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Editorial

This issue brings together six studies that embody the convergence of technology, engineering, and data-driven decision-making to solve pressing challenges in education, industry, energy, and commerce. Each contribution underscores the role of intelligent systems in shaping more responsive, efficient, and forward-looking environments—whether through targeted skill development, improved semiconductor behavior analysis, operational frameworks for AI integration, or optimized approaches to renewable energy and customer engagement. Together, these works reveal not only technical depth but also a consistent emphasis on actionable outcomes and system-level transformation.

One study focuses on the integration of generative artificial intelligence in higher education to address the gap in students' visual literacy skills. Using a robust quantitative framework, the research compares traditional instructional methods with AI-enhanced learning environments across four universities. The analysis anchored in post-test performance, observation, and student feedback reveals that a significant portion of learners struggle with translating visual information into meaningful outputs. By leveraging generative tools, the study demonstrates improved comprehension and design proficiency, offering a data-backed case for curriculum innovation. These findings highlight the need to integrate contemporary technologies into educational models to meet evolving cognitive demands in the digital era [1].

Another article examines the electrical behavior of AlGaIn/GaN high electron mobility transistors under high-frequency conditions. Specifically, it investigates current collapse recovery times and temperature-dependent transient responses. The experimental results expose a unique relationship between strain-induced defects and electron trapping behaviors influenced by the inverse piezoelectric effect. Observations of variable activation energy further illuminate the dynamics of charge transport and defect states, contributing to a deeper understanding of semiconductor reliability. These insights are vital for advancing GaN-based device performance, particularly in applications that require high efficiency and thermal stability [2].

A third contribution presents a sector-specific framework designed to assess the readiness of shipbuilding enterprises to adopt artificial intelligence. Based on a comparative analysis of leading shipbuilders and a review of more than 50 AI maturity models, the proposed structure introduces a four-tiered roadmap encompassing dimensions like organizational culture, resilience, customer integration, and production efficiency. This approach not only benchmarks technological adoption but links maturity levels with quantifiable outcomes such as production scalability and delivery performance. The model offers strategic recommendations for public-private coordination, skill development, and policy alignment, serving as a critical guide for accelerating digital transformation in a historically traditional sector [3].

In a separate investigation, researchers explore a new model for grid-interactive solar energy compensation by leveraging distributed energy resources in cooperative arrangements. Using cooperative game theory, the model replaces legacy net metering mechanisms with performance-based pricing strategies. These pricing schemes are aligned with energy arbitrage and peak load reduction objectives, allowing utility-led coordination of customer-owned resources like rooftop solar and battery systems. The framework introduces mechanisms such as a Grid Services Set and Grid Services Rider to formalize engagement, while an optimization algorithm manages real-time resource dispatch across operational and market contexts. This study contributes a structured, scalable alternative to grid management and renewable energy integration that supports flexibility, resilience, and equitable value sharing [4].

Another study delves into artificial intelligence applications for fault detection in photovoltaic systems, with an emphasis on explainability and active learning. While AI has been employed for

performance monitoring, this research highlights a critical underutilization of transparent methods that can aid adoption by engineers and stakeholders. Through bibliometric mapping and case analysis, the research identifies key contributors and methodologies, particularly those emerging from China's research institutions. The findings advocate for deeper integration of human expertise in labeling and model training, enabling systems that are not only technically sound but also intuitively interpretable. This shift is essential for enhancing long-term reliability and adoption in solar technology infrastructures [5].

Finally, an extensive machine learning-based analysis is conducted on customer response data from a retail marketing campaign. By employing models such as Random Forest, SVC, KNN, and logistic regression, the research dissects behavioral trends and campaign effectiveness. Pre-processing steps ensured data integrity, while exploratory data analysis revealed correlations between marketing efforts and consumer actions. The insights derived from model evaluation suggest that predictive analytics can uncover non-obvious patterns, informing decisions on campaign targeting and resource allocation. This work consolidates scattered approaches in previous literature, offering a cohesive methodology for retail stakeholders seeking to leverage AI for competitive advantage [6].

This collection of research illustrates how domain-specific innovations—guided by rigorous methodology and strategic foresight—can drive transformation across disciplines. Whether enhancing student skills, refining industrial processes, rethinking energy pricing, or decoding consumer behavior, the studies presented offer practical blueprints for intelligent, sustainable progress. As industries and institutions face rising complexity and digital demands, the value of targeted, explainable, and responsive solutions has never been clearer.

References:

- [1] A. Kristanto, U. Dewi, D. Fitria Murad, Y. iati, S. Dewiki, T. Sevi Nurmanita, "Utilization of Generative Artificial Intelligence to Improve Students' Visual Literacy Skills," *Advances in Science, Technology and Engineering Systems Journal*, 10(3), 1–8, 2025, doi:10.25046/aj100301.
- [2] J. Takeda, S. Sano, H. Taguchi, "Characteristics of crystal defects due to the inverse piezoelectric effect in aluminum gallium nitride / gallium nitride high electron mobility transistors," *Advances in Science, Technology and Engineering Systems Journal*, 10(3), 10–3, 2025, doi:10.25046/aj100302.
- [3] D. Salian, G. Sandeep Nadella, G. Elkhodari, R. Neouchi, S. Brown, E. Babulak, R. Sbeit, "The impact of digitalization on shipbuilding as measured by Artificial Intelligence (AI) maturity models: a systematic review," *Advances in Science, Technology and Engineering Systems Journal*, 10(3), 2025, doi:10.25046/aj100303.
- [4] F. Farhidi, Y. Baghzouz, M. Rusakov, "Cooperative Game Theory for Grid Service Pricing: A Utility-Centric Approach," *Advances in Science, Technology and Engineering Systems Journal*, 10(3), 21–28, 2025, doi:10.25046/aj100304.
- [5] F. Dieudonné Mengue, V. Rostand Nwokam, A.S. Tewa Kammogne, R. Yamapi, M. Ngossaha Justin, B. Tsakou Samuel, B. Kamsu Fogue, "Explainable AI and Active Learning for Photovoltaic System Fault Detection: A Bibliometric Study and Future Directions," *Advances in Science, Technology and Engineering Systems Journal*, 10(3), 29–44, 2025, doi:10.25046/aj100305.
- [6] khawla Alhasan, "Predictive Analytics in Marketing: Evaluating its Effectiveness in Driving Customer Engagement," *Advances in Science, Technology and Engineering Systems Journal*, 10(3), 45–51, 2025, doi:10.25046/aj100306.

Editor-in-chief

Prof. Hamid Mattiello

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Utilization of Generative Artificial Intelligence to Improve Students' Visual Literacy Skills

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ABSTRACT

This study aims to examine the impact of Gen AI utilization on students' visual literacy skills using a quantitative approach and data instruments in the form of post-test scores of the control class and experimental class which are analyzed to measure the effectiveness of GEN AI in improving students' visual literacy skills at four universities. Data processing is carried out through three stages of testing, namely the normality test using Shapiro-Wilk, the homogeneity test of variance with Levene, and the independent sample test to compare the results between two groups of students with questionnaire instruments, observation guidelines, and interviews. The data is processed using a t-test to determine the average difference between groups, especially between the control class that applies conventional learning methods and the experimental class that utilizes GEN AI. The results of the needs analysis show that around 65% of students still have low visual literacy skills based on the quality of graphic media products produced by students. These findings indicate an urgent need to improve visual literacy skills among students, especially in the context of utilizing modern technology such as GEN AI. This research makes a significant contribution to the development of a curriculum that is more responsive to the needs of visual literacy in the digital era, as well as encouraging the integration of technology in the learning process and is expected to be a reference for the development of more innovative and effective learning strategies to improve students' visual literacy skills in higher education.

1. Introduction

Generative AI (GEN AI) has become a highly relevant and widely discussed topic in recent years, especially with the rapid advancement of artificial intelligence technology. Various studies have shown a significant relationship between the application of GEN AI and the development of literacy skills among students and teachers, both at the elementary and tertiary levels. With the advancement of AI technology, we are now entering a new era known as AI literacy, where understanding and interacting with AI systems becomes an essential skill in [1] for further review. In this

context, "literacy" does not only include knowledge of how AI works, but also involves the ability to interact effectively with this technology, exploit the potential it offers, and critically evaluate the results and implications of using AI.

AI literacy covers various aspects, including an understanding of the algorithms underlying AI, the ability to provide appropriate input, and skills in interpreting and modifying the output produced by AI systems. This is becoming increasingly important considering that AI is now used in various fields, from education to the creative industry. Recent research suggests that as we move from the descriptive AI era to the generative AI era, there is an increase in the development of emerging literacy skills [2], [3]. In this context, the study aims to explore the literacy skills of students

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across campus, which include the ability to provide appropriate input to generative AI, interpret the resulting output, and modify commands to achieve desired outcomes [4]. In [4], the authors argue that in the GEN AI era, a new form of literacy is needed known as “fast literacy”. This fast literacy includes the ability to generate accurate commands as input to an AI system, interpret the resulting output, and refine the commands iteratively to achieve desired outcomes. These skills are especially important in the context of today’s AI deployments, where the speed and accuracy of interacting with AI systems can influence the outcomes obtained. On the other hand, research by [5] shows that generation Z generally has a positive view of the potential benefits offered by GEN AI, including increased productivity, efficiency, and more personalized learning. They show a strong desire to utilize GEN AI in various aspects of education, such as in the development of more interactive and adaptive teaching materials. Meanwhile, educators from generations X and Y are also aware of the potential benefits that GEN AI can provide, although they may have different approaches in integrating this technology into the learning process. These findings emphasize the need to develop evidence-based guidelines and policies for the integration of GEN AI in education. This includes instilling critical thinking skills and digital literacy among students, as well as promoting the responsible use of GEN AI technology in the context of higher education. Thus, it is important to create an educational environment that supports the development of literacy skills that are relevant to current technological advances. In addition, educational institutions need to provide training for educators to understand and implement GEN AI effectively in their curricula, so as to maximize the potential of this technology to enhance students' learning experiences. Overall, AI literacy and skills related to GEN AI are becoming increasingly important in this ever-evolving world. By understanding and mastering these skills, students will not only be better prepared to face future challenges but will also be able to contribute positively to a society that is increasingly influenced by technology. Therefore, the integration of GEN AI in education must be done carefully and strategically, taking into account the needs and context of students and the learning objectives to be achieved.

Smallino explains that visual literacy skills can be developed through two approaches, namely input strategies and output strategies. (1) Input strategy is the ability to interpret, understand and read or analyze visual messages such as images, colors, shapes and various other visual elements, (2) Output strategy is the ability to encode, create, design, design visual messages that are implemented in the development of learning media. When associated with Marcel's communication theory (2013), the encoding and decoding process is the most important concept in the birth of the message reception theory, namely encoding and decoding. Encoding is the process of creating messages that are in accordance with certain codes, while decoding is the process of using codes to interpret messages. Based on this theory, visual literacy skills can be defined as the technical ability to encode or produce, create, create visual symbols and decoding is the ability to interpret, read visual symbols. Literacy is not a human characteristic since birth like talent but is an ability that can be learned. The more often you do encoding and decoding of visual messages, the more your visual literacy skills will increase. It is hoped that students have adequate visual literacy skills as

developers of learning media. Based on the background description, this study aims to determine the effect of the use of GEN AI on students' visual literacy skills. Thus, the research question is how the use of GEN AI can improve students' visual literacy skills.

2. Related Work

2.1. Generative AI

Generative AI (GEN AI) is currently trending in education, where this technology is applied in learning to overcome various challenges faced by students and teachers. GEN AI helps improve student performance by providing more relevant feedback, accelerating the learning process, and increasing information retention. This trend is growing rapidly in the world of education, used to train students to improve their learning and performance. For example, students can use GEN AI to complete assignments, and GEN AI-based learning can also be applied in the classroom. Machine learning algorithms are designed to learn from data and make predictions, so GEN AI can be used in a variety of applications, from medical diagnosis to financial analysis. As student performance improves, GEN AI provides timely information based on the student's knowledge and experience.

Chat GPT has several understandings according to its needs. Chat GPT can be interpreted as a language model [6] that can analyze and generate text based on deep learning techniques or text in NLP and is considered human-like text [7].

2.2. Visual Literacy Skill

The term "visual literacy skills" refers to an individual's ability to understand and give meaning to information presented in the form of images or visual elements. This concept was first introduced by John Debes in 1969, who was one of the founders of the International Visual Literacy Association (IVLA). Debes defined visual literacy skills as the ability to interpret and create meaning from visual information. In [8], the authors emphasize the importance of this skill for learners in the 21st century, so it must be an integral part of the education system. And, in [9], the author explains that visual literacy skills include the ability to understand, use, and create images effectively. Meanwhile in [10], the researchers describes this skill as the ability to read, interpret, and understand information presented in the form of images or graphs, as well as the ability to transform this information into visual representations through visual thinking. Argue that visual literacy skills include the ability to interpret and produce or select images that can communicate ideas and concepts in [11]. They emphasize that students who have visual reading skills must be able to understand the objects they see and create visual representations to convey the intended concept.

According to [11], the visual literacy is the competence in interpreting and conveying visual messages. In an article on visual literacy skills, emphasized that students need to learn to communicate using visual language and understand terms such as composition, foreground, and background in order to interpret visual messages well [10]. Students are expected to be able to describe what they see and think critically about images, and apply this critical thinking to text. In [11], the authors added that visual literacy skills include a variety of abilities that enable individuals

The steps of the learning activity are sequential, starting with the introduction, core and conclusion.	5
The learning scenario reflects the scientific method (observing, asking, reasoning, trying and communicating)	6
Suitability of assessment techniques with learning indicators/objectives	7
Completeness of assessment instruments (questions, keys, scoring guidelines)	8

Table 3: Visual Literacy Skill Assessment Instrument Grid

Variable	Sub Variable	Indicator
Visual Literacy Skill	Visual reading	a. Able to interpret visuals according to their meaning correctly
		b. Able to analyze visuals accurately
	Creating visuals	a. Able to create a match between message design and visualization
		b. Able to apply visual principles
		c. Able to use appropriate illustrations
		d. Able to use appropriate typography
		e. Able to use appropriate color composition
		f. Able to use appropriate layout

3.4. Data Analysis Techniques

Test Result Analysis do by three step as:

a. Homogeneity Test

Homogeneity testing is used to see similarities in several parts of the sample and to find out the variation of one group with another group. The formula for the homogeneity test of variance is as follows:

$$\vartheta^2 = \frac{\sum X^2 - \frac{(\sum X)^2}{N}}{N} \tag{2}$$

note : ϑ^2 = Variance

b. Normality Test

To find out whether the research data used is normally distributed or not, namely by using the normality test. There are several normality test techniques, but this study to test the normality of the researcher's data uses the chi-square formula, as follows:

$$X^2 = \sum \frac{(f_o - f_h)^2}{f_h} \tag{3}$$

note :

X^2 = Chi- square

f_o = Observed frequencies

f_h = Expected frequency

c. T-test

The t-test is applied to analyze the mean difference between two groups, namely the control group and the experimental group. The purpose of this test is to verify the results of the pre-test and post-test in each class. The formula used in the t-test is as follows:

$$= \frac{M_y - M_x}{\sqrt{\left(\frac{\sum y + \sum x^2}{N_y + N_x - 2}\right) - \left(\frac{1}{N_y} + \frac{1}{N_x}\right)}} \tag{4}$$

Keterangan :

M_x : Mean of control group

M_y : Mean of the experimental group

4. Result

This study uses a quantitative approach with a Quasi Experimental Design and Non Equivalent Control Group Design. Data were collected from two groups of students, namely the experimental group that used the GEN AI generator tool in the Canva graphic design platform, and the control group that did not use the tool.

4.1. Research Data Description

The research data were obtained from 80 students who were divided into two groups, each consisting of 40 students. The experimental group attended lectures utilizing the GEN AI generator tool for 4 weeks with meetings twice a week, while the control group attended lectures conventionally. The data used in this study included the post-test results of both groups, namely the experimental group and the control group. This study was conducted at four universities, namely Universitas Negeri Surabaya, Universitas Terbuka Surabaya, Universitas Terbuka Jakarta, and Bina Nusantara University.

The data can be accessed online via the following link: <https://zenodo.org/records/15350813>. Data collection and processing adhere to research ethics standards and open data principles to ensure the validity and reliability of the findings.

4.2. Data analysis

Before conducting the hypothesis analysis, prerequisite tests were conducted including normality tests and homogeneity tests. These prerequisite tests are important to ensure that the data meets the requirements of the statistical analysis used. Then a hypothesis test was conducted using an independent sample t-test to determine the differences in the post-test results between the control group and the experimental group.

Table 4: Normality Assessment Using Shapiro-Wilk Test by University and Group

University	Group	Shapiro-Wilk Statistic	df	Sig.
Universitas Negeri Surabaya	Control	0.952	40	0.088
	Experiment	0.945	40	0.051
	Control	0.949	40	0.364

Universitas Terbuka Surabaya	Experiment	0.970	40	0.072
Universitas Terbuka Jakarta	Control	0.958	40	0.148
	Experiment	0.950	40	0.074
Bina Nusantara University	Control	0.961	40	0.185
	Experiment	0.985	40	0.856

The normality test was conducted using the Shapiro-Wilk test. Based on the table 4, all university have the sig. value in both groups is greater than 0.05, so it can be concluded that the data is normally distributed. Then the homogeneity test is carried out to ensure that the variance between the two groups is homogeneous.

Table 5: Homogeneity Test Results using Variable Post-test

University	Levene Statistic	df1	df2	Sig.
Universitas Negeri Surabaya	0.952	1	78	0.163
Universitas Terbuka Surabaya	1.268	1	78	0.264
Universitas Terbuka Jakarta	2.586	1	78	0.112
Bina Nusantara University	7.624	1	78	0.007

Based on table 5, it can be seen that:

1. Universitas Negeri Surabaya, the results of the Levene test show that the assumption of homogeneity of variance is met with a sig. value of 0.163 which is greater than 0.05. Hypothesis testing uses an independent sample t-test to determine the difference in the post-test results between the control group and the experimental group.
2. Universitas Terbuka Surabaya, the results of the Levene test indicate that the assumption of homogeneity of variance has been met, with a significance value of 0.264 which exceeds the threshold of 0.05. To test the hypothesis, an independent sample t-test is used to determine the difference in the post-test results between the control group and the experimental group.
3. Universitas Terbuka Jakarta, the assumption of homogeneity of variance is met with a significant GEN AI value of 0.112 which is greater than 0.05. Hypothesis testing uses an independent sample t-test to determine the difference in the post-test results between the control group and the experimental group.
4. Bina Nusantara University, the results of the Levene test indicate that the assumption of homogeneity of variance is met, with a significance value of 0.112 which is greater than 0.05. For hypothesis testing, an independent sample t-test is

used to identify differences in post-test results between the control group and the experimental group.

Table 6: T-Test Results with Post-test variables

University	t	df	Sig.	Mean Difference
Universitas Negeri Surabaya	9.473	78	0.000	17.625
Universitas Terbuka Surabaya	9.159	78	0.000	8.125
Universitas Terbuka Jakarta	11.918	78	0.000	13.650
Bina Nusantara University	8.890	78	0.000	12.700

Based on table 6, it can be seen that:

1. Universitas Negeri Surabaya, the calculated t value is 9.473 with a significance level of 0.000, indicating that this difference did not occur by chance. So, the use of GEN AI in graphic media learning has a significant influence on improving the visual literacy skills of students. The results of data analysis using the independent t-test showed a significant difference between the experimental group using GEN AI and the control group using conventional methods. The average post-test of the experimental group (84.50) was higher than the control group (69.88), with a difference of 17,625 points. This finding strengthens the hypothesis that the use of GEN AI can significantly improve learning outcomes, supporting the effectiveness of GEN AI in improving students' visual skills.
2. Universitas Terbuka Surabaya, The calculated t value is 9.156 with a significance level of 0.000, indicating that there is a significant difference. Data analysis shows that the application of GEN AI in graphic media learning has a significant impact on improving visual literacy skills of students. The results of the analysis using the independent t-test revealed a significant difference between the experimental group using GEN AI and the control group using conventional methods. The average post-test score of the experimental group reached 86.95, while the control group was only 78.82, with a difference of 8.125 points. This finding supports the hypothesis that the use of GEN AI can significantly improve learning outcomes, which shows the effectiveness of GEN AI in improving the visual skills of students.
3. Universitas Terbuka Jakarta, The calculated t value is 11.918 with a significance level of 0.000, it can be concluded that there is a significant difference between the control and experimental classes. Data analysis shows that the application of Generative AI (GEN AI) in graphic media learning has a significant impact on improving students' visual literacy skills. The results of the analysis using the independent t-test showed a significant difference between the experimental group using GEN AI and the control group

using conventional methods. The average post-test score for the experimental group reached 88.20, while the control group only obtained 74.55, with a difference of 13.65 points. This finding strengthens the hypothesis that the use of GEN AI can significantly improve learning outcomes, which shows the effectiveness of GEN AI in improving students' visual skills.

4. Bina Nusantara University, The calculated value is 8.890 with a significance level of 0.000, it can be concluded that there is a significant difference between the control and experimental classes. This study reveals that the application of Generative AI (GEN AI) in graphic media learning has a significant impact on improving visual literacy skills of students. Data analysis conducted through an independent t-test showed a significant difference between the experimental group utilizing GEN AI and the control group using conventional methods. The average post-test score in the experimental group was recorded at 85.92, which was higher than the control group which only reached 73.22, with a difference of 12.7 points. This finding strengthens the hypothesis that the use of GEN AI can substantially improve learning outcomes, thus supporting the effectiveness of GEN AI in developing visual skills.

5. Discussion

Based on the analysis of 4 universities, the recapitulation can be seen in the following graphic image in figure 1.

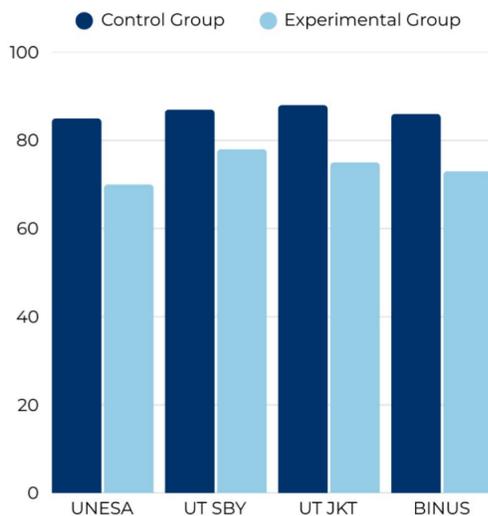


Figure 1: Recapitulation of analysis results of 4 universities

The results of this study at Universitas Negeri Surabaya, Universitas Terbuka Surabaya, Universitas Terbuka Jakarta, and Bina Nusantara University support the hypothesis that the use of GEN AI in graphic media learning significantly improves students' visual literacy skills. This finding is in line with previous studies showing that GEN AI is able to provide more personalized feedback and more adaptive learning (Smaldino, 2011; Felten & Barry, 2010). By utilizing GEN AI, students can access various visual sources and get help in interpreting and creating better and more innovative visuals. The results of this study also support Gestalt theory and information processing theory, which state that

visualization plays an important role in learning. As stated by Nugroho (2011), almost 50% of the human brain is involved in visual processing, and 70% of all sensory receptors are in the human eye. Increasing students' visual literacy through the use of GEN AI shows that this tool is effective in optimizing the visual processing potential of the human brain (see figure 1). We also found that differences in learning modes affect students' abilities, desires and interests in using GEN AI. Of the 4 universities, the sample of UNESA students were students with face-to-face learning modes, while the other 3 universities were students with online learning modes. And the results of this study show that the average score of UNESA students is below the average score of students at other universities (see figure 2).

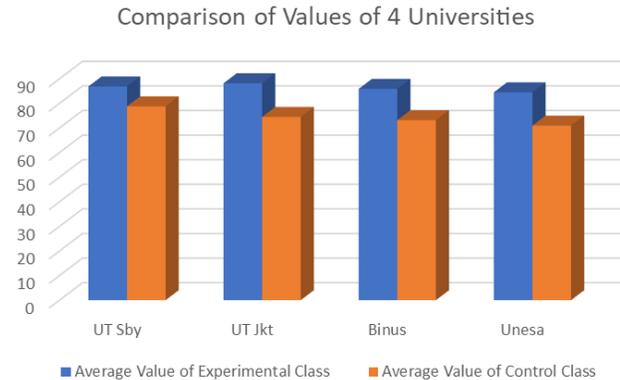


Figure 2: Comparison of values of 4 universities

Overall, the use of GEN AI in education, especially in graphic media learning, opens up great opportunities to improve students' visual literacy skills. The use of this technology not only improves the quality of learning but also prepares students to adapt to technological developments that continue to develop in the digital era.

5.1. Implications of Research Results

The implications of the results of this study are very broad and have a significant impact on the curriculum and learning process in higher education. Here are the main points that can be improved:

1. Improving the Quality of Learning

GEN AI algorithms can analyze each student's strengths and weaknesses, provide individualized feedback, and help students better understand concepts. GEN AI can provide fast and relevant feedback, helping students correct mistakes and strengthen their understanding.

2. Automate Routine Tasks

GEN AI can automate assignment grading, data analysis, and provision of teaching materials, thereby reducing the workload of lecturers. With routine tasks automated, lecturers can focus more on more important aspects of learning such as mentoring and curriculum development.

3. 21st Century Skills Development

GEN AI can help students develop visual literacy skills by providing a variety of visual resources and tools to create effective visuals. GEN AI can stimulate students' creativity

new ideas, encouraging innovation in media design and production.

4. Efficiency in the Learning Process

The use of GEN AI increases learning efficiency by automating tasks such as assessment and providing teaching materials. GEN AI increases accessibility to a variety of educational resources, allowing students to learn independently and at their own pace.

5. Curriculum Development

Educational institutions must work with GEN AI experts and educators to develop effective and relevant learning modules. The importance of developing a curriculum that includes GEN AI technology so that students are ready to face technological developments in today's digital era.

5.2. Recommendations for Integration of GEN AI in Higher Education Curriculum

Implementation GEN AI in higher education practically, there needs to be integration in an adaptive and interdisciplinary curriculum. The curriculum should be designed to be flexible and adaptive to the development of AI technology, with courses updated regularly to cover the latest technologies and methods.

Training and development of lecturers through regular workshops and trainings as well as collaboration with GEN AI experts or technology companies is also very important. Educational institutions need to invest in technologies that support the implementation of AI, including advanced GEN AI hardware and software, and establish GEN AI-based learning resource centers that provide GEN AI tools and applications as well as technical support and training.

In addition, GEN AI-based assessment and evaluation can be used to assess students' AI visual literacy skills more objectively and efficiently. The development of GEN AI assessment tools and ongoing evaluation processes are essential to ensure that GEN AI integration has a positive impact on learning. By adopting AI, educational institutions can create a more adaptive, innovative, and effective learning environment, preparing students to face the challenges of the digital era.

6. Conclusion

The results of this study indicate that the use of GEN AI significantly improves students' visual literacy skills in graphic media learning. GEN AI is able to provide various visual resources that support the learning process, provide more personalized feedback, and help students interpret and create better visuals. This research is in line with various studies that indicate that GEN AI can strengthen creativity, increase productivity, and enrich students' learning experiences. In the context of graphic media learning, GEN AI plays an important role in helping students access visual references, understand design principles, and produce more innovative works. In addition, GEN AI also increases students' engagement and imagination in

art classes, strengthens critical thinking skills, and prepares them to face challenges in the digital era.

Optimization the use of GEN AI in education and improve students' visual literacy skills, several strategic steps need to be taken: Curriculum Development, Continuous Training and Workshops, Improvement of Technology Infrastructure, Collaboration with Industry. Further research is needed to explore the impact of GEN AI in other disciplines and aspects of learning. Some directions for future research include: Exploration of the Use of GEN AI in Other Learning Areas, testing in Different Populations and Longitudinal studies.

