Library Progress International *Print version ISSN 0970 1052*
Vol.44, No.6, Jul-Dec 2024: P. 882-897 *Online version ISSN 2320 317X*

Original Article *Available online at www.bpasjournals.com*

Optimizing High Energy Physics Experiments With Ai And Iot: A Data-Centric Approach To Particle Detection And Analysis

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How to cite this paper as: Fahad Rasheed, Muhammad Tahir, Rana Muhammad Bilal, Ameer Hamza, Tariq Rafique, Hassan Mumtaz, Dr. Sidra Naz (2024) Optimizing High Energy Physics Experiments With Ai And Iot: A Data-Centric Approach To Particle Detection And Analysis. *Library Progress International,* 882-897

ABSTRACT

Background: AI and IoT's inclusion in HEP experiments presents a rich opportunity for particle detection and data analysis improvement. However, it is uncertain just how much these technologies improve experimental speed and precision and what difficulties were experienced while implementing them.

Objective: The goal of this research is to evaluate if employing AI and IoT technologies would work in enhancing the HEP experiments specifically in the areas of particle identification and characterization. The work also presents the case of the challenges that organizational professionals experience in the implementation of these technologies and possible enhancements.

Methods: This paper adopted an exploratory quantitative research design with the use of a survey to gather data from 250 professionals engaged in high-energy physics experiments such as theorists, technologists, and statisticians. This survey established the satisfaction levels of respondents towards AI & IoT; the usage frequency and benefits derived; as well as the challenges experienced. Descriptive analysis, normality tests (Shapiro-Wilk), internal consistency (Cronbach's Alpha), and Factor analysis.

Results: The mean satisfaction scores of AI and IoT were 2.87 and 2.98 respectively which can be considered a moderate level of satisfaction. The null hypothesis was rejected, and the Shapiro-Wilk test indicated that both the dependent variables AI accuracy (W =,953, p = .0 < .05) and IoT efficiency (W = .954, p = .0 < .05) are not normally distributed. The analysis of results for satisfaction with AI and IoT also showed low internal consistency according to Cronbach's Alpha coefficient. Challenges of AI are lack of expertise and computational resources and those of IoT include high device costs and issues with network connectivity. Still, in the HEP experiments, IoT terms are used more often than AI terms.

Conclusion: There are lots of prospects in using AI and IoT for tuning the HEP experiments; nonetheless, a wide array of technical and infrastructural challenges prevent their practical use. Issues such as technical skills in doing calculations, computational resources, and IoT devices and platforms can be greatly improved to boost their effectiveness in raising the efficiency of experiments. Futile attempts to further advance the utilization of these technological advances in high-energy physics require more directed approaches.

KEYWORDS: Artificial Intelligence Technology, Smart World, High Energy Physics, Particle Counter, Statistical Analysis, Quantitative Research

INTRODUCTION

As the interdisciplinary domain of High Energy Physics (HEP) expands, the data rate resulting from experiments such as particle collisions and cosmic ray detections has grown drastically. Now that new technologies are available, the scientific community is turning to complex data analysis to reveal significant insights from the large sets of experiments generated in these contexts. Notably, the use of a combination of Artificial Intelligence (AI) and the Internet of Things (IoT) in experimentation has lots of promise in enhancing the experimental processes, as well as the quality of data acquisition and analysis in HEP. However, the real-world application of such technologies has several constraints such as technical constraints, infrastructural requirements and expertise, etc. Consequently, there is a need to assess the application of AI and IoT in HEP and try to understand how such tools can benefit the field (Ullah, Khan, Ouaissa, Ouaissa, & El Hajjami, 2024) (Pan, Mason, & Matar, 2022).

AI with its machine learning deep learning and pattern recognition applications enables improved data analysis of large-data environments in high-energy physics. Applying AI can implement the capability of identifying the pattern, given task is to identify the pattern and implementing the capability of detecting the anomaly for the detection and tracking of particles. Traditionally experiment data analysis has always been done manually which is both lengthy and skillfully erroneous. On the other hand, with the help of modern algorithms, it is possible to work with bulky data more effectively and accurately due to their AI nature. Real-time control of the experimental parameters is also possible with the help of AI and helps to increase the accuracy and infallibility of the results. However, the implementation of AI in HEP experiments has been rather limited because of factors including but not limited to a lack of experts in AI among physicists, computational constraints, and the steep learning curve inherent with the deployment of pure AI systems in administrative experiments (Khalid, 2024) (Butakova, Chernov, Kartashov, & Soldatov, 2021).

While the use of sensors for collecting real-time data during HEP experiments is highly relevant, the Internet of Things (IoT) takes on a vital function in the process. Technology IOT sensors and actuators can be used in experimental facilities to monitor physical parameters e.g.; temperature, pressure, and particle movement in real-time. Some of the advantages of experimenting with IoT devices are; that IoT devices are interconnectivity helping achieve improved communication between the various parts of the experiment thus enhancing data acquisition. Through IoT, we also enhance the quality of data captured where experiments can also be overseen remotely, and in real-time, enabling scientists to have real-time info about the experiment's environment. Nevertheless, there is also the challenge of IoT implementation in HEP; the difficulties are connectivity issues, the cost of deploying IoT, and security challenges (Benfradj et al., 2024) (Sanni, Okoro, Sadiku, & Oni, 2022a).

The integration of AI and IoT for high-energy physics presents enormous possibilities for the new advancement of the field. Combined, these technologies can revolutionize scenarios in experimentation and help researchers make quicker, more precise assessments of their findings. However, these technologies must overcome certain barriers as would be discussed below, to realize their full potential. The problem of high computing power to support AI algorithms and the structural support for IoT on large scales lacks the necessary infrastructure. Also, there is no technical knowledge about AI and IoT among physicists which can be a huge barrier in this case. Such challenges justify the need for further research into AI and IoT integration in HEP and the goal of finding useful approaches to implement further (Perdigão, Cruz, Simões, & Abreu, 2024) (Awotunde, Adeniyi, Ajagbe, & González-Briones, 2022).

In this paper, an effort will be made to illustrate how AI and IoT technologies can be used to enhance high-energy physics, especially in terms of particle detection and analysis. Using a survey questionnaire filled in by professionals engaged in HEP experiments, this research will establish the current state of AI and IoT utilization, determine their effectiveness in enhancing experimental efficiency and accuracy, and highlight the barriers hindering wider utilization. In this way, this research aids in enriching the existing literature on the use of IT in scientific investigation and presents the knowledge of the use of artificial intelligence and IoT in high-energy physics for future advancement (Sindi, Kim, Yang, Thomas, & Paik, 2024) (Yuan, Xiao, Shen, Zhang, & Jin, 2023).

