# Bridging Research Gaps in AI-Enabled Electron Beam Lithography Through a Multidimensional Framework for Scalable, Sustainable, and SDG-Aligned Nanofabrication

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**Abstract**

One of the most adaptable nanofabrication techniques for creating ultra-high-resolution structures needed in advanced microelectronics, quantum computing, integrated photonics, biosensing, and biomedical engineering is still electron beam lithography (EBL). Low throughput, proximity effects, beam instability, process variability, high computational intricacy, and substantial use of energy are specific enduring hindrances to the mainstream manufacturing deployment of EBL, despite its remarkable patterning competency. Nevertheless, the rendition of contemporary AI-motivated EBL exploration into consistent, scalable fabrication settings is constrained since it is still dispersed and predominantly application-specific. Indispensable obstacles to AI-enabled EBL are highlighted in this paper, including data constraints, inadequate model generalization, a lack of intelligent control in real time, physics-informed and explainable AI integration, and the sustainability considerations. The review suggests a multifaceted framework that combines explainable and transferable machine learning, digital twins, adaptive process optimization, intelligent feedback control, physics-based modelling, and sustainability-driven performance metrics in line with the Sustainable Development Goals (SDGs) of the UN to address these issues. By linking scientific, computational, ecological and social facets, this hypothesis extends a line for switching EBL into a mountable, viable and smart nanomanufacturing platform.

**Keywords:** Electron Beam Lithography, Artificial Intelligence, Proximity Effect, Nanofabrication, Research gaps, Sustainable Nanomanufacturing.

## INTRODUCTION

Electron beam lithography (EBL) works with prominent exactness, maskless designing practice that facilitates deterministic creation of nano level configurations having a decisive size of sub-10 nm regime. A closely directed, highly powered flash of electrons is raster scanned over a resist coating which is sensitive to electrons for to creating the desired pattern. The procedure of resist development along with design pass on via the process of dry etching or lift-off measures are pursued. The intricate interactivity of beam-exposure aspects such as acceleration potential, electron-beam current range, location dimension, dwell interval, amount of exposed dose, resist disparity, developmental interaction and substrate/wafer backscattering features, are responsible for the achievable resolution range and design reliability in EBL. For the purpose of creating prototypes as well as low-scale manufacturing of unconventional semiconductor devices, nano level quantum structures/dots and wires, the photonic crystals, plasma-phase formations, biosensing devices and nano-structured biomedical facilities which assist the evolving socio-centric expertise, EBL endures for being the crucial tools because of its incomparable spatial resolution and layout workability [1, 2].

Although this technique has many benefits, still the large-scale implementation of EBL is profoundly restricted due to the core process constraints. The integrally serialized character writing with the electron beam enforces harsh output consequences and it limits its practicality for scaling it to a huge volume turn out. Above this, the electrons directed ahead and even the backscattered ones cause the proximity effects. Therefore, the non-deliberate energy accumulation

apart from the focussed exposure site and triggers expansion of linewidth, pattern/design distortion and alteration of critical dimension (CD). Supplementary reasons of process unpredictability such as beam drift, the locating misplays, resist charging, stochastic shot noise, and unequal resist layer wideness, may later concede the pattern duplicability. The outmoded proximity effect correction (PEC) arrangements, classically built on systematic point spread functions (PSFs), dose modulation rules, or experiential look-up tables, strive to attain the extremely nonlinear and reliant on tools for electron's interactivity with matter at nano-sized dimensions, usually requiring a wide-range iterative calibration and manual modification [3].

The current developments in artificial intelligence (AI) as well as in the field of machine learning (ML) have definitely unlocked the unfamiliar passageways for the purpose of focusing on these venerable obstructions in the large scale EBL. Data-driven approaches employing supervised learning models, convolutional neural networks (CNNs), Gaussian process regression, and deep neural networks (DNNs) have been applied to exposure dose optimization, resist process tuning, proximity effect correction, and post-exposure pattern fidelity prediction. Reinforcement learning and Bayesian optimization frameworks have also been explored for automated process window identification and adaptive parameter selection. These AI-assisted methodologies demonstrate superior capability in modelling complex, multivariate relationships among exposure parameters, resist responses, and pattern outcomes, thereby reducing reliance on heuristic rules and significantly improving pattern accuracy and process efficiency [4].

Nevertheless, a critical evaluation of the current state of AI-enabled EBL reveals that most reported implementations remain fragmented and largely confined to laboratory scale demonstrations. The scarcity of large, standardized, and cross-tool datasets limits model robustness and hinders transferability across different EBL platforms, resists, and substrates. Furthermore, many existing AI models function as opaque black-box systems, offering limited physical interpretability and raising concerns regarding reliability, reproducibility, and industrial adoption. Real-time, closed-loop control architectures integrating in situ metrology and adaptive beam modulation are rarely realized, and sustainability-driven objectives such as minimizing energy consumption, exposure time, and material waste are largely absent from current optimization frameworks [2,4].

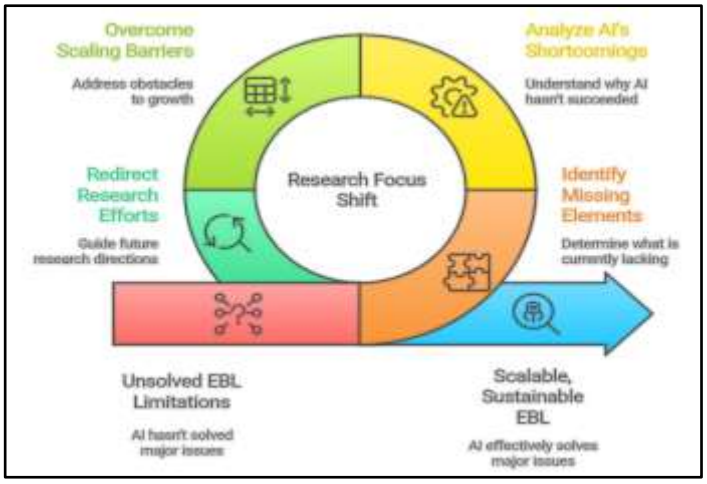



Figure 1: Addressing AI's limitations in electron beam lithography.

