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Perspective

From Sunlight to Solutions: Closing the Loop on Halide Perovskites

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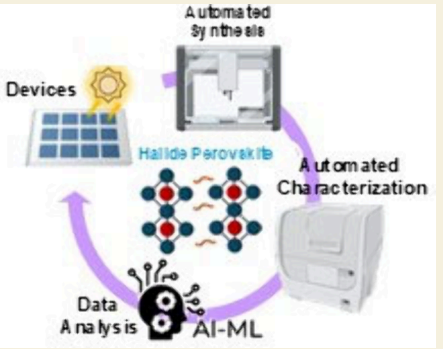
ABSTRACT: Halide perovskites (HPs) are emerging as key materials in the fight against global warming with well recognized applications, such as photovoltaics, and emergent opportunities, such as photocatalysis for methane removal and environmental remediation. These current and emergent applications are enabled by a unique combination of high absorption coefficients, tunable band gaps, and long carrier diffusion lengths, making them highly efficient for solar energy conversion. To address the challenge of discovery and optimization of HPs in huge chemical and compositional spaces of possible candidates, this perspective discusses a comprehensive strategy for screening HPs through automated high-throughput and combinatorial synthesis techniques. A critical aspect of this approach is closing the characterization loop, where machine learning (ML) and human collaboration play pivotal roles. By leveraging human creativity and domain knowledge for hypothesis generation and employing ML to test and refine these hypotheses efficiently, we aim to accelerate the discovery and optimization of HPs under specific environmental conditions. This synergy enables rapid identification of the most promising materials, advancing from fundamental discovery to scalable manufacturability. Our ultimate goal of this work is to transition from laboratory-scale innovations to real-world applications, ensuring that HPs can be deployed effectively in technologies that mitigate global warming, such as in solar energy harvesting and methane removal systems.



KEYWORDS: *Halide Perovskites, Automated Laboratories, Machine Learning, High-Throughput Synthesis, Hypothesis*

INTRODUCTION

The development of human civilization has inseparably been tied to the ability to harness chemical transformations across various length scales, from large-scale manufacturing and chemical synthesis to nanometer and soon atomically precise assembly. From the local control of atomic structures in electronics and quantum computing to the targeted manipulation of biological processes in precision medicine, technological advancements are fundamentally rooted in the mastery of chemistry. On the atomic scale, precise control is critical for the development of next-generation electronic devices and quantum computers.[1] At the biological level, precision medicine requires highly targeted treatments that can interact with human cells and organs in specific ways to improve health outcomes.[2] On a global scale, addressing the grand challenges of energy production, sustainable fuel generation,[3] and environmental remediation[4] requires robust and scalable chemical processes. Efficient conversion of solar energy into usable fuels,[5] CO_2 sequestration to mitigate climate change,[6] and methane removal to reduce greenhouse gas emissions[7] are all essential to creating a sustainable future.

At each of these scales, the demands for precision, volume, and cost vary significantly. High-precision control at the atomic level is crucial for advancements in electronics and quantum computing, where even the atomic-scale imperfections can lead to significant changes in functionality and efficiency. In the realm of precision medicine, the ability to deliver targeted treatments at the cellular level requires sophisticated chemical processes that can precisely probe and tailor biomolecular systems and small molecules.[8] The value of these electronic and medical applications is almost invariably based on the added cost in manufacturing, while the (initial) component cost is usually small. For global applications, considerations of cost, manufacturability, and energy consumption become primary. Energy production and storage, carbon sequestration, and greenhouse gas removal require chemical processes that can operate on a massive scale, with an emphasis on efficiency and sustainability.[9] These processes must be able to handle large volumes of material and produce results that are economically feasible for widespread adoption.