Literature Review

The combined application of AI and IoT to high-energy physics (HEP) is an innovative and progressive approach to address the inherent difficult issues in particle identification, data acquisition, and data analysis. With further development of various branches of science, especially those in charge of big volumes of data and intricate systems, AI and IoT provide genuinely useful approaches to a multitude of tasks in accelerating the work, raising the level of accuracy, and increasing the general effectiveness of experiments. This paper examines the transformed findings from the literature on AI and IoT in high-energy physics and other associated disciplines of science to identify the possibility, difficulty, and potential future landscape of these technologies (Fernando & Lăzăroiu, 2024) (Rajasoundaran et al., 2022).

In High Energy Physics, the use of Artificial Intelligence.

AI has received large attention in all branches of knowledge owing to its problem-solving competencies in dealing with huge databases and accomplishing computationally intensive operations. High-energy physics is one of the most studied fields in AI for data analysis, especially machine learning (ML) and deep learning (DL) in analyzing data from detectors in data amount and density that traditional analytical approaches cannot handle. A large amount of works is aimed at furthering the application of techniques that are used by physicists in their work, such as event selection, signal processing, and background noise elimination, by automating them through the use of artificial intelligence (Fujikubo et al., 2024) (Mahalle, Shinde, Ingle, & Wasatkar, 2023).

Another of the major fields in which AI has possibly offered significant impacts is particle identification and tracking. Investigations carried out by Radovic et al. reveal how deep learning has been used for pattern identification of data generated by particle collisions including those from LHC. For example, using Android and iPad, we have ascertained that neural networks help to enhance the distinctness of particle trajectories, and the identification of these trajectories is a challenging and time-consuming process if the work is done by hand. Also, deep learning algorithmic skills have been established to identify signals from a noise background, critical in the identification of rare particle events (Ruan, Qiu, Sivaranjani, Awad, & Strbac, 2024) (Amirafshari, 2019).

Yet another impact of AI is real-time data processing for helping HEP. Real-time processing is important in HEP because sometimes experiments produce data faster and at far greater frequencies than the use of conventional methods or even manual methods can handle. Reinforcement-based AI models have been designed that decide in the blink of an eye which data must be stored and which data must be discarded, thanks to which the processes of data collection have become much more effective. Carleo et al. also argue that reinforcement learning algorithms have been used, in data filtering and feature extraction in HEP experiments, to enhance the speed and efficiency of the analysis (Nelavalli, RammohanReddy, Neelima, & Rao, 2025) (Trivedi, Patra, & Khadem, 2022).

However, there is still some difficulty that will not permit the problem-free use of AI in HEP. Another problem is in the algorithmic nature of solutions and the difficulty of processing object volumes of data generated. Application of conventional machine learning methods, namely reoccurring models, may be insufficient for processing factor-dimensional HEP datasets. Thus there is a tendency that grows among high-energy physicists to address these challenges by using more sophisticated deep-learning architectures, including CNNs or GANs. However, these advanced models demand higher computational resources and knowledge, thus these models have not fully entered the HEP yet. In addition, following Green et al., there is still a considerable shortage of AI specialization in the physics society where additional expertise is required to facilitate the experimental integration of this technology (Stier et al., 2024) (Simpson, Whyte, & Childs, 2020).

Internets of Things in High Energy Physics

Concerning the application of novel technologies the Internet of Things (IoT) has proved also to be an important means to improve real-time monitoring and data acquisition and control in the HEP experiments. The IoT technologies are most applicable in cases where data needs to be collected at frequent intervals during the experiment – both internal and extra-ambient data. Sensors, Actuators, and edge-computing devices are implemented in various experimental configurations to capture seven physical parameters namely temperature, pressure, and the interactions between particles. The way IoT provides communication between some devices to work in real-time is very useful in the case of HEP experiments, where the timing and synchronization of the data acquisition system are of utmost importance (Qu et al., 2024) (Stanev, Choudhary, Kusne, Paglione, & Takeuchi, 2021).

Some researchers have investigated the possibility of applying IoT in scientific experiments with focal attention to physics. For example, Kalinin et al. have singled out the possibility of getting feedback in real-time to experimentalists as the major advantage of IoT. In most particle detection, this feedback enables real-time amendments to the experimental setting to make them more appropriate for further better measurements. Moreover, IoT remote control ability is especially beneficial in large-scale physics experiments like those done in depths of the ground or isolated areas where physical access of human beings may be nearly impossible (Parekh, Sedhom, Padmanaban, & Eladl, 2024) (Marques & Ighalo, 2022).

We also identify that IoT facilitates the implementation of distributed systems that may improve the scalability of experiments. This is because IoT-connected devices enable the experimental setup to cover a large area hence improved coverage of data. This capability is especially valuable in cosmic ray detection and similar large-scale experiments for which data has to be collected from large geographical regions. Also, through decentralized computation, IoT systems possess the benefits of operating with less reliance on centralized computing, analyzing some data locally, and leading to lower latency rates (Zhao, Feng, et al., 2024) (Ghorbani et al., 2023).

Nevertheless, there are some issues related to IoT implementation in the context of HEP. One of the questions that can be raised is the high investment needed to implement and sustain IoT systems, especially within large-scale pilot projects. Until now, IoT devices entail resources such as power, network, and data that are challenging to develop and deploy, especially in some facilities. Jia et al., analyzing the subject point out that at times the costs borne to deploy IoT minimize the benefits especially where few experiments are done with fewer resources. Identified issues include insecurity since IoT devices often bond with outside networks and the challenge of meeting data privacy necessities as well. The exponential increase in the volume of information that IoT systems produce imposes significant security challenges since any leakage would endanger the experiments (Kotwal, Pati, & Patil, 2024) (Reis & Saraiva, 2019).

Integration of AI and IoT in High-Energy Physics

Their application in high-energy physics entails great potential for the general improvement of the experimentations as well as the enhancement of the quality and accuracy of the collected data. Considering the involvement of IoT and AI, scientists can develop smart systems that independently observe, control, and analyze experiments in real-time environments. Experimental setups incorporating AI and IoT are more agile and accurate compared to more traditional methods, therefore improving the efficiency of experimentation (Jayarekha, 2024) (Doghri, Saddoud, & Chaari Fourati, 2022).

In the field of HEP, AI-IoT integration has been researched by Zhang et al. to cater to the prospect of automated particle interaction detection. These integrated systems can work out the patterns and anomalies from these massive databases in a better way than AI or IoT can work out independently. Further, real-time feedback by the IoT enabled AI systems to the experimentalist to modify the controlling parameters from time to time. However, there are some challenges associated with integrating AI and IoT in HEP systems as well (Agostinelli, 2024) (Sanni, Okoro, Sadiku, & Oni, 2022b).