This review explicitly positions these unresolved issues as central research challenges rather than peripheral constraints. It systematically examines the limitations associated with data scarcity, model generalization, physical interpretability, and real-time feedback integration in AI-assisted EBL. Furthermore, it outlines prospective solutions, including physics-informed and hybrid modelling approaches, transfer learning and domain adaptation strategies, closed-loop exposure control systems, and sustainability-aware optimization paradigms. Addressing these gaps is essential for advancing AI-enhanced EBL toward a robust, scalable, and energy efficient nanomanufacturing technology capable of supporting next-generation nanoscale devices and socially responsible technological innovation.

## OVERVIEW OF THE ELECTRON BEAM LITHOGRAPHY PROCESS

In the Electron beam lithography (EBL) technique a finely focused beam of high-energy electrons is used to directly write patterns onto an electron-sensitive resist coated on a substrate. The process begins with substrate preparation and spin-coating of a positive or negative electron-beam resist, followed by soft baking to remove residual solvents. A high-energy electron beam, generated by an electron gun and focused using electromagnetic lenses, scans the resist surface according to a predefined pattern. During exposure, electrons–resist interactions and electron scattering within the resist and substrate modify the resist solubility, forming a latent image. After exposure, the resist is developed using a suitable chemical developer to selectively remove either the exposed or unexposed regions, depending on resist type. The patterned resist then serves as a mask for subsequent pattern transfer processes such as reactive ion etching or metal lift-off. The final pattern resolution is governed by beam diameter, exposure dose, resist chemistry, and electron scattering effects.

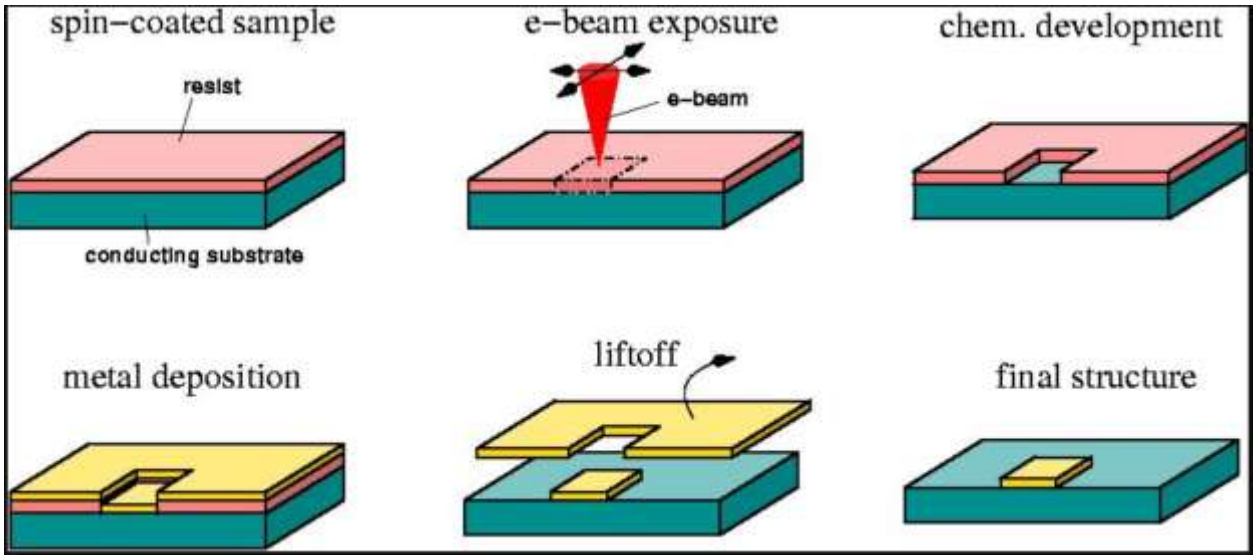



Figure 2: Schematic of the step-by-step electron beam lithography process: resist coating, electron beam exposure, development, and pattern transfer.

Some field-specific terminologies in EBL process are-

- **Writing field:** The largest region that can be patterned without moving the stage; its size balances reduced stage motion with achievable resolution. The location of the electron beam on the substrate is regulated via the electrostatic or electromagnetic deflectors and the electron ray's displacement is merely proportionate to the concerned deflection voltage:

$$x = kV_d \quad \text{.....[1]}$$

The term $x$ signifies the electron ray's displacement on the substrate body, $V_d$is the deflection voltage onto the deflector plates, and $k$ is the deflection sensitivity of the system [5].

- **Exposure element (EXEL):** The smallest controllable writing unit within a field, set by the system DAC; finer EXELs allow higher pattern accuracy.
- **Stitching:** The process of joining multiple writing fields through precise stage movements to create large-area patterns. The overall stitching error arises from the combined effects of inaccuracies in beam deflection and imperfections in the mechanical positioning of the stage. This relationship can be expressed as:

$$E_s = \sqrt{E_d^2 + E_m^2} \quad \text{.....[2]}$$

where $E_s$denotes the total stitching error, $E_d$represents the error due to beam deflection, and $E_m$corresponds to the positioning error of the mechanical stage. Reducing both of these error components is essential to ensure seamless pattern alignment and continuity over large, patterned areas [6].

