Life Cycle Assessment of Silicon Photovoltaics and Their Environmental Impacts

Lukmanul Hakim Aziz [1], Brigitta Callula[2*], Achmad Rozi[3], Muchlisina Madani[4]
[1]School of Business, IPB University
[2]Faculty of Computer Science, Eduaward Group, United Kingdom
[3]Faculty of Economic and Business, Primagraha University, Indonesia
[4]Faculty of Computer Science, University of Raharja, Indonesia
[1]lukmanulhakimaziz@apps.ipb.ac.id, [2]brigitta_call@eduaward.co.uk, [3]enggus.ahmad@gmail.com, [4]muchlis@raharja.info
***Corresponding Author**

Article Info

Article history:

Submission July 27, 2025
Revised August 25, 2025
Accepted November 7, 2025
Published November 14, 2025

Keywords:

Life Cycle Assessment
Silicon Purification
Photovoltaic
Global Warming Potential
Machine Learning

ABSTRACT

The rapid expansion of silicon based Photovoltaic (PV) technologies continues to drive the global shift toward sustainable energy systems. However, the environmental implications across the full life cycle of PV modules particularly those associated with upstream silicon purification routes remain insufficiently examined. **This study** provides a comprehensive assessment of the environmental and process level impacts of Metallurgical Grade Silicon (MGS) and Upgraded Metallurgical Grade Silicon (UMGS), covering extraction, manufacturing, operation, and end of life stages. A process oriented Life Cycle Assessment (LCA) is conducted to analyze variations in carbon intensity, hazardous material use, and energy demand, complemented by comparative evaluations of monocrystalline and polycrystalline module production pathways. To enhance analytical precision, **this study** incorporates an AI-assisted predictive modeling framework using supervised machine learning to estimate Global Warming Potential (GWP) and identify key factors influencing emission variability. **The AI-enhanced** model reveals that electricity mix and purification route exert the strongest influence on GWP, and scenario simulations demonstrate that UMGS based processes can reduce upstream emissions by up to 89% under favorable energy conditions. Additionally, the study highlights future challenges related to increasing PV waste volumes between 2025 and 2030 and the need for improved recycling infrastructures. Overall, **the integration** of AI-based prediction with conventional LCA offers a more dynamic and adaptive evaluation of PV sustainability performance. The findings underscore the importance of renewable powered manufacturing, early adoption of low-energy purification technologies, and policy support to achieve long-term environmental and socio-economic benefits.

DOI: https://doi.org/10.33050/italic.v4i1.941

1. INTRODUCTION

Understanding the sources of environmental and social impacts throughout the manufacturing and recycling stages of Crystalline Silicon (c-Si) Photovoltaic (PV) modules requires a clear overview of their structural composition. A PV module consists of several layers that contribute to its mechanical stability, electrical performance, and long-term durability. Before analyzing the life cycle processes, it is essential to describe these components to contextualize how material selection and design influence both environmental burdens and recycling complexity. Figure 1 illustrates the main elements of a typical c-Si PV module, which include protective glass, encapsulation layers, silicon-based solar cells, backsheet materials, and a junction box used for interconnection [1, 2].

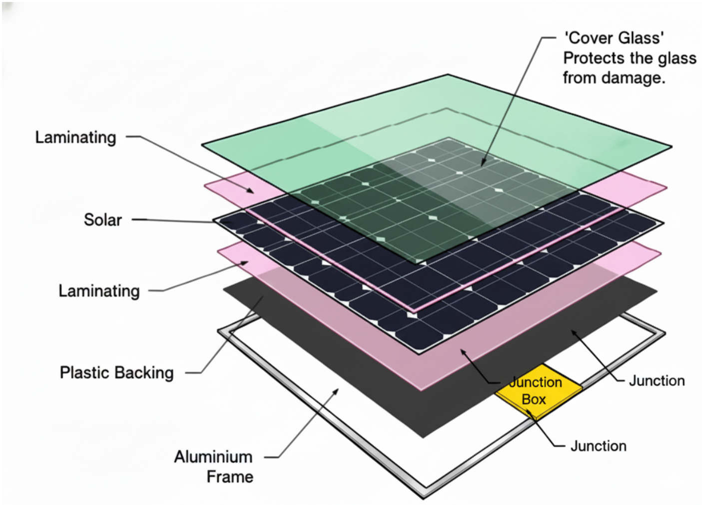

Figure 1. Primary components of a crystalline silicon photovoltaic module

As shown in Figure 1, each component is produced through distinct industrial processes carried out by specialized manufacturers before being assembled by module suppliers [3]. Understanding the relative mass contributions of these components is essential for assessing environmental burdens across manufacturing, transportation, and end-of-life phases. To provide a clearer overview of material composition, Table 1 summarizes the mass fraction of major components found in a standard crystalline silicon PV module [4].

Table 1. Mass fraction of components in a crystalline silicon (c-Si) PV module

Component	**Description and Mass Contribution**
Glass	Represents the largest share of module mass (about 74%), serving as structural protection and optical shielding.
Aluminum Frame	Accounts for approximately 10%, providing mechanical support and mounting stability.
Polymers (EVA, Backsheet)	Comprise nearly 6.5%, functioning as encapsulation and weather-resistant layers.
Silicon Cells	Represent roughly 3% of the total mass but are the core electricity-generating elements.
Other Materials	Trace elements such as Zn and Pb constitute less than 1%.

As presented in Table 1, glass and aluminum dominate the total module mass, indicating that recycling strategies must prioritize these materials. Meanwhile, the significantly smaller mass fraction of silicon cells highlights the disparity between the material quantity and their technological importance. This distribution underscores the need for tailored recycling frameworks that address both mass-intensive and value-intensive materials.