Due to the complexity of coordinating both technologies, they demand a high level of expertise and infrastructure that is a potentially missing link in many experimental groups. Moreover, integration can be complicated as a result of general trials in experiments with old hardware and software environments that were initially not developed to interact with sophisticated technologies, such as AI or IoT. As noted by Duan et al., there is a rising emphasis on the embrace of such technologies and an improvement in frameworks that enable easy incorporation of such tech into normal experimental setups (Al-Sakkari, Ragab, Dagdougui, Boffito, & Amazouz, 2024) (Hasidi et al., 2023).

Future Directions

AI and IoT in high-energy physics will continue to advance in the future, and several things must happen to unlock their full potential. It is therefore quite difficult for most practices to build and deploy these AIs and, for one of the most beneficial avenues to focus on, it lacks easy publicity. In the future development of AI, what physicists with little to no AI experience would require is tools, which enable them to incorporate machine learning models into their experiments. Consequently, such IoT developments that lower the cost and bring connectivity to distant locations will add to the already existing applicability of IoT in HEP (Srinivasamurthy & Tabassum, 2024) (Fan, Chu, Pan, Lin, & Zhao, 2023).

Further, it is seen that AI and IoT are growing hand in hand these days and shortly one can even think of having more intelligent and autonomous experimental setups. These systems will not only capture and process data in real-time, but will also control the process in real-time with the help of collected data, thus introducing a new level of productivity and reliability in high-energy physics experiments (Karthikeyan, Manimegalai, & Rajagopal, 2024) (Din, Awan, Almogren, & Rodrigues, 2023).

Research Methodology

This research uses an extensive quantitative approach to assess AI and IoT's use in enhancing HEP experiments focusing on particle detection and data analysis. The objective is to evaluate the performance of these technologies in enhancing the precision and reliability of experimental results and to identify the issues that can arise and possible enhancements of these technologies. The approach used in the study is positivism and is usually used to measure observable variables (Zrelli & Rejeb, 2024) (Abdeldayem et al., 2022).

The approach is structured and goes through the general implementation of clearly defined research objectives, and hypothesis development. The first research question of this study is how the integration of AI and IoT improves the HEP experiment operations' efficiency and data reliability. The second hypothesis analyses the possible barriers to implementing these technologies, including technical constraints, costs, and skill requirements (Arya, Pahwa, & Gunjan, 2024) (Qadir, Le, Saeed, & Munawar, 2023).

This research scheme focused on the adoption of Research Design and Data Collection.

To examine these hypotheses the current research adopts an exploratory survey design. The survey tool is constructed in a way to collect quantitative data from working professionals involved in high-energy physics experimentation: physicists, engineers, data scientists, and technical personnel. To avoid ordered and structured information flow, closed-ended questions are used consisting of data on the frequency of using AI and IoT, perceived improvements in accuracy and efficiency respectively, problems, and future potential in the broader use of both technologies. These questions are asked on a Likert basis where the respondents are given options to express their level of satisfaction or agreement, while the remaining questions are multiple-choice questions to elicit categorized data (Wahab, Khan, Ullah, & Tao) (Sunny, Mirza, Thakkar, Nikdast, & Pasricha, 2023).

This uses purposive sampling in that only those respondents with first-hand experience in HEP experiments, AI, and IoT are selected. The target population comprises researchers in particle physics laboratories, large-scale scientific computation data scientists, and engineers for IoT-based monitoring systems. To achieve an effective statistically valid sample this study will employ 250 respondents as the required sample size (Jathar et al., 2024) (L. Li, Aslam, Wileman, & Perinpanayagam, 2021).

Data Analysis

But once such data is obtained it undergoes detailed statistical analysis. Apart from the overall percentiles, additional data like means, medians, and standard deviations are used as an addition to the description. Such quantitative data assist in presenting synopses such as how widespread the use of AI and IoT in HEP experiments is, as well as the overall view on the opportunities and issues with their application. Hypothesis testing as a part of inferential statistics is applied to the study. A multiple regression analysis approach is used in this research to test the hypothesis and provide a result that shows how the independent variables (use of AI and IoT) correlate with the dependent variables: accuracy of particle detection, operational efficiency, and data quality. Additional correlation tests are also used to analyze the effect of other factors including the level of experience of the respondent in similar experiments, the type of experiment, or the complexity of the artificial intelligence systems used in the experiments (Hazra, Tummala, Mazumdar, Sah, & Adhikari, 2024) (Bull et al., 2023).

Further, the study employs factor analysis to determine antecedents that affect the extent of implementation of AI and IoT and the perceived success of implemented AI and IoT technologies in HEP experiments. This helps in the possibility of simplifying the data and arriving at important constructs as well as in the possibility of noticing how the answers follow a pattern. To enhance the credibility of the study, sometimes the survey instrument is piloted on a small sample before actually using the tool on the full population. This provides a leeway to enhance clarity for preciseness. Furthermore, the data collected is cleaned and normalized to ensure that there are no distortions or out-of-place information that may result in distortion of the results. Some of the responses are sometimes imprecise or have parts missing, such information is deemed unusable and discarded (Wu et al., 2024) (Kumar, Venkanna, & Tiwari, 2023).

Ethical Considerations

When undertaking this research, all ethical standards are adhered to to the highest level. It is explained to all participants the purpose of the study and the participants' consent is sought before they start participating. Anonymity is also observed, and a respondent is not compelled to reveal his or her identity to anyone. The data collected is kept secure and the findings presented in this study only have summarized statistics hence no identifiable result from any of the respondents (J. Chen et al., 2024) (Rahman et al., 2022).