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References

- [1] D. T. K. Ng, J. K. L. Leung, S. K. W. Chu, M. S. Qiao, "Conceptualizing AI literacy: An exploratory review", *Computers and Education: Artificial Intelligence*, **2**: 100041, 2021, DOI: 10.1016/j.caeai.2021.100041
- [2] A. Bozkurt, X. Junhong, S. Lambert, A. Pazurek, H. Crompton, S. Koseoglu, R. Farrow, M. Bond, C. Nerantzi, S. Honeychurch, M. Bali, J. Dron, K. Mir, B. Stewart, E. Costello, J. Mason, C. M. Stracke, E. Romero-Hall, "Speculative Futures on ChatGPT and Generative Artificial Intelligence (AI): A Collective Reflection from the Educational Landscape", *Asian Journal of Distance Education*, **18**(1): 53–130, 2023, DOI: 10.5281/zenodo.7636568
- [3] J. Su, W. Yang, "Unlocking the power of ChatGPT: A framework for applying generative AI in education", *ECNU Review of Education*, **6**(3): 355–366, 2023, DOI: 10.1177/209653112311684
- [4] Y. Hwang, J. H. Lee, D. Shin, "What is prompt literacy? An exploratory study of language learners' development of new literacy skill using generative AI", *arXiv preprint*, arXiv:2311.05373: 1–15, 2023, DOI: 10.48550/arXiv.2311.05373
- [5] C. K. Y. Chan, "AI as the therapist: Student insights on the challenges of using generative AI for school mental health frameworks", *Behavioral Sciences*, **15**(3): 287, 2025, DOI: 10.3390/bs15030287

- [6] H. H. Thorp, "ChatGPT is fun, but not an author", *Science*, **379(6630)**: 313–313, 2023, DOI: 10.1126/science.adg7879
- [7] Y. Shen, L. Heacock, J. Elias, K. D. Hentel, B. Reig, G. Shih, L. Moy, "ChatGPT and other large language models are double-edged swords", *Radiology*, **0(0)**: 230163, 2023, DOI: 10.1148/radiol.230163
- [8] M. S. Palmer, T. Matthews, "Learning to See the Infinite: Measuring Visual Literacy Skills in a 1st-Year Seminar Course", *Journal of the Scholarship of Teaching and Learning*, **15(1)**: 1–9, 2015, DOI: 10.14434/josotl.v15i1.13089
- [9] R. A. Branden, "Visual literacy", in L. L. Lohr (Ed.), *Creating Graphics for Learning and Performance*, p.13, Upper Saddle River, NJ, Pearson, 2008
- [10] S. Stokes, "Visual literacy in teaching and learning: A literature perspective", *Electronic Journal for the Integration of Technology in Education*, **1(1)**: 10–19, 2002
- [11] R. M. Branch, J. M. Brill, D. Kim, "Visual literacy defined—the results of a Delphi study: can IVLA (operationally) define visual literacy?", *Journal of visual literacy*, **27(1)**: 47-60, 2007, DOI: 10.1080/23796529.2007.11674645
- [12] L. J. Ausburn, F. B. Ausburn, "Cognitive styles: Some information and implications for instructional design", *Educational Communication and Technology Journal (ECTJ)*, **26(4)**: 337–354, 1978, DOI: 10.1007/BF02766370

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Characteristics of Crystal Defects due to the Inverse Piezoelectric Effect in Aluminum Gallium Nitride / Gallium Nitride High Electron Mobility Transistors

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ABSTRACT

Gallium nitride (GaN) is expected to be used as a material for power semiconductor devices. However, it is crucial to focus on the dielectric properties of GaN. In this study, we investigated the transient response of the drain current during high-frequency application after intentionally maintaining the current collapse in the AlGaN/GaN high electron mobility transistors. The experiment observed a long-term current recovery process of approximately 50 s and showed a temperature dependence that was opposite to the steady state at high temperatures. In addition, by changing the duration of the current collapse, it was suggested that the electron trapping in the crystal defects, generated by the strain expansion due to the inverse piezoelectric effect, was promoted by maintaining the current collapse. Furthermore, we analyzed the activation energy calculated from the current value using the temperature dependence of the transient response. The change in the activation energy from approximately 0.6 to 1.0 eV clarified the behavior of electron trapping and de-trapping, including the effect of the inverse piezoelectric effect. The experimental results suggested the existence of recoverable crystal defects caused by the inverse piezoelectric effect.

1. Introduction

In recent years, the performance of Si-based semiconductor devices has reached its limit; therefore, dielectric materials with large bandgaps have been used. Gallium nitride (GaN) has a bandgap energy of 3.4 eV and is expected to be used in power semiconductor devices [1], [2]. AlGaN/GaN high-electron-mobility transistors (HEMTs) can be implemented by heterojunction of aluminum gallium nitride (AlGaN) and GaN [3], [4]. The spontaneous polarization of AlGaN and GaN, as well as the piezoelectric polarization of the junction due to lattice mismatch, results in the accumulation of positive fixed charges at the bottom of the AlGaN layer and negative fixed charges at the top of the GaN layer. The greater number of positive fixed charges on the AlGaN side results in a concentration of electrons at the top of the GaN layer, thereby compensating for this imbalance and resulting in the formation of a two-dimensional electron gas (2DEG) [5], [6]. When a large reverse voltage is applied to the gate electrode, the inverse piezoelectric effect amplifies the tensile stress caused by the existing polarization, resulting in the expansion of strain and the generation of crystal defects [7]–[12]. In piezoelectric materials, the direct piezoelectric effect causes

polarization due to strain, while the inverse piezoelectric effect causes the distortion due to an electric field. In a GaN-HEMT, the former contributes to the formation of a 2DEG, and the latter results in performance degradation.

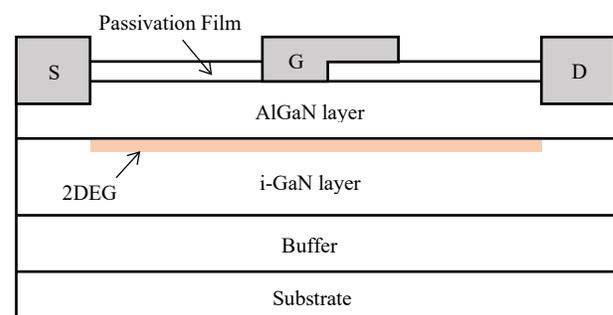


Figure 1: Schematic cross-section of AlGaN/GaN HEMT

In addition, GaN devices have numerous crystal defects that trap electrons, resulting in the expansion of the depletion layer and a decrease in the drain current [13]–[15]. Furthermore, electrons are trapped on the surface of the AlGaN layer due to the concentration of the electric field at the edge of the gate electrode

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in the direction of the drain electrode [15]–[17]. This problem, known as the current collapse phenomenon, results in performance degradation. A field-plate structure for the gate electrode is one way to suppress current collapse [18], [19]. This structure prevented electric field concentration. Additionally, the application of a high frequency to the gate electrode, which exceeds the time constant of the crystal defects, has been demonstrated to suppress electron trapping [20], [21]. Figure 1 shows a schematic cross-section of the AlGaIn/GaN HEMT, and Figure 2 shows the I-V characteristics when a high frequency (5 GHz) and DC are applied.

In this study, we investigated the transient response of the drain current during high-frequency applications after intentionally maintaining the current collapse in an AlGaIn/GaN HEMT. The experiment revealed a long-term current recovery process and showed a temperature dependence opposite to that of the steady state at high temperatures. Additionally, by changing the duration of the current collapse, the duration affected the current recovery rate. Furthermore, the change in activation energy calculated from the current value was analyzed. The experimental results suggested the occurrence of recoverable strain owing to the inverse piezoelectric effect. The present study investigated the influence of the inverse piezoelectric effect on a GaN-HEMT using a different method than previous studies [11], [12]. This method involved switching between promoting and suppressing the current collapse by changing the frequency, and calculating the change in activation energy from the difference in current values during transient response.

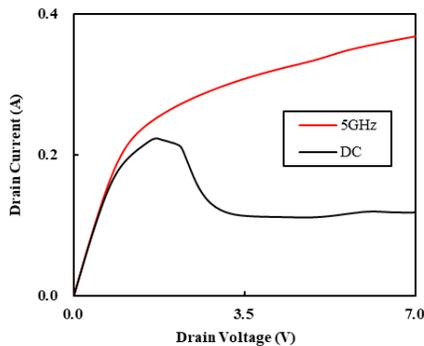


Figure 2: I-V characteristic of the GaN-HEMT used in this study

2. Experimental Methods

2.1. Measuring I-V characteristics after maintaining the current collapse

In this experiment, 10 MHz was applied to the AlGaIn/GaN HEMT (CGH40025F, CREE) in the operating state for a certain period. Following 5 s in the nonoperating state, we measured I-V characteristics when applying 5 GHz at room temperature. Time of the 10MHz operation was modulated from 100 s to 250 s. The gate voltage was set to -2.2 V. The drain voltage was set to 5 V for 10 MHz operation, and was swept from 0 V to 8 V in 0.1 V increments for I-V characteristic measurements. Frequency was applied to the gate electrode using a vector network analyzer (MS4644B, Anritsu). Switching between states was achieved by taking advantage of the fact that the current collapse could not be suppressed at 10 MHz but could be suppressed at 5 GHz.

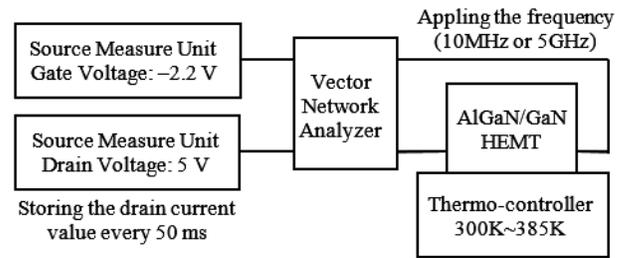


Figure 3: Experimental system used in this study

2.2. Measuring drain current transient response after maintaining the current collapse

In this experiment, 10 MHz was applied to the AlGaIn/GaN HEMT in the operating state for 150 s. Following 5 s in the nonoperating state, 5 GHz was again applied in the operating state for 150 s. Simultaneously, we measured the transient response of the drain current when 5 GHz was applied, using a source-measure unit (GS610, YOKOGAWA).

The gate voltage was set to -2.2 V and the drain voltage to 5 V, and measurements were performed from 300 K to 385 K. To eliminate the influence of the previous measurement, the device was operated at 5 GHz with a drain voltage of 10 V for 5 s before and after each measurement.

Additionally, measurements were conducted from 340 K to 385 K while modulating the time of the 10 MHz operation from 100 s to 250 s. Each measurement was performed after the temperature on the surface of the device package had stabilized. Figure 3 shows the experimental system used in this experiment.

3. Results and Discussion

3.1. I-V characteristics after maintaining the current collapse

Figure 4 shows the I-V characteristics after maintaining the current collapse for each duration. An enlarged view of the range from 4 V to 6 V is shown in Figure 5. The maintenance of the current collapse resulted in the occurrence of kink effect, the kink effect became stronger depending on the maintenance time. A decrease in drain current was observed at a bias where 2DEG formation and electron de-trapping were inadequate.

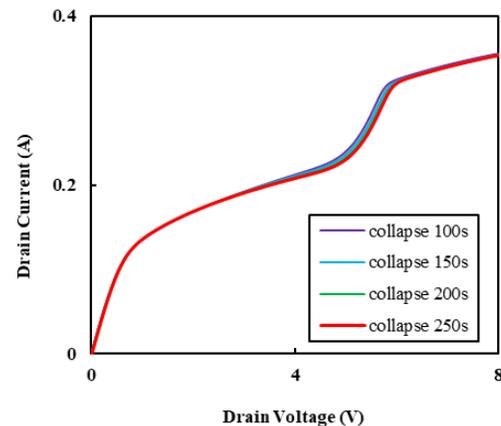


Figure 4: I-V characteristics after maintaining the current collapse for each duration

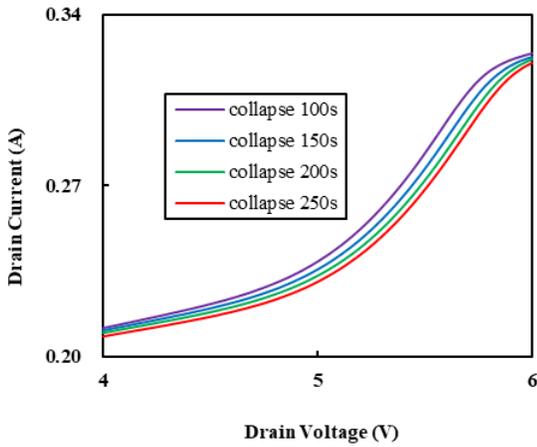


Figure 5: Enlarged view of the I-V characteristics

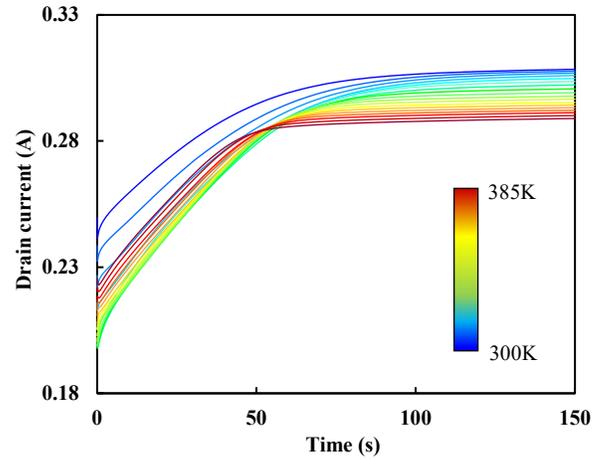


Figure 6: Temperature dependence of the drain current transient response after maintaining the current collapse

3.2. Drain current transient response after maintaining the current collapse

The temperature dependence of the drain-current transient response after the current collapse was maintained is shown in Figure 6. In the steady state, the higher the temperature, the lower the current. This was attributed to the inhibition of carrier transport caused by phonon scattering [22], [23]. However, in the transient region, the opposite of the steady state was observed at temperatures above approximately 340 K. Figure 7 shows the transient response above 350 K, where a reversal of the characteristics can be observed. Waveform crossings caused by the reversal were confirmed. The maintenance of the current collapse resulted in a limited number of carriers in the 2DEG following the resumption of operations. Therefore, the impact of increasing the number of thermal carriers and accelerating electrons owing to thermal energy was more pronounced than the inhibition of carrier transport owing to phonon scattering.

A high frequency was applied during the transient response measurement, thereby prompting the de-trapping of electrons from the crystal defects. However, because the transient response was long, there was an effect other than simple electron de-trapping. Therefore, we focus on the strain induced by the inverse piezoelectric effect. The inverse piezoelectric effect, caused by the electric field, results in strain and results in the formation of crystal defects [7], [8]. Assuming that the inverse piezoelectric effect caused by the gate voltage generated defects in the AlGaIn crystal while maintaining the current collapse, electrons were trapped in these defects. Although the polarization due to the inverse piezoelectric effect was unable to respond to a high frequency, the restoration of strain required a temporal span, resulting in current degradation.

Figure 8 shows the relationship between the current collapse maintenance time and drain current transient response at 350 and 385 K. The longer the duration of the current collapse, the slower the current recovery. As the duration of the current collapse increases, the strain induced by the inverse piezoelectric effect also increases. Figure 9 shows a band diagram representing how the strain induced by the inverse piezoelectric effect expands and traps electrons. As the electron trapping for strain progressed, the band shifted upward and the triangular potential well became shallower.

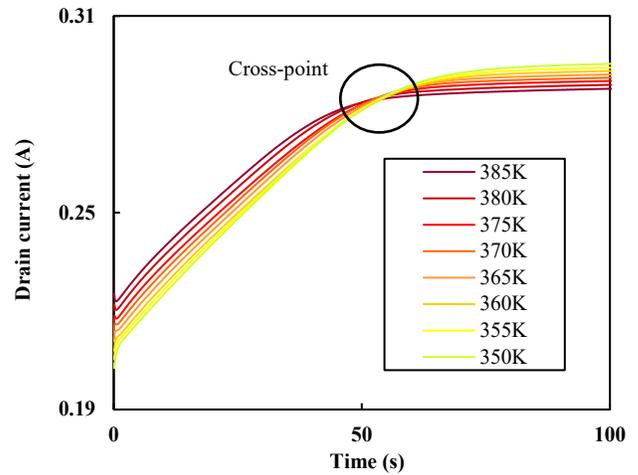


Figure 7: Transient response above 350 K

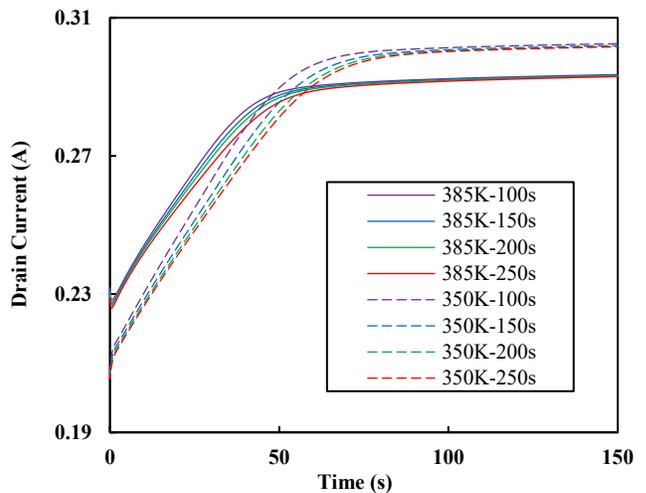


Figure 8: Relationship between the current collapse maintenance time and the drain current transient response, with 350 K and 385 K selected

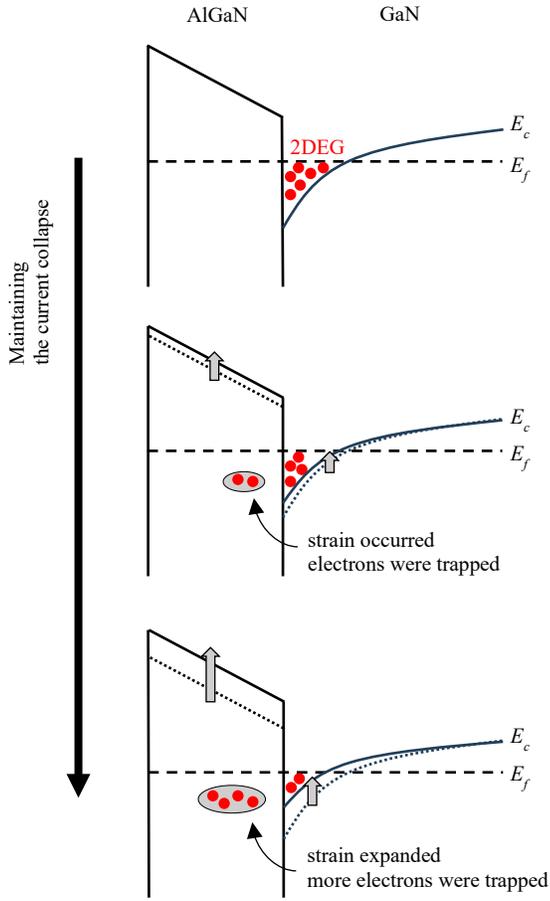


Figure 9: Band diagrams representing how the strain induced by the inverse piezoelectric effect expands and traps electrons

3.3. Analysis of activation energy

Next, the activation energy was calculated from the current values above 350 K. For current values above 355 K, the difference value was calculated based on the current value at 350 K. Specifically, the current value at the absolute temperature T was defined as I_T , and the difference from the standard value was defined as ΔI_T , and the following calculation was performed at each temperature.

$$\Delta I_{355} = I_{355} - I_{350} \quad (1)$$

$$\Delta I_{360} = I_{360} - I_{350} \quad (2)$$

⋮

$$\Delta I_{385} = I_{385} - I_{350} \quad (7)$$

The activation energy ΔE was calculated from ΔI_T and the following Arrhenius equation.

$$\Delta I_T = A \exp(-\Delta E / kT) \quad (8)$$

Here, A is a constant, and k is Boltzmann's constant. ΔE was calculated for each time of the transient response within the range

where (8) was accurate. As an example of ΔE calculation, Figure 10 shows an Arrhenius plot for a transient response time of 1 s at the current collapse time of 250 s. In this example, a precise Arrhenius plot was obtained with a coefficient of determination of 0.975.

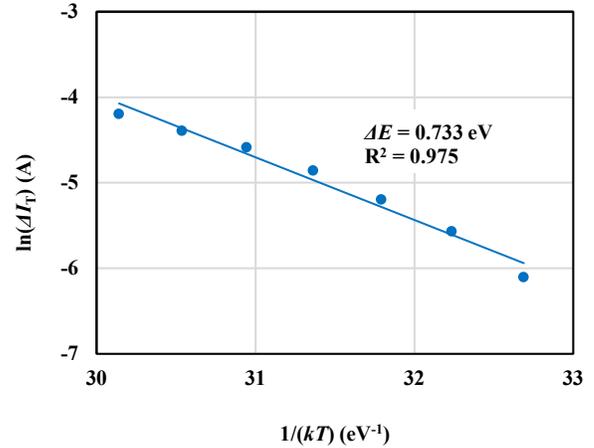


Figure 10: Arrhenius plot for a transient response time of 1 s

Figure 11 shows the change in activation energy for each duration of the current collapse. The energy value dropped sharply between 0.3 and 0.4 s, then rose and stabilized. The current collapse was maintained, thereby decreasing the activation energy immediately following the resumption of operation, owing to the de-trapping of electrons. Subsequently, as electron trapping progressed, the activation energy increased. When trapping and de-trapping reached equilibrium, the activation energy stabilized. The amount of the increase from the lower limit of the energy value to the point of stabilization was approximately 0.3 eV for a collapse time of 100 s and 0.2 eV for 250 s. When the duration of the current collapse was long, many of the crystal defects were filled with electrons; therefore, de-trapping progressed more easily than new trapping, resulting in only a small increase in activation energy. The strain induced by the inverse piezoelectric effect increased the timescale of the activation energy change. Furthermore, as the effect reached its saturation point, there was almost no difference between the 200 s and 250 s cases.

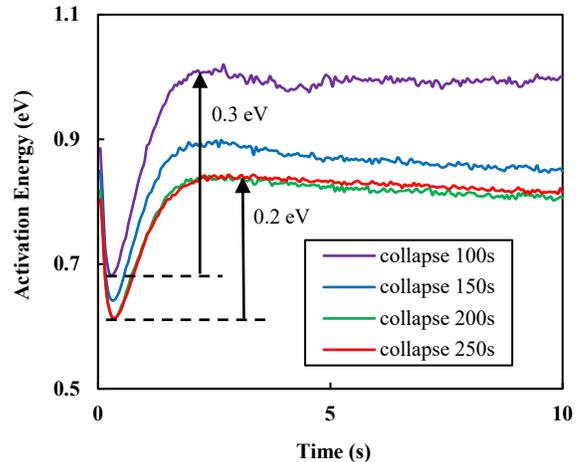


Figure 11: Change in activation energy at each duration of the current collapse

4. Conclusion

In this study, we investigated the transient response of the drain current during high-frequency applications by controlling the promotion and suppression of the current collapse by switching the frequency applied to the gate electrode in a GaN-HEMT. In the experiment, a long-term current recovery process was observed, suggesting that electron trapping in the crystal defects, generated by strain expansion owing to the inverse piezoelectric effect, was promoted by maintaining the current collapse. The activation energy was calculated using the temperature dependence, which was opposite to the steady state at high temperatures. The change in the obtained activation energy clarified the electron trapping and de-trapping behavior, including the inverse piezoelectric effect. Furthermore, extending the duration of the current collapse saturated the effect. The experimental results suggested the existence of recoverable crystal defects caused by the inverse piezoelectric effect. A critical focus in the research community is to emphasize the dielectric properties of GaN, a wide-bandgap material, in order to enhance our understanding of its unique characteristics and applications.

Conflict of Interest

The authors declare no conflict of interest.

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References

- [1] J. Millán, P. Godignon, X. Perpiñà, A. Pérez-Tomás, J. Rebollo, "A survey of wide bandgap power semiconductor devices," in *IEEE Transactions on Power Electronics*, **29**(5), 2155–2163, 2014, doi:10.1109/TPEL.2013.2268900.
- [2] E.A. Jones, F.F. Wang, D. Costinett, "Review of commercial GaN power devices and GaN-based converter design challenges," in *IEEE Journal of Emerging and Selected Topics in Power Electronics*, **4**(3), 707–719, 2016, doi:10.1109/JESTPE.2016.2582685.
- [3] N.A. Torkhov, L.I. Babak, A.A. Kokolov, "The influence of AlGaIn/GaN heteroepitaxial structure fractal geometry on size effects in microwave characteristics of AlGaIn/GaN HEMTs," *Symmetry*, **11**(12), 1495, 2019, doi:10.3390/sym11121495.
- [4] S. Ghosh, A.M. Hinz, M. Frentrup, S. Alam, D.J. Wallis, R.A. Oliver, "Design of step-graded AlGaIn buffers for GaN-on-Si heterostructures grown by MOCVD," *Semiconductor Science and Technology*, **38**(4), 044001, 2023, doi:10.1088/1361-6641/acb9b6.
- [5] K. Osipov, I. Ostermay, M. Bodduluri, F. Brunner, G. Tränkle, J. Würfl, "Local 2DEG density control in heterostructures of piezoelectric materials and its application in GaN HEMT fabrication technology," in *IEEE Transactions on Electron Devices*, **65**(8), 3176–3184, 2018, doi:10.1109/TED.2018.2850010.
- [6] J. He, W.C. Cheng, Q. Wang, K. Cheng, H. Yu, Y. Chai, "Recent advances in GaN - based power HEMT devices," *Advanced electronic materials*, **7**(4), 2001045, 2021, doi:10.1002/aelm.202001045.
- [7] J. Joh, L. Xia, J.A. del Alamo, "Gate current degradation mechanisms of GaN high electron mobility transistors," 2007 *IEEE International Electron Devices Meeting*, Washington, DC, USA, 385–388, 2007, doi:10.1109/IEDM.2007.4418953.
- [8] U. Chowdhury, J.L. Jimenez, C. Lee, E. Beam, P. Saunier, T. Balistreri, S.Y. Park, T. Lee, J. Wang, M.J. Kim, et al. "TEM observation of crack- and pit-shaped defects in electrically degraded GaN HEMTs," in *IEEE Electron Device Letters*, **29**(10), 1098–1100, 2008, doi:10.1109/LED.2008.2003073.
- [9] L. Shi, S. Feng, Y. Zhang, B. Shi and K. Liu, "Variation of dominant degradation mechanism in AlGaIn barrier layer with different voltage stress on the gate of AlGaIn/GaN high electron mobility transistors," in *IEEE Electron Device Letters*, **36**(4), 321–323, 2015, doi:10.1109/LED.2015.2399774.
- [10] K. Ahmada, B. Ubochi, B. Benbakhti, S.J. Duffy, A. Soltani, W.D. Zhang, K. Kalna, "Role of self-heating and polarization in AlGaIn/GaN-based heterostructures," in *IEEE Access*, **5**, 20946–20952, 2017, doi:10.1109/ACCESS.2017.2755984.
- [11] H. Shiomi, A. Ueda, T. Tohei, Y. Imai, T. Hamachi, K. Sumitani, S. Kimura, Y. Ando, T. Hashizume, A. Sakai, "Analysis of inverse-piezoelectric-effect-induced lattice deformation in AlGaIn/GaN high-electron-mobility transistors by time-resolved synchrotron radiation nanobeam X-ray diffraction," *Applied Physics Express*, **14**(9), 095502, 2021, doi:10.35848/1882-0786/ac1ee4.
- [12] Y. Zhang, L. Zhou, J.-F. Mao, "Inverse piezoelectric and trap effects with temperature dependence in AlGaIn/GaN HEMTs under narrowband microwave pulses," in *IEEE Transactions on Electromagnetic Compatibility*, **6**(53), 794–803, 2023, doi:10.1109/TEMC.2023.3237318.
- [13] S. Mukherjee, E.E. Patrick, M.E. Law, "Simulation of deep-level trap distributions in AlGaIn/GaN HEMTs and its influence on transient analysis of drain current," *ECS Journal of Solid State Science and Technology*, **6**(11), S3093, 2017, doi:10.1149/2.0211711jss.
- [14] R. Ye, X. Cai, C. Du, H. Liu, Y. Zhang, X. Duan, J. Zhu, "An overview on analyses and suppression methods of trapping effects in AlGaIn/GaN HEMTs," in *IEEE Access*, **10**, 21759–21773, 2022, doi:10.1109/ACCESS.2021.3139443.
- [15] M. Meneghini, A. Tajalli, P. Moens, A. Banerjee, E. Zanoni, G. Meneghesso, "Trapping phenomena and degradation mechanisms in GaN-based power HEMTs," *Materials Science in Semiconductor Processing*, **78**, 118–126, 2018, doi:10.1016/j.mssp.2017.10.009.
- [16] I. Rossetto, M. Meneghini, A. Tajalli, S. Dalcaneal, C. De Santi, P. Moens, A. Banerjee, E. Zanoni, G. Meneghesso, "Evidence of hot-electron effects during hard switching of AlGaIn/GaN HEMTs," in *IEEE Transactions on Electron Devices*, **64**(9), 3734–3739, 2017, doi:10.1109/TED.2017.2728785.
- [17] T. Mizutani, Y. Ohno, M. Akita, S. Kishimoto, K. Maezawa, "A study on current collapse in AlGaIn/GaN HEMTs induced by bias stress," in *IEEE Transactions on Electron Devices*, **50**(10), 2015–2020, 2003, doi:10.1109/TED.2003.816549.
- [18] W. Saito, T. Nitta, Y. Kakiuchi, Y. Saito, K. Tsuda, I. Omura, M. Yamaguchi, "Suppression of dynamic on-resistance increase and gate charge measurements in high-voltage GaN-HEMTs with optimized field-plate structure," in *IEEE Transactions on Electron Devices*, **54**(8), 1825–1830, 2007, doi:10.1109/TED.2007.901150.
- [19] H. Huang, Y.C. Liang, G.S. Samudra, T.-F. Chang, C.-F. Huang, "Effects of gate field plates on the surface state related current collapse in AlGaIn/GaN HEMTs," in *IEEE Transactions on Power Electronics*, **29**(5), 2164–2173, 2014, doi:10.1109/TPEL.2013.2288644.
- [20] H. Taguchi, K. Akahori, T. Shimazu, H. Tanabe, "Analysis of drain current transient response of gate pulse voltage in AlGaIn / GaN High electron mobility transistors," *Advances in Science, Technology and Engineering Systems Journal*, **3**(5), 216–219, 2018, doi:10.25046/aj030526.
- [21] Y. Shimizu, A. Fujiwara, H. Hayashi, S. Sano, K. Hirana, H. Taguchi, "Methodology for evaluating 2DEG carrier behavior in high-frequency bands in AlGaIn/GaN HEMTs," *TENCON 2023 - 2023 IEEE Region 10 Conference (TENCON)*, Chiang Mai, Thailand, 570–574, 2023, doi:10.1109/TENCON58879.2023.10322353.
- [22] C. Wang, Y. Xu, X. Yu, C. Ren, Z. Wang, H. Lu, T. Chen, B. Zhang, R. Xu, "An electrothermal model for empirical large- signal modeling of AlGaIn/GaN HEMTs including self-heating and ambient temperature effects," in *IEEE Transactions on Microwave Theory and Techniques*,

62(12), 2878–2887, 2014, doi:10.1109/TMTT.2014.2364821.