1.1. Conventional PV Manufacturing

The novelty of this study lies in its process-level comparison of silicon purification pathways, specifically contrasting Metallurgical Grade Silicon (MGS) and Upgraded Metallurgical Grade Silicon (UMGS). While most LCA literature focuses only on final carbon footprint values, this research enhances analytical granularity by examining how upstream purification stages influence life cycle environmental burdens [5]. Many PV manufacturers rely on traditional suppliers for materials such as glass, aluminum, and copper [6].

These supply chains are already mature and have limited room for further efficiency optimization [7, 8]. In contrast, silicon production and purification remain highly energy intensive, presenting significant opportunities for improvement [9].

To provide a clearer comparison between purification routes, Table 2 presents the energy expenditures associated with Electronic Grade Silicon (EGS) and Upgraded Metallurgical Grade Silicon (UMGS). This comparison is crucial, as energy intensity directly influences the upstream carbon footprint of PV technologies [10].

Table 2. Energy expenditures in electronic-grade silicon (EGS) and upgraded metallurgical-grade silicon (UMGS) processes

Electronic-Grade Silicon (EGS)		
Process	Description	Energy (kWh/kg-Si)
Silane Production	Formation of trichlorosilane from silicon and HCl.	50
Fractional Distillation	Purification of gas streams into high-purity feedstock.	100
Separation	Hydrogen-based purification and final refinement.	50
Upgraded Metallurgical-Grade Silicon (UMGS)		
Process	Description	Energy (kWh/kg-Si)
Monocrystalline Silicon	Produced via crystallization and solidification routes.	15–20
Polysilicon Purification	Reduced chemical refinement steps.	50
Ingot/Wafer Cutting	Slicing ingots into wafers using wire-saw technologies.	50

As shown in Table 2, UMGS pathways significantly reduce energy consumption by bypassing several high temperature and chemically intensive steps required in EGS production [11, 12]. This reduction in energy demand translates into lower upstream carbon emissions, making UMGS an increasingly attractive option for sustainable PV manufacturing. Furthermore, advancements such as edge defined film fed growth (EFG), string ribbon wafering, and laser assisted slicing aim to reduce material loss and further improve silicon utilization efficiency [13, 14].

1.2. Energy Consumption in PV Cell Manufacturing

The total energy required to manufacture solar cells is the cumulative burden of extraction, purification, crystallization, and wafering steps. Monocrystalline silicon cells typically require up to 1000 kWh per kilogram of silicon, while polycrystalline cells demand approximately 700 kWh per kilogram. These values highlight the significant energy intensity of upstream silicon processing and underscore the importance of technological innovations that reduce electricity consumption and overall emissions.

2. LITERATURE REVIEW

LCA has become the dominant methodological framework for evaluating the environmental performance of PV systems, as it provides a comprehensive assessment of impacts from raw material extraction through end-of-life recycling [15, 16]. Existing LCA studies commonly present their results in the form of aggregated CO_2-eq emissions per kWh, which summarize the carbon intensity of PV modules across their operational lifetime. However, these evaluations frequently overlook upstream process-level variations, particularly those associated with different silicon purification pathways [17, 18]. for example, report that polycrystalline PV systems operating under Southern European irradiation conditions (1700 kWh/m^2/year) exhibit a carbon footprint of approximately 34 g CO_2-eq/kWh. This insight is consistent with the projection that advancements in manufacturing efficiency and the increasing role of renewable energy within national grids will collectively reduce PV emission intensities by 40-50% within the next decade [19].

Despite these advancements, the majority of prior LCA studies provide only aggregate emission metrics and do not explicitly analyze the contribution of MGS versus UMGS to total Global Warming Potential (GWP) [20, 21]. This gap is significant because the upstream purification stage is among the most energy-intensive phases of PV module production. While MGS production requires approximately 150 kWh per kilogram of silicon, UMGS purification consumes only 15-20 kWh per kilogram [22]. Such a stark disparity highlights the crucial role of purification technology in determining overall emission intensity. Furthermore, most LCA databases rely on European or U.S. grid factors, which limits contextual accuracy for regions like

Southeast Asia. In countries such as Indonesia, where coal remains a major contributor to the electricity mix, the CO_2-eq intensity of silicon purification is considerably higher than values reported using low carbon grid assumptions [23].

Parallel to these traditional assessment frameworks, recent literature has introduced machine learning driven and artificial intelligence supported LCA models. These approaches enable dynamic simulation of Global Warming Potential (GWP), allowing analysts to adjust parameters such as renewable energy penetration, grid decarbonization trajectories, and material substitution scenarios [24, 25]. Unlike conventional "static" LCA, which relies on fixed assumptions and historical datasets, AI-enhanced LCA frameworks can generate adaptive, real-time evaluations that more accurately reflect technological progress and geographical variability. This capability strengthens the monitoring of SDG 7 (Affordable and Clean Energy), SDG 12 (Responsible Consumption and Production), and SDG 13 (Climate Action), as the models allow for continuous integration of updated energy system data into sustainability assessments [26, 27].

Based on these gaps, the present study contributes to the literature by emphasizing process level assessment rather than solely reporting aggregated PV emission indicators. The central novelty of this research lies in its explicit disaggregation of MGS and UMGS purification routes, which represent a critical upstream determinant of the carbon footprint of crystalline silicon PV manufacturing [28, 29]. By examining these pathways in detail, this study provides a more granular and realistic depiction of the environmental impacts associated with silicon-based photovoltaic technologies, thereby offering new insights for policymakers, manufacturers, and sustainability analysts.