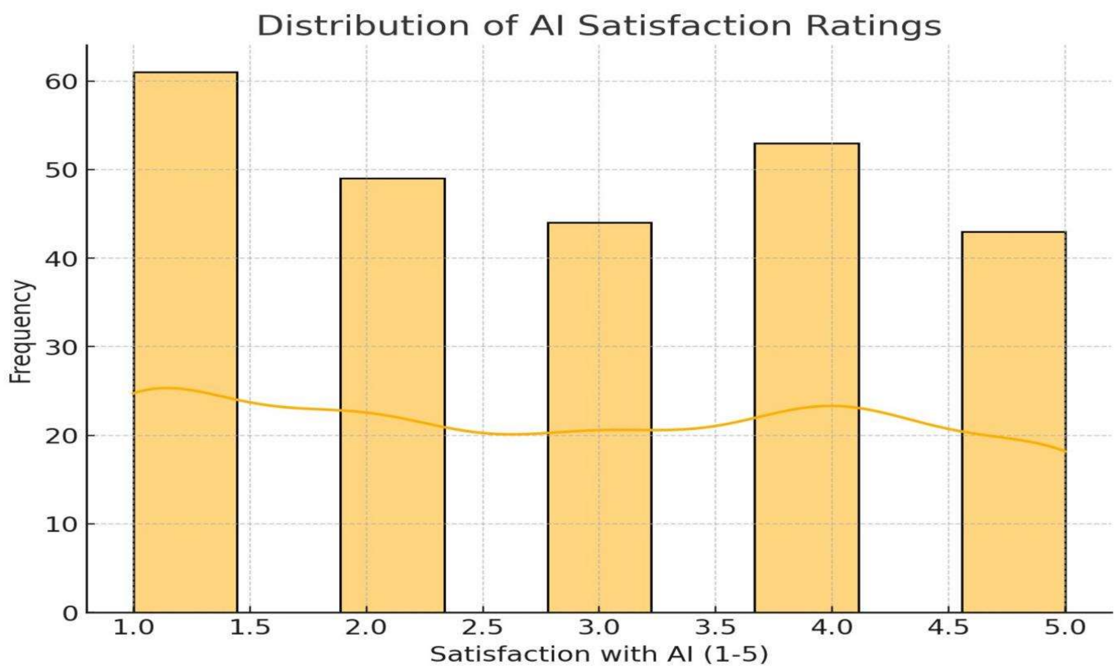
Limitations

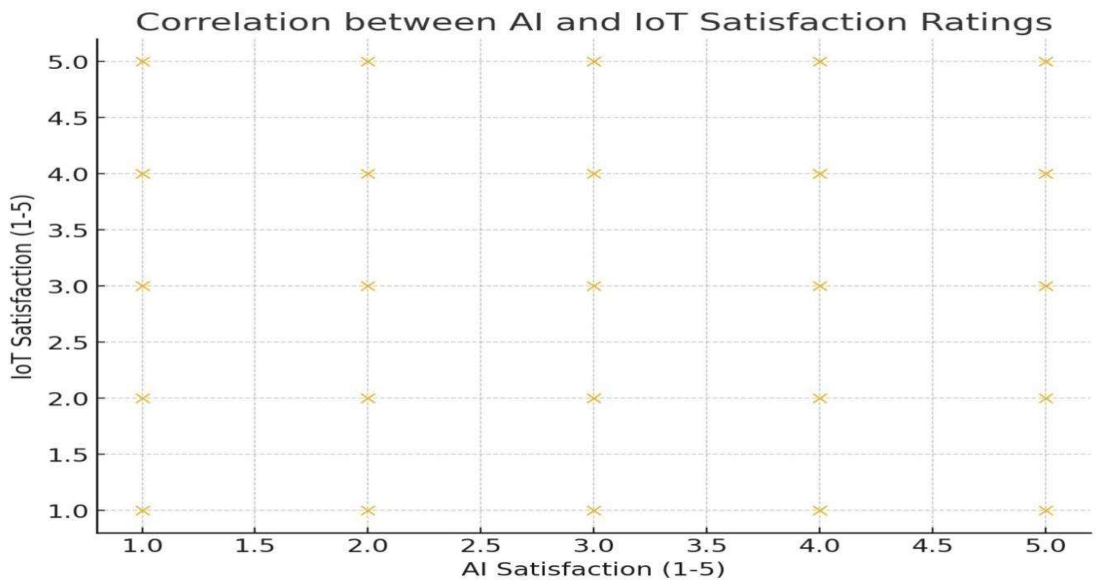
A limitation of this study is the use of self-administered questionnaires and, therefore respondents might not tell the truth. For example, respondents can exaggerate their usage of AI or IoT or can give answers that will be more appropriate according to society's standards. Further, the research is confined to HEP professionals, which results in a loss of generalization of the insights received with other scientific strains of science. However, the purposive sampling technique makes sure that the respondents have a certain level of knowledge in the subject area thereby increasing the validity of the findings in enhancing HEP experiments (Saoud et al., 2024) (Berggren et al., 2020).