- [23] L. Mitterhuber, R. Hammer, T. Dengg, J. Spitaler, "Thermal characterization and modelling of AlGaIn-GaN multilayer structures for HEMT applications," *Energies*, **13**(9), 2363, 2020, doi:10.3390/en13092363.

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The Impact of Digitalization on Shipbuilding as Measured by Artificial Intelligence (AI) Maturity Models: A Systematic Review

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ABSTRACT

Artificial Intelligence (AI) is reshaping the global shipbuilding sector, yet existing maturity models fail to capture the domain-specific complexities of this capital-intensive industry. This study reviews over 50 AI maturity models and introduces a specialized framework tailored for shipbuilding. The proposed model outlines four progressive stages—Beginner, Innovation, Integration, and Expert—across eight key dimensions: culture, resilience, sustainability, strategy, customer focus, organizational integration, connectivity, and production efficiency. A hybrid benchmarking approach involving comparative analysis of major shipbuilders such as China State Shipbuilding Corporation (CSSC), General Dynamics National Steel and Shipbuilding Company (NASSCO), and Hyundai Heavy Industries (HHI), as well as synthesis from literature, was used to validate the relevance and coverage of each dimension. The framework provides a roadmap for operational modernization and links digital maturity to measurable outcomes such as delivery timelines, production scalability, and environmental performance. Policy recommendations highlight the need for targeted investments, workforce reskilling, and public-private collaboration to enable sustainable and AI-enabled growth in the U.S. shipbuilding sector.

1. Introduction

Artificial intelligence (AI) is redefining industrial processes globally, with the shipbuilding sector increasingly adopting AI to improve efficiency, safety, and competitiveness [1]. Nations such as China, South Korea, and Japan dominate the global shipbuilding landscape due to superior infrastructure, automation, and AI-driven capabilities [2].

Training shipyard workers in modern shipbuilding techniques and using AI will be imperative for global shipyards [3]. Organizations must understand and adapt artificial intelligence to specific uses and requirements [4]. Real-time decision-making relies on statistics, econometrics, math,

simulations, and optimization to collect and analyze high-speed data from multiple sources [5]. Using current and new web data can assist organizations in identifying their competitors [6]. The Chinese shipyards enjoy state-of-the-art infrastructure, automation, and government subsidies, allowing them to reach economies of scale and construct multiple ships simultaneously [7]. China State Shipbuilding Corporation, the world's largest shipbuilding conglomerate, now owns numerous research institutes and various shipyards and builds a third of all ships worldwide. Government and shipyards work closely together to achieve their national strategic goal of being a world leader in the maritime industry [7].

The shipbuilding industry remains a vital contributor to national economies, particularly in the United States, where the sector supports over 100,000 jobs, generates \$9.9 billion in labor income, and contributes \$12.2 billion to GDP annually [4].

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However, despite its strategic significance, the U.S. shipbuilding sector has significant obstacles that limit its capacity to compete internationally, such as aging infrastructure, high labor costs, and a shortage of people with digital skills [8], [9]. Conversely, shipyards in China and South Korea enjoy substantial government backing, cutting-edge automation, and state-sponsored training programs, which allow them to increase production capacity and swiftly incorporate AI technologies [8]. As noted by the World Bank, the availability of a skilled labor force and policies promoting industrial transformation are key enablers of digital readiness and economic resilience in heavy industries [8]. These contrasts underscore the urgency for targeted digitalization strategies in U.S. shipyards, where AI maturity assessments can help guide sustainable modernization efforts [10].

The adoption of automation and artificial intelligence in shipbuilding can result in cost reductions, enhanced safety, and faster production cycles [11]. However, this transformation varies across regions. Chinese shipyards have rapidly embraced AI-powered robotics and analytics, whereas their U.S. counterparts continue to rely on conventional systems that prioritize operational resilience [7].

This paper aims to summarize and evaluate existing AI maturity models, assess the digitalization levels of leading shipbuilding nations, identify gaps in current AI maturity assessment frameworks as they apply to the shipbuilding industry, and propose a specialized AI maturity model tailored to address the sector's unique challenges and characteristics.

This paper evaluates how digitalization influences shipbuilding outcomes, using AI maturity models as the assessment tool. Our research objectives are:

1. To review global AI maturity models applicable to manufacturing and maritime sectors.
2. To identify limitations in existing frameworks when applied to shipbuilding.
3. To propose and validate a tailored AI maturity model for shipbuilding.
4. To assess how AI maturity affects efficiency, delivery timelines, and sustainability.

By answering research questions related to AI maturity's role in digital transformation, model effectiveness, and comparative insights, we provide a strategic lens for shipbuilding modernization.

2. Literature Review and Theoretical Foundation

We reviewed 50 scholarly sources across IEEE, Springer, ACM, and ScienceDirect databases using Boolean keywords ("AI maturity model," "shipbuilding," "digital transformation"). The review found that existing models, such as the Digital Maturity Model (DMM) [12], [13], Global Big Data Maturity Model [14], do not adequately reflect the shipbuilding sector's complexity.

Key dimensions such as resilience, sustainability, and connectivity are inconsistently applied. Moreover, few models account for shipbuilding's unique regulatory, infrastructural, and labor requirements. These dimensions can be used to quantitatively evaluate an organization's AI adoption maturity practices, providing a comprehensive framework for qualitatively evaluating and improving AI adoption maturity practices. Table 1 shows the dimensions of the available maturity models, and Figure 1 shows AI dimensions.

Table 1: Dimensions in Existing AI Maturity Models

Dimension	[1 5]	[1 6]	[1 7]	[1 8]	[1 9]	[2 0]	[2 1]	[2 2]	[2 3]	[1 4]
Culture		X		X	X		X	X	X	
Resilience	X	X	X		X					
Sustainability		X	X							
Strategy	X	X	X	X	X	X	X	X	X	X
Customer	X		X	X	X		X	X	X	
Organization	X	X	X	X	X	X	X	X	X	X
Connectivity	X	X	X	X	X		X	X	X	X
Expansive Growth	X	X		X	X		X	X	X	
Production	X		X	X		X		X		

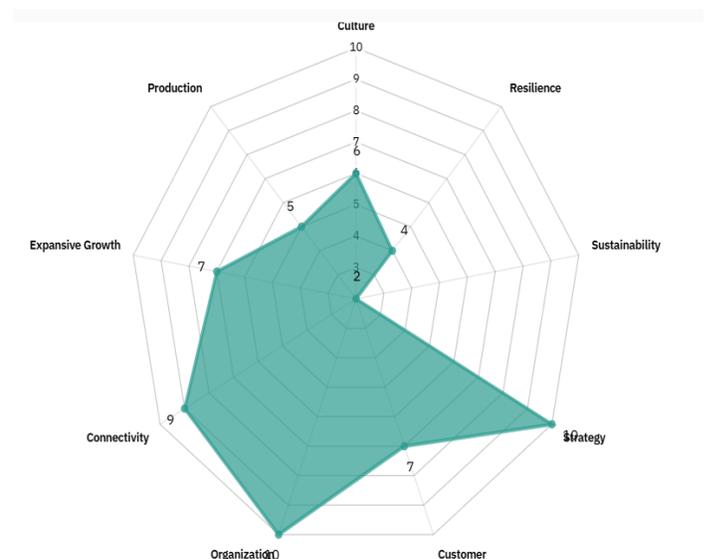


Figure 1: AI Dimensions

Note: The AI dimensions above are derived from the table and referenced models. This comparison highlights inconsistencies in

how different models address key elements relevant to digital transformation in complex industries such as shipbuilding.

3. Comparative Case Study: U.S. vs. China

U.S. Shipbuilding:

- General Dynamics NASSCO focuses on defense contracts, producing 2–3 vessels per year [24].
- 2023 revenue (Marine Systems): \$12.5B [24].
- Constraints: high labor costs, limited automation, reliance on military demand [25].

China Shipbuilding:

- China State Shipbuilding Corporation (CSSC) constructs ~33% of global ships [26].
- Backed by government subsidies, high R&D, and integrated AI systems [26].

Table 2 presents the annual turnover figures (in USD billions) for four major shipbuilding organizations from 2019 to 2023. China's CSSC shows a steady rise in turnover, from approximately \$7.19 billion in 2019 to around \$10.77 billion in 2023, reflecting its expanding global presence and state-backed initiatives. South Korea's HD Hyundai Heavy Industries (HDHHI) maintains moderate growth, with revenue climbing from \$7.12 billion in 2019 to \$9.2 billion in 2023. In contrast, Japan's Mitsubishi Heavy Industries (MHI) exhibits relative stability, with turnover fluctuating slightly between \$1.42 and \$1.67 billion, indicating a more consistent but less expansive market footprint than its peers.

Table 2: Annual Turnover (USD Billion)

Year	General Dynamics*	CSSC**	HD HHI***	Mitsubishi Heavy Industries Ltd. (MHI)****
2023	42.3	~10.77	9.2	1.42
2022	39.4	~8.14	7.05	1.42
2021	38.5	~8.16	7.25	1.50
2020	37.9	~7.55	7.03	1.67
2019	39.4	~7.19	7.12	1.66

*General Dynamics' total revenue includes revenue from other segments, including NASSCO. NASSCO does not disclose figures annually, but they are included in the segment's operations [24], [25]

**In 2019, China State Shipbuilding Industry Corporation and China Shipbuilding Industry Corporation merged, significantly boosting revenue for CSSC [26]

***HD Hyundai Heavy Industries Co., Ltd. (HHI) is a leading shipbuilding company based in Ulsan, South Korea [27]

****Historically, shipbuilding & ocean development have contributed approximately 3%–6% to MHI's total revenue [28]

4. Gaps in Existing AI Maturity Models

Most maturity models:

- Use generic stages (e.g., planning, integration, optimization)
- Lack of empirical application in the shipbuilding context
- Do not align AI dimensions with shipbuilding KPIs like delivery speed, modular construction, or regulatory compliance.

5. Proposed Shipbuilding AI Maturity Framework

Our framework includes four stages (Beginner, Innovation, Integration, Expert) and evaluates eight dimensions: Culture, Resilience, Sustainability, Strategy, Customer Focus, Organizational Integration, Connectivity, and Production Efficiency. Each stage is validated using benchmarking data.

Table 3 summarizes the four-stage progression across the eight proposed dimensions, offering a roadmap for shipbuilding organizations to assess and advance their AI maturity in alignment with industry goals.

Table 3: AI Maturity Framework

Dimension	Beginner	Innovation	Integration	Expert
Culture	Low AI literacy, resistance to change	Early experimentation with AI; supportive mindset emerging	AI embraced across teams; moderate adoption	The AI-centric culture embedded across the enterprise
Resilience	Reactive responses to disruptions	Basic forecasting using AI tools	Adaptive systems supported by AI for risk management	AI-driven autonomous resilience planning
Sustainability	Minimal awareness of green AI applications	Pilot initiatives for energy optimization	AI is used to optimize emissions and waste	Sustainability embedded as a strategic goal powered by AI

Strategy	No formal AI strategy	Isolated AI pilot programs aligned with select goals	AI aligned with business KPIs and strategic planning	AI drives strategic transformation across the organization
Customer Focus	Limited digital interaction	AI used in selected touchpoints (e.g., support bots)	Personalized services using AI analytics	Customer AI insights drive anticipatory service models
Organizational Integration	Siloed departments, ad-hoc AI efforts	Cross-functional AI collaboration begins	AI integrated into core business workflows	AI fully embedded in enterprise-wide processes
Connectivity	Low data integration, outdated systems	Partial IoT/IT-OT convergence	Real-time data pipelines and secure communications	Fully connected, interoperable, and secure digital ecosystem
Production Efficiency	Manual-heavy operations, low visibility	Initial automation in select operations	AI-optimized scheduling and predictive maintenance implemented	AI enhances throughput, uptime, and intelligent resource use

Benchmarking Approach:

A hybrid benchmarking approach validated the dimensions of the proposed AI maturity model (culture, strategy, connectivity, and sustainability):

- A literature-based review compared key dimensions across 10 AI maturity models from various domains (manufacturing, government, digital transformation). Commonly recurring dimensions were retained for inclusion.
- We conducted a benchmarking analysis using data from leading shipbuilders such as China State Shipbuilding Corporation (CSSC), Hyundai Heavy Industries (HHI) [27], and General Dynamics NASSCO [24], [25]. Publicly available performance data (e.g., delivery cycles, digital investment, vessel throughput, and automation level) were aligned with model dimensions to confirm relevance.

- The benchmarking highlighted that connectivity and sustainability dominate Asian shipyards (especially CSSC), while cultural alignment and strategic integration are critical for U.S. shipyards to improve resilience. Table 4 shows the benchmarking analysis along different dimensions.

Table 4: Benchmarking Analysis

Dimension	Found in Literature?	Evident in CSSC?	Evident in NASSCO?	Included in Model?
Culture	Yes	Partial	Partial	Yes
Strategy	Yes	Yes	Yes	Yes
Connectivity	Yes	High	Limited	Yes
Sustainability	Moderate	High	Developing	Yes

6. Future Outlook and Validation Roadmap

As shipbuilding evolves under the pressure of environmental regulations and global competition, integrating AI, robotics, digital twins, and IoT-driven systems will be central to enhancing shipyard performance and sustainability. Nations such as China and South Korea are already advancing smart shipyards with high levels of automation, supported by public R&D funding and specialized technical education. For the United States to remain globally competitive, it must invest in modernizing commercial shipyards, foster public-private innovation ecosystems, and develop AI-skilled talent pipelines.

While the benchmarking approach in this study aligns AI maturity dimensions with operational benchmarks from leading shipbuilders, future validation efforts are essential to strengthen the model’s practical application. These may include:

- Field trials in selected shipyards to assess maturity progression.
- Surveys of digital adoption across U.S. and international shipyards.
- Expert panels involving maritime engineers, defense contractors, and AI strategists will refine and validate model dimensions.
- Case-based longitudinal studies to track the impact of AI adoption on delivery efficiency and sustainability metrics.

Policymakers, business executives, and shipyard operators looking to speed up digital transformation in the maritime industry will find the model's acceptance as a strategic tool easier

with the help of a well-organized validation roadmap offering empirical support.

7. Conclusion

This study proposes a sector-specific AI maturity model to guide digital transformation in shipbuilding. It bridges the gap between generic models and shipyards' unique operational challenges. Future validation through real-world pilots and international benchmarking is recommended.

Amid fierce global competition, particularly from shipbuilding powerhouses such as China, Japan, and South Korea, these nations have secured leadership through advancements in automation, AI integration, and proactive industrial policy [7] In contrast, American shipyards face structural challenges such as higher labor and material costs, aging infrastructure, and limited automation in commercial operations [24], [25]. America must reduce reliance on foreign shipbuilders and re-establish the U.S. as a key player in the global maritime landscape. It bridges the gap between generic models and the unique operational challenges of shipyards.

Conflict of Interest

The authors declare no conflict of interest.

References

- [1] Y.-G. Lee, C.-H. Lee, Y.-H. Jeon, and J.-H. Bae, "Transformative Impact of the EU AI Act on Maritime Autonomous Surface Ships," *Laws*, **13**(5): 61, 2024, DOI: 10.3390/laws13050061.
- [2] P. C. Hong, Y. S. Park, D. W. Hwang, and M. J. Sepehr, "A growth theory perspective on the competitive landscape of shipbuilding: a comparative study of Japan, Korea, and China," *Maritime Economics & Logistics*, **26**(3): 462–489, 2024, DOI: 10.1057/s41278-023-00279-5.
- [3] B. F. Socoliuc, A. A. Suciuc, M. E. Popescu, D. A. Plesea, and F. Nicolae, "Shipyard Manpower Digital Recruitment: A Data-Driven Approach for Norwegian Stakeholders," *Economies*, **13**(1): 16, 2025, DOI: 10.3390/economies13010016.
- [4] "The Big Data bandwagon," *Strategic Direction*, **36**(10): 13–14, 2020, DOI: 10.1108/SD-08-2020-0144.
- [5] A. Cakir, Ö. Akin, H. F. Deniz, and A. Yilmaz, "Enabling real time big data solutions for manufacturing at scale," *Journal of Big Data*, **9**(1): 118, 2022, DOI: 10.1186/s40537-022-00672-6.
- [6] G. Cappellesso and K. M. Thomé, "Technological innovation in food supply chains: systematic literature review," *British Food Journal*, ahead-of-print (ahead-of-print), 2019, DOI: 10.1108/BFJ-03-2019-0160.
- [7] L. Jiang and S. P. Strandenes, "Assessing the cost competitiveness of China's shipbuilding industry," *Maritime Economics & Logistics*, **14**(4): 480–497, 2012, DOI: 10.1057/mel.2012.17.
- [8] World Bank, "Skilled Labor Force and Industrial Transformation," *Global Competitiveness Report*, [vol. and issue missing], [pages missing], [year missing].
- [9] D. Nadolny and M. Block, "Labor cost structures and competitiveness in U.S. shipbuilding," *International Journal of Maritime Engineering*, **165**(A2): 123–134, 2021.
- [10] F. K, "Legacy Systems and Interoperability in Large-Scale Engineering Projects: A Case Study of U.S. Shipyards," *System Engineering*, **24**(3): 210–225, 2022.
- [11] A. Martins, "Dynamic capabilities and SME performance in the COVID-19 era: the moderating effect of digitalization," *Asia-Pacific Journal of Business Administration*, **15**(2): 188–202, 2023, DOI: 10.1108/APJBA-08-2021-0370.
- [12] E. Omo, P. Abuonji, and L. Mburu, "SMEs' digital maturity: analyzing influencing factors and the mediating role of environmental factors," *Journal of Innovative Digital Transformation*, **2**(1): 19–36, 2025, DOI: 10.1108/JIDT-01-2024-0002.
- [13] M. Khraiwesh, "Measures of Organizational Training in the Capability Maturity Model Integration (CMMI)," *International Journal of Advanced Computer Science and Applications*, **11**(2): [pages missing], 2020, DOI: 10.14569/IJACSA.2020.0110274.
- [14] S. Mouhib, H. Anoun, M. Ridouani, and L. Hassouni, "Towards a Global Big Data Maturity Model," in *2020 Fourth International Conference On Intelligent Computing in Data Sciences (ICDS)*, IEEE, pp. 1–5, 2020, DOI: 10.1109/ICDS50568.2020.9268720.
- [15] J. Hu and S. Gao, "Research and Application of Capability Maturity Model for Chinese Intelligent Manufacturing," *Procedia CIRP*, **83**: 794–799, 2019, DOI: 10.1016/j.procir.2019.05.013.
- [16] N. B. Yams, V. Richardson, G. E. Shubina, S. Albrecht, and D. Gillblad, "Integrated AI and Innovation Management: The Beginning of a Beautiful Friendship," *Technology Innovation Management Review*, **10**(11): 5–18, 2020, DOI: 10.22215/timreview/1399.
- [17] W. Chen, C. Liu, F. Xing, G. Peng, and X. Yang, "Establishment of a maturity model to assess the development of industrial AI in smart manufacturing," *Journal of Enterprise Information Management*, **35**(3): 701–728, 2022, DOI: 10.1108/JEIM-10-2020-0397.
- [18] T. Paschou, M. Rapaccini, C. Peters, F. Adrodegari, and N. Sacconi, "Developing a Maturity Model for Digital Servitization in Manufacturing Firms," [Conference Book Title Missing], pp. 413–425, 2020, DOI: 10.1007/978-3-030-43616-2_44.
- [19] "Digital Maturity Model: Achieving digital maturity to drive growth," *Deloitte*, [year missing], [volume/issue/page missing].
- [20] L. Canetta, A. Bami, and E. Montini, "Development of a Digitalization Maturity Model for the Manufacturing Sector," in *2018 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)*, IEEE, pp. 1–7, 2018, DOI: 10.1109/ICE.2018.8436292.
- [21] G. Valdés, M. Solar, H. Astudillo, M. Iribarren, G. Concha, and M. Visconti, "Conception, development and implementation of an e-Government maturity model in public agencies," *Government Information Quarterly*, **28**(2): 176–187, 2011, DOI: 10.1016/j.giq.2010.04.007.
- [22] F. Blatz, R. Bulander, and M. Dietel, "Maturity Model of Digitization for SMEs," in *2018 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)*, IEEE, pp. 1–9, 2018, DOI: 10.1109/ICE.2018.8436251.
- [23] M. Kırmızı and B. Kocaoglu, "Digital transformation maturity model development framework based on design science: case studies in manufacturing industry," *Journal of Manufacturing Technology Management*, **33**(7): 1319–1346, 2022, DOI: 10.1108/JMTM-11-2021-0476.
- [24] P. Novakovic, "General Dynamics: Annual Report 2023," *General Dynamics*, Mar. 2024.
- [25] J. Saballa, "General Dynamics to Build More US Navy Replenishment Ships in \$6.7B Deal," *The Defense Post*, [vol./issue/page/year missing].
- [26] S. Wang, "China State Shipbuilding Corporation's Role in Smart Shipbuilding," *Marine Technology Reports*, **58**(2): 21–26, 2023.

- [27] HD Hyundai, "Annual Report 2023," *Hyundai Heavy Industries Group*, 2024.
- [28] Mitsubishi Heavy Industries Ltd., "Mitsubishi Heavy Industries Shipbuilding News," *Report*

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Cooperative Game Theory for Grid Service Pricing: A Utility-Centric Approach

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ABSTRACT

This study presents a novel alternative to traditional Net Energy Metering (NEM) by proposing a set of innovative pricing schemes for solar customers participating in utility-led grid service programs through the aggregation of Distributed Energy Resources (DERs). Grounded in cooperative game theory, the proposed framework facilitates equitable and efficient value allocation among key stakeholders, namely customers, utilities, and aggregators—based on their respective marginal contributions to grid performance and system cost reductions. In contrast to legacy NEM structures, which typically remunerate customers at retail rates and inadequately incentivize storage adoption, load flexibility, or temporal optimization, this approach enables new revenue opportunities by embedding DERs within coordinated grid service portfolios. The pricing mechanisms developed herein are centered on two critical grid services: energy arbitrage and peak load management. These services are provisioned by the excess capacity of customer-owned DERs, particularly rooftop photovoltaic systems and behind-the-meter battery storage. Through the implementation of a Grid Services Set (GSS) and a complementary Grid Services Rider (GSR) tariff structure, participating customers voluntarily permit automated utility coordination of their devices in return for performance-based compensation. An integrated optimization algorithm co-optimizes DER dispatch across both distribution-level operational requirements and real-time wholesale market opportunities, such as those found in the Energy Imbalance Market. This enables strategic charging during periods of surplus or negative pricing and discharging during price peaks. The proposed model contributes to the advancement of Non-Wires Alternatives (NWAs) by reducing reliance on conventional infrastructure upgrades and enhancing grid flexibility and resilience. It also offers a regulatory-aligned pathway for harmonizing DER integration with utility planning objectives, renewable energy targets, and climate adaptation strategies. By fostering a cooperative paradigm between utilities and customers, the framework promotes prosocial grid behavior, scalable DER participation, and innovation in the evolving landscape of decentralized energy systems.

List of Abbreviations:

- DER: Distributed Energy Resource
- GSS: Grid Services Set
- GSR: Grid Services Rider
- ISB: Integrated Service Bundle
- NEM: Net Energy Metering
- MSP: Marginal Supply Price
- AC: Avoided Costs
- CR: Customer Revenue (Compensation Rate)
- EIM: Energy Imbalance Market
- VoLL: Value of Lost Load
- LMP: Locational Marginal Price
- PBR: Performance-Based Regulation

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1. Introduction

The Grid Services Set (GSS) is designed to effectively leverage customer-owned Distributed Energy Resources (DERs) to enhance grid operational efficiency and reduce system-wide costs of service delivery [1]. This framework reimagines the role of customer DERs—such as rooftop solar, battery storage, and smart appliances—not as passive elements, but as dynamic assets that can contribute to real-time grid reliability and resilience [2].

In the proposed approach, residential customers voluntarily opt into an Integrated Service Bundle (ISB) authorizing automated control of their DER assets within a utility-managed framework that ensures consumer protection, incentivizes energy storage adoption, and facilitates scalable energy savings through home energy management systems. By providing a more integrated and dynamic mechanism for DER participation, the ISB approach seeks to address the shortcomings of existing policies, such as net energy metering (NEM). Traditional NEM programs, implemented through net metering tariff riders (NMR), compensate customers at the retail rate for the electricity exported to the grid. This has raised equity concerns, reduced dispatch efficiency, and provided limited incentives for adopting flexible loads or storage technologies [3].

In jurisdictions such as California and Nevada, rapid adoption of Distributed Energy Resources (DERs) has outpaced the evolution of compensation models, creating policy and operational challenges. For example, California's Net Billing Tariff (NBT), also known as NEM 3.0, has replaced traditional Net Energy Metering (NEM) with a value-based export rate that better reflects grid impacts. Similarly, Nevada's revised NEM program, established under Assembly Bill 405, implements a tiered rate structure and time-of-use pricing to incentivize consumption-shifting and storage adoption. Yet both approaches often fail to fully capture the grid value of flexible DER dispatch and offer limited support for coordinated grid services.

The GSS model enables the parallel development of a Grid Services Rider (GSR)—a new tariff mechanism that outlines how participating customers are compensated for providing grid services. These services include but are not limited to voltage support, frequency regulation, peak shaving, and load shifting. The design of the GSR involves establishing metering protocols, defining billing determinants, quantifying the locational and temporal value of grid services, and implementing equitable and transparent settlement procedures.