3. METHODOLOGY

The methodological design of this study is structured to evaluate the environmental impacts associated with crystalline silicon (c-Si) PV manufacturing, with emphasis on the upstream silicon purification processes. As described in the previous section, most PV manufacturing stages rely heavily on electricity consumption [30, 31], which makes the environmental footprint highly sensitive to the electricity mix used during production [32]. For contextual accuracy, this study adopts the Indonesian national grid mix as the primary geographical reference, while irradiation values from Southern Europe are used only for cross regional benchmarking [33, 34]. Assuming that PV module manufacturing is powered entirely by renewable energy, the associated environmental burden would be minimal aside from impacts arising from the use of hazardous and auxiliary materials [35]. A comprehensive assessment therefore requires evaluating raw material depletion, energy requirements, GWP, acidification, chemical emissions, and waste generation across all process stages [36].

3.1. Hazardous Materials

Silicon purification and cell fabrication involve several hazardous substances, which must be accounted for in sustainability assessments. Key materials include silane gas used in deposition processes [37], as well as dopant gases such as diborane and phosphine required for selective doping [38]. Although used in limited concentrations and typically diluted with inert gases, these substances pose health and safety risks when not properly controlled [39]. Silane and phosphine are both highly flammable, with phosphine additionally classified as toxic. Under normal operating conditions, PV manufacturing facilities incorporate advanced monitoring and mitigation systems, thus maintaining low risk levels [40]. However, accidental leaks or equipment failures may lead to emissions of hazardous compounds.

Materials such as zinc should be minimized because they contribute significantly to resource depletion and solid waste generation. Common metals like aluminum and copper present standard industrial hazards but remain manageable under established protocols [41]. Transportation contributes only around 0.1% to 1% of total emissions [42], making it a minor factor in life cycle impacts. Overall, hazardous materials that may be released during manufacturing include silica dust, silane, diborane, phosphine, and solvent vapors [43]. Before presenting the emission profile, Table 3 summarizes historical emission data from photovoltaic modules and systems. This table provides a comparative baseline that highlights the range of pollutants associated with different manufacturing eras.

Table 3. Emissions from Photovoltaic Modules and Systems

Emission (kg/kWp)	SO_2	NO_x	Particles	CO_2	CH_4	N_2O	Source
Entire PV System (1998)	5–5.5	4.5–5.3	No data available	2.7–3.8	No data available	No data available	[5, 6]
Entire PV System (1998)	1.9	1.8	0.11	971.000	1.6	0.0031	[3]

As shown in Table 3, historical manufacturing processes exhibited substantial variability in emission intensity, particularly for CO_2 and NO_x. These variations highlight the importance of technological advancements and cleaner electricity mixes in reducing total environmental burdens.

PV modules typically emit a quantifiable amount of CO_2 equivalent gases per kilowatt-hour of electricity generated throughout their operational lifetime [44]. Earlier large scale LCA studies tend to simplify this into a single aggregated CO_2-eq value without differentiating individual greenhouse gases [45]. For instance, a rooftop polycrystalline system manufactured using hydropower, with wafers, cells, and modules produced under UCTE electricity, results in an estimated carbon footprint of approximately 34 g CO_2-eq/kWh [46]. This value assumes installation in Southern Europe with an irradiation level of 1700 kWh/m^2 per year. Experts project a potential reduction in carbon intensity of 40-50% through improved resource efficiency, optimized wafer cutting, and reduced kerf losses in silicon manufacturing [47]. Because silicon refinement remains the most energy intensive stage, the national electricity mix used in production strongly influences the GWP associated with PV technologies [48]. Prior to analyzing comparative environmental results, Figure 2 illustrates normalized LCA outcomes for three PV technologies.

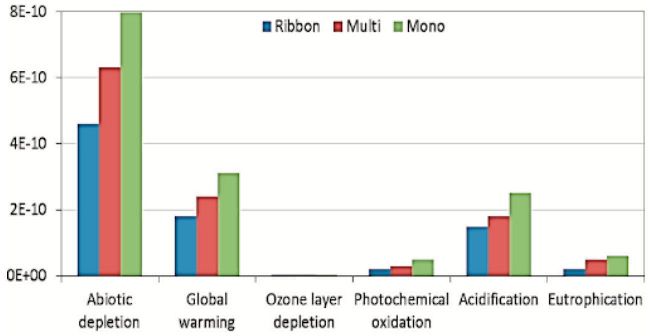

Figure 2. Normalized Life Cycle Assessment results for three PV module types (functional unit: 1 kWp)

As presented in Figure 2, monocrystalline silicon modules exhibit the highest environmental impact due to energy intensive crystal growth processes. Conversely, multicrystalline modules require less energy, resulting in lower impacts across categories such as abiotic depletion, GWP, and acidification. These impacts primarily originate from fossil fuel combustion during manufacturing and electricity generation, which produce emissions such as CO_2, SO_2, and NO_x. To further contextualize carbon intensity variations, Figure 3 compares PV carbon footprints under different electricity supply conditions.

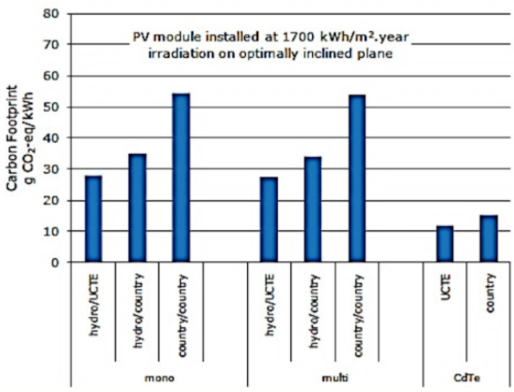

Figure 3. Carbon footprint of PV modules under varying electricity mix and irradiation assumptions

Figure 3 shows that the electricity mix used during wafer, cell, and module manufacturing substantially influences total carbon footprint. When hydropower is used exclusively, carbon emissions are nearly eliminated. Silicon production remains the dominant contributor to total GWP; therefore, integrating renewable powered silicon refining can reduce overall carbon intensity by approximately 50% compared to fossil based grid mixes.