- **Exposure dosage:** The exposure dose refers to the quantity of electron charge deposited per unit area on the resist surface, which directly influences the degree of chemical transformation within the resist layer. It can be mathematically expressed as [7]:

$$D = \frac{I \times t}{A} \quad \text{.....[3]}$$

where $D$ denotes the exposure dose in $(C/cm^2)$, $I$ is the beam current, $t$ is the exposure duration, and $A$ represents the area being exposed. Maintaining an appropriate dose is crucial for achieving precise pattern dimensions and ensuring proper resist development.

- **System clock (writing speed):** The rate at which the beam scans EXELs; higher clock frequencies enable faster exposure.
- The effective writing speed depends on the dwell time of the beam at each pixel and the spatial resolution of the pattern grid:[5]

$$v = \frac{\Delta x}{t_d} \quad \text{.....[4]}$$

Here $v$ is the scanning speed, $\Delta x$ is the EXEL size, and $t_d$ is the dwell time per exposure element. Higher clock frequencies increase throughput but may reduce exposure precision

- **Proximity effect:** Pattern distortion caused by electron scattering beyond the target area, typically reduced using correction algorithms or higher beam energy.

$$E(r) = \frac{1-\eta}{\pi\alpha^2}\exp\left(-\frac{r^2}{\alpha^2}\right) + \frac{\eta}{\pi\beta^2}\exp\left(-\frac{r^2}{\beta^2}\right) \quad \text{.....[5]}$$

where $E(r)$is the energy distribution at radial distance $r$, $\alpha$represents the forward scattering range, $\beta$ represents the backscattering range, and $\eta$ is the backscattering coefficient. Proximity correction algorithms are commonly applied to compensate for these scattering effects and maintain pattern fidelity [6].

- **Beam current:** The electron flow reaching the sample per second; lower currents improve resolution but increase exposure time [8].

## INTELLIGENT CONTROL STRATEGIES FOR EBL BY ARTIFICIAL INTELLIGENCE.

EBL offers unmatched patterning resolution but fails to meet industrial throughput and sustainability requirements. Artificial intelligence (AI) is increasingly applied in electron beam lithography to enhance process efficiency, accuracy, and reliability. By leveraging machine learning algorithms and data-driven models, AI enables optimization of exposure dose, proximity effect correction, beam drift prediction, and defect detection. These techniques capture complex, nonlinear relationships among lithographic parameters that are difficult to model using conventional physics-based approaches. As a result, AI-assisted EBL improves critical dimension control, reduces process variability, and supports adaptive and automated nanofabrication workflows.

AI offers adaptive intelligence but lacks adequate data and process maturity. The intersection between these technologies remains conceptually promising yet practically underdeveloped. Current literature confirms AI success in the processes like the dose estimation, proximity effect modelling, defect detection, drift correction and pattern deformation prediction.

By facilitating data-driven process optimization, predictive modeling, intelligent error correction, and autonomous process control, artificial intelligence is becoming a revolutionary tool for electron beam lithography, as shown in Figure 3. The core AI application fields that enhance EBL resolution, accuracy, throughput, flexibility, and scalability in the direction of next-generation sustainable nanomanufacturing are summed up in the figure.

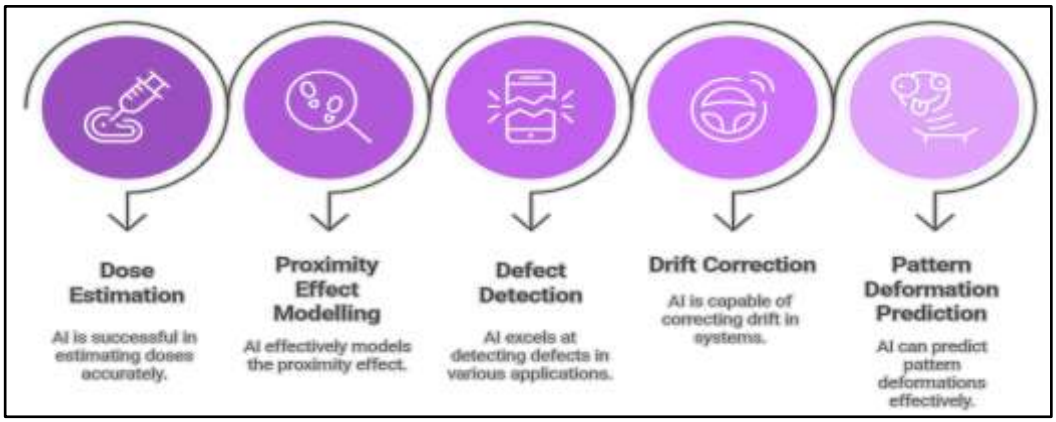



Figure 3: Key Applications of Artificial Intelligence in Electron Beam Lithography.

The relationship between lithography platforms, resist materials, learning algorithms, targeted applications, and improvements in process accuracy, efficiency, and adaptability is highlighted in Table 1, which illustrates representative AI-driven modelling approaches applied to EBL processes.