Historically, customer-owned DERs have participated in utility-administered programs (e.g., demand response, interruptible tariffs) or in regional transmission organization/independent system operator (RTO/ISO) markets through aggregators [4]. However, participation has been limited due to the complexity of compliance, technical barriers, and a lack of coordination across devices and programs. Large commercial and industrial (C&I) customers with advanced energy management capabilities often dominate such programs, while smaller residential customers remain underrepresented [5].

In response, utilities and third-party aggregators are exploring new paradigms that simplify participation for residential customers and enable DER coordination through bundled

offerings such as the ISB. Unlike conventional price-based coordination (e.g., “price-to-devices” strategies where utilities broadcast dynamic price signals to IoT-connected devices for self-scheduling [6]), the ISB emphasizes direct automated control and pre-negotiated compensation structures, simplifying participation and ensuring performance fidelity. This approach also supports distribution-level grid optimization—an increasingly important goal as electrification and DER penetration accelerate.

Moreover, competitive procurement mechanisms, where utilities solicit grid services from third-party aggregators, represent another emerging strategy, albeit with distinct implementation complexities and scalability challenges [7]. In contrast, the GSR/ISB framework offers a scalable, utility-centric pathway for integrating DERs into grid operations while maintaining regulatory oversight and aligning with public policy goals.

A foundational element of this work is the concept of excess DER capacity, which refers to the portion of a customer's DER resource that is not consumed onsite and is thus available to provide grid services. Properly tracking and monetizing this capacity requires accurate measurement of behind-the-meter energy flows and clear attribution of services performed. The proposed GSR tariff defines the mechanisms through which this excess capacity is converted into Grid Services Revenue (GS Revenue), offering solar customers an alternative to traditional NEM compensation schemes. Two specific grid services—(1) capacity reservation during critical system peaks and (2) responsive discharge during load ramps—are identified as illustrative use cases for this compensation model [8, 9].

To ensure fair and efficient distribution of the benefits arising from the aggregation and deployment of DER assets, this paper applies a cooperative game theory framework. In doing so, it proposes a utility-centric mechanism to allocate value among stakeholders—including utilities, aggregators, and individual customers—based on their marginal contributions to system reliability and cost reduction. The cooperative game theory lens has been previously applied to energy markets to explore fair revenue distribution, coalition formation, and incentive compatibility [10, 11]. In this context, the framework ensures that all parties benefit proportionately from participation, which is critical to sustained engagement and trust in utility programs.

This paper presents a game-theoretic pricing framework for DER-enabled grid services, drawing on cooperative game theory to ensure fair value allocation among stakeholders. It develops and simulates new pricing models for energy arbitrage and peak load management, incorporates real-world tariff examples, and evaluates the potential of DER coordination to support Non-Wires Alternatives (NWAs). The remainder of the paper details the design of the GSS/GSR mechanism, the cooperative value-sharing structure, simulation results, and policy implications.

2. Methodology: Cooperative Game Theory and Tariff Modeling

This service targets energy arbitrage opportunities within the Western Energy Imbalance Market (EIM), a real-time wholesale electricity market operated by the California Independent System

Operator (CAISO) that allows participants to buy and sell electricity in five-minute and fifteen-minute intervals across balancing authority areas. By leveraging co-optimization strategies, the proposed model enables Distributed Energy Resources (DERs), when aggregated under utility or aggregator management, to actively participate in this market and generate incremental Grid Services Revenue (GS Revenue) beyond local distribution-level benefits.

The underlying optimization algorithm is designed to maximize the net economic value derived from arbitrage by dynamically scheduling DER charging and discharging cycles. Specifically, the algorithm identifies periods of surplus generation—such as midday hours when solar production exceeds load demand—characterized by low or negative locational marginal prices (LMPs). During these periods, energy is stored in DER systems (e.g., home batteries, electric vehicles) under utility or aggregator control. Later, during periods of high system stress or elevated market prices, the stored energy is discharged and sold back into the grid, creating a price spread from which revenue is derived.

This model aligns with prior work demonstrating the potential of DERs to participate in energy arbitrage and ancillary services markets [12, 13]. By operating across both temporal price differentials and locational constraints, the model contributes to overall market efficiency while providing system-level benefits such as load balancing, renewable integration support, and peak demand reduction. Moreover, it highlights the dual-use potential of DERs, which can simultaneously serve local reliability needs and generate value in wholesale markets supported by recent developments in FERC Orders 2222 and 841, which expand access for aggregated DERs to wholesale markets [14].

Importantly, the cooperative game theory approach proposed in this paper ensures that the value generated through arbitrage is equitably distributed among participating customers, the utility, and other stakeholders based on their contributions to system performance. This contrasts with more centralized optimization paradigms, offering a fair and incentive-compatible structure for residential DER participation. The model also incorporates risk-adjusted dispatch constraints, including availability, degradation cost of storage devices, customer-defined operational limits, and forecast uncertainty, ensuring both robustness and customer satisfaction.

In sum, this arbitrage service extends the Grid Services Set (GSS) from a purely distribution-grid operational model to one that is interoperable with real-time market signals, supporting the vision of a transactive, prosumer-enabled grid.

To establish a transparent and equitable pricing mechanism for event-based grid services, this paper draws upon foundational principles from cooperative game theory [15, 16], particularly in scenarios where bargaining power is assumed to be equally distributed among stakeholders. The core intuition is to determine a “fair market rate” for DER-enabled grid services that simultaneously improves the net payoff for both the utility and participating customers. This framework departs from competitive or adversarial pricing schemes and instead focuses on joint value creation and benefit sharing, which is central to achieving a sustainable “win-win” equilibrium.

The cooperative model is conceptualized as a two-state system, distinguishing between the baseline case of non-cooperation and the potential for enhanced collaboration through contractual participation in grid service programs.

2.1 Non-Cooperative Baseline

In the non-cooperative scenario, the utility continues its operations under business-as-usual conditions without engaging customers in DER-driven event-based services. Customers consume energy and are billed according to their existing rate structures—typically flat rates or tiered pricing—without receiving compensation for any grid-supporting actions their DERs might be capable of. Under this scenario, no formal coordination exists between the utility and its customers regarding resource dispatch or grid service contributions.

The financial outcomes for each party in this state are modeled as follows:

- Utility Payoff per kWh:

$$U_{\text{baseline}} = \text{FR} - \text{MSP} - \text{AC}$$

Where:

- FR = Flat Rate charged to the customer per kWh
- MSP = Marginal Supply Price (i.e., cost to procure electricity from the wholesale market or EIM)
- AC = Avoided Costs, including capacity deferral, ancillary service costs, or reduced grid congestion, attributable to potential DER participation

This formulation defines the utility’s net revenue per kWh without DER compensation or coordination, excluding fixed charges for simplicity. This condition is particularly relevant when $\text{FR} < \text{MSP} + \text{AC}$, as it suggests the utility may be incurring a loss for each kilowatt-hour delivered, making cooperative alternatives more attractive.

- Customer Payoff:

$$CR_{\text{baseline}} = 0$$

Since customers are not compensated for their flexibility or DER participation, they accrue no financial benefit from supporting grid services and only incur standard retail charges. This scenario sets the baseline for evaluating the marginal improvement offered by cooperation.

2.2 Cooperative Agreement with Grid Service Compensation

In the cooperative scenario, customers enter into a formalized grid service arrangement with the utility, wherein they agree to allow their DERs (e.g., batteries, smart inverters, thermostats) to be dispatched or managed in alignment with grid needs. In exchange, customers receive credit or payment (CR) for their

participation, while the utility benefits from the avoided costs and potentially enhanced operational efficiency.

For such cooperation to be rationally attractive to both parties, their respective payoffs under cooperation must exceed those under non-cooperation. The utility revenue in this case adjusts to reflect the cost of compensating the customer:

• **Utility Revenue under Cooperation:**

$$U_{coop} = FR - MSP - AC - CR$$

The condition for utility participation is:

$$U_{coop} \geq 0 \Rightarrow FR - MSP - AC - CR \geq 0$$

This inequality implies that the utility will only agree to share a portion of the avoided cost (via CR) if its net revenue remains non-negative, or ideally, improves. If the utility is experiencing a negative margin in the baseline case (i.e., $FR < MSP + AC$), the cooperative arrangement becomes not only viable but economically advantageous, as the avoided losses can be partially reallocated to customer compensation without creating a net loss.

• **Customer Revenue:**

$$CR > 0$$

Under this scheme, customers receive a tangible benefit for their grid contributions, creating a clear economic incentive to participate. The cooperative framework, particularly when modeled through Shapley values or Nash bargaining solutions, can further refine the exact division of surplus based on marginal contributions, ensuring allocative efficiency and fairness.

2.3 Simulation of Tariff Schemes

The cooperative model offers several compelling advantages. It transforms passive energy consumers into active grid participants, incentivizes demand flexibility, and internalizes DER benefits into utility planning processes. Furthermore, because the model is grounded in mutual surplus generation, it creates self-enforcing agreements that do not rely on heavy-handed regulatory mandates or subsidies.

In practice, this framework can be expanded to accommodate a variety of rate designs, including time-of-use pricing, critical peak pricing, or even real-time locational prices, depending on market maturity and metering infrastructure. Moreover, the model is extensible to scenarios where customer bargaining power is not equal—e.g., in low-income or underserved communities—by incorporating weighted utility functions or social welfare constraints into the cooperative solution.

Customers’ payoffs would be $CR + FR$, not only do they avoid paying the rate, but they also receive compensation for helping to improve grid reliability. To derive the fair rate for the grid service, we solve the following Nash equation incorporating the bargaining powers for both sides:

$$Max U \{ (| - MSP - AC - CR + FR |)^p (CR)^{1-p} \}$$

Where $FR < MSP + AC$, and p is the bargaining power between the utility and the customers.

By solving the first-order condition, we derive the customer compensation rate (CR) as:

$$CR = (1-p)(MSP + AC - FR)$$

For simplicity, we can assume 50-50 benefit sharing (an equal bargaining power between utility and customers, where $p = 0.5$); thus, CR would be $0.5 * (MSP + AC - FR)$.

We can use any real time EIM nodal price as the MSP in the above formula.

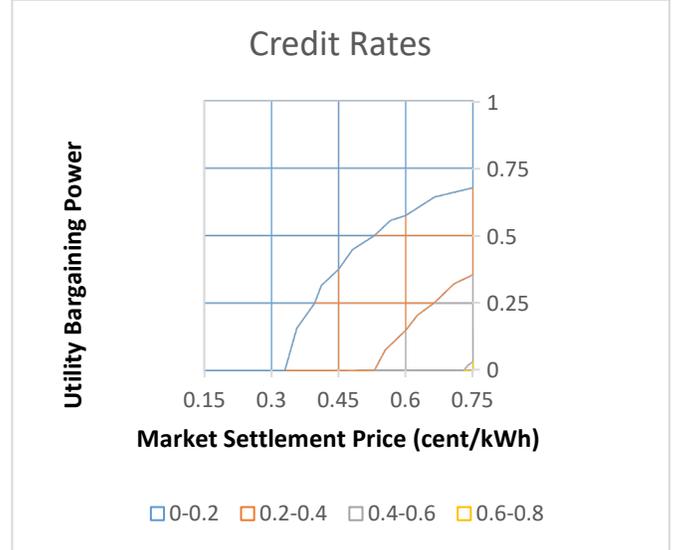


Figure 1: Simulated credit rates under different scenarios

Figure above shows a basic simulation when utility’s bargaining power (P : vertical axis) changes from 0 to 1, and market price (MSP: horizontal axis) changes from 15 to 75 cents per kWh.

2.4 Energy Arbitrage Tariff Scheme Structure

The following formula can be used to compensate the customers when such service is being called:

$$CR = 0.5 * [MSP + ACGC + ACTC]$$

The avoided costs are subject to change based on the annual confirmation of the GRC filing for each utility. Here, I assume arbitrary rounded values for the purpose of this practice.

AC could be one or a combination of the costs:

Avoided cost of generation capacity (ACGC) = \$ 0.03 kWh

Avoided cost of transmission capacity (ACTC) = \$ 0.01 kWh

Avoided cost of distribution capacity (ACDC) = \$ 0.015 kWh.

Substituting the above values, and setting a random market settlement price (MSP) to \$50 MWh, we get the customers’ compensation as follow:

$$CR = 0.5 * [0.05 + 0.03 + 0.01] = \$0.045.$$

3. Peak Load Management

The peak load management service seeks to minimize both the system peak load and the distribution peak load at managed aggregation points through load shaping and load shed [17]. The

proposed grid service offers a dual-purpose economic and emergency dispatch framework for Distributed Energy Resource (DER) assets, targeting both peak load management and distribution-level reliability enhancement. It plays a foundational role in the Grid Services Set (GSS) by enabling utilities to optimize DER dispatch across time and space in alignment with system-wide operational objectives. At its core, the service executes a real-time or near real-time optimization process whose primary objective function is to minimize total system energy procurement costs, specifically during peak demand periods, while simultaneously mitigating local distribution grid stress through location-specific dispatch incentives.

From a systems integration perspective, the formulation harmonizes transmission-level and distribution-level objectives by embedding dual-pricing signals within a single optimization framework. On the transmission side, the model ingests real-time wholesale market prices, particularly those related to system peak events or high locational marginal prices (LMPs), typically observed in the Energy Imbalance Market (EIM) or day-ahead markets. On the distribution side, it incorporates locational “shadow prices”, derived from distribution-level constraints such as transformer loading, feeder congestion, or equipment thermal limits. These shadow prices act as proxies for the marginal reliability value of DER dispatch at specific nodes, enabling the system operator to prioritize areas of the grid that are more vulnerable to overload or failure during high demand.

Operationally, when the probability of distribution equipment overload—such as transformer overheating or feeder voltage violations—exceeds a defined threshold, the dispatch algorithm adjusts DER instructions to prioritize local reliability over broader system economic objectives. In such scenarios, devices located within constrained zones are directed to export energy or reduce consumption in a way that alleviates stress on the most at-risk aggregation points, thus preventing equipment damage or service interruptions. Conversely, during periods of normal or low distribution system risk, the same optimization algorithm reverts to a market-cost minimization objective, leveraging DER flexibility to reduce utility exposure to wholesale market price volatility, particularly during regional peaks or scarcity pricing events.

Importantly, this dynamic optimization process respects the operational constraints and preferences of DER-owning customers. It factors in variables such as state-of-charge limitations for batteries, comfort bands for smart thermostats, and usage patterns for behind-the-meter systems to ensure that customer experience and participation willingness are preserved. This constraint-sensitive design is critical for maintaining trust and ensuring consistent engagement in voluntary or incentive-based programs.

In cases of unexpected emergency conditions, such as system faults, weather-related disruptions, or load-forecasting errors that result in unforeseen peaks, the service includes a pre-configured rapid dispatch protocol. This protocol allows eligible DERs—particularly battery storage systems and fast-responding inverter-based technologies—to act as 10-minute spinning reserves. Devices enrolled under this protocol receive advanced configuration settings that dictate their behavior in emergency

events, allowing them to respond without requiring real-time optimization or operator intervention. This capability not only strengthens distribution system resilience, but also aligns with broader grid modernization goals, such as increasing non-wire reliability options and reducing reliance on traditional spinning reserve sources.

By merging economic dispatch with reliability-based dispatch logic and enabling rapid fallback mechanisms, this service represents a multifunctional tool for modern grid operations. It enhances distribution system reliability, reduces peak demand charges, facilitates renewable integration by improving grid flexibility, and enables DERs to participate meaningfully in both energy and ancillary services markets. Moreover, architecture establishes a platform for future market-based dispatch mechanisms, potentially allowing DERs to participate in locational capacity markets or transactive energy systems where grid constraints and energy prices are jointly optimized.

3.1. Peak Load Management Tariff Schemes

To ground the proposed methodology in a realistic context, we construct a stylized example of a utility service area with moderate DER penetration. The scenario includes customer-owned rooftop solar, battery systems, and smart inverters, operating under typical Western U.S. pricing dynamics. For simulation purposes, we assume a market settlement price of \$50/MWh, avoided generation costs of \$0.03/kWh, and a residential VoLL of \$7/kWh. These inputs are used to demonstrate the energy arbitrage and peak load management compensation formulas developed in this study.

$$CR = 0.5 * [MSP*(1+LL) + ACGC + ACTC + ACDC + E(ICE| \text{Utility Residents}) * CDF.Norm] \text{ (load forecast, } 1.1 * \text{transformer rate, load STD)}$$

Value of lost load (VoLL) = Expected value of interruption cost estimation (\$7 kWh for residents, that can be adjusted for inflation based on the CPI in 2016 [when the ICE calculation was estimated] and current year) * cumulative normal distribution, where X is the forecasted load, mean is the transformer/feeder capacity, and the standard deviation of the historical load on that transformer/feeder; the probability function looks as follow using excel formula:

$$CDF.Norm(\text{Forecasted load, transformer rate, standard deviation between actual and backtest/backcast, True})$$

$$\text{Line loss (LL)} = 8\% \text{ of the load at the peak}$$

As an illustrative example, consider a standard substation transformer in the western region of Las Vegas with a rated capacity of 37 MVA. If the forecasted load is 36 MVA and the historical load standard deviation is 6.74 MVA, and assuming a market settlement price (MSP) of \$50/MWh, the resulting customer credit would be:

$$CR = 0.5 * [0.05*(1.08) + 0.03 + 0.01 + 0.015 + 7*(0.24)] = \$0.8945 \text{ kWh.}$$

4. Discussion

The proposed Grid Services Set (GSS) and its associated cooperative pricing schemes represent a paradigmatic shift in the integration of Distributed Energy Resources (DERs) into

regulated utility frameworks. Traditionally, customer-sited solar and storage assets have been compensated through static models such as net energy metering (NEM), which, despite their simplicity, have increasingly been critiqued for their misalignment with the actual value streams that DERs provide to the grid [18]. By moving beyond NEM toward a dynamic, service-based compensation framework, the GSS introduces a game-theoretic, value-reflective approach that fosters symbiotic cooperation between utilities and DER-owning customers.

From a cooperative game theory perspective, the proposed tariff design formalizes a benefit-sharing coalition between utilities and customers. Customers, in return for providing real-time grid services—such as energy arbitrage, peak shaving, and voltage support—are compensated not just for their exported kWh, but for the marginal grid value their actions create. This aligns with the Shapley value framework for cooperative games [19], where each participant is remunerated in proportion to their contribution to the coalition's total value. Such structuring addresses the free-rider problems inherent in flat or volumetric compensation schemes.

4.1. Energy Arbitrage and Market Synergies

A central component of the GSS is the energy arbitrage pricing model, which leverages hourly price signals from the Energy Imbalance Market (EIM) and enables DER participants to buy and store electricity during low-price periods and discharge or export during high-price windows. This approach mirrors utility-scale arbitrage strategies already employed by grid operators and independent power producers but adapts them to the residential and commercial customer scale through automated control systems and smart contracts.

This democratized arbitrage model benefits utilities by:

- Shaving peaks and reducing marginal procurement costs
- Improving load shape and net demand predictability
- Minimizing dependence on peaker plants, which are often carbon-intensive and expensive to operate

Simultaneously, customers gain access to non-linear revenue streams beyond flat-rate bill reductions, making participation more economically attractive and sustainable long-term. The application of formula-based compensation models, adjusted dynamically to market prices and system needs, ensures transparency and predictability in customer payments while remaining value-aligned with system conditions.

4.2 Peak Load Management and Reliability Contributions

Another key innovation in the proposed framework is the integration of DERs into distribution-level peak load management. By deploying localized DER dispatch in a coordinated fashion, either through virtual power plant (VPP) aggregations or utility-orchestrated demand response, the grid can mitigate distribution and system-level constraints more efficiently [20]. This is especially critical in high-DER penetration environments where feeder-level constraints, reverse power flow, and voltage excursions become more prevalent.

Importantly, the use of Value of Lost Load (VoLL) as part of the compensation metric recognizes the reliability value that customer DERs contribute during high-stress grid events. This valuation approach is consistent with reliability-centered planning in utilities and reflects current best practices in performance-based ratemaking and resource adequacy compensation [21]. Incorporating VoLL reinforces customer engagement while addressing equity concerns by compensating for both energy and capacity value provided.

4.3 Implementation Challenges and Regulatory Considerations

Despite the theoretical and practical benefits of the GSS model, several challenges require careful consideration for successful implementation:

- Automated DER Participation and Customer Trust

Effective participation in the GSS framework depends heavily on real-time automated control of DERs, either via customer-side energy management systems or utility aggregation platforms. This raises concerns around customer autonomy, data privacy, and cybersecurity—areas that are increasingly scrutinized under evolving federal and state guidelines. Transparent governance structures, opt-in/opt-out flexibility, and clear data ownership policies will be essential for fostering long-term customer trust.

- Advanced Metering and Billing Infrastructure

The proposed pricing schemes require granular metering (e.g., 5-minute intervals) and advanced billing platforms capable of real-time settlements and post-hoc performance validation. While many utilities are investing in AMI (Advanced Metering Infrastructure), not all service territories are equally prepared. Therefore, regulatory support and cost recovery mechanisms must be aligned to facilitate these capital expenditures, particularly in vertically integrated utility structures.

- Policy Alignment and Market Integration

Full deployment of the GSS model will also require harmonization with state-level policy directives, including renewable portfolio standards, decarbonization mandates, and equity goals. Pilot programs, sandbox testing environments, and performance-based regulation (PBR) models may serve as intermediaries to test the framework's effectiveness before wider rollout. Moreover, coordination with wholesale markets (e.g., ISO/RTOs) is necessary to avoid value duplication and ensure accurate settlement of grid services at both distribution and transmission levels.

4.4 Statistical Inference on Value Distribution

To evaluate the robustness of the proposed pricing scheme, we simulated a range of market settlement prices (MSP) from \$30/MWh to \$75/MWh and applied corresponding avoided cost values with $\pm 20\%$ variability, reflecting annual utility cost filings. The resulting customer compensation rates (CR) varied between \$0.035/kWh and \$0.10/kWh. A Monte Carlo simulation with 10,000 trials, drawing MSP and avoided cost parameters from triangular distributions, yielded an expected CR of \$0.062/kWh with a standard deviation of \$0.011. This inference supports the conclusion that even under cost volatility, the cooperative scheme consistently generates nontrivial value for participating

customers. Moreover, 95% of the simulated outcomes exceeded a baseline zero-compensation NEM scenario, indicating statistical dominance of the cooperative framework.

5. Conclusion and future directions

This paper proposes a utility-centric, cooperative game-theoretic framework for pricing distributed energy resources (DERs) that participate in grid service programs. The study introduces the Grid Services Set (GSS) and the associated Grid Services Rider (GSR) tariff as scalable mechanisms to integrate customer-owned DERs—such as rooftop solar and battery storage—into both distribution-level operations and real-time wholesale markets. The proposed compensation structure departs from traditional Net Energy Metering (NEM) models by reflecting the marginal grid value of DER contributions, rather than static volumetric offsets. Through cooperative value-sharing principles, particularly those derived from Shapley value and Nash bargaining concepts, the framework ensures equitable distribution of system benefits among utilities, aggregators, and customers.

Key findings include:

- The demonstration of cooperative pricing schemes that internalize avoided capacity, reliability, and market arbitrage benefits into customer compensation.
- A dual optimization approach that co-optimizes DER dispatch for both grid resilience (e.g., peak load management) and market revenue (e.g., energy arbitrage in the Energy Imbalance Market).
- The use of risk-adjusted and customer-sensitive constraints to balance economic efficiency with customer participation willingness and equity.

These findings collectively support a shift toward dynamic, service-based DER valuation that can align utility financial interests with policy goals around decarbonization, affordability, and grid modernization.

Future research directions include:

- Empirical testing and validation through pilot programs in diverse regulatory and market environments to assess the real-world feasibility and customer responsiveness to cooperative DER pricing.
- Integration of advanced forecasting and optimization tools, including machine learning algorithms, to enhance the precision of dispatch schedules and pricing signals under uncertainty.
- Exploration of differentiated pricing strategies to account for socioeconomic factors, ensuring equitable participation across income levels and geographies.
- Institutional design and governance research to determine optimal structures for utility-aggregator-customer coordination, particularly in vertically integrated versus deregulated markets.
- Regulatory analysis to identify pathways for harmonizing GSR-type tariffs with performance-based regulation and

wholesale market participation frameworks, such as those enabled by FERC Orders 841 and 2222.

By advancing both the theoretical and practical foundations for cooperative DER integration, this study contributes to a more adaptive and equitable energy system in the face of increasing decentralization and climate imperatives.

Conflict of Interest

The authors declare no conflict of interest.

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References

- [1] P. Denholm, R. M. Margolis, J.M. Milford, "Production cost modeling for high levels of photovoltaics penetration," National Renewable Energy Laboratory 2010, doi: 10.2172/924642
- [2] T. Navidi, A. El Gamal, R. Rajagopal, "Coordinating distributed energy resources for reliability can significantly reduce future distribution grid upgrades and peak load," *Joule*, 7(8), 1769-1792, 2023, DOI: 10.1016/j.joule.2023.06.015.
- [3] S. Borenstein, "The Private Net Benefits of Residential Solar PV: The Role of Electricity Tariffs, Tax Incentives, and Rebates," *Journal of the Association of Environmental and Resource Economists*, 4(S1), S85–S122, 2017, DOI: 10.1086/691978.
- [4] R. Matsuda-Dunn, L. Leddy, E. Hotchkiss, M. Gautam, M. Abdelmalak, "What Role Do Aggregators Play in Power System Security and Resilience?" Preprint. Golden, CO: National Renewable Energy Laboratory. NREL/CP6A40-85649, 2023, DOI: 10.1109/RWS58133.2023.10284615.
- [5] S.P. Burger, M. Luke, "Business models for distributed energy resources: A review and empirical analysis," *Energy Policy*, 109, 230–248, 2017, DOI: 10.1016/j.enpol.2017.07.007.
- [6] J.L. Mathieu, D.S. Callaway, S. Kiliccote, "Examining uncertainty in demand response baseline models and variability in automated responses to dynamic pricing," In *IEEE Conference on Decision and Control*, 2011, DOI: 10.1109/CDC.2011.6160795.
- [7] R. Hledik, T. Lee, "Load flexibility: Market potential and opportunities in the United States," In *Variable Generation, Flexible Demand* (pp. 195-210). Academic Press, 2021, DOI: 10.1016/B978-0-12-823810-3.00001-7.
- [8] E. Hittinger, J. Siddiqui, "The challenging economics of US residential grid defection." *Utilities Policy* 45: 27-35, 2017, DOI: 10.1016/j.jup.2016.11.003.
- [9] F. Farhidi, M. Rusakov, M. "An Application of Excess Solar and Storage Capacity Optimization for Grid Services," *Journal of Energy and Power Technology*, 6(3), 1-25, 2024, DOI: 10.21926/jept.2403017.
- [10] W. Saad, Z. Han, H.V. Poor, T. Başar, "A noncooperative game for double auction-based energy trading in microgrids," In *2011 IEEE International Conference on Smart Grid Communications*, 2011, DOI: 10.1109/SmartGridComm.2011.6102323.
- [11] K. Khezeli, H. Firoozi, "A Cooperative Game Theory Approach for Fair Cost Allocation in Peer-to-Peer Energy Trading," *Sustainable Energy, Grids and Networks*, 21, 100299, 2020, DOI: 10.1016/j.segan.2020.100299.
- [12] R. Sioshansi, P. Denholm, T. Jenkin, J. Weiss, J. "Estimating the value of electricity storage in PJM: Arbitrage and some welfare effects," *Markets Operated by Regional Transmission Organizations and Independent System Operators*, 2020, Docket No. RM18-9-000.
- [13] F. Farhidi, K. Madani, "A game theoretic analysis of the conflict over

- Iran's nuclear program," IEEE International Conference on Systems, Man, and Cybernetics, pp. 617-622, 2015, DOI: 10.1109/SMC.2015.118.
- [14] K. Madani, F. Farhidi, S. Gholizadeh. "Bargaining Power in Cooperative Resource Allocations Games," Algorithms 15, no. 12: 445, 2022, DOI: 10.3390/a15120445.
- [15] S. Iqbal, M. Sarfraz, M., Ayyub, M., Tariq, R.K. Chakraborty, M.J. Ryan, B. Alamri, "A comprehensive review on residential demand side management strategies in smart grid environment," Sustainability, 13(13), 7170, 2021, DOI: 10.3390/su13137170.
- [16] S. Borenstein, "The Private Net Benefits of Residential Solar PV: The Role of Electricity Tariffs, Tax Incentives and Rebates," Journal of the Association of Environmental and Resource Economists, 4(S1), S85-S122. 2017, DOI: 10.1086/691978.
- [17] L.S. Shapley, "A Value for n-person Games," Ann. Math. Stud. 28, 307–318, 1953, DOI: 10.1515/9781400881970-018.
- [18] H. Gao, T. Jin, C. Feng, C. Li, Q. Chen, C. Kang, "Review of virtual power plant operations: Resource coordination and multidimensional interaction," Applied energy, 357, 122284, 2024, DOI: 10.1016/j.apenergy.2023.122284.
- [19] M. Najafi, A. Akhavein, A. Akbari, M. Dashtdar, "Value of the lost load with consideration of the failure probability," Ain Shams Engineering Journal, 12(1), 659-663, 2021, DOI: 10.1016/j.asej.2020.05.012.
- [20] Energy Economics, 31(2), 269–277, 2009, DOI: 10.1016/j.eneco.2008.10.005.
- [21] E. Hittinger, J.F. Whitacre, J. Apt, J. "What properties of grid energy storage are most valuable?" Journal of Power Sources, 206(1), 436–449, 2010, DOI: 10.1016/j.jpowsour.2011.12.023.