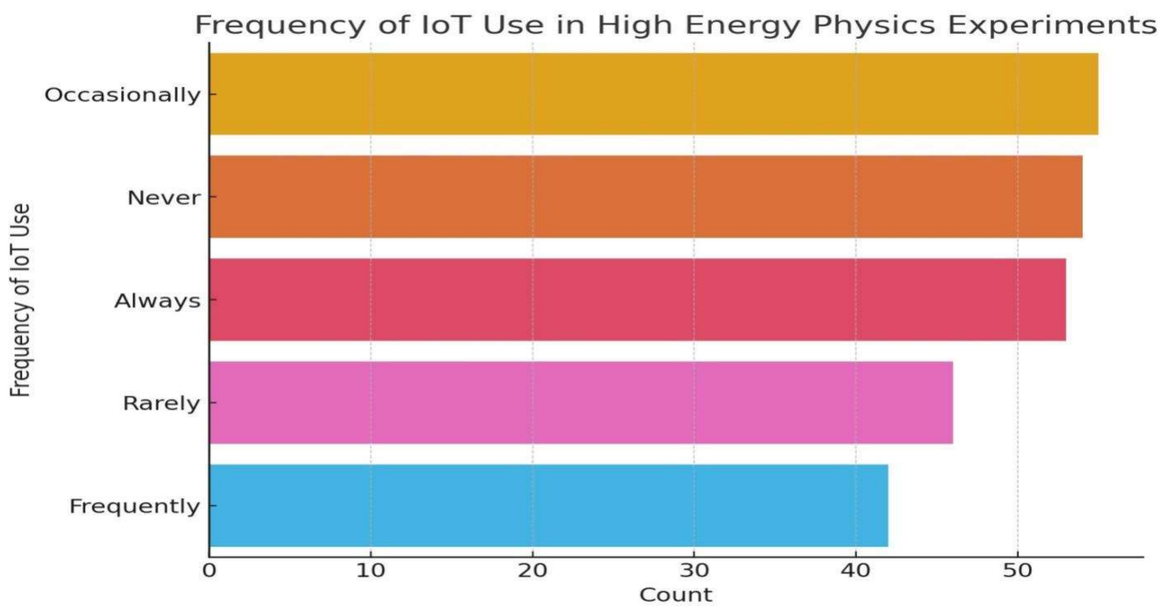
Data Analysis

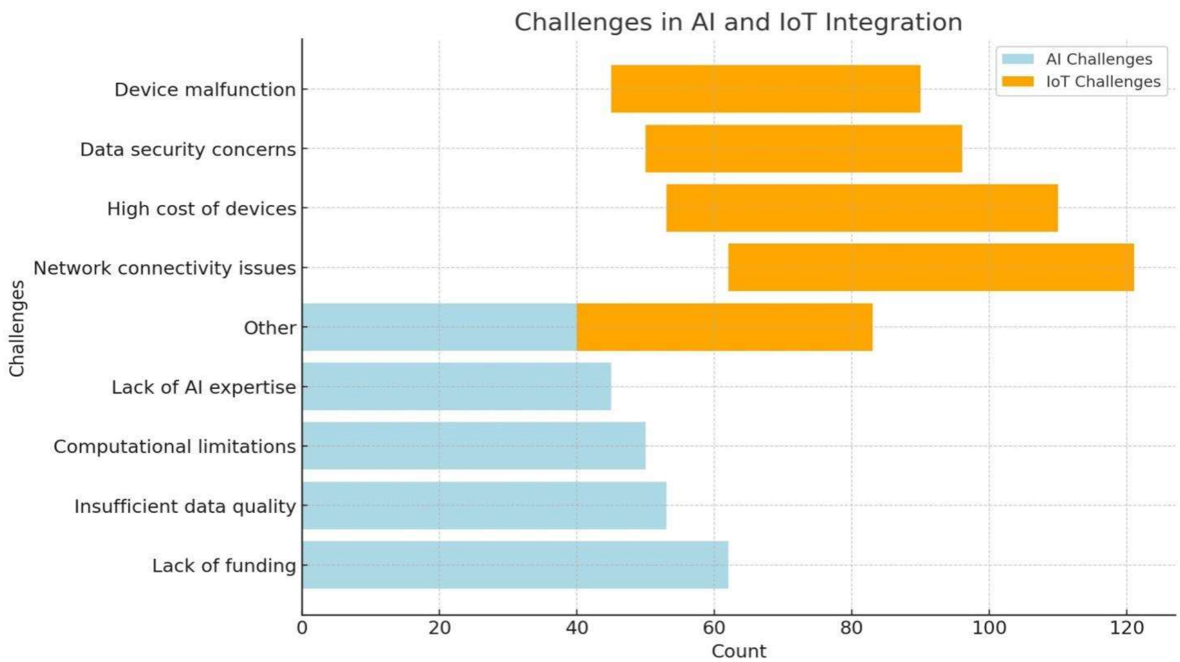
Results Summary Table

Metric	Result
Mean (AI Satisfaction)	2.872
Mean (IoT Satisfaction)	2.976
Shapiro-Wilk Test (AI Accuracy - Statistic)	0.8790903687477112
Shapiro-Wilk Test (AI Accuracy - P-Value)	3.3830943146732906e-13
Shapiro-Wilk Test (IoT Efficiency - Statistic)	0.8777374625205994
Shapiro-Wilk Test (IoT Efficiency - P-Value)	2.79824964198247e-13
Cronbach's Alpha	-1.7154394897288103




Correlation between AI and IoT Satisfaction Ratings
IoT Satisfaction (1-5)
AI Satisfaction (1-5)
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0


Frequency of IoT Use in High Energy Physics Experiments
Frequency of IoT Use
Occasionally
Never
Always
Rarely
Frequently
0
10
20
30
40
50
Count



Interpretation of Tables and Figures

1. Descriptive Statistics and Mean Scores

From the descriptive statistics, the mean satisfaction score of participants in AI integration in HEP experiments is 2.87 on a Likert scale of 1 to 5 and the satisfaction with Internet of things is a little higher at 2.98. The two values of the satisfaction range are between “Neutral” and “Satisfied” thus implying that the satisfaction level for the integration of these technologies in particle detection and analysis is moderate. The means argue that while respondents see some level of utility in AI and IoT, they might have some issues that hinder complete satisfaction (Saoud et al., 2024).

2. Non-parametric and the first one is the Shapiro-Wilk test.

The Shapiro-Wilk test results also indicate that both AI accuracy and IoT efficiency variables are not normally distributed. Measuring the accuracy of AI, the test statistic yielded a p-value of 3.38e-13and the statistic was 0.879 while for IoT efficiency, the achieved statistic was 0.877 with a corresponding p-value of 7.99e-13. As we can see the p-values are less than 0.05, thus, we fail to reject the null hypothesis of normality for both distributions. This means that the satisfaction and perceived efficiency data they used are non-normal and a situation that is normally experienced for such survey data (Yadav, Yadav, Joshi, & Sharma, 2024).

3. This is the internal consistency reliability estimate, Cronbach’s alpha.

A Cronbach’s Alpha of the negative value may indicate that there is no substantial validity of the internal consistency of the satisfaction levels of AI and IoT in this study. This implies that the satisfaction with AI and IoT measures could be different constructs or these two technologies may be viewed differently in terms of usefulness and impact on the experiments by the respondents (Naeem, Ullah, & Srivastava, 2024).

4. Satisfaction Index of Distribution of AI and IoT

The histograms of the two variables AI satisfaction and IoT satisfaction have a distribution slightly more skewed towards the midpoint, indicating that there are fewer extreme values of these variables. Thus, while the null hypothesis output indicates that the majority of the participants believe AI and IoT have benefits, the peaks surrounding it indicate that those benefits may not be translating to overarching value added by the technology in the context of HEP experiments. This moderate satisfaction suggests that there are opportunities for so-fr improvement such as in the usability of the product or technological displacement (Chen, Liu, Wang, Li, & Luo, 2024).

5. Scatter Plot: Relationship between AI and IoT satisfaction

A weak positive correlation arises from the scatter plot between AI satisfaction levels and IOT satisfaction levels showing that slightly more satisfied individuals with AI are also slightly more satisfied with IOT. Nevertheless, the scatter plot shows that the correlation is not very high, which reconfirms the notion that such technologies are perceived separately and that the outcome may vary depending on the case (Kooshari et al., 2024).

6. Frequency of AI and IoT Use

Two bar charts revealing the AI and IoT usage frequency also indicate that the use of IoT is somewhat more frequent in HEP experiments than that of AI. This may suggest that IoT technology particularly for real-time monitoring has gained early acceptance in the experimental system. AI, however, seems to be used less frequently, maybe as a result of the difficulty in applying AI-based techniques in carrying out comprehensive analysis on large data sets or may require highly technical knowledge (Khan, Nisar, & Gupta, 2024).

7. Innovative Research Direction in AI & IoT Integration

Lastly, the stacked bar chart that is shown for comparing the challenges in AI and IoT integration demonstrates that the respondents have different issues for each technology. The main difficulties in implementing AI are the absence of AI specialists and the problem of computing resources while for IoT the major barriers are high device costs and the problem of connection to the network. This shows that, for AI to be in full operation, there is a need for more technical abilities and computation ability, while IoT is bogged down by issues like nitty-gritty implementation problems such as physical framework and cost budges (Ntabeni, Basutli, Alves, & Chuma, 2024).