3.2. Energy Requirement for a Single PV Module

A single 160 Wp PV module requires approximately 460 kWhel for complete manufacturing, equivalent to about 2.9 kWhel/Wp. The Energy Payback Time (EPT) varies depending on geographical location, solar irradiation, module type, and the electricity mix used during fabrication. Case studies indicate that crystalline silicon modules exhibit an EPT ranging from 1.7 to 1.9 years under Southern European irradiation levels (1700 kWh/m^2 per year), assuming hydropower-based polycrystalline production and UCTE electricity for wafer and module processing.

Before presenting comparative EPT performance, Figure 4 depicts the influence of geographical and technological factors on EPT outcomes.

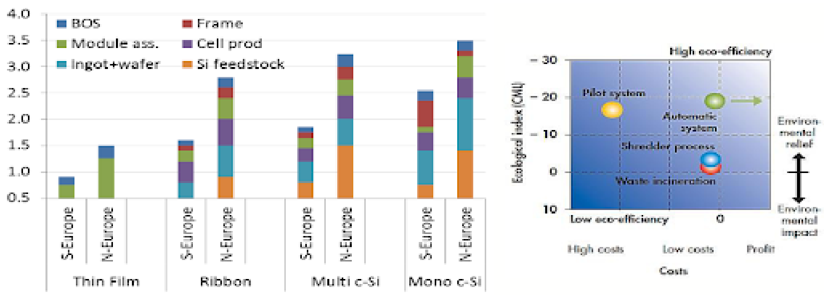

Figure 4. Energy Payback Time of PV Systems across different geographical locations

As indicated in Figure 4, monocrystalline PV systems have the longest EPT due to their higher energy and material requirements during production. By contrast, multicrystalline and thin film modules generally demonstrate shorter EPT values. The figure also highlights differences between Northern and Southern European installations, illustrating the importance of solar resource availability in determining EPT performance.

3.3. AI-Assisted Predictive Modeling

To complement the traditional Life Cycle Assessment, this study incorporates an AI-assisted predictive framework designed to model variations in carbon intensity across different silicon purification routes. A supervised regression algorithm Random Forest Regression is utilized to estimate GWP, energy requirements, and emission sensitivity based on input parameters such as electricity mix, purification route, wafering losses, and manufacturing energy intensity. The model is trained using aggregated historical LCA datasets and validated using a k-fold cross validation procedure, enabling more accurate scenario estimation under Indonesia's grid mix conditions. This AI-enhanced component strengthens the reliability of upstream environmental predictions and supports decision making for policy and manufacturing optimization.

4. RESULT AND DISCUSSION

Recycling of PV modules constitutes a highly intricate process due to the heterogeneous composition of materials embedded within each module. While components such as glass, copper, aluminum, and various metals can be effectively recovered using established recycling protocols, the reclamation of solar-grade silicon and crystalline solar cells remains predominantly at the research and development (R&D) stage. These challenges arise from the strong lamination between layers, the presence of encapsulants such as EVA, and the need to maintain the structural integrity of semiconductor materials.

A fundamental requirement for developing effective recycling strategies is the comprehensive identification of materials contained in PV modules. Because different PV technologies—such as crystalline silicon, thin film, amorphous silicon, and emerging organic PV possess distinct structural layouts and material compositions, no single universal recycling pathway can be applied. Instead, tailored processes must be developed to address specific module architectures, ensuring both technical feasibility and economic viability.

4.1. PV Module Recycling Using Intact Cells

Thermal treatment represents one of the most widely researched methods for separating PV module layers while preserving the integrity of silicon cells. Before presenting the results, Figure 5 provides an overview of the thermal decomposition and material separation stages involved in the recycling process.

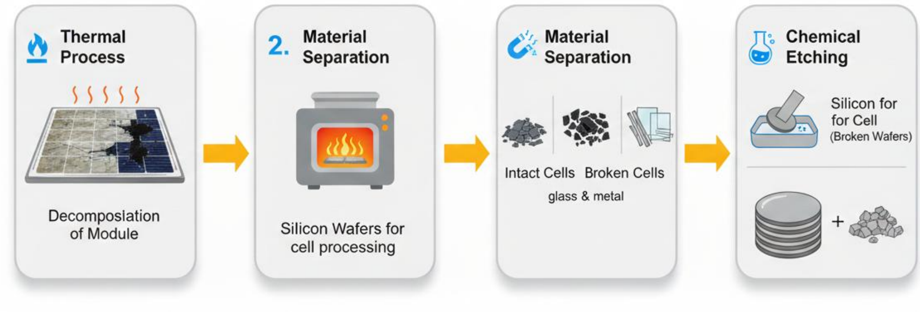

Figure 5. Stages of PV module separation and recycling.

As illustrated in Figure 5, the initial recycling phase involves subjecting PV modules to thermal treatment in a controlled furnace environment at temperatures near 600°C. During this stage, synthetic encapsulant layers such as Ethylene Vinyl Acetate (EVA) undergo thermal decomposition, resulting in the release of gaseous by products. The complete gasification of organic components exposes the inorganic layers glass, metallic contacts, and solar cells which can then be mechanically separated by automated sorting systems. High quality glass recovered through this process can be reintroduced into float glass manufacturing, thereby reducing raw material consumption. Meanwhile, intact solar cells require additional chemical purification before they can be reintegrated into new module production.