Table 1. Representative AI-assisted modeling and optimization approaches demonstrated in electron beam lithography.

| **EBL Tool / Platform** | **Resist** | **AI Method** | **Application** | **Key Outcome** | **Reference** |
|---|---|---|---|---|---|
| Electron-beam lithography system | PMMA / general resist systems | Neural Network | Proximity Effect Correction (PEC) | Improved correction accuracy and faster computation compared with conventional iterative PEC methods | Frye et al. (1990); Shimoaoki et al. (1995) [9, 10] |
| Electron-beam lithography system | Resist-dependent exposure processes | Machine Learning (ML) | Dose optimization and process parameter prediction | Reduced experimental iterations and accelerated exposure optimization | Zhao et al. (2024) [4] |
| Electron-beam lithography system | General EBL resist platforms | Neural Network / ML-based correction models | Exposure modeling and process optimization | Improved prediction of lithographic outcomes using learned process relationships | Zhang et al. (2000); Shin (2021) [11,12] |

| | | | | | |
|---|---|---|---|---|---|
| Electron-beam lithography system | PMMA and nanophotonic materials | Machine Learning | Adaptive in situ EBL optimization | Enhanced fabrication accuracy through data-driven optimization of patterning parameters | Hu et al. (2022) [13] |
| Electron-beam lithography pattern analysis | Various resist systems | Deep Learning (CNN-based methods) | Defect detection and pattern recognition | Automated identification and classification of lithographic defects | Zhao et al. (2024); Shin (2021) [4, 12] |

However, nearly every outcome reported remains limited to laboratory scale, small pattern areas, and highly controlled environments. There are fundamental gaps where AI has not yet solved the core industrial barriers of EBL.

**MANUAL OPTIMIZATION AND AI-GUIDED ELECTRON BEAM LITHOGRAPHY**

Traditional electron beam lithography depends mainly on predefined physical models and repeated trial-and-error adjustments to control exposure dose and correct proximity effects. While effective, this approach is often slow and limited in handling complex pattern interactions and process fluctuations. AI-based electron beam lithography introduces data-driven algorithms that learn directly from process data to predict and optimize writing parameters. This allows automatic adaptation to varying conditions, leading to better pattern accuracy and reduced processing time. Consequently, AI-assisted techniques improve efficiency, reliability, and scalability compared to conventional EBL methods.

Lithography research has seen a dramatic change in recent years because to the growing need for high-throughput manufacturing, nanoscale patterning, and improved semiconductor technologies. In order to increase pattern fidelity, process efficiency, and defect reduction, computational techniques including machine learning, deep learning, inverse lithography, and optimization algorithms are being used more quickly due to the increasing complexity of next-generation devices. These new AI-assisted techniques are now crucial instruments for overcoming the drawbacks of traditional lithographic techniques and facilitating data-driven process improvement. The annual publishing trend in computational lithography techniques and optimization approaches across all indexed papers is shown in Figure 4, demonstrating the quick growth of research interest and the growing incorporation of computational intelligence into contemporary lithography workflows.

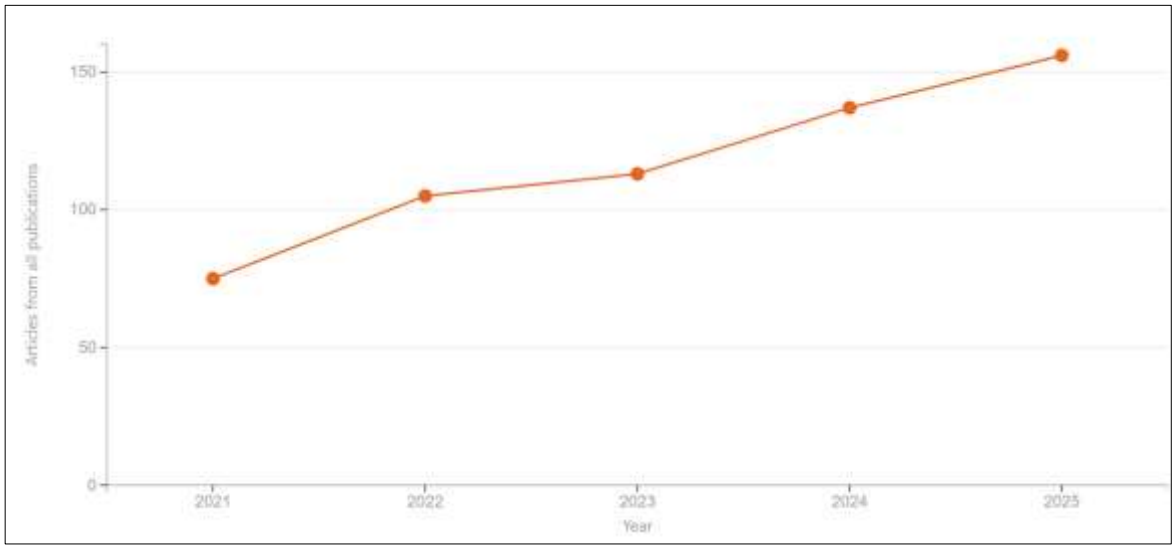



Figure 4: Illustrates the annual publication trend in computational lithography techniques and optimization methods across all indexed publications (Source-Nature Index).

The below Table 2 contrasts traditional EBL techniques with cutting-edge AI-driven approaches, highlighting enhancements in process control, predictive capability, optimization efficiency, scalability, and prospects for sustainable nanomanufacturing, in order to comprehend the revolutionary role of AI in advancing electron beam lithography.