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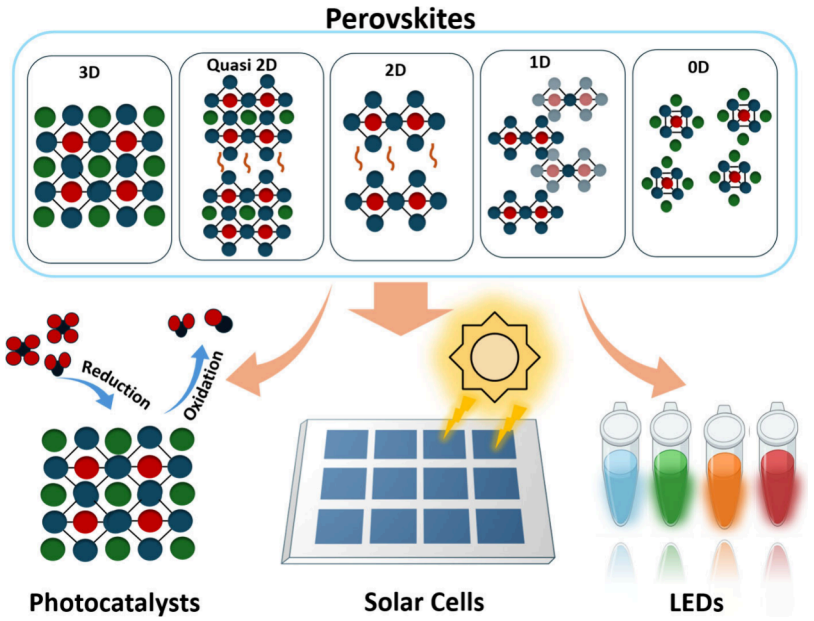

Figure 1. Illustration of the various dimensional structures that HPs can form and their applications in photocatalysis, solar cells, and LEDs, demonstrating their versatility in climate technology solutions.

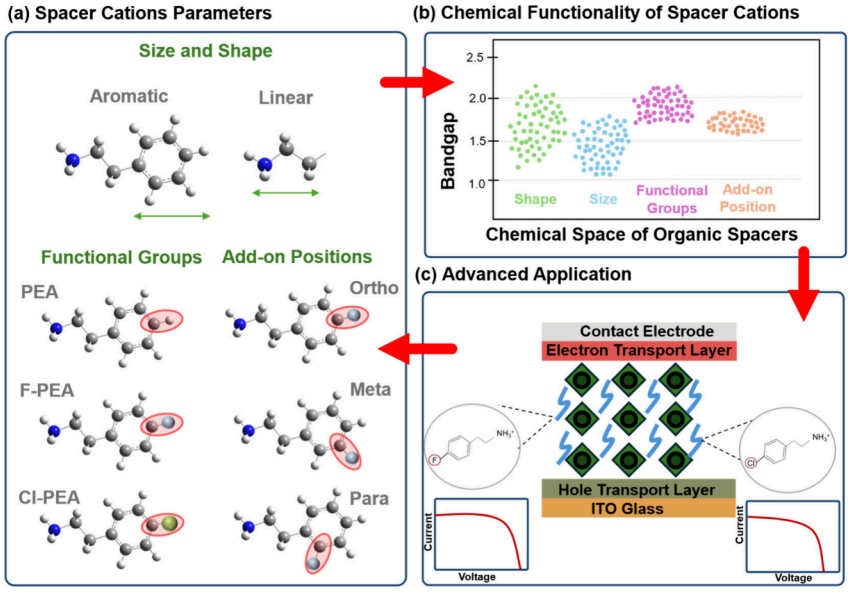

Figure 2. Several examples of molecular structures of organic spacers and their integration in HP solar cells: (a) Molecular parameters categorized by the properties of the spacer cations, (b) variation in bandgap based on the selection of spacer cation parameters, and (c) impact of spacer on solar cell performance.

Solar energy stands as the most abundant and accessible energy source on our planet, offering the pathway to a sustainable future.[10] Yet, its distributed and intermittent nature poses significant challenges, necessitating efficient solutions for collection and storage. Solar energy boasts a high exergy and chemical potential, with photons carrying energy in the 1−3 eV range, making it a potent force for driving chemical transformations. Traditionally, the applications focus on converting solar energy into electricity, which is then used in various applications, or into thermal energy.[11,12] However, envisioning a future where we harness solar energy directly for chemical processes opens up a realm of possibilities. By bypassing the electricity stage, we can directly utilize solar energy to power large-scale climate technologies, potentially revolutionizing our approach to global challenges such as CO_2 sequestration, methane removal, and sustainable fuel production.[13,14]

To achieve this vision, the desired materials are the materials that can seamlessly integrate the physical functionality of collecting photons with the chemical functionality of catalyzing or mediating useful reactions, such as methane oxidation and CO_2 conversion to hydrocarbons. These materials must be available at scale, cost-effective, and environmentally friendly to be practical for widespread deployment. Most importantly, these materials need to be manufacturable and ideally tunable for a broad range of environmental and operational conditions across the globe.