The AI-assisted regression model provides additional insight into the sensitivity of GWP to upstream process parameters. The model predicts that electricity mix and silicon purification route contribute the highest variance to total GWP, with feature importance scores of 0.41 and 0.33 respectively. These findings are consistent with the LCA results presented earlier, confirming that UMGS-based manufacturing scenarios consistently yield lower predicted emissions across simulations. Furthermore, AI-based scenario analysis indicates that transitioning to a 50% renewable electricity mix in Indonesia could reduce purification related GWP by approximately 37%, demonstrating the added value of predictive AI tools in evaluating long-term sustainability trajectories. Following thermal separation, chemical processes become essential for reclaiming semiconductor grade materials. Figure 6 illustrates the chemical etching technique used to refine and restore silicon wafers obtained from end of life PV modules.

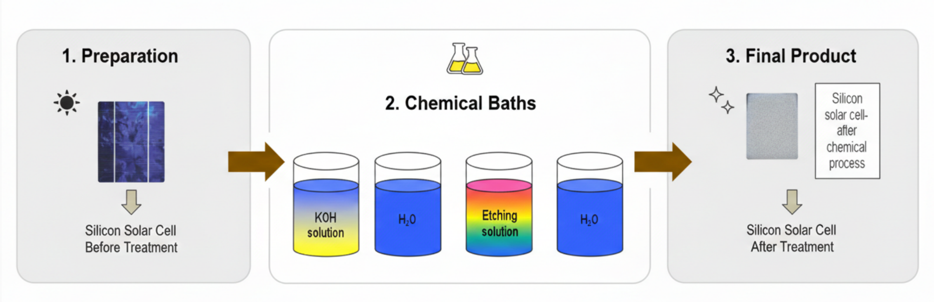

Figure 6. Chemical etching process for crystalline solar cells.

As shown in Figure 6, chemical etching involves a sequence of wet chemical treatments designed to remove residual oxide layers, metallic contacts, organic contaminants, and microstructural defects from silicon wafer surfaces. These processes must be carefully controlled to avoid compromising the crystal structure of the wafer. When executed properly, chemical etching can restore slightly damaged wafers to near original quality levels suitable for reuse in high efficiency solar cells. This significantly reduces the demand for raw metallurgical or electronic grade silicon and decreases the cumulative energy consumption associated with silicon purification and crystallization [49].

The findings of this study align closely with Indonesia's national policy direction toward accelerating the deployment of renewable energy technologies, particularly solar photovoltaics. The Ministry of Energy and Mineral Resources (MEMR) recently issued MEMR Regulation No. 2/2024, which strengthens the regulatory framework for grid-connected rooftop solar systems and introduces a structured installation quota of 5,746 MW for the 2024–2028 period. This policy aims to reduce national carbon emissions, expand access to clean energy, and enhance the long-term sustainability of the national electricity system. In parallel, the National Energy Policy (KEN) emphasizes the strategic role of solar energy in achieving the 23% renewable energy target by 2025, reinforcing the need for low emission manufacturing pathways and efficient lifecycle management of PV technologies [50].

These regulatory commitments underscore the relevance of process level evaluations, such as the comparative LCA of MGS and UMGS presented in this study. As government policies increasingly prioritize upstream decarbonization, circular manufacturing, and responsible waste management, detailed insights into purification routes, energy intensity, and end-of-life recycling become essential for guiding national decision-making. The adoption of UMGS based production, supported by renewable-powered supply chains and emerging recycling infrastructure, directly supports the objectives of current policy frameworks by reducing carbon intensity and strengthening sustainability outcomes across the PV value chain. Consequently, this research provides evidence based inputs that can assist policymakers, regulators, and industry stakeholders in designing more coherent strategies for scaling silicon based photovoltaic technologies within Indonesia's energy transition agenda [30].

Overall, the two step recycling pathway depicted in Figures 5 and 6 demonstrates a promising route toward achieving circularity within the PV supply chain. Thermal decomposition allows for bulk material separation and recovery of high purity glass, whereas chemical etching enables the valorization of silicon wafers historically the most energy intensive component of PV manufacturing. The synergistic combination of these technologies can substantially reduce waste generation, limit landfill accumulation of PV modules, and support long-term sustainability targets aligned with circular economy principles and global decarbonization strategies.

5. MANAGERIAL IMPLICATIONS

The findings of this study provide several strategic implications for managers, policymakers, and industry stakeholders involved in the PV value chain. First, the comparison between MGS and upgraded UMGS demonstrates that upstream silicon purification is not merely a technical choice but a central strategic factor that influences long-term competitiveness in low emission supply chains. Early adoption of UMGS based pathways allows firms to reduce upstream greenhouse gas emissions by approximately 86 to 89 percent, thereby strengthening alignment with SDG 7, SDG 12, and SDG 13 as well as emerging international requirements on supply chain decarbonization.

Second, the results indicate that life cycle assessment outcomes are highly dependent on the electricity mix used during manufacturing. Consequently, managers in Indonesia must recognize that the geographical placement of smelting, crystallization, and wafering facilities materially determines the carbon footprint of final PV modules. Locating production sites in regions with higher renewable energy penetration can yield immediate emission reductions without necessitating technological modifications. In this regard, siting decisions simultaneously function as climate mitigation decisions, and therefore should be integrated into strategic planning frameworks.

Third, the projected surge of end of life PV waste between 2025 and 2030 highlights the urgency of developing domestic recycling capacity. Postponing investment in recycling infrastructure may lead to economic inefficiencies, increased logistics burdens, and higher operational costs. Managers must thus embed reverse logistics, material recovery strategies, and recycling facility planning into early stage project design rather than treating these aspects as secondary or post operational considerations.