Table 2: Comparison of Conventional vs AI-Based EBL Techniques

| **Aspect** | **Conventional EBL limitation** | **AI-based EBL improvement** | **Recommended references** |
|---|---|---|---|
| **Proximity Effect Correction** | Analytical PEC models rely on simplified assumptions of electron scattering and resist behavior, which can limit correction accuracy for complex patterns. | Machine learning models can learn nonlinear relationships between exposure conditions, scattering effects, and pattern outcomes for improved PEC prediction. | Kyser et al. (1975); Shimoaoki et al., (1995) [14, 10] |
| **Dose Optimization** | Conventional dose determination depends on experimental calibration, dose matrices, and manual optimization, which is time-consuming. | ML models enable predictive dose optimization by learning from experimental process data. | Zhao et al [2024]; Mack et. al (2007) [15, 25] |
| **Process Adaptability** | Conventional EBL processes require manual adjustment for different resists, substrates, and tool conditions. | AI-based models provide adaptive learning and can update predictions based on new process data. | Shin et. al (2021); Lecun et. al (2015) [12, 16] |
| **Throughput** | EBL is inherently slow because serial writing and repeated calibration increase fabrication time. | AI-assisted optimization reduces experimental iterations and accelerates process tuning. | Hu et. al (2022); Zhao et. al (2024) [13, 25] |

| | | | |
|---|---|---|---|
| **Accuracy** | Accuracy depends strongly on physical models, operator experience, and calibration quality. | AI improves prediction accuracy by extracting complex relationships from large experimental datasets. | Bishop et. al (2006); Zhao et. al (2024) [ 17, 25] |
| **Scalability** | Conventional EBL optimization is often tool-, material-, and process-specific. | Transfer learning, physics-informed AI, and adaptive models provide opportunities for cross-platform generalization. | Karniadakis et. al (2021); Goodfellow et. al (2016) [18, 19]] |

## PRIMARY RESEARCH GAP AREAS

### Data Scarcity and Dataset Fragmentation

The application of artificial intelligence (AI) in electron beam lithography (EBL) is constrained by limited data availability and fragmented datasets due to the lack of standardized data acquisition and reporting. Strong dependence of EBL outcomes on electron scattering, resist response, and exposure conditions leads to significant variability across tools and fabrication environments [20]. As a result, datasets such as scanning electron microscope (SEM) images, dose maps, and critical dimension measurements are often tool-specific and difficult to reuse. Although AI models for proximity effect correction and dose optimization perform well under controlled conditions, they are typically trained on small datasets and show poor generalization across different processes [21].

**Gap:** The absence of standardized, shared datasets prevents the development of robust and transferable AI models for EBL.

### Poor Cross-Tool and Cross-Material Transferability

AI models trained on a specific electron beam lithography tool, resist, or substrate often show poor performance when applied to different systems due to variations in beam parameters, resist chemistry, and electron scattering behavior. These differences alter dose response and proximity effects, causing prediction errors outside the original training conditions. As a result, AI-based proximity effect correction and optimization methods lack reproducibility across fabrication environments, limiting their industrial reliability [21, 22].

**Gap:** AI architectures are not transferable across machines, fabs, or materials.

### Absence of Sustainability Metrics

Most existing AI-driven studies in electron beam lithography focus primarily on improving pattern accuracy and dimensional control, while environmental aspects are largely overlooked. Key factors such as energy consumption during exposure, resist and developer chemical waste, total writing time, and associated carbon emissions are rarely quantified or included in optimization objectives. As a result, AI models tend to enhance technical performance without considering process sustainability. This omission limits the development of environmentally responsible and energy-efficient EBL workflows.

**Gap:** No sustainability-driven AI optimization frameworks.

**Limited Industrial Scalability**

Most AI-assisted electron beam lithography (EBL) studies demonstrate their effectiveness only on small test patterns or limited chip areas under laboratory conditions. The scalability of these approaches to full-wafer patterning, large writing fields, or high-throughput multi-beam EBL systems has not been systematically validated. Factors such as long exposure times, stage stability, data volume, and real-time control complexity become significantly more challenging at the industrial scale. As a result, the applicability of AI–EBL methods to mass-production environments remains largely unexplored [2].

**Gap:** Missing large-scale performance validation.

**Weak Integration with Real-Time Feedback Systems**

Electron beam lithography (EBL) operates under continuously changing conditions, where beam drift, thermal fluctuations, mechanical vibrations, and resist charging evolve during exposure. These dynamic effects can significantly alter pattern placement and linewidth accuracy in real time. However, most AI-based EBL studies rely on post-exposure analysis using SEM data rather than in situ monitoring and adaptive control. The lack of real-time, closed-loop AI frameworks limits the ability to correct process variations during exposure, reducing overall pattern reliability [8].

**Gap:** No robust AI framework operating during exposure.

**Lack of Social, Economic, and Ethical Alignment**

Most current AI-enabled lithography research concentrates on improving pattern accuracy and process efficiency, while broader human and environmental impacts are rarely addressed. Issues such as workforce displacement due to automation, unequal access to advanced AI-driven fabrication tools, and accountability of autonomous decision-making systems remain largely unexamined [2]. Ethical considerations related to transparency, responsibility, and long-term societal impact are often outside the scope of technical optimization studies. This narrow focus limits the development of responsible and inclusive AI–EBL frameworks.

**Gap:** AI–EBL research lacks social responsibility considerations.

**PROBABLE SOLUTIONS**

Several strategies have been proposed to tackle the main challenges in AI-assisted electron beam lithography (AI-EBL). To overcome data limitations, global AI-EBL data consortia can be established, enabling the sharing of anonymized datasets and standardized data logging. Model transferability can be improved through multi-domain neural networks combined with transfer learning and domain adaptation. Sustainability can be enhanced by adopting carbon-conscious optimization metrics and minimizing exposure energy and resist waste. Explainability can be addressed with hybrid physics and ML models that incorporate rule-based interpretability. Scalability requires validation under wafer-scale, multi-beam, and industrial throughput conditions, while real-time control can be achieved via closed-loop reinforcement systems for adaptive dosing and drift correction. Additionally, promoting social sustainability involves workforce training programs and emphasizing ethical and inclusive research practices. The individual issues are discussed as-

**1. Transferability**

To improve the transferability of AI models in electron beam lithography, future research should focus on multi-domain learning frameworks that can generalize across different resist materials, pattern geometries, beam energies, and fabrication environments. Transfer learning and domain adaptation techniques can reduce the need for extensive retraining when process conditions change, thereby accelerating model deployment in diverse EBL applications. Such approaches would enable AI systems trained on one dataset or fabrication platform to maintain high predictive accuracy in previously unseen manufacturing scenarios [23].

