https://iac.university/technicalDocs/ARC_list_9.1.pdf (accessed on 4 December 2023).
72. Bauman MJ. Analysis of Energy Recommendations in the US Wood Products Industry. Doctoral Dissertation, Virginia Tech, Blacksburg, VA, 2016. Available online: https://vtechworks.lib.vt.edu/server/api/core/bitstreams/62c96a88-200a-4dc5-a962-b6e2f80ed2b5/content (accessed on 4 December 2023).
73. Muller MR, Rossi T, Barber K, Murphy C, Sajewski D. Industrial Assessment Center Assessment Recommendation Code (ARC), New Brunswick, NJ, 2022. Available online: https://iac.university/technicalDocs/ARC%20List%20-%20V19.1.pdf (accessed on 4 December 2023).
74. Coutinho RW, Boukerche A. Modeling and analysis of a shared edge caching system for connected cars and industrial IoT-based applications. *IEEE T. Ind. Inform.* **2019**, *16*, 2003–2012.
75. Swamy SN, Kota SR. An empirical study on system level aspects of Internet of Things (IoT). *IEEE Access* **2020**, *8*, 188082–188134.
76. Lam AN, Haugen O, Delsing J. Dynamical orchestration and configuration services in industrial iot systems: An autonomic approach. *IEEE Open J. Ind. Electron. Soc.* **2022**, *3*, 128–145.
77. Boyes H, Hallaq B, Cunningham J, Watson T. The industrial internet of things (IIoT): An analysis framework. *Comput. Ind.* **2018**, *101*, 1–12.
78. Gilchrist A. *Industry 4.0: The Industrial Internet of Things*; Springer: New York, NY, USA, 2016.
79. Moura R, Ceotto L, Gonzalez A, Toledo R. Industrial Internet of Things Platforms–An Evaluation Model. In Proceedings of the International Conference on Computational Science and Computational Intelligence (CSCI), Las Vegas, NV, USA, 12–14 December 2018.
80. Vasylenko O, Ivchenko S, Snizhnoi H. Design of information and measurement systems within the Industry 4.0 paradigm. *Radioelectron. Comput. Syst.* **2023**, 45–54.
81. Akan OB, Dinc E, Kuscu M, Cetinkaya O, Bilgin BA. Internet of Everything (IoE)-From Molecules to the Universe. *IEEE Commun. Mag.* **2023**, *61*, 122–128.

82. Solano F, Krause S, Wöllgens C. An internet-of-things enabled smart system for wastewater monitoring. *IEEE Access* **2022**, *10*, 4666–4685.
83. Sall J, Stephens ML, Lehman A, Loring S. *JMP Start Statistics: A Guide to Statistics and Data Analysis Using JMP*; SAS Institute: Cary, NC, USA, 2017.
84. Kim H-Y. Statistical notes for clinical researchers: assessing normal distribution (2) using skewness and kurtosis. *Restor. Dent. Endod.* **2013**, *38*, 52–54.
85. Mann HB, Whitney DR. On a test of whether one of two random variables is stochastically larger than the other. *Ann. Math. Statist.* **1947**, *18*, 50–60.