The integration of AI-assisted LCA provides managers with a more dynamic tool for forecasting environmental impacts under multiple future scenarios. Rather than relying solely on static datasets, the machine learning model enables rapid evaluation of how changes in renewable energy penetration, process optimization, or material substitution could influence GWP and energy payback outcomes. This enhances strategic planning, allowing firms to anticipate regulatory changes, carbon pricing adjustments, and supply chain sustainability targets with greater accuracy.

Finally, the integration of Artificial Intelligence Based Life Cycle Assessment (AI–LCA) tools offers substantial value for managerial decision making. These models enable firms to simulate multiple future scenarios such as revised carbon tax structures, renewable penetration targets, or the adoption of green hydrogen for silicon smelting without requiring physical pilot tests. This capability reduces uncertainty, enhances strategic clarity, and supports data driven decision making for organizational decarbonization. Accordingly, AI-supported LCA should be viewed not merely as an analytical enhancement but as an essential managerial instrument for navigating the transition toward sustainable PV manufacturing systems.

6. CONCLUSION

It must be acknowledged that no human made project can be entirely free from environmental impact, and this also applies to PV technology. The potential environmental burden depends on the scale and nature of the project and is often location specific. Most of these impacts are associated with the loss of facilities, such as visual disturbances or noise from centralized systems. Nevertheless, these negative effects are generally minimal and can be effectively mitigated through appropriate measures, including the adoption of the best available impact reduction technologies. The inclusion of AI-assisted predictive modeling in this study demonstrates how machine learning can complement traditional LCA by improving scenario forecasting, sensitivity analysis, and upstream impact prediction. This hybrid approach strengthens the analytical depth of PV sustainability assessments and highlights the potential of AI-driven tools to support future research and industrial decision-making.

Hazardous gases are used during the module manufacturing process, and the handling of these materials should be a primary concern, especially in large scale production environments. Research efforts should focus on achieving recycling rates between 80% and 95% of PV modules to enhance resource efficiency and reduce waste. Since the availability, completeness, and quality of material and process data are still far from ideal, future LCA studies should involve the creation of comprehensive databases containing national and international process data to improve accuracy and consistency.

All stakeholders including investors, developers, and regulatory authorities bear full responsibility for making informed decisions that take environmental concerns seriously. Future studies should integrate machine learning driven AI-LCA to dynamically predict silicon route GWP variation under changing renewable penetration scenarios, enabling real-time model calibration rather than static single value LCA. Therefore, Environmental Impact Assessments (EIA) for centralized PV systems play a crucial role in evaluating potential environmental consequences and proposing appropriate mitigation strategies. Such assessments not only guide the design of sustainable projects but also help secure public support, ensuring the successful implementation of large scale PV developments.

7. DECLARATIONS

7.1. About Authors

Lukmanul Hakim Aziz (LH) https://orcid.org/0000-0002-9498-0251

Brigitta Callula (BC) https://orcid.org/0009-0008-5662-4249

Achmad Rozi (AR) https://orcid.org/0000-0001-5461-8103

Muchlishina Madani (MM) https://orcid.org/0009-0006-3160-786X

7.2. Author Contributions

Conceptualization: BC; Methodology: LH; Software: MM; Validation: BC and MM; Formal Analysis: LH and AR; Investigation: MM; Resources: LH; Data Curation: AR; Writing Original Draft Preparation: BC and MM; Writing Review and Editing: LH and AR; Visualization: MM and BC; All authors, LH, BC, AR, and MM, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request. Due to confidentiality considerations and the nature of the datasets used, access may be granted for academic and non-commercial purposes only.

7.4. Funding

This research did not receive any specific grant, financial assistance, or institutional funding from public, commercial, or not-for-profit sectors. All activities related to the design of the study, data collection, analysis, interpretation, and manuscript preparation were conducted independently by the authors.

7.5. Declaration of Conflicting Interest

The authors declare that there are no known competing financial interests, conflicts of interest, or personal relationships that could have influenced the research outcomes, data interpretation, or conclusions presented in this article. All authors have reviewed and approved the final version of the manuscript.

REFERENCES

[1] M. Murod, S. Anhar, D. Andayani, A. Fitriani, and G. Khanna, "Blockchain based intellectual property management enhancing security and transparency in digital entrepreneurship," *Aptisi Transactions on Technopreneurship (ATT)*, vol. 7, no. 1, pp. 240–251, 2025.

[2] A. Omidkar, A. Alagumalai, Z. Li, and H. Song, "Machine learning assisted techno-economic and life cycle assessment of organic solid waste upgrading under natural gas," *Applied Energy*, vol. 355, p. 122321, 2024.

[3] M. R. Anwar and L. D. Sakti, "Integrating artificial intelligence and environmental science for sustainable urban planning," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 5, no. 2, pp. 179–191, 2024.

[4] R. Bhandari and M. V. A. Sin, "Optimizing digital marketing in hospitality industries," *Startupreneur Bisnis Digital (SABDA Journal)*, vol. 2, no. 1, 2023.

[5] D. Robert, F. P. Oganda, A. Sutarman, W. Hidayat, and A. Fitriani, "Machine learning techniques for predicting the success of ai-enabled startups in the digital economy," *CORISINTA*, vol. 1, no. 1, pp. 61–69, 2024.

[6] A. Williams, C. S. Bangun, and Y. Shino, "The urgency of digital literacy in indonesia on covid-19 pandemic," *Startupreneur Business Digital (SABDA Journal)*, vol. 1, no. 2, pp. 183–190, 2022.

[7] R. A. Sunarjo, M. H. R. Chakim, S. Maulana, and G. Fitriani, "Management of educational institutions through information systems for enhanced efficiency and decision-making," *International Transactions on Education Technology (ITEE)*, vol. 3, no. 1, pp. 47–61, 2024.