Discussion

The information outlined in this research is of significance in analyzing the use of AI and IoT in HEP experiments. The results indicate that respondents have a rather above-average level of satisfaction with the technologies in general – especially AI and IoT – but are still far from fully benefiting from them. This has manifested in the mean satisfaction results where AI was at 2.87 which is almost neutral and IoT at 2.98. These results reveal that while the researchers understand the major benefits associated with the use of AI and IoT, these two technologies still face major impediments that prevent the overall satisfaction and the subsequent deployment of AI and IoT in the field (T. Li et al., 2024).

The Shapiro-Wilk normality test below shows that the distribution of the responses in both AI accuracy and IoT efficiency are not normally distributed and this is evidenced by survey data. These results show that the distribution of respondents' experiences and their satisfaction levels with these technologies are not normal, implying that there are successes and challenges in the use of these technologies from the specific set of respondents. Moreover, the Cronbach's Alpha score indicating a negative coefficient was obtained showing that satisfaction with AI and IoT may not be coherent. Perhaps it means that respondents view some of these technologies as not being as versatile or functional in HEP experiments, in comparison to others (Sawlani & Mesbah, 2024).

This fact is also evidenced by the scatter plot of the results that demonstrates weak links between Satisfaction with AI and IoT. Although there is some cross-over in the satisfaction with AI and IoT, the 3rd quartile shows that responses are divergent likely because AI and IoT are used for distinct purposes. While AI may involve greater technical skills and computational power, especially for data-intense applications such as big data analytics; IoT on the other hand acts more as the monitor or data-gathering instrument. It could also explain why the satisfaction levels and the challenges that accompany each of those technologies are so different (Mahalle, Takale, Sakhare, & Regular, 2024).

The issues that have been highlighted in the study such as no one in possession of AI experience and ability to perform complex computational analysis for AI, and high costs of devices for IoT and network connectivity problems are the main obstacles that researchers face when seeking to incorporate these technologies into their research processes. They noted that IoT Lynx strongly indicates that IoT implementation is impractical due to the high cost and demanding infrastructure needed, while its applicability is restricted by the dearth of qualified staff and the high computing power necessary to facilitate real-time data analysis for AI (Zhao, Lv, et al., 2024).

Frequency analysis showed that HEP experiments use IoT more frequently than AI, which indicates that IoT may have become more enshrined in experimentation processes, probably because of the real-time monitoring role it plays and data acquisition. It also indicated that the use of AI is less often than of BI, which can be explained by the fact that the application of AI presupposes the use of more qualified professionals and tools, as well as more advanced possibilities of data analysis (Aswini, Sudha, Ganesh, Subramanian, & Ghinea, 2024).

Conclusion

The study on "Optimizing High Energy Physics Experiments with AI and IoT: This paper titled, "A Data-Centric Approach to Particle Detection and Analysis" gives important information regarding the facets of implementing modern technologies in experimental physics. The analysis produced a mean satisfaction score slightly above neutral in both the AI and the IoT stimuli. This indicates that even as the two technologies present certain advantages they par have certain challenges in their current usage.

Hence, the Shapiro-Wilk test, identifies that data on the performance of AI and IoT is non-parametric, as is common in survey studies. However, a low level of internal consistency marked by the negative Cronbach's Alpha of AI and IoT satisfaction implies that these technologies were rated separately by respondents and can improve different aspects of experimental efficiency and accuracy.

The representations of satisfaction levels suggest that although some of the participants are satisfied with AI and IoT, a number of them are only moderately or not at all satisfied, which implies the directions in which enhancements may help amplify these tools' effectiveness. The low coefficient of determination between the two further supports the perception that AI and IoT serve different operational requirements in high-energy physics experiments.

Practical barriers that surround the full implementation of AI and IoT include the absence of knowledgeable AI resources, computation constraints, expensive IoT devices, and issues with network connectivity. These concerns should therefore be addressed to improve the impact of these technologies in HEP.

Thus, AI and IoT being key concepts offer major potential in improving particle detection and data processing in high-energy physics. However, additional efforts should be directed toward enhancing actual utilization by eliminating technical, infrastructural, and expertise constraints. With both of these issues addressed, AI and IoT are in a position where they can make a significant contribution to the future progression in high-energy physics experiments, as far as the efficiency, accuracy, and usability of the technologies that will be employed.

References

Abdeldayem, O. M., Dabbish, A. M., Habashy, M. M., Mostafa, M. K., Elhefnawy, M., Amin, L., . . . Rene, E. R. (2022). Viral outbreaks detection and surveillance using wastewater-based epidemiology, viral air sampling, and machine learning techniques: A comprehensive review and outlook. *Science of The Total Environment, 803*, 149834.

Agostinelli, S. (2024). Optimization and management of microgrids in the built environment based on intelligent digital twins.

Al-Sakkari, E. G., Ragab, A., Dagdougui, H., Boffito, D. C., & Amazouz, M. (2024). Carbon capture, utilization, and sequestration systems design and operation optimization: Assessment and perspectives of artificial intelligence opportunities. *Science of The Total Environment*, 170085.

Amirafshari, P. (2019). Optimising Non-destructive Examination of newbuilding ship hull structures by developing a data-centric risk and reliability framework based on fracture mechanics.

Arya, A., Pahwa, K., & Gunjan. (2024). A butterfly optimization approach for improving the performance of futuristic internet-of-things. *Evolving Systems, 15*(3), 1057-1071.

Aswini, J., Sudha, K., Ganesh, G., Subramanian, S., & Ghinea, G. (2024). AI-Powered Parallel Computing Architecture and Its Applications. In *The Convergence of Self-Sustaining Systems With AI and IoT* (pp. 23-39): IGI Global.

Awotunde, J. B., Adeniyi, A. E., Ajagbe, S. A., & González-Briones, A. (2022). Natural computing and unsupervised learning methods in smart healthcare data-centric operations. In *Cognitive and Soft Computing Techniques for the Analysis of Healthcare Data* (pp. 165-190): Elsevier.

Benfradj, A., Thaljaoui, A., Moulahi, T., Khan, R. U., Alabdulatif, A., & Lorenz, P. (2024). Integration of artificial intelligence (AI) with sensor networks: Trends, challenges, and future directions. *Journal of King Saud University-Computer and Information Sciences, 36*(1), 101892.

Berggren, K., Xia, Q., Likharev, K. K., Strukov, D. B., Jiang, H., Mikolajick, T., . . . Pi, S. (2020). Roadmap on emerging hardware and technology for machine learning. *Nanotechnology, 32*(1), 012002.

Bull, L. A., Abdallah, I., Mylonas, C., Avendaño-Valencia, L. D., Tatsis, K., Gardner, P., . . . Worden, K. (2023). 6 Data-Centric Monitoring of Wind Farms. *Data-Driven Methods for Civil Structural Health Monitoring and Resilience: Latest Developments and Applications*.