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Explainable AI and Active Learning for Photovoltaic System Fault Detection: A Bibliometric Study and Future Directions

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ABSTRACT

Persistent anomalies in modern photovoltaic (PV) systems present a formidable challenge, impeding optimal power output and system resilience. Artificial Intelligence (AI) has surfaced as a game-changing solution, yet existing research has merely scratched the surface of solar panel prognosis, leaving a critical void in leveraging AI's explainable nature and active learning capabilities. This pioneering study investigates AI methods for detecting and classifying critical faults in PV systems, pushing the boundaries of innovative methodologies for fault identification. We acknowledge that the opacity of AI methods can hinder their adoption, particularly among practitioners, thus emphasizing Explainable AI (XAI) in an exhaustive bibliometric analysis. This study showcases authors who thoroughly detail their development processes and underscores the indispensable role of human/expert interaction in active learning for labeling the most informative data. Our findings unveil a glaring underutilization of XAI in the solar panel domain, with China at the forefront of this field. This leadership is likely attributed to the robust research focus in Chinese universities and China's position as the world's leading solar panel producer. We delve into the potential role of human/expert involvement in designing and deploying deep learning predictive applications, highlighting methods that harmoniously integrate practical knowledge from human end-users through active learning. Our methodology encompasses extensive data collection, bibliometric analysis of collaborations between entities, researchers, and nations, and an examination of the most prevalent persistent faults. We conclude by strongly advocating for future studies to address the underutilization of XAI and active learning in AI-based defect prediction. Bridging this gap is crucial for pinpointing the root causes of solar panel defects and enhancing prognosis, positioning this research as indispensable for both scientists and industry professionals at the forefront of PV technology.

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1. Introduction

1.1. Photovoltaic System

Photovoltaic energy is derived from the direct conversion of sunlight into electricity through solar cells, also known as photovoltaic cells, which form the basic component of a photovoltaic production chain. The assembly of multiple photovoltaic cells forms a photovoltaic module, commonly referred to as a solar panel [1]. A photovoltaic power plant is a solar installation comprised of numerous interconnected modules to generate electricity on a large scale, often intended to supply an electrical grid [2].

Over the past few decades, photovoltaic electricity production has experienced extremely significant growth worldwide. The International Energy Agency's forecasts for the year 2025 indicate that solar energy will provide approximately 60% of the total demand for renewable energy, placing it at the forefront of the most promising sources [3]. In terms of production, China positions itself as the world's leading producer of solar panels and has strongly committed to increasing its share of non-fossil fuel energy usage to 25% by 2030, aiming to satisfy 27.5% of the world's energy demand with solar energy by 2050 [4]. It is worth noting, however, that African nations are not lagging behind in this crucial fight against global warming and the adoption of green energies. For instance, Ghana has embarked on a major transition towards renewable energy. The Ghanaian government has adopted a master plan aimed at increasing electricity production capacity from 42.5 MW in 2015 to 1363.63 MW by 2030, with photovoltaic solar sources representing more than 50% of the total capacity [5]. Solar highways also offer enormous opportunities for Bangladesh [6]. However, the use of photovoltaic (PV) modules for energy production is not a simple task, due to potential degradation that can lead to a decrease in the performance and efficiency of PV solar installations [7]. According to recent studies, the degradation rate varies between 0.6% and 0.7% per year [8]. Therefore, it is imperative to examine the defects that may compromise the proper functioning of photovoltaic solar installations.

1.2. Fault Detection

Solar panel defects refer to any abnormalities or problems affecting the structure, performance, or durability of photovoltaic solar panels. These imperfections may encompass manufacturing, transportation, installation, environmental, or electrical defects that can cause a decrease in energy efficiency, a reduction in useful lifespan, or safety risks. Failures in PV systems result from various factors such as shading, module contamination, inverter failure, and variations in manufacturing or aging of photovoltaic modules, among others [9-10]. These elements can lead to a performance decrease of over 2.5%, progressively contributing to the deterioration of the affected component's longevity [10].

Generally, these defects can be classified into three main categories: abrupt, intermittent, and incipient faults. Ground-fault or line-to-line short circuits, open-circuit defects, connector disconnections, and junction box anomalies are examples of abrupt faults that occur when part or all of the PV network is damaged. Partial shading or environmental fluctuations represent examples of temporary or intermittent fault sources that may fade or evolve over time (such as dust or contamination). The third type, called incipient faults, manifests as minor but potentially dangerous anomalies that evolve slowly over time, making their initial detection difficult. If not identified timely, their consequences can be hard to control. These faults can occur on both the DC side, i.e., PV module and DC-DC converter parts (such as yellowing and browning of solar cells, delamination, cracks, bubbles, and anti-reflective coating defects), as well as on the AC side, i.e., the inverter side (examples include bipolar transistor faults, overheating, aging, and degradation of connection cabling) [11-12].

In the literature, several approaches to detecting and diagnosing faults in solar systems are distinguished. These methods are primarily characterized by their ability to quickly detect malfunctions, to instantly analyze the necessary input data (whether climatic or electrical), and to be selective, i.e., able to distinguish the type of fault in question. Thus, they can be classified into two main families: Visual and thermal methods specific to detecting malfunctions such as discoloration, browning, soiling, hotspots, breakage, delamination, etc., and Electrical methods that focus on defective PV modules, strings, and matrices, including arc, ground, and diode faults, etc. [13-15]. However, it often happens that both approaches are combined to solve specific malfunctions, as is the case with Artificial Intelligence methods.

1.3. Contributions and Research Objectives of the Paper

Bibliometric research is a quantitative analysis method used to study scientific publications. It aims to measure and evaluate different aspects of scientific production, such as the number of publications, citations, journal impact, and collaboration networks between researchers and institutions. Bibliometrics also quantifies researchers' contributions, identifies research trends, tracks field evolution, and assesses research impact on the scientific community. It is widely employed in scientific policy decision-making, resource allocation, and researcher and institution performance evaluation. In recent years, numerous researchers and fields have shown interest in bibliometrics. References [16-18] respectively present the use of bibliometric techniques to examine basic research on blockchain technology in the energy sector, the state of research on using blockchain technology for environmental sustainability in the building sector, and recent progress in electrolyzer control technologies for hydrogen production. Other works like reference [19] analyze research trends in big data analysis of the Internet of Things (IOT) and fog computing in the health sector, and reference [20] performs a

comprehensive analysis of research in Energy System Analysis (ESA) using statistical techniques. Reference [21] provides a detailed analysis of research on predictive maintenance 4.0 by artificial intelligence, while references [22-23] focus on emerging techniques and trends in equipment maintenance systems, and reference [24] presents the evolution of artificial intelligence. Reference [25] offers a literature review on machine learning in industrial applications.

In the field of solar energy, bibliometric analysis has been integrated to identify emerging research areas and provide an impartial overview of current research status. A key work to date is that of [26], where bibliometrics was used to analyze a large number of documents on artificial intelligence methods for detecting and diagnosing faults in photovoltaic systems published since 2023.

To our knowledge, no bibliometric study on the prognosis by artificial intelligence of critical anomalies for predictive maintenance of photovoltaic systems has been identified. This gap in the literature pertains to the targeted faults, which can lead to total or partial shutdown of electricity production in photovoltaic systems, remaining unexplored.

In this research, we undertake a bibliometric analysis of publications indexed in the Scopus database, focusing specifically on the prognosis of critical faults in photovoltaic systems through artificial intelligence methods. We pay particular attention not only to the explanatory and descriptive aspect of the design and application procedures of AI methods but also to highlighting studies on human involvement in the AI integration process. In photovoltaic engineering, fault diagnosis identifies and locates current anomalies through real-time or historical data analysis and inspection techniques, aiming for quick detection for immediate corrective measures. Prognosis predicts the evolution and severity of future problems using degradation models and historical data, enabling planning of preventive maintenance actions to extend solar system life and minimize production interruptions.

Several questions arise in this work, including: What are the current trends in AI involvement in diagnosing and prognosing faults in PV systems? What is the role of active learning (human/expert involvement) in machine learning implementation for this problem? What are the main challenges related to AI methods application in PV system lifespan prognosis?

Figure 1 presents the flowchart of actions for this work: (1) and (2): Data collection from the Scopus database using specific keywords related to the topic. (3): Selection of important documents based on quality criteria, aiming to create a database containing necessary and relevant information to determine hidden relationships automatically. (4) and (5): Processing, analysis, and visualization of selected documents using tools such as R Bibliometrix (Biblioshiny) [27] or VOSviewer [28]. Highlighted information includes main trends, collaboration networks, most cited documents, challenges in AI prognosis of defects, XAI trends, human involvement in AI implementation,

publication trends over time, most productive authors, leading countries, and frequent keywords.

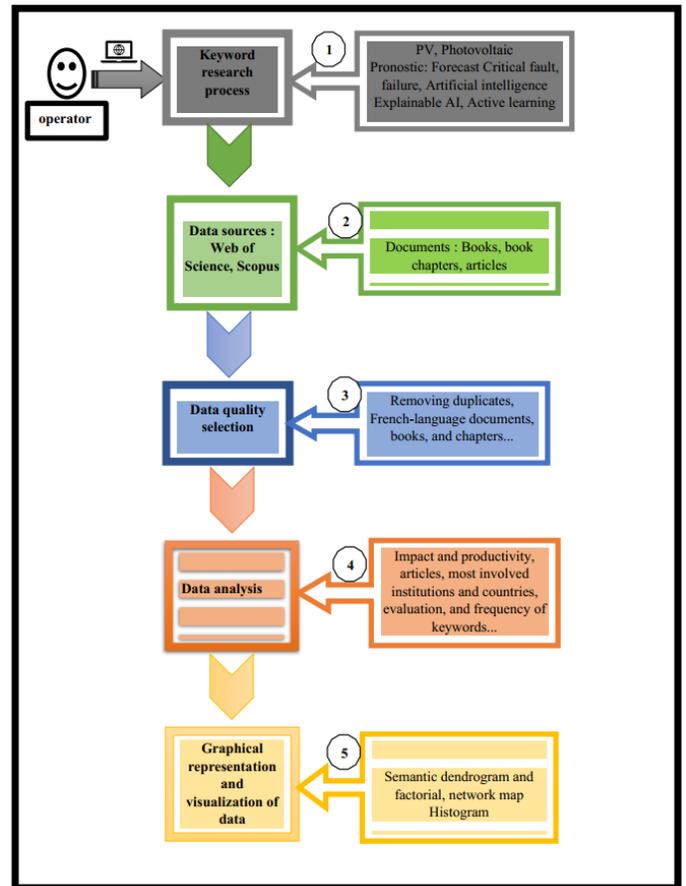


Figure 1: Methodological Framework for Bibliometric Analysis. Each step is color-coded and corresponds to a specific number

1.4. Explainable IA Learning and Active Learning

1.4.1. Explainable IA

Machine learning methods, particularly with the advent of neural networks (NN), are now widely used in engineering applications. This success has led to considerable adoption of machine learning (ML) in many scientific fields, including photovoltaic energy. However, most modern AI techniques suffer from the concept of the black box nature, which hinders their adoption by practitioners in many application areas. Explainability is a prerequisite to ensure the scientific value of the result. In this context, research directions such as explainable artificial intelligence (AI) [29], informed machine learning [30], or intelligible intelligence [31] have emerged.

The term XAI, for "eXplainable Artificial Intelligence," refers to a set of processes and methods aimed at making every result calculated by artificial intelligence understandable. It is a field of Machine Learning that seeks to precisely justify a given result by a model. Explainable AI (or XAI) is thus a research area in artificial intelligence that aims to create AI systems capable of explaining their decisions, actions, or results in a way that is understandable to humans. This approach distinguishes itself

from many current AI systems, particularly those based on deep learning, which are often considered "black boxes" due to the difficulty in understanding their internal functioning [32-33].

Figure 2 above highlights the contrast between precision and explainability of the most commonly used models. Special attention is given to Artificial Neural Networks (ANNs), which constitute the majority of the most used AI methods in PV fault detection and prognosis. From this graph, it is clear that ANNs are very precise but have low explainability. The explainability of AI in general, or machine learning in particular, helps to answer questions such as: why did you make this decision? Why didn't you act differently? When will you succeed or fail? How do you correct the error? These questions should be addressed in the development and implementation of different AI methods.

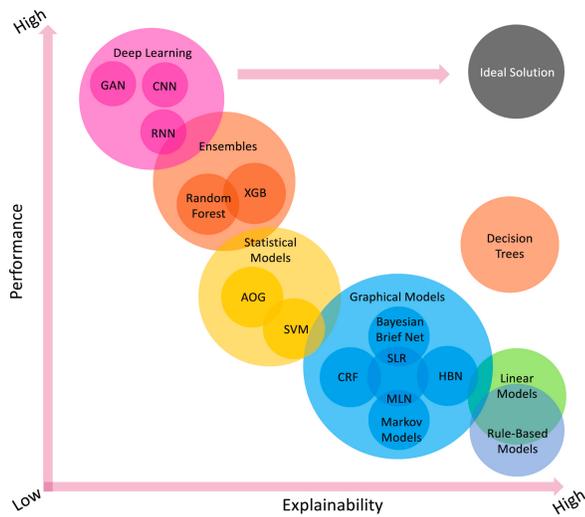


Figure 2: Comparison between Explainability and Accuracy for Different Machine Learning Approaches. [34]

To be more precise, terms and indicators that highlight this concept may include: AI interpretability, model transparency, explainability of algorithms, post-hoc analysis of decisions, methods for visualizing decision-making processes, detailed documentation of AI models, interpretation of AI results, identification of explanatory factors in AI predictions, etc.

1.4.2. Active Learning

Nowadays, discussing deep learning and artificial intelligence without addressing image analysis and interpretation, as well as their use for extracting essential information for purposes such as computer-aided detection, prognosis, treatment planning, intervention, and preventive maintenance of systems, is essential. However, the unique challenges posed by data analysis, particularly in the context of detecting and predicting defects in photovoltaic systems, suggest that it would be beneficial to maintain the presence of a human end-user in any system using deep learning, specifically, or artificial intelligence, in general [35].

Active learning is an approach to artificial intelligence that involves humans in the learning process to improve the efficiency and accuracy of the AI algorithm. In this approach, the algorithm selects the most informative data for which it needs labels, rather than relying on randomly labeled data [36]. Human involvement in the active learning process can take different forms, such as providing labels for data selected by the algorithm, correcting errors made by the algorithm, or providing feedback on the results of the algorithm. Active learning has many advantages over traditional machine learning, such as reducing the amount of labeled data required to train the AI algorithm and improving the accuracy of the AI algorithm [37-38].

Specifically, some terms and indicators that may highlight this method are: Interactive learning, Active data selection, Human feedback in the learning process, User query systems, Data labeling optimization, Data acquisition methods, Iterative improvement of the model through human interaction, Dynamic adaptation of the learning process to user needs.

2. Research Methodology

2.1. Bibliometric Analysis

Conducting a rigorous bibliometric analysis requires a structured approach. It begins with the clear formulation of research questions and the selection of suitable bibliometric methods. Data collection is then performed using reputable sources such as Web of Science, Scopus (as in this study), Google Scholar, or ScienceDirect, ensuring the reliability of the information. Once collected, the data is analyzed using advanced statistical techniques to uncover trends and correlations. The results are then carefully interpreted and visualized through specialized tools, enabling a comprehensive understanding of the research dynamics.

2.2. Data Collection from Scopus

For this study, we used Scopus as the primary source of bibliographic data [39-40]. This platform offers a wide range of scientific publications in various fields. Data were collected using relevant keywords for our research topic. We then applied data exploration techniques to identify the most relevant publications. The collected data includes information such as article titles, authors, affiliations, keywords, abstracts, and citation counts. Table 1 provides a recapitulation of the information gathered after the search.

2.3. Scanning and Keywords Search

To ensure robust and relevant conclusions, we developed a rigorous data collection methodology. On April 23, 2024, we began by exploring Scopus, a leading bibliometric database. Our search strategy was built around carefully selected keywords relevant to the field: "PV," "Photovoltaic," "Fault," "Failure," "Anomaly," "Detection," "Diagnosis," "Prognosis,"

"Classification," "Artificial Intelligence," "Machine Learning," "AI explainable," "XAI," "Active learning," and "Feedback experiment." These terms guided the identification of documents likely to inform our understanding of current issues and technological advances. Next, we applied strict selection criteria: only English-language documents published in internationally recognized journals and conferences were retained. This ensured the inclusion of high-quality, relevant materials.

The process yielded a curated corpus of 225 documents. Despite their volume, we noted a relative scarcity of studies addressing explainable AI and active learning in photovoltaic fault prediction. Nonetheless, the selected literature provides a solid foundation for analyzing trends and innovations in this area.

Overall, this rigorous and selective approach enhances the credibility of our findings and contributes meaningfully to academic discourse on contemporary energy challenges [41]

3. Analysis and Results

In bibliometric analysis, it is important to discuss the two main approaches for creating bibliometric maps: distance-based methods, such as multidimensional scaling [42], visualization of similarities (VOS) [43], force-directed placement [44-45], among others, and graph-based methods [46].

In the photovoltaic research field, a distance-based bibliometric mapping was performed using VOSviewer [47] and R-bibliometrix. This approach enables the visualization of relationships between different entities such as authors, laboratories, and countries, and measures their strength [48-49]. Using association strength as a similarity metric, co-occurrence maps of keywords were created to identify research subdomains in the photovoltaic field.

3.1. Main Information About the Collection

Table 1 provides an overview of the 225 publications collected from the Scopus search engine based on the selection criteria. It contains a total of 776 keywords and over 900 authors, with a detailed distribution between unique and multiple authors.

Table 1: Main Information about the Data Comprehensive Analysis Over 20 Years: 173 Sources, 225 Documents, highlighting 12.37% Annual Growth, Emphasizing Explainable AI and Active Learning for PV Fault Detection.

MAIN INFORMATION ABOUT DATA	
<i>Timespan</i>	2002:2024
<i>Sources (Journals, Books, etc)</i>	173
<i>Documents</i>	225
<i>Annual Growth Rate %</i>	12,37
<i>Document Average Age</i>	4,37
<i>Average citations per doc</i>	58,97
<i>References</i>	0
DOCUMENT CONTENTS	
<i>Keywords Plus (ID)</i>	2002

<i>Author's Keywords (DE)</i>	776
AUTHORS	
<i>Authors</i>	927
<i>Authors of single-authored docs</i>	36
AUTHORS COLLABORATION	
<i>Single-authored docs</i>	41
<i>Co-Authors per Doc</i>	4,58
<i>International co-authorships %</i>	0
DOCUMENT TYPES	
<i>article</i>	89
<i>Book</i>	43
<i>book book</i>	1
<i>book chapter</i>	10
<i>conference paper</i>	17
<i>editorial</i>	1
<i>review</i>	63
<i>review book</i>	1

Table 1 provides an overview of the main information from the research conducted over a period of more than 20 years, from 2002 to 2024. The research was based on 173 sources and analyzed 225 documents, indicating its comprehensive nature. The annual growth rate of 12.37% suggests evolving research in this field, particularly in the areas of explainable AI and active learning for PV fault detection. With an average of 58.97 citations per document, the work is increasingly recognized and utilized within the scientific community, bolstering its credibility. Involving 927 authors and encompassing various document types, including articles, books, book chapters, conference proceedings, editorials, and reviews, the research was conducted exhaustively to provide a comprehensive analysis of the subject. The significant number of authors highlights the importance of collaborative ideas in this field.

3.1.1. Annual Scientific Publication Trend

This section examines the annual trend of scientific publications in the field of interest. Analysis was conducted on the number of documents published each year between 2002 and 2024 using the Scopus database. Table 2 presents bibliometric data for articles published during this period, including measures such as the average number of citations per article (MeanTCperArt), the total number of articles (N), the average number of citations per year (MeanTCperYear), and the number of citable years (CitableYears).

Table 2: Annual Scientific Publication Trend: Average citations per article in solar panel defect research vary widely annually, ranging from 0.08 in 2024 to 395 in 2010, indicating evolving trends in explainable AI.

<i>YEA</i>	<i>MEANT</i>	<i>N</i>	<i>MEANTCPERYEA</i>	<i>CITAB</i>
<i>R</i>	<i>CPERA</i>		<i>R</i>	<i>LEYE</i>

	RT			ARS
2002	22	1,00	0,96	23
2003	50	1,00	2,27	22
2004	38	1,00	1,81	21
2006	21	1,00	1,11	19
2007	135,5	2,00	7,53	18
2009	88,5	2,00	5,53	16
2010	395	4,00	26,33	15
2011	8,5	2,00	0,61	14
2012	270,17	6,00	20,78	13
2013	69	2,00	5,75	12
2014	90,33	3,00	8,21	11
2015	413,56	9,00	41,36	10
2016	63,75	4,00	7,08	9
2017	89,14	14,00	11,14	8
2018	56,44	9,00	8,06	7
2019	57,23	13,00	9,54	6
2020	42,38	26,00	8,48	5
2021	24,58	24,00	6,14	4
2022	16	39,00	5,33	3
2023	5,47	49,00	2,73	2
2024	0,08	13,00	0,08	1

It can be observed that the average number of citations per article (MeanTCperArt) varies significantly from year to year, with values ranging from 0.08 in 2024 to 395 in 2010. The total number of articles (N) has also increased over the years, from 1 in 2002 to 49 in 2023; this low value of MeanTCperArt in 2024 may be due to the fact that explainable AI is still under development in the field of prognosis and diagnosis of defects in solar panels. As indicated in the article by [50], there are still significant challenges to be addressed to make AI models more transparent and understandable to end-users.

The average number of citations per year (MeanTCperYear) has also varied over the years, with values ranging from 0.08 in 2024 to 41.36 in 2015. Regarding this downward trend in recent years, this may be partly due to the time it takes for articles to be read, cited, and integrated into the literature. As noted by Pan 2019 [49], there can be a lag of several years between the publication of an article and its actual impact on the field.

Finally, the decrease in the number of citable years (CitableYears) may be related to the rapid evolution of technology and methods used in the field of prognosis and diagnosis of defects in solar panels. Utama and colleagues highlighted this in their work in [50], where they explain that as more new AI methods are constantly being developed and implemented, this could make previous work obsolete more quickly.

3.1.2. Most Productive, Impact and Source Growth Dynamics

The data presented in Table 3 below show the most productive, impactful, and source journals in the field of solar energy, based on different bibliometric indicators such as the h-

index, g-index, m-index, total number of citations (TC), number of publications (NP), and year of first publication (PY_start).

Table 3: Most Productive, Impact, and Source Growth Dynamics

Element	h_index	g_index	m_index	TC	NP	PY_start
Energies	7	13	1	187	16	2018
Renewable and Sustainable Energy Reviews	6	6	0,667	635	6	2016
IEEE Access	4	7	0,8	91	7	2020
Solar Energy	4	5	0,5	419	5	2017
Chemical Reviews	3	3	0,3	3493	3	2015
IEEE Transactions on Power Electronics	3	3	0,375	201	3	2017
Sustainability (Switzerland)	3	3	0,75	34	3	2021
Applied Energy	2	2	0,667	36	2	2022
Electronics (Switzerland)	2	3	0,333	24	3	2019
IEEE Power And Energy Society General Meeting	2	2	0,182	6	2	2014
International Journal of Heat and Mass Transfer	2	2	0,087	72	2	2002
International Journal of Hydrogen Energy	2	2	0,182	322	2	2014
International Transactions on Electrical Energy Systems	2	2	0,5	53	2	2021

It's apparent that the journal "ENERGIES" boasts the highest h-index (7), indicating it has published at least 7 articles each cited 7 times or more. However, "RENEWABLE AND SUSTAINABLE ENERGY REVIEWS" leads in total citations, with its articles garnering 635 out of 1759 total citations (36.1%).

Moreover, this journal has published the highest number of articles (6) since 2016, showcasing its influence. "IEEE ACCESS," although relatively recent, starting in 2020, has an h-index of 4 and 91 citations, representing 5.2% of the total, placing it third in impact and productivity. "SOLAR ENERGY" shares an

h-index of 4 but boasts a higher total citation percentage of 23.8% (419 out of 1759), despite having fewer publications (5) since 2017. This indicates its articles have a significant impact in the solar energy field. Notably, some journals exhibit a high m-index, indicating uniform citations across their articles, like "CHEMICAL REVIEWS," with an m-index of 0.3. Additionally, newer journals such as "SUSTAINABILITY (SWITZERLAND)" and "APPLIED ENERGY" have also made an impact, starting in 2021 and 2022, respectively. "INTERNATIONAL JOURNAL OF HYDROGEN ENERGY" received 322 citations, representing 18.3% of total citations, making it a vital source in solar energy research, particularly regarding hydrogen energy.

This information aids in focusing on influential journals in solar energy and AI, guiding research toward high-quality, consistently cited articles. It underscores the growing interest in explainable AI and active learning in PV fault prognosis, despite their current underrepresentation. The involvement of prestigious journals like "ENERGY," "RENEWABLE AND SUSTAINABLE ENERGY REVIEWS," and "IEEE ACCESS" signals the necessity for further research in these areas. This suggests a potential pathway for enhancing solar panel defect detection using explainable AI and active learning, ultimately improving the reliability and performance of solar energy systems.

3.1.3. Most Globally Cited Papers and References

Table 4 presents an overview of the 20 most cited documents published in the Scopus database during the study period, with accompanying graphical representation in Figure 3. The columns include Total Citations, TC per Year, and Normalized TC, accounting for publication year and field.

Table 4: Most Globally Cited Papers

Paper	Total Citations	TC per Year	Normalized TC
[51]	2285	228,50	5,53
[52]	1256	96,62	4,65
[53]	1173	78,20	2,97
[54]	1096	109,60	2,65
[55]	421	52,63	4,72
[56]	291	48,50	5,08
[57]	255	17,00	0,65
[58]	232	29,00	2,60
[59]	231	46,20	5,45
[60]	224	17,23	0,83

[61]	206	18,73	2,28
[62]	190	23,75	2,13
[63]	189	27,00	2,98
[64]	187	23,38	2,10
[65]	157	8,72	1,16
[66]	152	21,71	2,39
[67]	152	9,50	1,72
[68]	150	2,35	2,35
[69]	147	29,40	3,47
[70]	138	69,00	25,23

From the table data, it can be seen that the most cited article is "LU L, 2015, Chem. Rev." with a total of 2285 citations, which also represents the highest number of citations per year (228.50) and normalized citations (5.53). This article has therefore had a significantly important impact in the studied research field. Other articles also have high citation numbers, such as "JØRGENSEN M, 2012, Adv. Mater." with 1256 citations and "TODESCHINI R, 2010, Mol. DESCRIPTORS CHEMOINFORMATICS" with 1173 citations. However, some articles have lower citation numbers, such as "SABNIS RW, 2010, Handb. Biol. Dye. Stain. Synth. Ind. Appl." with 255 citations and "MANNAN S, 2012, LEES' LOSS Prev. Process. Ind. Hazard Identif. Assess. Control. Fourth Ed." with 224 citations.