[8] J. Liu, J. Zhao, H. Wei, Q. Zhu, and Y. Li, "Comparative environmental assessment of methanol production technologies: A cradle-to-gate life cycle analysis," *Energy Conversion and Management*, vol. 302, p. 118128, 2024.

[9] Q. Aini, D. Manongga, U. Rahardja, I. Sembiring, and Y.-M. Li, "Understanding behavioral intention to use of air quality monitoring solutions with emphasis on technology readiness," *International Journal of Human–Computer Interaction*, pp. 1–21, 2024.

[10] A. N. Islam, M. Mäntymäki, S. Laato, and O. Turel, "Adverse consequences of emotional support seeking through social network sites in coping with stress from a global pandemic," *International Journal of Information Management*, vol. 62, p. 102431, 2022.

[11] P. Agarwal, S. Swami, and S. K. Malhotra, "Artificial intelligence adoption in the post covid-19 new-normal and role of smart technologies in transforming business: a review," *Journal of Science and Technology Policy Management*, vol. 15, no. 3, pp. 506–529, 2024.

[12] Y. F. Nassar, H. J. El-Khozondar, M. M. Khaleel, A. A. Ahmed, A. H. Alsharif, M. H. Elmnifi, M. A. Salem, and I. Mangir, "Design of reliable standalone utility-scale pumped hydroelectric storage powered by pv/wind hybrid renewable system," *Energy Conversion and Management*, vol. 322, p. 119173, 2024.

[13] T. Mariyanti, I. Wijaya, C. Lukita, S. Setiawan, and E. Fletcher, "Ethical framework for artificial intelligence and urban sustainability," *Blockchain Frontier Technology*, vol. 4, no. 2, pp. 98–108, 2025.

[14] B. K. Bintoro, N. Lutfiani, D. Julianingsih *et al.*, "Analysis of the effect of service quality on company reputation on purchase decisions for professional recruitment services," *APTISI Transactions on Management*, vol. 7, no. 1, pp. 35–41, 2023.

[15] Y. F. Nassar, H. J. El-Khozondar, W. El-Osta, S. Mohammed, M. Elnaggar, M. Khaleel, A. Ahmed, and

A. Alsharif, "Carbon footprint and energy life cycle assessment of wind energy industry in libya," *Energy conversion and management*, vol. 300, p. 117846, 2024.

[16] Q. Aini, P. Purwanti, R. N. Muti, E. Fletcher *et al.*, "Developing sustainable technology through ethical ai governance models in business environments," *ADI Journal on Recent Innovation*, vol. 6, no. 2, pp. 145–156, 2025.

[17] A. O. Adekanmbi, N. Ninduwezuor-Ehiobu, U. Izuka, A. Abatan, E. C. Ani, and A. Obaigbena, "Assessing the environmental health and safety risks of solar energy production," *World Journal of Biology Pharmacy and Health Sciences*, vol. 17, no. 2, pp. 225–231, 2024.

[18] L. S. Lutfiani, A. Birgithri, and Z. Queen, "Technological aspects in the era of digital transformation leading to the adoption of big data," *Startupreneur Business Digital (SABDA Journal)*, vol. 3, no. 1, pp. 43–53, 2024.

[19] R. Aprianto, E. P. Lestari, E. Fletcher *et al.*, "Harnessing artificial intelligence in higher education: Balancing innovation and ethical challenges," *International Transactions on Education Technology (ITEE)*, vol. 3, no. 1, pp. 84–93, 2024.

[20] M. Hatta, W. N. Wahid, F. Yusuf, F. Hidayat, N. A. Santoso, and Q. Aini, "Enhancing predictive models in system development using machine learning algorithms," *International Journal of Cyber and IT Service Management*, vol. 4, no. 2, pp. 80–87, 2024.

[21] M. U. Nawaz, S. Umar, and M. S. Qureshi, "Life cycle analysis of solar-powered electric vehicles: environmental and economic perspectives," *International Journal of Advanced Engineering Technologies and Innovations*, vol. 1, no. 3, pp. 96–115, 2024.

[22] R. Royani, S. D. Maulina, S. Sugiyono, R. W. Anugrah, and B. Callula, "Recent developments in healthcare through machine learning and artificial intelligence," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 6, no. 1, pp. 86–94, 2024.

[23] T. S. Goh, D. Jonas, B. Tjahjono, V. Agarwal, and M. Abbas, "Impact of ai on air quality monitoring systems: A structural equation modeling approach using utaut," *Sundara Advanced Research on Artificial Intelligence*, vol. 1, no. 1, pp. 9–19, 2025.

[24] W. Zhang, Y. Li, H. Li, S. Liu, J. Zhang, and Y. Kong, "Systematic review of life cycle assessments on carbon emissions in the transportation system," *Environmental Impact Assessment Review*, vol. 109, p. 107618, 2024.

[25] R. Widayanti and T. Mariyanti, "Ai dialog: Utilization, challenges, and ethics in the age of artificial intelligence," *International Transactions on Artificial Intelligence*, vol. 2, no. 1, pp. 40–48, 2023.

[26] B. Rawat and R. Bhandari, "Cloud computing applications in business development," *Startupreneur Business Digital (SABDA Journal)*, vol. 2, no. 2, pp. 143–154, 2023.

[27] A. Hasheminezhad, D. King, H. Ceylan, and S. Kim, "Comparative life cycle assessment of natural and recycled aggregate concrete: A review," *Science of The Total Environment*, vol. 950, p. 175310, 2024.