**2. Social Sustainability**

The thriving integration of AI in EBL demands investment in workforce development programs that combine semiconductor manufacturing expertise with data science and machine learning competencies. Emphasis should also be placed on ethical AI practices, transparency, and inclusive participation to ensure equitable access to emerging nanofabrication technologies.

Developing interdisciplinary training initiatives can help bridge the skills gap and facilitate broader adoption of AI-assisted lithography systems in both academia and industry [24].

**3. Sustainability**

AI-driven optimization can significantly enhance the sustainability of EBL processes by minimizing unnecessary exposures, reducing resist consumption, and lowering energy usage during pattern generation. Intelligent process optimization algorithms can identify resource-efficient operating conditions while maintaining pattern fidelity and throughput. Furthermore, AI-enabled predictive control can reduce material waste associated with process trial-and-error, contributing to more environmentally responsible nanomanufacturing practices [25].

**4. Explainability**

Increasing the explainability of AI models used in EBL is essential for industrial acceptance and process reliability. Hybrid physics-informed machine learning frameworks can combine established lithographic principles with data-driven learning, enabling users to understand the physical rationale behind model predictions. Incorporating interpretable layers and feature-attribution methods can further improve transparency, facilitate troubleshooting, and strengthen confidence in AI-assisted decision-making for nanofabrication processes [26].

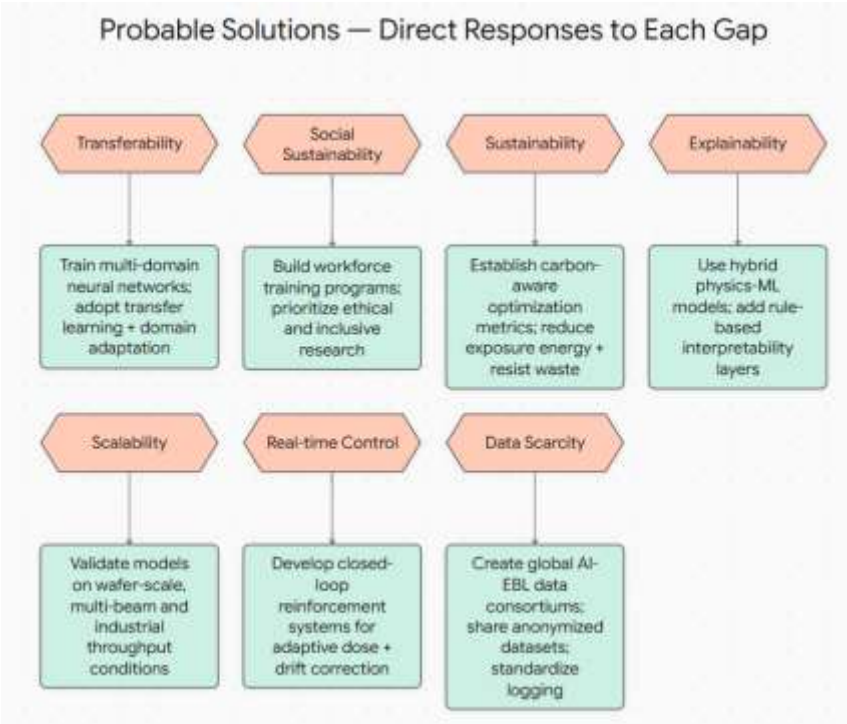



Figure 5: Potential solutions and targeted responses addressing each gap in EBL.

**5. Scalability**

For AI-enabled EBL to support industrial manufacturing, models must be validated under wafer-scale conditions and across high-throughput multi-beam lithography platforms. Large-scale validation studies can assess model robustness,

computational efficiency, and consistency under realistic production environments. Such efforts are necessary to bridge the gap between laboratory demonstrations and commercial semiconductor fabrication [27].

**6. Real-Time Control**

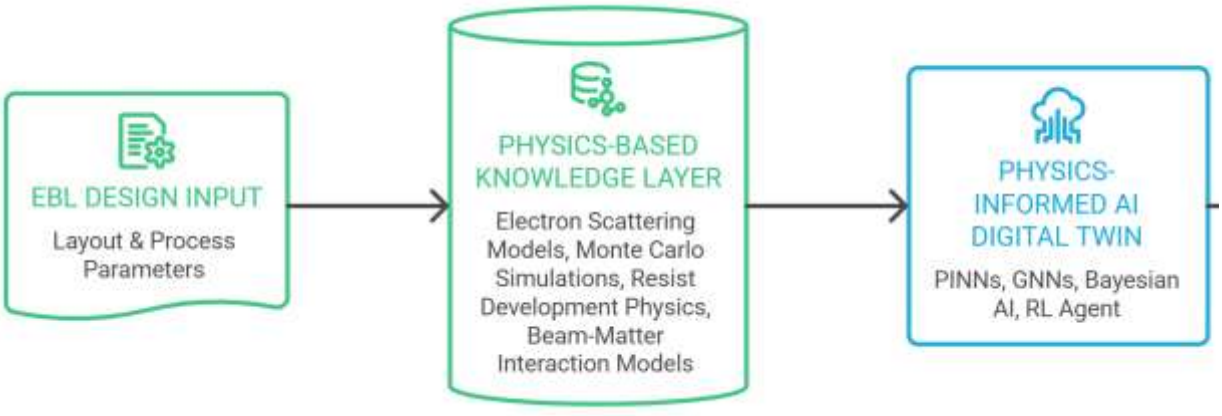
The implementation of closed-loop AI control systems represents a promising direction for adaptive EBL. By continuously monitoring process outputs and updating exposure parameters in real time, reinforcement learning and feedback-driven optimization techniques can compensate for drift, beam instability, and process variability. Such adaptive systems have the potential to improve pattern accuracy, reduce defects, and enhance manufacturing efficiency [28].