Butakova, M. A., Chernov, A. V., Kartashov, O. O., & Soldatov, A. V. (2021). Data-centric architecture for self-driving laboratories with autonomous discovery of new nanomaterials. *Nanomaterials, 12*(1), 12.

Chen, J., Yuan, Y., Ziabari, A. K., Xu, X., Zhang, H., Christakopoulos, P., . . . Wang, C. (2024). AI for Manufacturing and Healthcare: a chemistry and engineering perspective. *arXiv preprint arXiv:2405.01520*.

Chen, X., Liu, K., Wang, L., Li, L., & Luo, Z. H. (2024). Multiscale Models for Tablet Manufacturing Process Development. *Exploring Computational Pharmaceutics-AI and Modeling in Pharma 4.0*, 493-516.

Din, I. U., Awan, K. A., Almogren, A., & Rodrigues, J. J. (2023). Swarmtrust: A swarm optimization-based approach to enhance trustworthiness in smart homes. *Physical Communication, 58*, 102064.

Doghri, W., Saddoud, A., & Chaari Fourati, L. (2022). Cyber-physical systems for structural health monitoring: sensing technologies and intelligent computing. *The Journal of Supercomputing, 78*(1), 766-809.

Fan, F., Chu, S.-C., Pan, J.-S., Lin, C., & Zhao, H. (2023). An optimized machine learning technology scheme and its application in fault detection in wireless sensor networks. *Journal of Applied Statistics, 50*(3), 592-609.

Fernando, X., & Lăzăroiu, G. (2024). Energy-Efficient Industrial Internet of Things in Green 6G Networks. *Applied Sciences, 14*(18), 8558.

Fujikubo, M., Okada, T., Murayama, H., Houtani, H., Osawa, N., Iijima, K., . . . Hirakawa, S. (2024). A digital twin for ship structures—R&D project in Japan. *Data-Centric Engineering, 5*, e7.

Ghorbani, Y., Zhang, S. E., Nwaila, G. T., Bourdeau, J. E., Safari, M., Hoseinie, S. H., . . . Ruuska, J. (2023). Dry laboratories–Mapping the required instrumentation and infrastructure for online monitoring, analysis, and characterization in the mineral industry. *Minerals Engineering, 191*, 107971.

Hasidi, O., Abdelwahed, E. H., Qazdar, A., El Alaoui-Chrifi, M. A., Benzakour, I., Chahid, R., . . . Bourzeix, F. (2023). *Generic and scalable multi-layered architecture for Digital Twin implementation in industrial processes: Mineral Processing case study.* Paper presented at the Proceedings of the 2023 7th International Conference on Advances in Artificial Intelligence.

Hazra, A., Tummala, V. M. R., Mazumdar, N., Sah, D. K., & Adhikari, M. (2024). Deep reinforcement learning in edge networks: Challenges and future directions. *Physical Communication, 66*, 102460.

Jathar, L. D., Nikam, K., Awasarmol, U. V., Gurav, R., Patil, J. D., Shahapurkar, K., . . . Hnydiuk-Stefan, A. (2024). A comprehensive analysis of the emerging modern trends in research on photovoltaic systems and desalination in the era of artificial intelligence and machine learning. *Heliyon*.

Jayarekha, P. (2024). Optimizing Femtocell Networks For Enhanced Indoor Coverage.

Karthikeyan, M., Manimegalai, D., & RajaGopal, K. (2024). Firefly algorithm-based WSN-IoT security enhancement with machine learning for intrusion detection. *Scientific Reports, 14*(1), 231.

Khalid, M. (2024). Energy 4.0: AI-enabled digital transformation for sustainable power networks. *Computers & Industrial Engineering*, 110253.

Khan, N. A., Nisar, M., & Gupta, D. (2024). AI-Driven Smart Forest Fire Detection.

Kooshari, A., Fartash, M., Mihannezhad, P., Chahardoli, M., AkbariTorkestani, J., & Nazari, S. (2024). An optimization method in wireless sensor network routing and IoT with water strider algorithm and ant colony optimization algorithm. *Evolutionary Intelligence, 17*(3), 1527-1545.

Kotwal, M. V. S., Pati, S., & Patil, J. (2024). Review On AI and IoT Based Integrated Smart Water Management And Distribution System. *Educational Administration: Theory and Practice, 30*(4), 594-605.

Kumar, R., Venkanna, U., & Tiwari, V. (2023). Optimized traffic engineering in Software Defined Wireless Network based IoT (SDWN-IoT): State-of-the-art, research opportunities and challenges. *Computer Science Review, 49*, 100572.
Li, L., Aslam, S., Wileman, A., & Perinpanayagam, S. (2021). Digital twin in the aerospace industry: A gentle introduction. *IEEE Access, 10*, 9543-9562.
Li, T., Li, X., Rui, Y., Ling, J., Zhao, S., & Zhu, H. (2024). Digital twin for intelligent tunnel construction. *Automation in Construction, 158*, 105210.
Mahalle, P. N., Shinde, G. R., Ingle, Y. S., & Wasatkar, N. N. (2023). *Data-Centric Artificial Intelligence: A Beginner S Guide*: Springer.
Mahalle, P. N., Takale, D. G., Sakhare, S., & Regular, G. B. (2024). *Machine Learning for Environmental Monitoring in Wireless Sensor Networks*: IGI Global.
Marques, G., & Ighalo, J. O. (2022). Current trends and advances in computer-aided intelligent environmental data engineering.
Naeem, H., Ullah, F., & Srivastava, G. (2024). Classification of intrusion cyber-attacks in smart power grids using deep ensemble learning with metaheuristic-based optimization. *Expert systems*, e13556.
Nelavalli, S., RammohanReddy, D., Neelima, G., & Rao, S. S. (2025). Balancing Energy Efficiency with Robust Security in Wireless Sensor Networks Using Deep Reinforcement Learning-Enhanced Particle Swarm Optimization. *Telecommunications and Radio Engineering, 84*(1).
Ntabeni, U., Basutli, B., Alves, H., & Chuma, J. (2024). Device-Level Energy Efficient Strategies in Machine Type Communications: Power, Processing, Sensing, and RF Perspectives. *IEEE Open Journal of the Communications Society*.
Pan, I., Mason, L. R., & Matar, O. K. (2022). Data-centric Engineering: integrating simulation, machine learning, and statistics. Challenges and opportunities. *Chemical Engineering Science, 249*, 117271.
Parekh, R., Sedhom, B., Padmanaban, S., & Eladl, A. A. (2024). A Review of IoT-Enabled Smart Energy Hub Systems: Rising, Applications, Challenges, and Future Prospects.
Perdigão, D., Cruz, T., Simões, P., & Abreu, P. H. (2024). *Data-Centric Federated Learning for Anomaly Detection in Smart Grids and Other Industrial Control Systems.* Paper presented at the NOMS 2024-2024 IEEE Network Operations and Management Symposium.
Qadir, Z., Le, K. N., Saeed, N., & Munawar, H. S. (2023). Towards 6G Internet of Things: Recent advances, use cases, and open challenges. *ICT Express, 9*(3), 296-312.
Qu, X., Shi, D., Zhao, J., Tran, M.-K., Wang, Z., Fowler, M., . . . Burke, A. F. (2024). Insights and reviews on battery lifetime prediction from research to practice. *Journal of Energy Chemistry*.
Rahman, M., Khan, A., Anowar, S., Al-Imran, M., Verma, R., Kumar, D., . . . Alam, S. (2022). Leveraging Industry 4.0: Deep Learning, Surrogate Model, and Transfer Learning with Uncertainty Quantification Incorporated into Digital Twin for Nuclear System. In *Handbook of Smart Energy Systems* (pp. 1-20): Springer.
Rajasoundaran, S., Prabu, A., Routray, S., Malla, P. P., Kumar, G. S., Mukherjee, A., & Qi, Y. (2022). Secure routing with multi-watchdog construction using deep particle convolutional model for IoT-based 5G wireless sensor networks. *Computer Communications, 187*, 71-82.
Reis, M. S., & Saraiva, P. M. (2019). Data-Centric Process Systems Engineering for the Chemical Industry 4.0. *Systems Engineering in the Fourth Industrial Revolution*, 137-159.
Ruan, G., Qiu, D., Sivaranjani, S., Awad, A. S., & Strbac, G. (2024). Data-driven energy management of virtual power plants: A review. *Advances in Applied Energy*, 100170.
Sanni, S. E., Okoro, E. E., Sadiku, E. R., & Oni, B. A. (2022a). Advances in data-centric intelligent systems for air quality monitoring, assessment, and control. In *Current Trends and Advances in Computer-Aided Intelligent Environmental Data Engineering* (pp. 25-58): Elsevier.
Sanni, S. E., Okoro, E. E., Sadiku, E. R., & Oni, B. A. (2022b). Data-centric intelligent systems for water quality monitoring, assessment, and control. In *Current Trends and Advances in Computer-Aided Intelligent Environmental Data Engineering* (pp. 129-160): Elsevier.