[28] M. H. R. Chakim, A. Kho, N. P. L. Santoso, and H. Agustian, "Quality factors of intention to use in artificial intelligence-based aiku applications," *ADI Journal on Recent Innovation*, vol. 5, no. 1, pp. 72–85, 2023.

[29] A. I. Osman, B. Fang, Y. Zhang, Y. Liu, J. Yu, M. Farghali, A. K. Rashwan, Z. Chen, L. Chen, I. Ihara *et al.*, "Life cycle assessment and techno-economic analysis of sustainable bioenergy production: a review," *Environmental Chemistry Letters*, vol. 22, no. 3, pp. 1115–1154, 2024.

[30] A. Sutarman, J. Williams, D. Wilson, and F. B. Ismail, "A model-driven approach to developing scalable educational software for adaptive learning environments," *International Transactions on Education Technology (ITEE)*, vol. 3, no. 1, pp. 9–16, 2024.

[31] Y. Nassar, H. El-Khozondar, A. Alatrash, B. Ahmed, R. Elzer, A. Ahmed, I. Imbayah, A. Alsharif, and M. Khaleel, "Assessing the viability of solar and wind energy technologies in semi-arid and arid regions: a case study of libya's climatic conditions," *Applied solar energy*, vol. 60, no. 1, pp. 149–170, 2024.

[32] U. Rahardja, "Camera trap approaches using artificial intelligence and citizen science," *International Transactions on Artificial Intelligence*, vol. 1, no. 1, pp. 71–83, 2022.

[33] G. Kumar and S. K. Goyal, "Energizing the future: A comprehensive review and evaluation of artificial intelligence based solar irradiance forecasting model with swot analysis of solar energy," in *2025 International Conference on Electronics and Renewable Systems (ICEARS)*. IEEE, 2025, pp. 307–314.

[34] A. Sutarman and A. Nuriman, "Pengaruh kegiatan market day terhadap minat entrepreneur," *ADI Pengabdian Kepada Masyarakat*, vol. 4, no. 1, pp. 7–12, 2023.

[35] S. Ahmed, A. Ali, J. A. Ansari, S. A. Qadir, and L. Kumar, "A comprehensive review of solar photovoltaic systems: Scope, technologies, applications, progress, challenges and recommendations," *IEEE Access*, 2025.

[36] R. Esteban-Amaro, S. Estellés-Miguel, and C. Roldan-Porta, "Advancing sustainability in the spanish photovoltaic value chain: A life-cycle analysis using the infinite framework," in *2025 IEEE International Conference on Engineering, Technology, and Innovation (ICE/ITMC)*. IEEE, 2025, pp. 1–8.

[37] L. Giusti, M. Rotilio, G. Di Giovanni, P. Bonomo, and L. G. Henriquez, "An integrated methodology for assessing circularity and environmental sustainability in bipv systems," *Developments in the Built Environment*, p. 100746, 2025.

[38] H. W. W. Kyaing, "A study on solar systems development in myanmar (hnin wai wai kyaing, 2025)," Ph.D. dissertation, MERAL Portal.

[39] M. F. Ali, D. Biswas, M. R. I. Sheikh, A. Al Mamun, and M. J. Hossen, "Techno-economic optimization of battery storage technologies for off-grid hybrid microgrids in multiple rural locations of bangladesh," *Frontiers in Energy Research*, vol. 13, p. 1654615, 2025.

[40] W. M. Metwally, "Biomimicry and green architecture: Nature-inspired innovations for sustainable buildings," *Sustainability*, vol. 17, no. 16, p. 7223, 2025.

[41] P. F. Borowski, "Renewable energy sources towards a zero-emission economy," p. 5473, 2025.

[42] H. Alghanem, "Modelling the spatial distribution of installed solar photovoltaic capacity," Ph.D. dissertation, University of Sheffield, 2025.

[43] P. Jouannais, M. Marchand-Lasserre, M. Douziech, and P. Pérez-López, "When is agrivoltaism environmentally beneficial? a consequential lca and scenario discovery approach," *Environmental Science & Technology*, 2025.

[44] M. Al Saadi, "Solar energy utilisation:: towards sustainable energy transition in jordan," Ph.D. dissertation, University of Greater Manchester, 2025.

[45] M. Mahmoud, S. Haridy, A. Mdallal, A. H. Alami, M. A. Abdelkareem, and A. G. Olabi, "Energy nexus," *Energy*, vol. 18, no. 10043, p. 6, 2025.

[46] M. V. F. Corrêa, G. T. Tractz, G. A. R. Maia, H. E. S. Fonseca, L. O. Berbel, L. J. de Almeida, and E. do Prado Banczek, "Dye-sensitized solar cells application of tio2 using spirulina and chlorella algae extract," *Colorants*, vol. 4, no. 3, p. 25, 2025.

[47] F. S. Islam, "The convergence of ai and nature: Advancing carbon dioxide capture, removal, and storage technologies through integrated ecosystem-based strategies," *International Journal of Applied and Natural Sciences*, vol. 3, no. 1, pp. 90–130, 2025.

[48] L. Hofman, "Towards a co2-free electricity system: Analysis of the dutch mission-oriented innovation system for a co2-free electricity system," Master's thesis, 2025.

[49] W. Manurian, R. Supriati, D. Cahyadi, G. P. Cesna *et al.*, "Durability prediction model of reflector material against solar energy in corrosive environment," in *2022 International Conference on Science and Technology (ICOSTECH)*. IEEE, 2022, pp. 01–10.

[50] Ministry of Energy and Mineral Resources of Indonesia, "Memr regulation no. 2/2024 on rooftop solar pv systems," Government Regulation, 2024, replaces Regulation No. 26/2021. [Online]. Available: https://iesr.or.id