**7. Data Scarcity**

A major challenge in applying AI to EBL is the limited availability of large, standardized datasets. Establishing international data-sharing consortia and creating anonymized repositories of lithographic process parameters, exposure conditions, and pattern outcomes would facilitate the development of more robust machine learning models. Standardized data collection and logging practices would also improve reproducibility and enable more effective benchmarking of AI algorithms across research institutions [25].

**A Proposed Framework**

To overcome the major constraints associated with Electron Beam Lithography (EBL) and enhance its potential for large-scale implementation, a multidimensional integrated framework is proposed. The framework combines advancements in process control, exposure optimization, resist engineering, computational correction techniques, and system-level integration within a unified platform. By addressing the interconnected challenges such as limited throughput, proximity-induced inaccuracies, pattern deformation, and fabrication inefficiencies, the proposed model aims to substantially reduce existing technological gaps. This integrated approach not only improves pattern precision and operational consistency but also enhances the overall adaptability of EBL for high-resolution and large-area nanofabrication applications. The accompanying infographic map conceptually represents the structure of the framework and demonstrates how the coordinated interaction of multiple parameters can contribute toward making EBL a more scalable and industrially feasible technology.



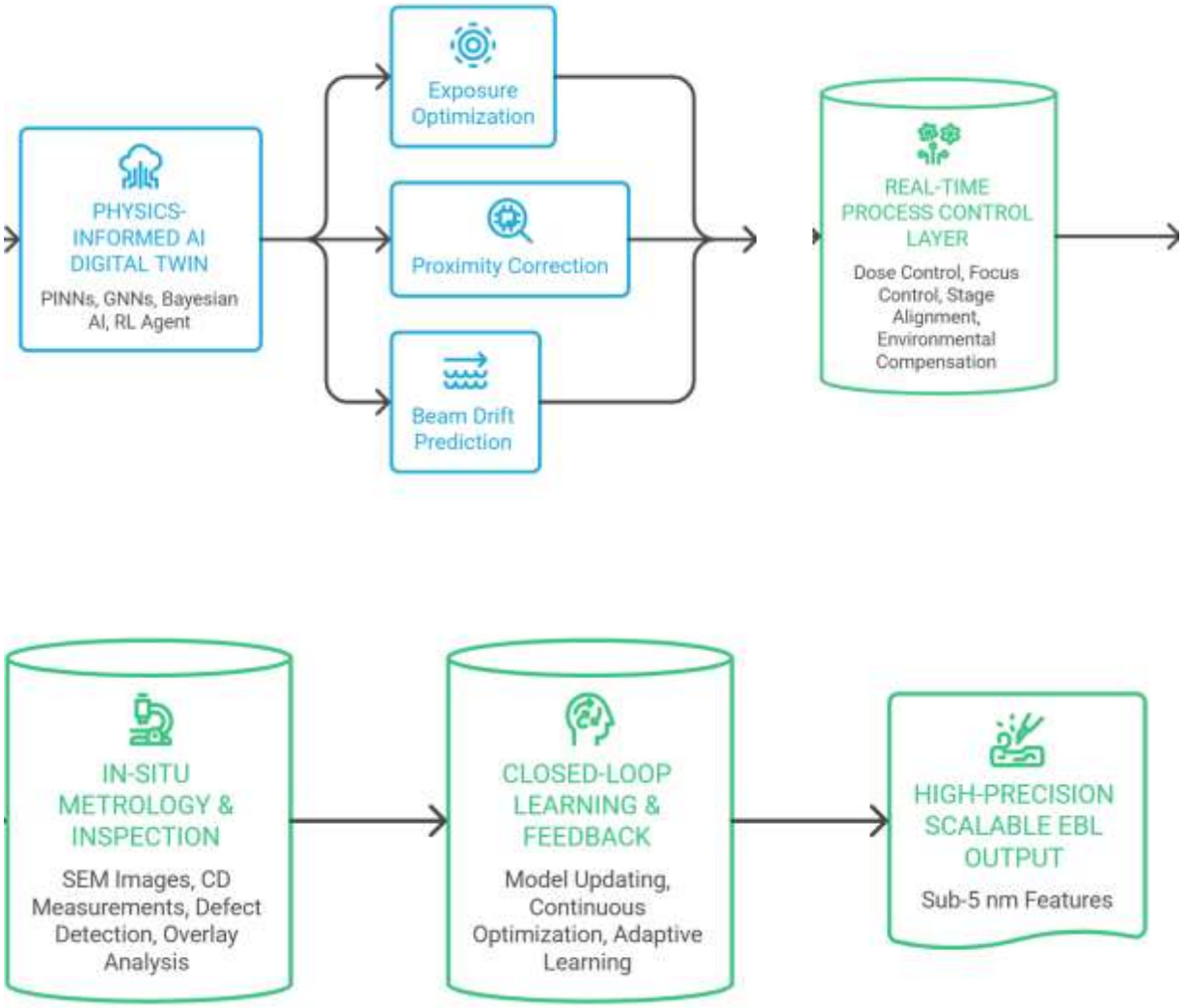



Figure 6: Representation of the proposed multidimensional framework for enhancing the scalability and efficiency of Electron Beam Lithography (EBL).