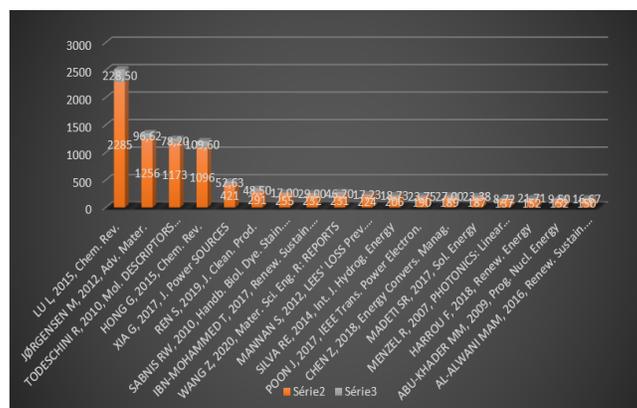


Figure 3: Most Global Cited Papers: Highlighting Significant Impact and Emerging Trends in Solar Panel Technology Through AI Applications, Especially in Explainable AI and Active Learning

By examining the normalized citation data, it can be seen that some articles have high numbers, such as "REN S, 2019, J. Clean. Prod." with 5.08 and "WANG Z, 2020, Mater. Sci. Eng. R: REPORTS" with 5.45, indicating that these articles have had a significant impact in their respective research fields, despite their lower total number of citations.

Figure 3 highlights the articles that have attracted the most attention in the domains of explainable AI and active learning. While some do not explicitly mention these fields, they contribute significantly by applying AI and machine learning to related areas such as solar technology, chemistry, materials science, and renewable energy. As noted in [71], explainable AI and active learning are rapidly growing research areas, marked by a steady rise in publications and citations across disciplines.

However, it is important to note that most of these articles focus on the use of AI and machine learning to improve the performance and efficiency of PV solar systems, rather than on the explainability and transparency of the models themselves. This highlights the need for more in-depth research in the field of explainable AI and active learning to develop more interpretable models and build trust in AI systems.

Furthermore, it should be noted that this analysis is based solely on data from the Scopus database, which may limit the generalizability of the results. Future studies could consider including other databases for a more comprehensive analysis of the literature on explainable AI and active learning applied to PV fault prognosis.

3.1.4. Most Productive and Highly Cited Authors

Table 5 shows the number of articles published by the most productive authors in the studied field, as well as their fractionalized number of articles and their number of citations.

Table 5: Most Productive and Highly Cited Authors: The table highlights the most productive and highly cited authors in the field, emphasizing their significant contributions to the research on solar panel fault diagnosis and prognosis, particularly through the use of AI methods.

Authors	Articles	Articles Fractionalized
SUN Y	5	1,15
ZHANG Y	5	1,03
HARROU F	4	0,90
LIU Z	4	0,46
TAGHEZOUIT B	4	0,90
WANG C	4	0,10
WANG H	4	0,41
WANG Z	4	0,69
YU H	4	0,10
BANSAL RC	3	1,37
BLAABJERG F	3	0,73
LIU C	3	0,29
LIU J	3	0,45

The table shows that SUN Y is the most productive author in this research field, with 5 published articles. However, when considering fractionalized articles—which account for each

author’s specific contribution to a publication—SUN Y attains a higher score (1.15) than other authors with the same number of publications. This indicates that SUN Y’s contributions are relatively more substantial. Authors HARROU F, LIU Z, TAGHEZOUIT B, and WANG Z each published 4 articles, yet their fractionalized scores vary between 0.46 and 0.90, reflecting differences in their levels of involvement. Notably, BANSAL RC, despite having only 3 publications, holds the highest fractionalized article score of 1.37 among all authors, emphasizing the significant impact of his contributions to the field.

The relatively low number of articles and authors may be attributed to a lack of explicit focus on the explainability of artificial intelligence in the development process of AI methods for PV fault diagnosis and prognosis.

Regarding co-authorship, Table 6 presents data concerning the collaboration network between authors, where each line represents a node in this network. The "Cluster" field indicates that all nodes belong to the same cluster (Cluster 1).

Table 6: Most Cited Authors

Node	Cluster	Betweenness	Closeness	PageRank
zhang y	1	0	0,0178571 43	0,0070704 92
liu z	1	33	0,0277777 78	0,0287819 46
wang c	1	6,1166666 67	0,03125	0,0363684 97
wang h	1	6,1166666 67	0,03125	0,0363684 97
wang z	1	0	0,0192307 69	0,0064788 59
yu h	1	6,1166666 67	0,03125	0,0363684 97
blaabje rg f	1	0	0,0172413 79	0,0052358 47
liu c	1	42	0,0263157 89	0,0261822 15
liu p	1	21,783333 33	0,0322580 65	0,0390462 76
liu y	1	30,5	0,0270270 27	0,0259008 6

The table presents the centrality measures of 10 nodes in a network, grouped into a single cluster. The centrality measures include betweenness centrality, closeness centrality, and PageRank. It can be observed that the node "liu z" has the highest betweenness centrality value (33), indicating that it is most often on the shortest paths between other nodes in the network. The nodes "wang c", "wang h", "yu h", and "blaabjerg f" all have low betweenness centrality values (less than 7), suggesting that they are less frequently on the shortest paths between other nodes. In terms of closeness centrality, the nodes "wang c", "wang h", and

"yu h" have the highest value (0.03125), which means that they are closest to all other nodes in the network. Finally, the node "liu p" has the highest PageRank value (0.039046276), indicating that it is the most important in terms of incoming and outgoing connections with other important nodes in the network.

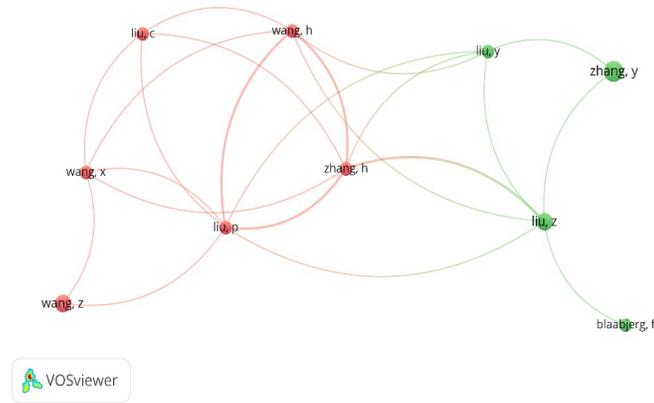


Figure 4: Co-author Network: Illustrates limited collaboration among authors in the specialized field, influenced by technical complexity and interdisciplinary communication challenges

Indeed, one can observe a limited number of active authors and less collaboration in the studied field, as depicted in the figure, which could be explained by several factors. Firstly, the domain's specificity and the specialized technical skills required to integrate approaches such as explainable AI and active learning may restrict the number of active authors. Secondly, the complexity of these methods and the communication challenges between researchers from different fields may diminish collaboration opportunities. Finally, in a developing field, competition to publish the first significant results may also hinder collaboration among researchers.

3.2. Citation Analysis

3.2.1. Co-Occurrence

The aim of this co-occurrence analysis is to illuminate potential relationships between two elements present in bibliographic works that appear together [72-73]. Utilizing certain standardized and automated methodologies [74-75], data can be extracted and visually represented using tools such as VOSviewer, R Bibliometrix, as demonstrated in this study for widespread application in conducting co-occurrence analyses of keywords across various areas of expertise.

a. Co-occurrence of all keywords.

Table 7: Most Cited Keywords

Words	Occurrences
fault detection	32
solar power generation	30

solar energy	22
photovoltaic cells	14
photovoltaics	13
electric inverters	12
photovoltaic systems	12
failure analysis	11
solar panels	11
deep learning	10
power quality	10
wind power	10
fault tolerance	9
learning systems	9

Table 7 presents the main keywords along with their frequency of occurrence. It is evident that specific learning techniques are currently utilized as scientific methodologies, producing favorable results in defect detection within photovoltaic systems. However, the explainability of AI is notably underrepresented, as reflected by its absence among the most frequently cited keywords. To deepen understanding of key terms, their clusters, associations, and temporal relevance, two bibliometric maps were generated. For clarity and focus, only keywords appearing at least five times were included in these maps.

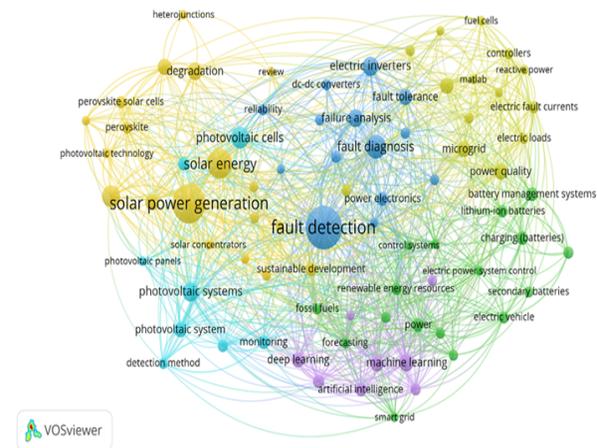


Figure 5: Visualization Map of Co-occurring Keywords Identifying 6 Main Clusters: Displays relationships between co-occurring keywords, highlighting thematic groupings and their associations within the research domain

The first map presents six keyword clusters, reflecting associations among the articles. Keyword co-occurrence—indicating simultaneous appearance—is shaped by proximity and similarity. Figure 5 visualizes these clusters, highlighting groups of keywords that frequently appear together and are organized by associated methods. Table 8 provides a summary of these co-occurring keyword clusters.

Table 8: Clusters of Co-occurring Keywords showcase thematic groupings

N cluster	Node
Cluster1	Carbon, degradation, heterojunction, life cycle, perovskite, perovskite solar cells, photovoltaic modules, photovoltaic technology, photovoltaics, renewable energies, renewable energy, renew, solar celles, solar concentrators, solar energy, solar panels, solar power generation, sustainable developmer
Cluster2	Batteremy management system, charging (batteries), control systems, diital storage, electric power system control, electric power transmission, electric vehicle, electric vehicles, energy storage, forecasting, fossils fuels, lithium-ion batteries, optimization, power, renewable energy resource, secondary batteries, smart grid.
Cluster3	dc-dc converters, electric drives, electric inverters, failure analysis, fault detection, fault diagnosis, fault tolerance, faults diagnosis, neural networks, power converters, power electronics, reability, timing circuits, topology.
Cluster4	Controllers, electric fault currents, electric loads, energy conversion, fault, fuel cells, MATLAB, microgrid, microgrids, performance, power quality, reactive power, sliding mode control, wind power.
Cluster5	Artificial intelligence, condition monitoring, deep learning, electric power system protection, fault detection, learning system, machine learning.
Cluster6	Detection method, efficiency, monitoring, photovoltaic cells, photovoltaic panels, photovoltaic system, photovoltaic systems, solar photovoltaic system.

Cluster 1 emphasizes carbon degradation, perovskite solar cells, photovoltaic technology, and renewable energy, highlighting sustainable development and the use of solar energy for electricity generation. Cluster 2 centers on battery management, electrical control systems, energy transmission, electric vehicles, and energy storage, addressing issues related to fossil fuels, lithium-ion batteries, and smart electrical grids. Cluster 3 focuses on electric power converters, electric drives, neural networks, and circuit reliability, dealing with fault detection, fault tolerance, and power electronics system topologies. Cluster 4 covers controllers, electrical fault currents, energy conversion, fuel cells, microgrids, as well as power quality, reactive power, and sliding mode control. Cluster 5 revolves around artificial intelligence, deep learning, state monitoring, and machine learning, targeting power supply protection and fault and failure detection. Finally, Cluster 6 concentrates on detection methods, efficiency, monitoring, photovoltaic cells, panels, and systems, specifically addressing fault detection and diagnosis in photovoltaic solar energy. The last two clusters primarily focus on PV fault diagnosis and related methodologies.

Moreover, human involvement in AI and the explainability of AI are less evident in several clusters outlined in the table. However, Cluster 5 focuses on machine learning, deep learning, and artificial intelligence, while also considering state monitoring and the protection of electrical power systems, implying human intervention to ensure system safety and reliability. Similarly, Cluster 6 addresses the detection and diagnosis of faults in photovoltaic systems, necessitating human interpretation of results and informed decision-making.

b. Co-occurrence of keywords by authors

In this map depicted in Figure 6, associations of keywords by author are linked to each other through three clusters. Similar to the previous case, the degree of co-occurrence of keywords, indicating their simultaneous appearance, is influenced by their proximity and similarity. Table 9 provides an overview of the clusters associated with the map.

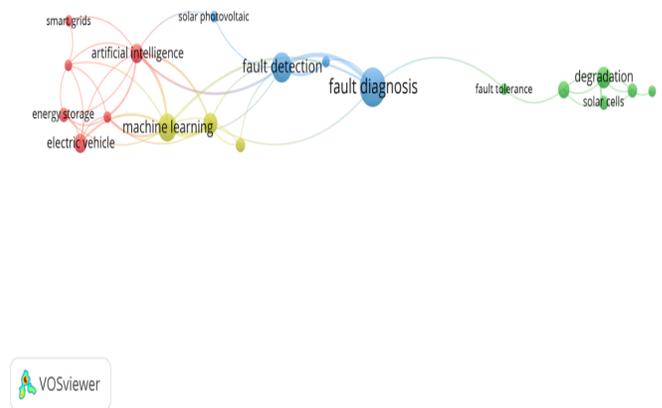


Figure 6: Visualization Map of Co-occurring Authors Keywords

Table 9: Clusters of Authors' Co-occurring Keywords illustrate diverse research focuses in photovoltaic systems, encompassing AI applications, system reliability, fault detection, and optimization for sustainable energy solutions.

N cluster	Node
Cluster1	Artificial intelligence, electric vehicle, energy storage, power electronics, prediction, smart grids
Cluster2	Degradation, fault tolerance, photovoltaics, reliability, solar cells, solar energy,
Cluster3	Fault detection, fault diagnosis, fault location, solar photovoltaic
Cluster4	Deep learning, machine learning, photovoltaic systems

Cluster 1 focuses on the applications of artificial intelligence, power electronics, and energy storage systems in smart electrical grids and electric vehicles. The authors of this cluster may be experts in areas such as machine learning, signal processing, and electrical system design. Research trends in this cluster may

include the development of new machine learning algorithms for energy demand prediction, electric vehicle charging optimization, and energy management in smart grids or microgrids.

Cluster 2 focuses on the reliability and sustainability of photovoltaic systems, with a particular emphasis on degradation, fault tolerance, and reliability assessment. The authors of this cluster have expertise in materials, photovoltaic system design, and degradation modeling. Research trends in this cluster may include the development of new materials and system designs to improve the lifespan of photovoltaic systems, as well as the use of machine learning techniques to predict degradation and assess reliability.

Cluster 3 is centered on the detection, diagnosis, and localization of faults in photovoltaic systems. The authors of this cluster may be experts in signal processing, photovoltaic system design, and fault modeling. Research trends in this cluster include the development of new intelligent algorithms for fault detection and localization, as well as the use of machine learning techniques for fault diagnosis and classification.

Cluster 4 focuses on the applications of deep learning and machine learning in photovoltaic systems, with a particular emphasis on energy production prediction and system optimization. The authors of this cluster have expertise in machine learning, signal processing, and photovoltaic system design. Research trends in this cluster are focused on the development of new deep learning algorithms for energy production prediction and system optimization, as well as the use of machine learning techniques for fault detection and diagnosis.

Overall, the results of the cluster analysis suggest that research in the field of photovoltaic systems is diverse and rapidly evolving. Researchers are focusing on a wide range of topics, from the reliability and sustainability of systems to the optimization and prediction of energy production. The increasing use of machine learning and deep learning in photovoltaic research is also evident, with many authors exploring the applications of these techniques in fault detection. Furthermore, these results highlight the importance of collaboration and interdisciplinarity in photovoltaic research. Researchers need to work together to combine their expertise in materials, system design, signal processing, and machine learning to address the complex challenges facing the photovoltaic industry. Additionally, the research trends in the clusters suggest that the use of machine learning and deep learning in fault detection and diagnosis remains a promising avenue for improving the reliability and sustainability of photovoltaic systems.

3.2.2. Thematical Map and Thematic Evolution

To identify key research themes, keyword co-occurrence analysis is used to trace thematic evolution [76]. Each cluster reflects a conceptual theme, with the research period considered. Callon centrality measures inter-cluster connections, while Callon density assesses their internal strength and influence over time

[77]. The size of each sphere in the diagram corresponds to the frequency of publications on that theme. The resulting strategic diagram places these sub-clusters in a two-dimensional space, offering a global view of the field's thematic evolution [78].

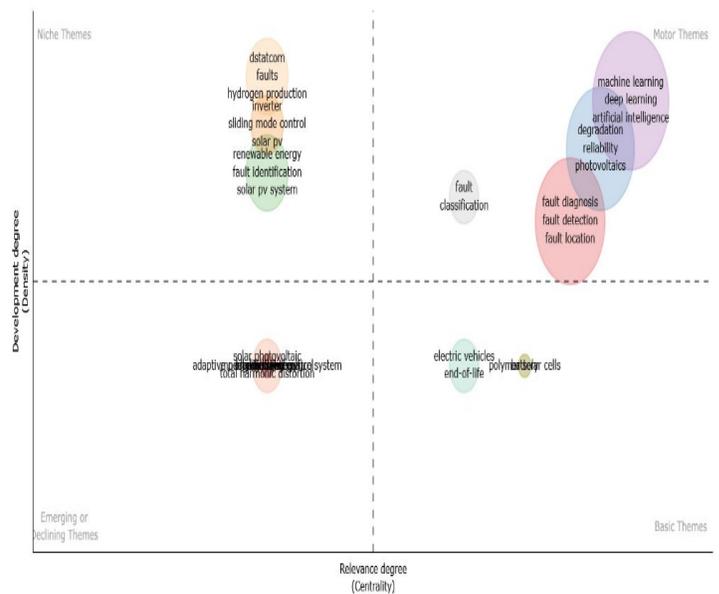


Figure 7: Strategic Map of Author Keywords illustrates thematic trends in solar panel defect diagnosis and prognosis using artificial intelligence, emphasizing improvements in system reliability and efficiency

Using keyword co-occurrence analysis to identify thematic trends in the research field, we generated a strategic map highlighting the main themes over the studied period (see Figure 7). The most frequent keywords, derived from author keywords, were analyzed. This analysis revealed ten themes, with four grouped into primary clusters. The first cluster comprising machine learning, deep learning, and artificial intelligence centers on AI techniques aimed at enhancing solar energy production systems. The second cluster, including degradation, reliability, and photovoltaics, addresses the durability and reliability of photovoltaic systems. The third cluster focuses on fault detection and location, featuring keywords such as fault degradation, fault detection, and fault location. Lastly, the fourth cluster pertains to fault classification within photovoltaic systems.

Examining these keyword clusters, it is clear that they all converge towards a central theme: the diagnosis/prognosis of solar panel defects using artificial intelligence. This trend reflects the growing importance of using artificial intelligence to improve the reliability and performance of photovoltaic systems, as well as to reduce maintenance and repair costs.

4. Issues Identified, Key Challenges and Future Directions

To interpret the results and the color legends of keywords in this figure, readers are referred to the corresponding colors.

Utilizing keyword co-occurrence analysis to identify thematic trends in a research field, we constructed a strategic map

delineating the main themes for the studied period (refer to Figure 7). We considered the most frequent keywords in relation to author keywords. In this depiction, ten themes were identified, four of which were amalgamated into primary clusters.

The first cluster (machine learning, deep learning, artificial intelligence) concentrates on leveraging machine learning and artificial intelligence techniques to enhance the efficiency of solar energy production systems. The second cluster (degradation, reliability, photovoltaics) delves into the reliability and durability aspects of photovoltaic systems. The third cluster (fault degradation, fault detection, fault location) revolves around the detection and localization of faults within photovoltaic systems. Lastly, the fourth cluster (fault classification) pertains to the classification of faults within photovoltaic systems.

Upon scrutinizing these keyword clusters, it becomes apparent that they all converge towards a central theme: the diagnosis/prognosis of solar panel defects using artificial intelligence. This trend underscores the increasing significance of employing artificial intelligence to enhance the reliability and performance of photovoltaic systems while mitigating maintenance and repair costs.

Identified Problems, Key Challenges, and Future Directions in the Implementation of Explainable Artificial Intelligence and Active Learning for Solar Panel Defect Prognosis

Addressing the question of current trends in explainable AI in PV fault diagnosis/prognosis, it's essential to acknowledge that challenges associated with deploying AI systems on photovoltaic solar systems can stem from operational, organizational, technical, and data-related factors, alongside interpretability, transparency, and trust. However, our findings indicate that explainable AI (XAI) remains underutilized in the deployment of AI algorithms for PV fault prognosis. This is evidenced by the scant presence of XAI among the most cited keywords, the limited number of documents and authors retrieved from the Scopus database, and the minimal collaboration between institutions in this specific field.

Concerning human involvement in the machine learning process to emphasize active learning, a similar observation arises. Active learning, an AI method necessitating human interaction to refine algorithmic efficiency and accuracy, encounters challenges primarily related to data collection [36]. While data is pivotal for machine learning, its collection remains a formidable challenge. Human involvement, in various forms such as labeling data selected by algorithms or providing feedback on algorithmic results, is essential to optimize the learning process and enhance algorithmic performance. However, our findings indicate that active learning remains underutilized in the detection, diagnosis, and prognosis of solar panel defects.

Regarding the main challenges related to the application of AI methods in the prognosis of the lifetime of PV systems, several key points emerge:

- The availability and quality of data are paramount for training AI algorithms. Data must be massive, secure, accessible, and of high quality to ensure accurate predictions. Advanced data collection techniques such as drone-based or wireless sensor data collection can alleviate this challenge. Moreover, human involvement in labeling significant data can facilitate user understanding.
- PV systems are complex, influenced by numerous factors like solar irradiation, temperature, and humidity. Advanced AI models such as deep neural networks are increasingly being used to account for these complexities, yet there remains a gap between their precision and user-friendliness.
- The interpretability of AI models is crucial. While accurate, AI models can be challenging to interpret, hindering informed decision-making. Explainable AI techniques such as decision trees can enhance model interpretability and facilitate informed decision-making.

In summary, addressing challenges related to AI methods in PV system prognosis necessitates considering advanced data collection techniques, complex AI models, explainable AI techniques, and continuous model learning and adaptation. Recent studies have shown that these approaches can enhance the accuracy and interpretability of AI models, thus facilitating informed decision-making regarding PV system maintenance and replacement [79-80].

5. Discussion

In this section, we'll delve into the future trends and benefits of our bibliometric study on the use of artificial intelligence (AI) for detecting and diagnosing anomalies and defects in modern photovoltaic systems (PV), alongside presenting the limitations of this work.

Our bibliometric study has shed light on the promising emergence of Explainable Artificial Intelligence (XAI) and active learning as means to enhance the transparency and comprehension of AI methods applied to photovoltaic systems. Particularly, integrating human expertise in the data labeling process has proven to be a decisive simplifying approach for effective AI utilization in this field. The benefits of XAI and active learning have been substantiated by several recent studies, showcasing their potential to augment the accuracy and reliability of AI methods deployed in the photovoltaic domain. Moreover, our analysis has unveiled the predominant influence of China in the realm of explainable AI applied to photovoltaic systems. This dominance can be attributed to the pronounced focus of Chinese universities on research in this sector, coupled with China's status as the world's leading producer of solar panels. However, our

study has also underscored a notable underinvestment in the domain of AI explainability (XAI) concerning solar panels. Additional initiatives aimed at exploring the utilization of XAI in this field are advocated to enhance the transparency and understanding of the employed AI methods.

Regarding future trends, we anticipate a continuous proliferation in the utilization of AI for detecting and diagnosing anomalies and failures in modern photovoltaic systems. Specifically, the ascendancy of deep learning and machine learning is projected to persist in this domain, owing to their capacity to process vast datasets and identify intricate patterns that would be challenging to discern using conventional methods.

Lastly, we believe that our study confers several benefits. Firstly, it furnishes a comprehensive overview of AI utilization in the photovoltaic systems domain, with particular emphasis on XAI and active learning. Furthermore, our work accentuates the advantages of incorporating human expertise in the data labeling process, thereby significantly facilitating AI utilization in this context. Lastly, our study identifies promising trends and research directions in this field, which can guide future endeavors for both researchers and practitioners.

5.1. Limitations

While this bibliometric study has provided valuable insights into the utilization of AI in detecting and diagnosing defects in photovoltaic systems, it bears certain limitations.

Primarily, the study focused solely on articles published in journals and conferences, thereby overlooking research works published as technical reports, theses, or patents. This might have led to an underrepresentation of certain trends or developments in the field. Additionally, employing specific keywords to identify relevant articles may have excluded pertinent works that did not utilize these keywords, potentially introducing a bias towards certain AI methods or approaches. Furthermore, the utilization of a single database, namely Scopus, may be perceived as a limitation, as it might not encompass all relevant publications in the domain of AI applied to photovoltaic systems. Lastly, the study exclusively focused on articles published in English, potentially excluding relevant articles published in other languages.

In summary, these limitations warrant consideration when interpreting the results of this bibliometric study. Future research could broaden the scope of the study by incorporating additional data sources such as Web of Science, IEEE Xplore, or Google Scholar, adopting different keywords, and considering languages other than English.

5.2. Future Word Orientation

To enhance the results and steer advancements and initiatives in the studied field, we propose the following recommendations:

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- Encourage research on Explainable AI and Active Learning in the domain of photovoltaic systems to bolster the transparency and understanding of AI methods utilized.
- Develop standards for Explainable AI in photovoltaic systems to ensure the transparency, comprehensibility, reliability, and accessibility of the employed AI methods.
- Foster collaboration between AI researchers and solar energy experts to develop effective AI methods tailored to photovoltaic systems, emphasizing interdisciplinary collaboration to grasp the challenges and opportunities in this domain.

6. Conclusion

In conclusion, this bibliometric study has underscored the significance of explainable AI and active learning in detecting dysfunctions in photovoltaic systems. Despite the rapid increase in publications in this field, the majority of proposed methods often overlook the explainability aspect of AI and the necessity for human interaction in the learning process. This oversight has resulted in a proliferation of AI methods in theory but limited real-world applications. Additionally, we've identified key players in this domain, including prolific authors, active countries, and fruitful collaborations. These findings serve as a valuable resource for researchers to discern current trends and gaps in the literature and to forge productive collaborations to propel the field forward.

Based on our results, we have formulated several recommendations to improve future research. Firstly, it is crucial to consider the explainability aspect of AI in methods for detecting dysfunctions in photovoltaic systems. Secondly, integrating human interaction in the learning process is essential to enhance the accuracy and reliability of the proposed methods. Finally, encouraging collaborations between researchers, domain engineers, and social scientists is vital to develop more effective and practically applicable methods.

In summary, this bibliometric study has emphasized the significance of explainable AI and active learning in detecting dysfunctions in photovoltaic systems, while also highlighting current gaps in the literature. The proposed recommendations aim to facilitate the development of more effective and applicable methods, thereby contributing to the global energy transition towards more reliable and sustainable renewable energy sources.

Conflict of Interest

The authors declare no conflict of interest.