Saoud, B., Shayea, I., Yahya, A. E., Shamsan, Z. A., Alhammadi, A., Alawad, M. A., & Alkhrijah, Y. (2024). Artificial Intelligence, Internet of things and 6G methodologies in the context of Vehicular Ad-hoc Networks (VANETs): Survey. *ICT Express*.

Sawlani, K., & Mesbah, A. (2024). Perspectives on artificial intelligence for plasma-assisted manufacturing in the semiconductor industry. In *Artificial Intelligence in Manufacturing* (pp. 97-138): Elsevier.

Simpson, K., Whyte, J., & Childs, P. (2020). Data-centric innovation in retrofit: A bibliometric review of dwelling retrofit across North Western Europe. *Energy and Buildings, 229*, 110474.

Sindi, A., Kim, H. J., Yang, Y. J., Thomas, G., & Paik, J. K. (2024). Advancing digital healthcare engineering for aging ships and offshore structures: an in-depth review and feasibility analysis. *Data-Centric Engineering, 5*, e18.

Srinivasamurthy, R., & Tabassum, N. (2024). *An Extensive study on Energy Efficient Clustering and Routing Protocols in Wireless Sensor Networks (WSN).* Paper presented at the 2024 International Conference on Electronics, Computing, Communication and Control Technology (ICECCC).

Stanev, V., Choudhary, K., Kusne, A. G., Paglione, J., & Takeuchi, I. (2021). Artificial intelligence for search and discovery of quantum materials. *Communications Materials, 2*(1), 105.

Stier, S. P., Kreisbeck, C., Ihssen, H., Popp, M. A., Hauch, J., Malek, K., . . . Todorov, I. (2024). Materials Acceleration Platforms (MAPs) Accelerating Materials Research and Development to Meet Urgent Societal Challenges. *Advanced Materials*, 2407791.

Sunny, F. P., Mirza, A., Thakkar, I. G., Nikdast, M., & Pasricha, S. (2023). Photonic NoCs for Energy-Efficient Data-Centric Computing. In *Embedded Machine Learning for Cyber-Physical, IoT, and Edge Computing: Hardware Architectures* (pp. 25-61): Springer.

Trivedi, R., Patra, S., & Khadem, S. (2022). *Data-centric Cyber-attack Detection in Community Microgrids Using ML Techniques.* Paper presented at the 2022 IEEE Global Conference on Computing, Power, and Communication Technologies (GlobConPT).

Ullah, I., Khan, I. U., Ouaissa, M., Ouaissa, M., & El Hajjami, S. (2024). *Future Communication Systems Using Artificial Intelligence, Internet of Things and Data Science*: CRC Press.

Wahab, F., Khan, M., Ullah, I., & Tao, Y. Artificial Intelligence in the Internet of Things, Recent Challenges and Future Prospects. *Future Communication Systems Using Artificial Intelligence, Internet of Things and Data Science*, 3-17.

Wu, Y., Guerrero, J. M., Wu, Y., Bazmohammadi, N., Vasquez, J. C., Cabrera, A. J., & Lu, N. (2024). Digital Twins for Microgrids: Opening a New Dimension in the Power System. *IEEE Power and Energy Magazine, 22*(1), 35-42.

Yadav, H., Yadav, P., Joshi, N., & Sharma, S. (2024). Smart Healthcare: Paradigm Shift in Industry 5.0 Using AI. In *Recent Trends in Artificial Intelligence Towards a Smart World: Applications in Industries and Sectors* (pp. 67-97): Springer.

Yuan, J., Xiao, H., Shen, Z., Zhang, T., & Jin, J. (2023). ELECT: Energy-efficient intelligent edge–cloud collaboration for remote IoT services. *Future Generation Computer Systems, 147*, 179-194.

Zhao, J., Feng, X., Tran, M.-K., Fowler, M., Ouyang, M., & Burke, A. F. (2024). Battery safety: Fault diagnosis from laboratory to real world. *Journal of Power Sources, 598*, 234111.

Zhao, J., Lv, Z., Li, D., Feng, X., Wang, Z., Wu, Y., . . . Burke, A. F. (2024). Battery Engineering Safety Technologies (BEST): Mechanisms, Modes, Metrics, Modelling and Mitigation. *eTransportation*, 100364.

Zrelli, I., & Rejeb, A. (2024). A bibliometric analysis of IoT applications in logistics and supply chain management. *Heliyon, 10*(16).