**SUSTAINABILITY IMPLICATIONS**

By integrating concepts that promote sustainable nanomanufacturing, the suggested multifaceted framework for AI-enabled Electron Beam Lithography (EBL) goes beyond enhancing fabrication accuracy and process efficiency. The environmental effects of sophisticated production techniques, such as high energy consumption, intense water use, greenhouse gas emissions, hazardous chemical use, and material waste, are becoming more widely acknowledged as semiconductor manufacturing continues to grow [29, 30]. Because it necessitates several repeated exposures, extended equipment operation, and the use of specialized materials to reach nanoscale precision, conventional EBL is especially resource intensive. These elements raise operating expenses and worsen the environmental impact of semiconductor production [29, 31]. The suggested approach could greatly increase the sustainability of EBL-based nanofabrication by incorporating artificial intelligence into process planning, exposure parameter optimization, defect prediction, process monitoring, and predictive maintenance. AI-driven optimization can eliminate experimental trial-and-error, cut down on needless fabrication iterations, optimize beam exposure techniques, maximize equipment utilization, and improve resource efficiency. As a result, without sacrificing fabrication precision, these advancements can minimize electricity usage, eliminate material waste, increase manufacturing throughput, and reduce greenhouse gas emissions. AI- and simulation-driven factory optimization can significantly minimize physical experimentation, increase production efficiency, and help reduce environmental impacts across semiconductor manufacturing, according to recent studies [29].

From a sustainability standpoint, the Sustainable Development Goals (SDGs) of the UN are directly supported by the suggested framework. By promoting intelligent, robust, and sustainable semiconductor manufacturing technologies through AI-enabled process optimization, it supports SDG 9 (Industry, Innovation, and Infrastructure). Additionally, it helps achieve SDG 12 (Responsible Consumption and Production) by supporting resource-efficient production processes, decreasing defective fabrication cycles, cutting process waste, and maximizing the efficient use of raw materials. Additionally, by promoting energy-efficient manufacturing techniques that can lower the carbon footprint associated with semiconductor manufacture, the framework supports SDG 13 (Climate Action). A comprehensive approach to sustainable nanomanufacturing would be promoted by integrating sustainability indicators such as energy consumption, carbon emissions, material utilization efficiency, water usage, waste generation, and process yield into AI optimization models. This would allow environmental performance to be assessed alongside conventional manufacturing metrics [30]. Future studies should concentrate on employing standardized sustainability evaluation techniques, such as life cycle assessment (LCA), carbon footprint analysis, energy-efficiency assessment, and resource-efficiency metrics, to quantitatively validate the environmental benefits of the suggested framework. These methods would allow researchers and business professionals to assess the long-term sustainability, economic, and environmental effects of AI-enabled EBL systems in addition to their technical performance. Future research on AI-enabled nanofabrication will benefit from the integration of such assessment techniques, which will support evidence-based decision-making, hasten the adoption of greener semiconductor manufacturing technologies, and help achieve global sustainability goals while addressing the semiconductor industry's increasing environmental challenges [30, 31].

## CONCLUSIONS

While artificial intelligence has the potential to significantly improve optimization, precision, and process control in electron beam lithography (EBL), its practical application is still at an early stage of development. Many challenges remain before AI-driven approaches can be fully integrated into industrial lithography systems. Addressing these challenges requires collaborative and multidisciplinary research that brings together expertise from several fields, including lithography physics, control theory, machine learning, and system engineering. A deeper understanding of beam material interactions and process dynamics is necessary to develop reliable AI models, while advanced control strategies are required to maintain stability and accuracy during operation. At the same time, machine learning algorithms must be designed to be robust, adaptable, and capable of handling large and complex datasets generated during lithography processes. Effective integration of these technologies with existing fabrication systems is also essential to ensure real-time decision-making and process optimization. By combining these diverse areas of knowledge and technological development, researchers can move closer to creating dependable, scalable, and real-time AI-assisted EBL systems that are suitable for practical industrial manufacturing. In conclusion, the proposed multidimensional framework advances AI-enabled Electron Beam Lithography by addressing key research gaps while promoting sustainable nanofabrication. Through AI-driven process optimization and predictive maintenance, the framework has the potential to reduce energy consumption, material waste, and carbon emissions associated with semiconductor manufacturing. These outcomes support SDG 9 (Industry, Innovation and Infrastructure) by fostering sustainable industrial innovation, SDG 12 (Responsible Consumption and Production) through efficient resource utilization and waste reduction, and SDG 13 (Climate Action) by encouraging energy-efficient, low-carbon manufacturing practices. Future validation using sustainability metrics, such as life cycle assessment and carbon footprint analysis, will further demonstrate the framework's contribution to environmentally responsible semiconductor manufacturing.

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**Authors' Contributions**

Abhilasha Saini had done a comprehensive literature survey, and preliminary drafting of the manuscript. Ravish R. Singh had contributed to the review of the content and guided in the formatting part. Sudhir B. shared his critical review and editing of the content and supervised the overall work.

**Abbreviations**

Electron beam lithography (EBL), Artificial intelligence (AI), Critical dimension (CD), Proximity effect correction (PEC), Point spread functions (PSFs), Machine learning (ML), Convolutional neural networks (CNNs), Scanning electron microscope (SEM).

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