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References

- [1] S. Arya, P. Mahajan, "Introduction to Solar Cells," *In: Solar Cells*, Springer, Singapore, 2023, [10.1007/978-981-99-7333-0_1](https://doi.org/10.1007/978-981-99-7333-0_1)
- [2] P.G.V. Sampaio, M.O.A. González, "Photovoltaic solar energy: Conceptual framework," *Renewable and Sustainable Energy Reviews*, 74, 590–601, 2017, [10.1016/j.rser.2017.02.081](https://doi.org/10.1016/j.rser.2017.02.081).
- [3] L. Melnyk, H. Sommer, O. Kubatko, M. Rabe, S. Fedyna, "The economic and social drivers of renewable energy development in OECD countries," *Problems and Perspectives in Management*, 18(4), 37–48, 2020, [10.21511/ppm.18\(4\).2020.04](https://doi.org/10.21511/ppm.18(4).2020.04)
- [4] F. Chien, C.C. Hsu, Z. Andlib, M.I. Shah, T. Ajaz, M.G. Genie, "The role of solar energy and eco-innovation in reducing environmental degradation in China: Evidence from QARDL approach," *Integrated Environmental Assessment and Management*, 18(2), 555–571, 2022, [10.1002/ieam.4500](https://doi.org/10.1002/ieam.4500)
- [5] A. Afful-Dadzie, S.K. Mensah, E. Afful-Dadzie, "Ghana renewable energy master plan: The benefits of private sector participation," *Scientific African*, 17, e01353, 2022, [10.1016/j.sciaf.2022.e01353](https://doi.org/10.1016/j.sciaf.2022.e01353).
- [6] J. Jung, S. Han, B. Kim, "Digital numerical map-oriented estimation of solar energy potential for site selection of photovoltaic solar panels on national highway slopes," *Applied Energy*, 242, 57–68, 2019, [10.1016/j.apenergy.2019.03.101](https://doi.org/10.1016/j.apenergy.2019.03.101).
- [7] S. Ansari, A. Ayob, M.S.H. Lipu, M.H.M. Saad, A. Hussain, "A review of monitoring technologies for solar PV systems using data processing modules and transmission protocols: Progress, challenges and prospects," *Sustainability*, 13(15), 8120, 2021, [10.3390/su13158120](https://doi.org/10.3390/su13158120)
- [8] J.E.F. da Fonseca, F.S. de Oliveira, C.W.M. Prieb, A. Krenzinger, "Degradation analysis of a photovoltaic generator after operating for 15 years in southern Brazil," *Solar Energy*, 196, 196–206, 2020, [10.1016/j.solener.2019.11.086](https://doi.org/10.1016/j.solener.2019.11.086)
- [9] A. Mellit, G.M. Tina, S.A. Kalogirou, "Fault detection and diagnosis methods for photovoltaic systems: A review," *Renewable and Sustainable Energy Reviews*, 91, 1–17, 2018, [10.1016/j.rser.2018.03.062](https://doi.org/10.1016/j.rser.2018.03.062)
- [10] A.A. Al-Katheri, E.A. Al-Ammar, M.A. Alotaibi, W. Ko, S. Park, H.J. Choi, "Application of artificial intelligence in PV fault detection," *Sustainability*, 14(21), 13815, 2022, [10.3390/su142113815](https://doi.org/10.3390/su142113815).
- [11] R.G. Vieira, M. Dhimish, F.M. de Araújo, M.I. Guerra, "PV module fault detection using combined artificial neural network and sugeno fuzzy logic," *Electronics*, 9(12), 2150, 2020, [10.3390/electronics9122150](https://doi.org/10.3390/electronics9122150).
- [12] T. Rahman, A.A. Mansur, M.S. Hossain Lipu, M.S. Rahman, R.H. Ashique, M.A. Houran, E. Hossain, "Investigation of degradation of solar photovoltaics: A review of aging factors, impacts, and future directions toward sustainable energy management," *Energies*, 16(9), 3706, 2023, [10.3390/en16093706](https://doi.org/10.3390/en16093706).
- [13] F. Aziz, A.U. Haq, S. Ahmad, Y. Mahmoud, M. Jalal, U. Ali, "A novel convolutional neural network-based approach for fault classification in photovoltaic arrays," *IEEE Access*, 8, 41889–41904, 2020, [10.1109/ACCESS.2020.2977116](https://doi.org/10.1109/ACCESS.2020.2977116).
- [14] G. Tina, F. Cosentino, C. Ventura, "Monitoring and Diagnostics of Photovoltaic Power Plants," in *Renewable Energy in the Service of Mankind Vol II*, A. Sayigh (ed.), Springer, Cham, 2016, [10.1007/978-3-319-18215-5_45](https://doi.org/10.1007/978-3-319-18215-5_45).
- [15] J.A. Tsanakas, L.D. Ha, F. Al Shakarchi, "Advanced inspection of photovoltaic installations by aerial triangulation and terrestrial georeferencing of thermal/visual imagery," *Renewable Energy*, 102, 224–233, 2017, [10.1016/j.renene.2016.10.046](https://doi.org/10.1016/j.renene.2016.10.046).
- [16] J.A. Tsanakas, L. Ha, C. Buerhop, "Faults and infrared thermographic diagnosis in operating c-Si photovoltaic modules: A review of research and future challenges," *Renewable and Sustainable Energy Reviews*, 62, 695–709, 2016, [10.1016/j.rser.2016.04.079](https://doi.org/10.1016/j.rser.2016.04.079).
- [17] Q. Wang, R. Li, L. Zhan, "Blockchain technology in the energy sector: From basic research to real world applications," *Computer Science Review*, 39, 100362, 2021, [10.1016/j.cosrev.2021.100362](https://doi.org/10.1016/j.cosrev.2021.100362).
- [18] Z. Yang, C. Zhu, Y. Zhu, X. Li, "Blockchain technology in building environmental sustainability: A systematic literature review and future perspectives," *Building and Environment*, 245, 110970, 2023, [10.1016/j.buildenv.2023.110970](https://doi.org/10.1016/j.buildenv.2023.110970)
- [19] S.M. Abu, M.A. Hannan, P.J. Ker, M. Mansor, S.K. Tiong, T.I. Mahlia, "Recent progress in electrolyser control technologies for hydrogen energy production: A patent landscape analysis and technology updates," *Journal of Energy Storage*, 72, 108773, 2023, [doi:10.1016/j.est.2023.108773](https://doi.org/10.1016/j.est.2023.108773).
- [20] T. Saheb, L. Izadi, "Paradigm of IoT big data analytics in the healthcare industry: A review of scientific literature and mapping of research trends," *Telematics and Informatics*, 41, 70–85, 2019, [10.1016/j.tele.2019.03.005](https://doi.org/10.1016/j.tele.2019.03.005).
- [21] D.F. Dominković, J.M. Weinand, F. Scheller, M. D'Andrea, R. McKenna, "Reviewing two decades of energy system analysis with bibliometrics," *Renewable and Sustainable Energy Reviews*, 153, 111749, 2022, [10.1016/j.rser.2021.111749](https://doi.org/10.1016/j.rser.2021.111749)
- [22] A.T. Keleko, B. Kamsu-Foguem, R.H. Ngouna, et al., "Artificial intelligence and real-time predictive maintenance in industry 4.0: a bibliometric analysis," *AI Ethics*, 2, 553–577, 2022, [10.1007/s43681-021-00132-6](https://doi.org/10.1007/s43681-021-00132-6).
- [23] V.V.F. Grubisic, J.P.F. Aguiar, Z. Simeu-Abazi, "A Review on Intelligent Predictive Maintenance: Bibliometric analysis and new research directions," in *2020 International Conference on Control, Automation and Diagnosis (ICCAD)*, IEEE, Oct. 2020, pp. 1–6, [10.1109/ICCAD49821.2020.9260504](https://doi.org/10.1109/ICCAD49821.2020.9260504).
- [24] M.A. Noman, E.S.A. Nasr, A. Al-Shayea, H. Kaid, "Overview of predictive condition-based maintenance research using bibliometric indicators," *Journal of King Saud University - Engineering Sciences*, 31(4), 355–367, 2019, [10.1016/j.jksues.2018.02.003](https://doi.org/10.1016/j.jksues.2018.02.003).
- [25] M. Bertolini, D. Mezzogori, M. Neroni, F. Zammori, "Machine Learning for industrial applications: A comprehensive literature review," *Expert Systems with Applications*, 175, 114820, 2021, [10.1016/j.eswa.2021.114820](https://doi.org/10.1016/j.eswa.2021.114820).
- [26] E.H. Sepúlveda-Oviedo, L. Travé-Massuyès, A. Subias, M. Pavlov, C. Alonso, "Fault diagnosis of photovoltaic systems using artificial intelligence: A bibliometric approach," *Heliyon*, 2023, [10.1016/j.heliyon.2023.e21491](https://doi.org/10.1016/j.heliyon.2023.e21491).
- [27] M. Aria, C. Cuccurullo, "bibliometrix: An R-tool for comprehensive science mapping analysis," *Journal of Informetrics*, 11(4), 959–975, 2017, [10.1016/j.joi.2017.08.007](https://doi.org/10.1016/j.joi.2017.08.007)
- [28] N.J. van Eck, L. Waltman, "Visualizing Bibliometric Networks," in *Measuring Scholarly Impact*, Y. Ding, R. Rousseau, D. Wolfram (eds), Springer, Cham, 2014, pp. 285–320, [10.1007/978-3-319-10377-8_13](https://doi.org/10.1007/978-3-319-10377-8_13).
- [29] W. Samek, T. Wiegand, K.R. Müller, "Explainable artificial intelligence: Understanding, visualizing and interpreting deep learning models," *arXiv preprint arXiv:1708.08296*, 2017, [10.48550/arXiv.1708.08296](https://doi.org/10.48550/arXiv.1708.08296)
- [30] L. Von Rueden, S. Mayer, K. Beckh, B. Georgiev, S. Giesselbach, R. Heese, ... J. Schuecker, "Informed machine learning – a taxonomy and survey of integrating prior knowledge into learning systems," *IEEE Transactions on Knowledge and Data Engineering*, 35(1), 614–633, 2021, [DOI :10.1109/TKDE.2021.3079836](https://doi.org/10.1109/TKDE.2021.3079836).
- [31] X. Liang, A. Mead, M.S.R. Siddiqui, L. Van Waerbeke, A. Zhitnitsky, "Axion quark nugget dark matter: Time modulations and amplifications," *Physical Review D*, 101(4), 043512, 2020, [10.1103/PhysRevD.101.043512](https://doi.org/10.1103/PhysRevD.101.043512)
- [32] A. Adadi, M. Berrada, "Peeking inside the black-box: a survey on explainable artificial intelligence (XAI)," *IEEE Access*, 6, 52138–52160, 2018, [10.1109/ACCESS.2018.2870052](https://doi.org/10.1109/ACCESS.2018.2870052)
- [33] G. Yang, Q. Ye, J. Xia, "Unbox the black-box for the medical explainable AI via multi-modal and multi-centre data fusion: A mini-review, two showcases and beyond," *Information Fusion*, 77, 29–52, 2022, [10.1016/j.inffus.2021.07.016](https://doi.org/10.1016/j.inffus.2021.07.016)

- [34] S. Budd, E. C. Robinson, B. Kainz, "A survey on active learning and human-in-the-loop deep learning for medical image analysis," *Medical Image Analysis*, 71, 102062, 2021, [10.1016/j.media.2021.102062](https://doi.org/10.1016/j.media.2021.102062)
- [35] D. Gissin, S. Shalev-Shwartz, "Discriminative active learning," *arXiv preprint arXiv:1907.06347*, 2019, [10.48550/arXiv.1907.06347](https://doi.org/10.48550/arXiv.1907.06347).
- [36] P. Ren, Y. Xiao, X. Chang, P. Y. Huang, Z. Li, B. B. Gupta, ... & X. Wang, "A survey of deep active learning," *ACM Computing Surveys (CSUR)*, vol. 54, no. 9, pp. 1–40, 2021. [10.1145/3472291](https://doi.org/10.1145/3472291).
- [37] Z. Tu et Z. Xu, « Deep active learning for object detection: A survey », *IEEE Transactions on Neural Networks and Learning Systems*, vol. 31, no 11, pp. 4417–4430, 2020. [10.32604/cmcs.2023.028018](https://doi.org/10.32604/cmcs.2023.028018)
- [38] D. S. Weld et G. Bansal, "The challenge of crafting intelligible intelligence", *Communications of the ACM*, vol. 62, no 6, pp. 70-79, 2019. [10.1145/3282486](https://doi.org/10.1145/3282486)
- [39] M. R. Hosseini, M. Maghrebi, A. Akbarnezhad, I. Martek, M. Arashpour, "Analysis of citation networks in building information modeling research," *Journal of Construction Engineering and Management*, 144(8), 04018064, 2018, [10.1061/\(ASCE\)CO.1943-7862.0001492](https://doi.org/10.1061/(ASCE)CO.1943-7862.0001492).
- [40] Y. Hong, D. W. Chan, A. P. Chan, J. F. Yeung, "Critical analysis of partnering research trend in construction journals," *Journal of Management in Engineering*, 28(2), 82–95, 2012, [doi:10.1061/\(ASCE\)JME.1943-5479.0000084](https://doi.org/10.1061/(ASCE)JME.1943-5479.0000084).
- [41] M. K. Lim, Y. Li, C. Wang, M. L. Tseng, "A literature review of blockchain technology applications in supply chains: A comprehensive analysis of themes, methodologies and industries," *Computers & Industrial Engineering*, 154, 107133, 2021, [doi:10.1016/j.cie.2021.107133](https://doi.org/10.1016/j.cie.2021.107133).
- [42] S. Chung, L. F. Abbott, "Neural population geometry: An approach for understanding biological and artificial neural networks," *Current Opinion in Neurobiology*, 70, 137–144, 2021, [doi:10.1016/j.conb.2021.10.010](https://doi.org/10.1016/j.conb.2021.10.010).
- [43] N.J. van Eck, L. Waltman, J. van den Berg, U. Kaymak, "Visualizing the computational intelligence field [Application Notes]," *IEEE Computational Intelligence Magazine*, 1(4), 6–10, 2006, [doi:10.1109/MCI.2006.329702](https://doi.org/10.1109/MCI.2006.329702).
- [44] R. Klavans, K. W. Boyack, "Quantitative evaluation of large maps of science," *Scientometrics*, 68(3), 475–499, 2006, [doi:10.1007/s11192-006-0125-x](https://doi.org/10.1007/s11192-006-0125-x).
- [45] N. Van Eck, L. Waltman, "Software survey: VOSviewer, a computer program for bibliometric mapping," *Scientometrics*, 84(2), 523–538, 2010, [doi:10.1007/s11192-009-0146-3](https://doi.org/10.1007/s11192-009-0146-3).
- [46] N. J. Van Eck, L. Waltman, R. Dekker, J. Van Den Berg, "A comparison of two techniques for bibliometric mapping: Multidimensional scaling and VOS," *Journal of the American Society for Information Science and Technology*, 61(12), 2405–2416, 2010, [doi:10.1002/asi.21421](https://doi.org/10.1002/asi.21421).
- [47] J. Wang, X. Zhao, X. Guo, B. Li, "Analyzing the research subjects and hot topics of power system reliability through the Web of Science from 1991 to 2015," *Renewable and Sustainable Energy Reviews*, 82, 700–713, 2018, [doi:10.1016/j.rser.2017.09.064](https://doi.org/10.1016/j.rser.2017.09.064).
- [48] J. Wang, M. K. Lim, C. Wang, M. L. Tseng, "The evolution of the Internet of Things (IoT) over the past 20 years," *Computers & Industrial Engineering*, 155, 107174, 2021, [doi:10.1016/j.cie.2021.107174](https://doi.org/10.1016/j.cie.2021.107174).
- [49] W. Pan, L. Jian, T. Liu, "Grey system theory trends from 1991 to 2018: a bibliometric analysis and visualization," *Scientometrics*, 121, 1407–1434, 2019, [doi:10.1007/s11192-019-03256-z](https://doi.org/10.1007/s11192-019-03256-z).
- [50] C. Utama, C. Meske, J. Schneider, R. Schlatmann, C. Ulbrich, "Explainable artificial intelligence for photovoltaic fault detection: A comparison of instruments," *Solar Energy*, 249, 139–151, 2023, [doi:10.1016/j.solener.2022.11.018](https://doi.org/10.1016/j.solener.2022.11.018).
- [51] R. Todeschini, V. Consonni, *Molecular descriptors for chemoinformatics: volume I: alphabetical listing/volume II: appendices, references*, John Wiley & Sons, 2009.
- [52] G. Hong, S. Diao, A. L. Antaris, H. Dai, "Carbon nanomaterials for biological imaging and nanomedical therapy," *Chemical Reviews*, 115(19), 10816–10906, 2015, [doi:10.1021/acs.chemrev.5b00008](https://doi.org/10.1021/acs.chemrev.5b00008).
- [53] G. Xia, L. Cao, G. Bi, "A review on battery thermal management in electric vehicle application," *Journal of Power Sources*, 367, 90–105, 2017, [doi:10.1016/j.jpowsour.2017.09.046](https://doi.org/10.1016/j.jpowsour.2017.09.046).
- [54] S. Ren, Y. Zhang, Y. Liu, T. Sakao, D. Huisingh, C. M. Almeida, "A comprehensive review of big data analytics throughout product lifecycle to support sustainable smart manufacturing: A framework, challenges and future research directions," *Journal of Cleaner Production*, 210, 1343–1365, 2019, [doi:10.1016/j.jclepro.2018.11.025](https://doi.org/10.1016/j.jclepro.2018.11.025).
- [55] R. W. Sabnis, *Handbook of biological dyes and stains: synthesis and industrial applications*, John Wiley & Sons, 2010.
- [56] K. Amasyali, N. M. El-Gohary, "A review of data-driven building energy consumption prediction studies," *Renewable and Sustainable Energy Reviews*, 81, 1192–1205, 2018, [doi:10.1016/j.rser.2017.04.095](https://doi.org/10.1016/j.rser.2017.04.095).
- [57] Z. Wang, X. Wang, S. Cong, F. Geng, Z. Zhao, "Fusing electrochromic technology with other advanced technologies: A new roadmap for future development," *Materials Science and Engineering: R: Reports*, 140, 100524, 2020, [doi:10.1016/j.mser.2019.100524](https://doi.org/10.1016/j.mser.2019.100524).
- [58] V. Venkatasubramanian, R. Rengaswamy, K. Yin, S. N. Kavuri, "A review of process fault detection and diagnosis: Part I: Quantitative model-based methods," *Computers & Chemical Engineering*, 27(3), 293–311, 2003, [doi:10.1016/S0098-1354\(02\)00160-6](https://doi.org/10.1016/S0098-1354(02)00160-6).
- [59] R. E. Silva, R. Gouriveau, S. Jemei, D. Hissel, L. Boulon, K. Agbossou, N. Y. Steiner, "Proton exchange membrane fuel cell degradation prediction based on adaptive neuro-fuzzy inference systems," *International Journal of Hydrogen Energy*, 39(21), 11128–11144, 2014, [doi:10.1016/j.ijhydene.2014.05.005](https://doi.org/10.1016/j.ijhydene.2014.05.005).
- [60] J. Poon, P. Jain, I. C. Konstantakopoulos, C. Spanos, S. K. Panda, S. R. Sanders, "Model-based fault detection and identification for switching power converters," *IEEE Transactions on Power Electronics*, 32(2), 1419–1430, 2016, [doi:10.1109/TPEL.2016.2541342](https://doi.org/10.1109/TPEL.2016.2541342).
- [61] W. Wu, S. Wang, W. Wu, K. Chen, S. Hong, Y. Lai, "A critical review of battery thermal performance and liquid based battery thermal management," *Energy Conversion and Management*, 182, 262–281, 2019, [doi:10.1016/j.enconman.2018.12.051](https://doi.org/10.1016/j.enconman.2018.12.051).
- [62] S. R. Madeti, S. N. Singh, "A comprehensive study on different types of faults and detection techniques for solar photovoltaic system," *Solar Energy*, 158, 161–185, 2017, [doi:10.1016/j.solener.2017.08.069](https://doi.org/10.1016/j.solener.2017.08.069).
- [63] R. Menzel, *Photonics: linear and nonlinear interactions of laser light and matter*, Springer Science & Business Media, 2007.
- [64] F. Harrou, Y. Sun, B. Taghezouit, A. Saidi, M. E. Hamlati, "Reliable fault detection and diagnosis of photovoltaic systems based on statistical monitoring approaches," *Renewable Energy*, 116, 22–37, 2018, [doi:10.1016/j.renene.2017.09.048](https://doi.org/10.1016/j.renene.2017.09.048).
- [65] M. M. Abu-Khader, "Recent advances in nuclear power: A review," *Progress in Nuclear Energy*, 51(2), 225–235, 2009, [doi:10.1016/j.pnucene.2008.05.001](https://doi.org/10.1016/j.pnucene.2008.05.001).
- [66] M. A. Al-Alwani, A. B. Mohamad, N. A. Ludin, A. A. H. Kadhum, & K. Sopian, "Dye-sensitised solar cells: Development, structure, operation principles, electron kinetics, characterisation, synthesis materials and natural photosensitisers," *Renewable and Sustainable Energy Reviews*, 65, 183–213, 2016, [doi:10.1016/j.rser.2016.06.045](https://doi.org/10.1016/j.rser.2016.06.045).
- [67] C. B. Pandey, U. Kumar, M. Kaviraj, K. J. Minick, A. K. Mishra, & J. S. Singh, "DNRA: a short-circuit in biological N-cycling to conserve nitrogen in terrestrial ecosystems," *Science of the Total Environment*, 738, 139710, 2020, [doi:10.1016/j.scitotenv.2020.139710](https://doi.org/10.1016/j.scitotenv.2020.139710).
- [68] M. Ghiasi, T. Niknam, Z. Wang, M. Mehrandezh, M. Dehghani, & N. Ghadimi, "A comprehensive review of cyber-attacks and defense mechanisms for improving security in smart grid energy systems: Past, present and future," *Electric Power Systems Research*, 215, 108975, 2023, [doi:10.1016/j.epsr.2022.108975](https://doi.org/10.1016/j.epsr.2022.108975).
- [69] A. Das, P. Rad, "Opportunities and challenges in explainable artificial intelligence (XAI): A survey," *arXiv preprint arXiv:2006.11371*, 2020, [doi:10.48550/arXiv.2006.11371](https://doi.org/10.48550/arXiv.2006.11371)
- [70] Y. Hong, D. W. Chan, A. P. Chan, J. F. Yeung, "Critical analysis of partnering research trend in construction journals," *Journal of Management in Engineering*, 28(2), 82–95, 2012, [doi:10.1061/\(ASCE\)JME.1943-5479.0000084](https://doi.org/10.1061/(ASCE)JME.1943-5479.0000084).
- [71] R. Machlev, L. Heistrene, M. Perl, K. Y. Levy, J. Belikov, S. Mannor, Y. Levron, "Explainable Artificial Intelligence (XAI) techniques for energy

- and power systems: Review, challenges and opportunities," *Energy and AI*, 9, 100169, 2022, doi: [10.1016/j.egyai.2022.100169](https://doi.org/10.1016/j.egyai.2022.100169).
- [72] B. Dong, G. Xu, X. Luo, Y. Cai, W. Gao, "A bibliometric analysis of solar power research from 1991 to 2010," *Scientometrics*, **93**(3), 1101–1117, 2012, doi: [10.1007/s11192-012-0675-0](https://doi.org/10.1007/s11192-012-0675-0).
- [73] M. Hajji, M. F. Harkat, A. Kouadri, K. Abodayeh, M. Mansouri, H. Nounou, M. Nounou, "Multivariate feature extraction based supervised machine learning for fault detection and diagnosis in photovoltaic systems," *European Journal of Control*, 59, 313–321, 2021, doi: [10.1016/j.ejcon.2020.03.004](https://doi.org/10.1016/j.ejcon.2020.03.004).
- [74] M. Callon, J. P. Courtial, W. A. Turner, S. Bauin, "From translations to problematic networks: An introduction to co-word analysis," *Social Science Information*, **22**(2), 191–235, 1983, doi: [10.1177/05390188302200200](https://doi.org/10.1177/05390188302200200).
- [75] M. J. Cobo, A. G. López-Herrera, E. Herrera-Viedma, F. Herrera, "Science mapping software tools: Review, analysis, and cooperative study among tools," *Journal of the American Society for Information Science and Technology*, **62**(7), 1382–1407, 2011, doi: [10.1002/asi.21525](https://doi.org/10.1002/asi.21525).
- [76] C. Cheng, F. Wang, Y. Tian, X. Wu, J. Zheng, J. Zhang, ... & J. Zhao, "Review and prospects of hydrate cold storage technology," *Renewable and Sustainable Energy Reviews*, 117, 109492, 2020, doi: [10.1016/j.rser.2019.109492](https://doi.org/10.1016/j.rser.2019.109492).
- [77] C. Koch, L. Hirth, "Short-term electricity trading for system balancing: An empirical analysis of the role of intraday trading in balancing Germany's electricity system," *Renewable and Sustainable Energy Reviews*, 113, 109275, 2019, doi: [10.1016/j.rser.2019.109275](https://doi.org/10.1016/j.rser.2019.109275).
- [78] X. Liang, A. Mead, M. S. R. Siddiqui, L. Van Waerbeke, A. Zhitnitsky, "Axion quark nugget dark matter: Time modulations and amplifications," *Physical Review D*, **101**(4), 043512, 2020, doi: [10.1103/PhysRevD.101.043512](https://doi.org/10.1103/PhysRevD.101.043512).
- [79] D. Rodríguez-Gracia, M. de las Mercedes Capobianco-Uriarte, E. Terán-Yépez, J. A. Piedra-Fernández, L. Iribarne, R. Ayala, "Review of artificial intelligence techniques in green/smart buildings," *Sustainable Computing: Informatics and Systems*, 38, 100861, 2023, doi: [10.1016/j.suscom.2023.100861](https://doi.org/10.1016/j.suscom.2023.100861).
- [80] J. Hmad, A. Houari, A. E. M. Bouzid, A. Saim, H. Trabelsi, « A review on mode transition strategies between grid-connected and standalone operation of voltage source inverters-based microgrids », *Energies*, vol. 16, no. 13, p. 5062, 2023, doi: [10.3390/en16135062](https://doi.org/10.3390/en16135062).

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Predictive Analytics in Marketing: Evaluating its Effectiveness in Driving Customer Engagement

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ABSTRACT

Understanding and responding to customer feedback is critical for business success. Customer response data offers valuable insights into preferences, behaviours, and sentiment. By analysing this data, businesses can optimize strategies, enhance customer experiences, and drive growth. Many analysis have been conducted in this field, while the review covers a broad range of AI and ML applications in marketing, all of these analysis were done separately ending with scattered conclusions and recommendations. This study explores a big set of machine learning (ML) techniques to analyse customer response data from a marketing campaign in a retail superstore. The dataset was subjected to thorough pre-processing steps, including handling missing values, outlier detection and feature engineering. Exploratory data analysis (EDA) was conducted to gain awareness of customer behaviour and campaign effectiveness. Various ML models, including Decision Trees, Logistic Regression, Random Forest, K-Nearest Neighbour (KNN), as well as Support Vector Classifier (SVC), were trained and evaluated regarding the balanced dataset. Essentially, our findings propose that ML techniques can effectively analyse customer response and provide valuable information to uncover hidden patterns, make informed decisions, and gain a competitive advantage to assist with optimising marketing strategies in retail environments

1. Introduction

Artificial Intelligence (AI), defined as the simulation of human intelligence by machines, is transforming marketing through its capacity to analyze customer data and predict trends and preferences [1]. The increasing sophistication of machine capabilities, driven by improved algorithms, cost-effectiveness, and the availability of large datasets, empowers businesses to refine their marketing strategies for enhanced customer engagement [2]. Industries such as fashion are leveraging AI-powered trend analysis and predictive analytics [3] to gain a competitive edge. While the integration of AI into marketing presents significant opportunities, the analysis of unstructured data introduces complexities and potential risks [4]. Ultimately, the successful application of AI in marketing holds the promise of improving customer satisfaction and fostering business growth.

Leading companies like Amazon and Domino's Pizza are utilizing AI to optimize delivery logistics and customer service. Similarly, Red Balloon and Macy's are employing AI-driven platforms to enhance customer service and personalize purchasing experiences, while Lexus and Affectiva are exploring AI's potential in designing emotionally resonant advertising campaigns

[5]. Despite the growing adoption of AI in marketing practice, academic research rigorously examining its effective application remains limited. This gap in the literature motivates the present study.

This research addresses the need for empirical investigation into predictive analytics in marketing, with a specific focus on evaluating its effectiveness in driving customer engagement. Marketing, defined as the process of promoting, selling, and distributing products or services, encompasses understanding customer needs, creating value propositions, and effectively communicating these offerings to target audiences [6]. This study innovatively applies a suite of machine-learning techniques to analyze customer response data acquired from a real-world marketing campaign within a retail superstore environment. To ensure data quality, the dataset undergoes meticulous pre-processing, including robust methods for handling missing values, identifying and mitigating outliers, and feature engineering to maximize the informative value of the data.

Machine Learning (ML), a subset of AI, provides the capability for computers to learn from data and improve performance autonomously, without explicit programming [7]. This study leverages the predictive power of several ML algorithms: Decision Trees, Logistic Regression, Random Forest,

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K-Nearest Neighbour, and Support Vector Classifier. A key methodological contribution is the careful balancing of the dataset to overcome potential biases introduced by class imbalance, a common challenge in customer response data. The performance of the predictive models is rigorously evaluated using a comprehensive set of metrics, including accuracy, precision, and recall, providing a nuanced understanding of each model's strengths and weaknesses.

This research seeks to answer the following key questions:

RQ 1: How effectively can machine learning techniques analyze customer response data derived from a marketing campaign within a retail superstore setting?

RQ 2: Among the machine learning models of Decision Trees, Logistic Regression, Random Forest, K-Nearest Neighbor, and Support Vector Classifier, which demonstrate optimal predictive performance for customer responses to marketing campaigns?

RQ 3: What are the implications of these findings for the optimization of marketing strategies in retail environments, specifically concerning enhancements to customer engagement and the facilitation of business growth? What theoretical contributions does this study offer to the understanding of AI's role in marketing?

The subsequent sections of this paper detail the related literature, the research methodology employed, the interpretation of the developed models, a thorough analysis of the results, and a discussion of the theoretical and practical implications of the findings

2. Literature Review

This section provides a comprehensive literature review of recent studies focusing on the assimilation of artificial intelligence and machine learning techniques in various aspects of marketing and customer experience management. The section also discusses the findings and concludes the aim of this research.

2.1. Previous work

The literature review presents a comprehensive exploration of recent studies focusing on the assimilation of artificial intelligence and machine learning techniques in various aspects of marketing and customer experience management. These studies explore the potential of AI and ML to revolutionise customer interactions, optimise marketing strategies and support business outcomes in general.

In [8], the authors assessed the field of customer experience management (CEM) and investigated how AI and machine learning can autonomously upgrade customer experiences. They examined the challenges associated with implementing AI-driven solutions concerning CEM and proposed strategies to establish critical business drivers using AI and ML techniques. By employing these technologies, businesses can better understand customer needs and preferences, resulting in more personalised and effective customer interactions.

In [9], the authors focused on the application of AI-driven chatbots with Natural Language Processing (NLP) capabilities to improve customer experiences. They demonstrated how these chatbots can engage with customers in natural language conversations, providing timely assistance and support. By harnessing NLP and AI, businesses can automate customer service

processes, reduce response times and improve overall customer satisfaction.

In [10], the authors investigated the role of AI and ML algorithms in processing large volumes of data to make informed marketing decisions. Their study highlighted how AI-powered data analysis can uncover valuable insights into customer behaviour, market trends and competitor strategies. By employing AI-driven data processing, businesses can formulate more accurate and effective marketing strategies, ultimately generating better business outcomes.

The application of AI in marketing is explored by [11], specifically focusing on understanding and analysing customer habits, preferences and behaviours. They discussed how AI-powered analytics can assist businesses to gain further information into customer segments, allowing more targeted and personalised marketing. By exploiting AI, businesses can reinforce customer relationship management roles and tailor marketing strategies to individual customer needs.

In [12], the authors examined the evolution of CRM functions via the adoption of Artificial Intelligence User Interface (AIUI). Their research illustrated how AIUI technologies can simplify customer interactions, improve response times and improve overall customer satisfaction. By integrating AIUI into CRM systems, businesses can provide more efficient and personalised customer support, promoting robust customer relationships and increased loyalty.

In [13], the authors focused on the transformation of traditional retail stores into smart retail stores via the integration of AI and IoT technologies. The authors explored how AI and IoT can enhance customer experiences by providing personalised recommendations, streamlining checkout processes and optimising inventory management. By incorporating smart retail solutions, businesses can produce more engaging and convenient shopping experiences for their customers, generating increased sales and loyalty.

In [14], the researchers investigated advanced AI applications in e-commerce, particularly focusing on AI-supported machines that are capable of tracking human emotions. Their research highlighted how these AI-driven technologies can improve consumer-brand associations and boost product recommendations in e-commerce settings. By exploiting AI to better understand and respond to customer preferences, businesses can establish more tailored and engaging online shopping experiences, ultimately generating higher conversion rates and customer satisfaction.

2.2. Discussion

The previous work, while providing valuable recommendations and findings, lacks a critical analysis of the studies, focusing instead on a broad overview of AI and ML applications in marketing. It overlooks the challenges and limitations of these techniques, particularly in the context of customer response data analysis. Additionally, the review fails to integrate the findings of the individual studies into a cohesive whole, hindering a deeper understanding of the topic.

This research aims to investigate the practical implementation of AI and ML in enhancing customer experiences. While the potential benefits of these technologies are clear, real-world application faces significant challenges. This study seeks to

address these challenges by providing actionable insights and strategies to facilitate the successful integration of AI and ML into business operations. By overcoming these hurdles, businesses can improve customer satisfaction and drive sustainable growth

3. Research Methodology

This section details the methodology employed to investigate customer response prediction. The approach encompasses data collection and preprocessing, data exploration and visualization, model development and evaluation, and subsequent analysis. Each stage is designed to ensure the development of a robust and effective customer response detection model.

3.1. Data Set

The dataset utilized in this research was obtained from Kaggle. It comprises customer attributes relevant to demographics, purchasing behaviors, and interactions within a retail superstore, collected during the previous year's campaign. The dataset includes customer age, education level, marital status, household composition, income, and purchasing history across various product categories over the past two years. Additionally, it incorporates data on customer complaints, enrollment dates, and recent purchases. The application of this dataset and the construction of a predictive model aim to enhance the effectiveness of the superstore's marketing campaign, specifically targeting existing customers, thereby reducing promotional costs while maximizing revenue potential.

3.2. Data Acquisition and Exploration

The research commenced with the importation of essential libraries, including Pandas, NumPy, Matplotlib, Seaborn, and datetime. The dataset, named 'superstore_data.csv', was loaded using Pandas, and its dimensions (number of rows and columns) were printed for initial assessment. Furthermore, the first few rows of the dataset were displayed to gain insight into its structure.

Pandas functions, such as columns, duplicated, isnull, and info, were used to scrutinize the dataset columns, duplicated rows, and null values. Observations indicated that the 'Income' column contained null values, and the 'Dt_Customer' column was of Object type instead of the Date type.

3.3. Data Preparation

Data preparation involved several steps to ensure dataset integrity and suitability for analysis. First, the 'Dt_Customer' column was standardized by converting its format to Date, replacing '/' with '-', and applying the pd.to_datetime function. Missing values in the 'Income' column were imputed using the median value. Outlier detection and management were conducted on 'Year_Birth' and 'Income' by filtering out birth years before 1900 and excessively high-income values beyond a predetermined threshold. Additional outliers were identified and removed from columns associated with product purchase amounts to maintain a distribution representative of realistic consumer behavior.

3.4. Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) involved employing various techniques to comprehend the data's distribution and relationships among variables. Pie charts were used to exhibit the distribution of positive and negative responses from the marketing

campaign (Fig. 1). Box plots illustrated the relationships between categorical variables, such as education and marital status, and campaign response. Additionally, box plots underlined the correlations between continuous variables, such as expenditure on different products, and campaign response (Figs. 2 and 3). This analysis provided insights into customer behavior and campaign effectiveness, informing subsequent investigation and modeling.

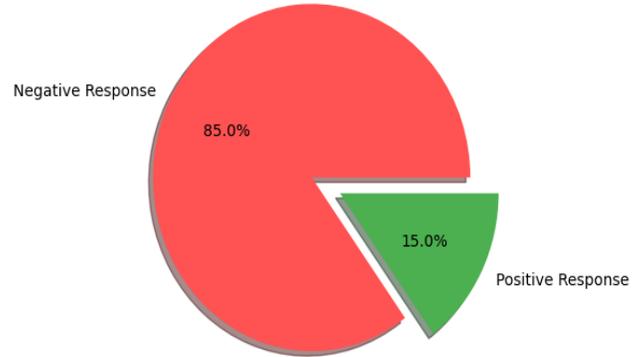


Figure 1: Percentage of negative and positive responses gathered from the marketing campaign

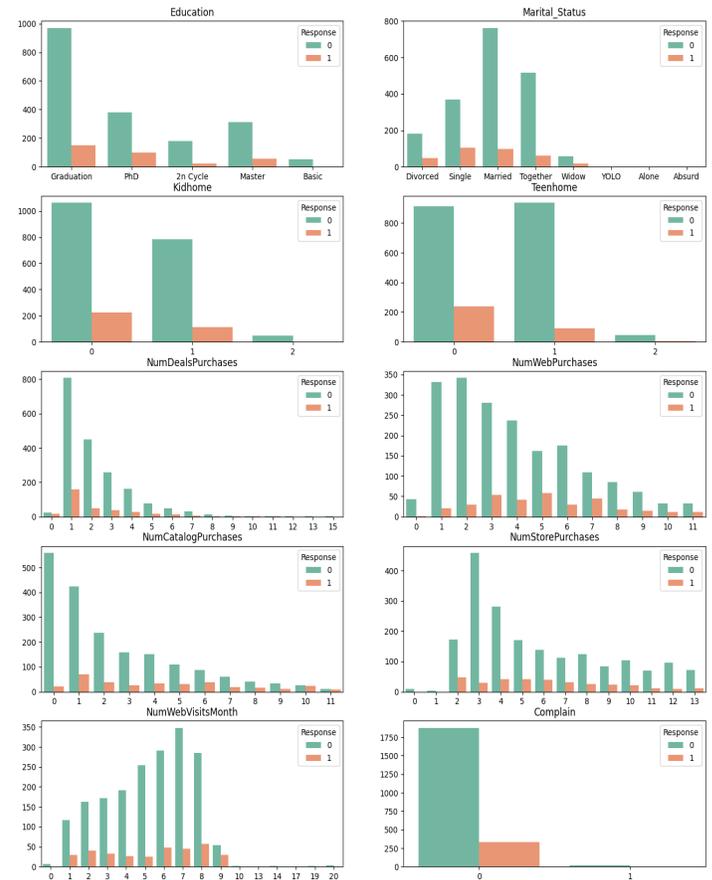


Figure 2: Bar plots illustrating the relationships between the categorical variables and continuous variables with campaign responses

3.5. Preprocessing and Modelling

To prepare the data for effective machine learning, several preprocessing steps were undertaken. Initially, date-type columns were converted to integer representations. This conversion streamlines both the analytical process and the computational

efficiency of subsequent modeling, as machine learning algorithms typically handle numerical data more efficiently. Redundant columns, deemed irrelevant to the predictive task (e.g., 'Id'), were removed to reduce dimensionality and potential noise in the data. This step is crucial for improving model performance by focusing on the most relevant features. Categorical variables were then transformed into a numerical format using one-hot encoding. This technique was chosen to enable machine learning algorithms to effectively process categorical information by creating binary columns for each category.

Prior to model training, the dataset underwent standardization. Standardization scales all features to have a mean of zero and a standard deviation of one. This process ensures that all features contribute equally to the model training process and prevents any single feature from unduly influencing the model due to its scale, which is crucial for algorithms sensitive to feature scaling. To mitigate class imbalance, a common issue in classification tasks, Random Oversampling was employed. This technique was selected to balance the class distribution by duplicating instances from the minority class, providing the model with more training examples for the under-represented class and potentially improving predictive accuracy, particularly for the minority class.

Finally, the preprocessed dataset was partitioned into training and testing sets. This partitioning allows for rigorous evaluation of the model's predictive performance on unseen data, providing an unbiased estimate of its generalization ability and preventing overfitting, thus providing a realistic assessment of its performance in a real-world setting.

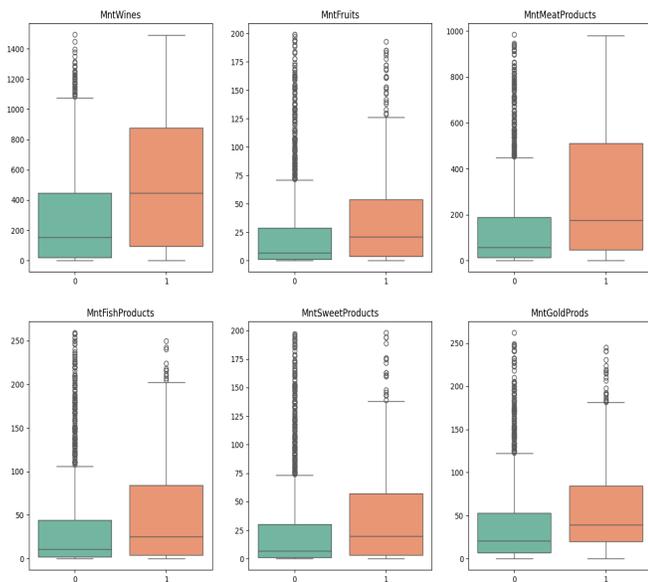


Figure 3: Box Plots illustrating the relationships between the categorical variables and continuous variables with campaign responses

3.6. Model Selection and Evaluation

Classification algorithms, including Decision Tree, Logistic Regression, Random Forest, KNN, and SVC, were applied. Model hyperparameters were optimized using GridSearchCV. Model evaluation metrics, including precision, recall, and accuracy, were calculated using cross-validation and confusion matrices. The Random Forest model demonstrated the best performance in terms of precision, recall, and accuracy.

4. Results Analysis

This section clarifies the results achieved with Random Forest, Decision Trees, Support Vector Classifier, K-Nearest Neighbour and Logistic Regression machine learning models.

4.1. Random Forest

Random Forest exhibited an exceptional performance across each of the evaluation metrics. Fig. 4 shows the confusion matrix of the Random Forest ML technique that report a precision score of 0.952, it accurately identified positive instances, reducing false positives.

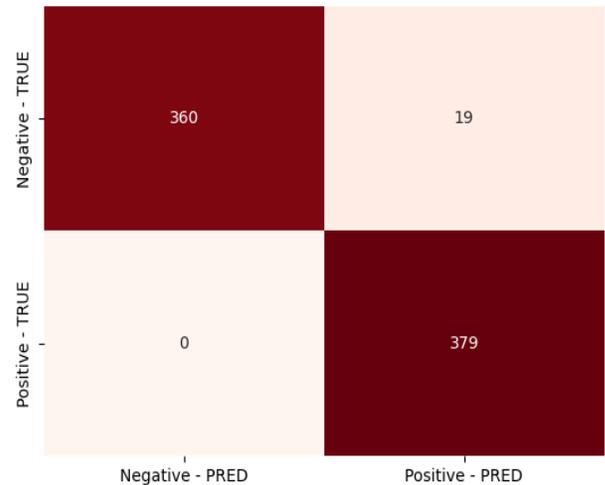


Figure 4: Random Forest Confusion Matrix

The perfect recall score of 1.000 signifies that it successfully described each true positive case, demonstrating its ability to comprehensively detect positive outcomes. Similarly, Random Forest achieved an impressive accuracy score of 0.975, reflecting its overall correctness in predicting both positive and negative instances. Hence, this denotes that Random Forest is a robust model, capable of accurately identifying positive cases while maintaining high accuracy levels.

4.2. Decision Tree

Decision Tree exhibited a strong performance, particularly in recall and precision. With a precision score of 0.883, it effectively identified true positive instances with a relatively low rate of false positives. Additionally, the recall score of 0.992 denotes high sensitivity to positive cases, obtaining the majority of true positives. Fig. 5 shows the confusion matrix of the Random Forest ML technique. Although slightly lower than Random Forest pertaining to accuracy, Decision Tree achieved a creditable accuracy score of 0.930, revealing its capability to make correct predictions throughout the dataset. Basically, Decision Tree's performance strengthens its effectiveness in accurately identifying positive outcomes while maintaining competitive accuracy levels.

4.3. Support Vector Classifier

Support Vector Classifier demonstrated a solid performance across the precision, recall and accuracy metrics. With a precision score of 0.891, it exhibited a high level of accuracy in identifying positive instances while minimising false positives. Fig. 6 illustrates the Support Vector Classifier Confusion Matrix. Its recall score of 0.966 signifies that SVC effectively acquired the

majority of true positive cases, indicating its robustness in detecting positive outcomes.

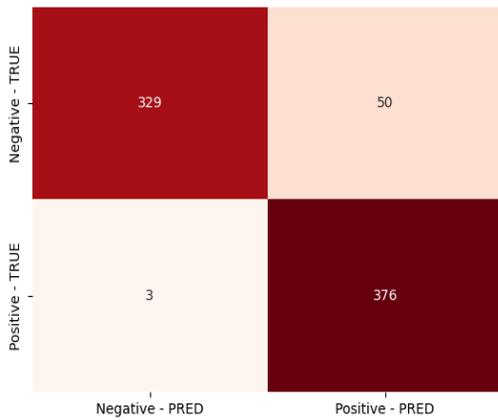


Figure 5: Decision Tree Confusion Matrix

Despite a slightly lower accuracy score compared to Random Forest and Decision Tree, SVC achieved a commendable accuracy score of 0.923, reflecting its overall correctness in predicting both positive and negative instances. This emphasises SVC as a reliable model to accurately predict positive outcomes with competitive accuracy levels.

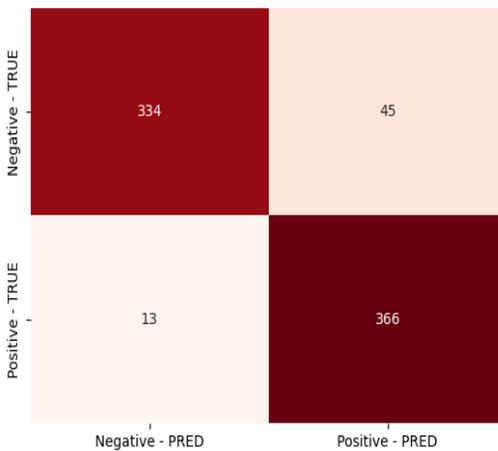


Figure 6: Support Vector Classifier Confusion Matrix

4.4. K-Nearest Neighbour

K-Nearest Neighbour displayed a notable performance, particularly regarding recall, indicating its effectiveness in obtaining positive instances. Fig. 7 illustrates the Confusion Matrix of the k-Nearest Neighbour ML technique that reports a precision score of 0.843. It accurately identified positive cases while maintaining a reasonable false positive rate. Its high recall score of 0.992 denotes that KNN effectively recorded the majority of true positive instances, displaying its sensitivity to positive outcomes. Notwithstanding a slightly lower accuracy score compared to other models, KNN attained a respectable accuracy score of 0.904, reflecting its ability to make correct predictions throughout the dataset.

Principally, KNN's performance confirms its efficacy in accurately identifying positive outcomes while maintaining competitive accuracy levels.

4.5. Logistic Regression:

While Logistic Regression established a slightly lower performance compared to other models, it demonstrated reasonable accuracy in predicting positive outcomes.

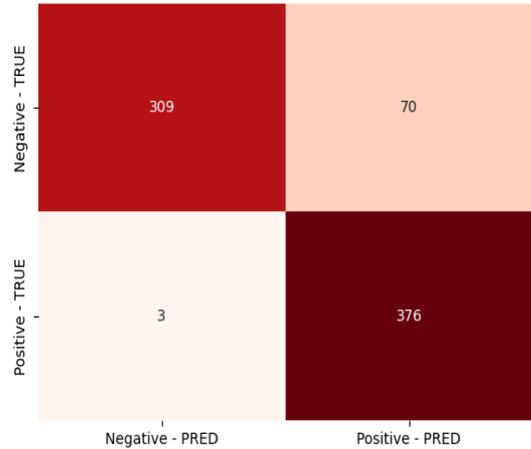


Figure 7: K-Nearest Neighbour Confusion Matrix

Fig. 8 illustrates the Confusion Matrix of the Logistic Regression ML technique that reports a precision score of 0.793, it accurately identified positive instances with a moderate rate of false positives. The recall score of 0.836 indicates that Logistic Regression effectively represented a good portion of true positive cases, demonstrating its sensitivity to positive outcomes. Despite a lower accuracy score in comparison to other models, Logistic Regression achieved a reasonable accuracy score of 0.809, revealing its overall correctness in predicting both positive and negative instances. Essentially, Logistic Regression provides a reliable approach that can be applied to predict positive outcomes, albeit with a slightly lower performance compared to other models.

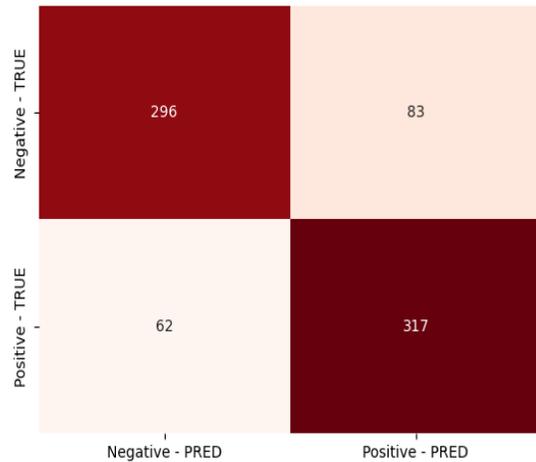


Figure 8: Logistic Regression Confusion Matrix

Table 1: Comparative Analysis of Precision, Recall, Accuracy

Model	Precision	Recall	Accuracy
Random Forest	0.952	1.0	0.975
Decision Tree	0.883	0.992	0.93
SVC	0.891	0.966	0.923
KNN	0.843	0.992	0.904
Logistic Regression	0.793	0.836	0.809

Classification reports deliver a detailed breakdown of each model's performance, permitting a comprehensive evaluation. Table 1 and Fig.9 provides a performance comparison between all the ML techniques addressed in the study.

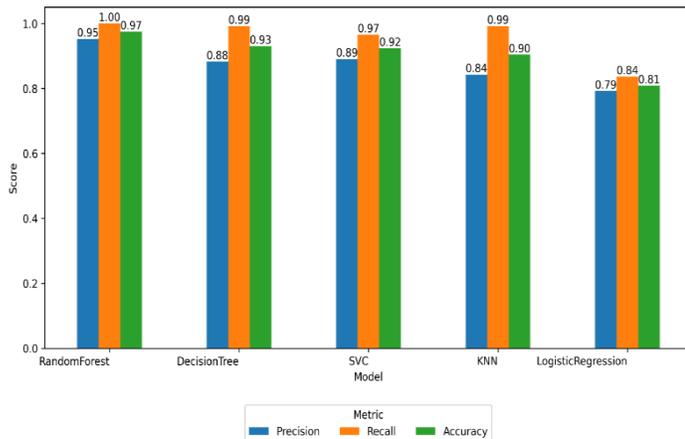


Figure 9: Comparative Performance of Different Models

5. Conclusion and Future Work

The evaluation of multiple machine learning models to predict customer response has yielded significant insights into the effectiveness of these techniques within marketing contexts. Notably, the Random Forest model demonstrated superior predictive capabilities, achieving a high accuracy of 97.5%, a precision of 95.2%, and a recall of 100%. This strong performance underscores Random Forest's ability to accurately identify both positive and negative customer responses, highlighting its potential as a valuable tool for marketing professionals. Decision Tree and Support Vector Classifier (SVC) also exhibited robust predictive power, further validating the utility of machine learning in this domain, while K-Nearest Neighbors (KNN) provided reasonably accurate predictions, albeit with slightly lower performance metrics. In contrast, Logistic Regression showed the least effective performance, with an accuracy of 80.9%, a precision of 79.3%, and a recall of 83.6%.

These findings collectively emphasize the capacity of machine learning techniques to effectively analyze customer response data in marketing scenarios. The Random Forest model's exceptional recall, in particular, suggests its strength in capturing a high proportion of positive customer responses, which is critical for targeted marketing interventions. The comparative performance analysis of the models provides valuable guidance for selecting appropriate algorithms for specific marketing objectives. Ultimately, this study reinforces the importance of leveraging advanced analytics to enhance the precision and efficacy of marketing decision-making processes and customer targeting strategies, leading to improved resource allocation and campaign ROI.

However, to further refine predictive accuracy and expand the applicability of these models, future research should prioritize several key areas. First, exploring ensemble methods, which strategically combine the predictive strengths of multiple individual models, holds promise for achieving even higher predictive performance. Second, a systematic investigation of feature engineering and selection techniques is warranted to optimize model inputs and potentially uncover more salient predictors of customer behavior. This could provide valuable

insights into which customer attributes are most influential in driving campaign response. Third, integrating domain-specific knowledge and external data sources, such as social media activity, sentiment analysis, and broader demographic information, could enrich the models' predictive capabilities and provide a more holistic understanding of customer behavior. Finally, conducting longitudinal studies to assess the temporal stability and generalizability of the developed models is essential to validate their robustness and effectiveness in dynamic real-world marketing environments. Such studies would contribute to a more comprehensive understanding of the models' long-term utility and inform adaptive marketing strategies.

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References

- [1] Y. Kulkarni; A. Mahamuni; S. Sane; P. Kalshetti; K. Patil; R. Jarad, "Analysing How Marketing Management and Artificial Intelligence are used to Change Customer Engagement," in 2024 International Conference on Trends in Quantum Computing and Emerging Business Technologies, 1-6, 2024, doi: 10.1109/TQCEBT59414.2024.10545064.
- [2] N. Rane, M. Paramesha, S. Choudhary, J. Rane, "Artificial Intelligence in Sales and Marketing: Enhancing Customer Satisfaction, Experience and Loyalty," *Advances in Artificial Intelligence*, 17, 2024. doi: 10.18178/JAAI.2024.2.2.245-264.
- [3] K. Dhiwar, M. Bedarkar, "Circular Economy for Fashion Waste in the Indian Fashion Industry: Challenges and Opportunities," *Fashion Practice*, 16(3), 344, 2024. doi.org/10.1080/17569370.2024.2393495.
- [4] R. Gill, P. Kumar, M. Patel, H. Kumar, "Integrating Marketing Data Ecosystems: Merging Diverse Data Sources for Holistic Insights," *Data Engineering for Data-driven Marketing*, Emerald, 2025.
- [5] S. Verma, R. Sharma, S. Deb, and D. Maitra, "Artificial intelligence in marketing: Systematic review and future research direction," *Information Management Data Insights*, 1, 100002, 2021. doi.org/10.1080/17569370.2024.2393495.
- [6] M. Shaffer, I. Okundaye, *Marketing, Sales, and Distribution*, Innovation in Nephrology, Elsevier, 2025.
- [7] H. Sarker, "Machine Learning: Algorithms, Real-World Applications and Research Directions," *SN Computer Science*, 2, 160, 2021. doi: 10.1007/s42979-021-00592-x.
- [8] H. Gacanin, M. Wagner, "Artificial intelligence paradigm for customer experience management in next-generation networks: Challenges and perspectives," *IEEE Network*, 33(2), 188-194, 2019. doi: 10.1109/MNET.2019.1800015.
- [9] Q. Nguyen, A. Sidorova, "Understanding user interactions with a chatbot: a self-determination theory approach," in 2018 AMCIS Proceedings, 3, 2018.
- [10] A. Maxwell, S. Jeffrey, M. Lévesque, "Business angel early-stage decision making," *Business Venturing*, 26(2), 212-225, 2011. doi.org/10.1016/j.jbusvent.2009.09.002.
- [11] S. Chatterjee, S. Ghosh, R. Chaudhuri, B. Nguyen, "Are CRM systems ready for AI integration? A conceptual framework of organizational readiness for effective AI-CRM integration," *The Bottom Line*, 32(2), 144-157, 2019. doi.org/10.1108/BL-02-2019-0069.
- [12] R. Seranmadevi, A. Kumara, "Experiencing the AI emergence in Indian retail - Early adopters approach," *Management Science Letters*, 9, 33-42, 2019. doi: 10.5267/j.msl.2018.11.002.

- [13] W. Wisetsri, C. Aarthy, V. Thakur, D. Pandey, K. Gulati, "Systematic Analysis and Future Research Directions in Artificial Intelligence for Marketing," *Computer and Mathematics Education*, **12**(11), 43-55, 2021. doi: 10.17762/turcomat.v12i11.5825.
- [14] S. Nazim, M. Rajeswari, "Creating a Brand Value and Consumer Satisfaction in E-Commerce Business Using Artificial Intelligence with the Help of Vosag Technology," *Innovative Technology and Exploring Engineering (IJITEE)*, **8**(8), 2019.

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