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HALIDE PEROVSKITES: THE TUNABLE SOLUTION

The confluence of chemical and physical properties of halide perovskites (HPs) makes them almost ideal for solar applications.[15] These materials possess high absorption coefficients, tunable band gaps, and long carrier diffusion lengths, which contribute to their outstanding solar to electrical power conversion efficiencies.[16] Since their development, the efficiency of perovskite solar cells has soared, now rivaling that of traditional silicon-based solar cells. The unique structure of perovskites allows for a broad compositional range, enabling precise tuning of their properties for specific applications,[17] as schematically shown in Figure 1. This versatility makes them suitable for both single- and multijunction solar cells.[18] Moreover, their ambipolar carrier transport abilities and large carrier mobilities further optimize the efficiency of charge separation and collection processes in solar cells.[19,20]

Beyond the intrinsic properties of HPs, their two-dimensional (2D) analogs offer enhanced chemical tunability and functionalization capabilities.[21,22] Their layered structures allow for further customization of electronic and optical properties by altering the organic and inorganic components. This chemical flexibility enables the creation of materials with functionalities tailored for advanced applications, such as selective catalysis and light emission and energy conversion processes.[23] By combining the physical functionality of photon collection with the chemical functionality of catalyzing or mediating reactions, HPs, particularly 2D variants, could play a pivotal role in future solar energy and other optoelectronic systems. As an example, Figure 2 highlights how varying the molecular properties of spacer cations—such as size, shape, functional groups, and add-on positions—allows for chemical flexibility in tailoring the electronic properties of (quasi-) 2D HPs. This tunability directly impacts the bandgap and solar cell performance, emphasizing the role of molecular design in optimizing perovskite-based energy conversion systems.

One of the most significant advantages of HPs is their potential for low-cost production. These materials can be synthesized through relatively simple and scalable methods, which is crucial for large-scale deployment.[23] For broad solar applications, challenges such as stability, integration with functional materials and organic layers for making full device structure, and environmental impact remain.[24,25] The materials offering the best photovoltaic properties often lack sufficient stability or environmentally friendly chemistry.[26] Critical questions arise: Can the exceptional properties of Pb-containing HPs be replicated in other benign materials? Can the stability be enhanced? Achieving efficient coupling to light-induced chemistries further complicates the matter. The chemical space of these systems is vast, with numerous candidates for the A-site and B-site cations and halogen and a high-dimensional space of organic molecules and spacers.[24] Navigating this complexity requires advanced computational methods and systematic exploration to identify optimal compositions and achieve practical and scalable solutions. For the applications in methane removal, the new and almost unexplored challenge becomes the functionalization of the materials surface by the light stimulated chemistries to enable controlled oxidation of atmospheric CH_4 while maintaining overall stability of the perovskite matrix, reliable removal of the oxidation products, and minimization of the reaction pathways leading to nonvolatile products.

By now, the preponderant paradigm for materials discovery is the large scale theoretical prediction followed by the experimental validation.[27−29] However, the computational modeling of these materials poses significant challenges. Solid solutions and the involvement of heavy elements complicate the calculations. The dynamic behavior of organic cations within the lattice, rich defect chemistry, and large number of possible structural variants add layers of complexity. Most importantly, the composition space of the HPs and the chemical space of molecules are individually intractable spaces. Despite the power of modern computational methods, we face combinatorially large chemical spaces that far exceed classical problems such as molecules and defects in solids. This necessitates innovative approaches to efficiently explore and understand these expansive chemical landscapes. With respect to these, we note that, while the chemical spaces of molecules can be scalably explored via high-veracity simulations, the compositional spaces of solid solutions are ideally suited by the automated experiment.

AUTOMATED LAB: FIRST STEP

The first step toward accelerating experimental materials discovery is the implementation of automated laboratories,[30,31] simply as the way to bypass the limitations of human execution. These laboratories integrate robotics and high-throughput screening to conduct thousands of experiments simultaneously, drastically reducing the time needed for identifying and optimizing new materials. Automated systems ensure precise control over experimental conditions, enhancing the reproducibility and reliability, which are essential for generating high-quality data. Additionally, this approach minimizes materials consumption during exploration and discovery phases, as only small amounts of chemicals are used in each experiment.[32,33] This not only improves sustainability but also reduces carbon emissions, contributing to more environmentally friendly research practices.[34−37]

In these automated settings, robots prepare and dispense precise reagent quantities, mix solutions, and carry out complex synthesis procedures as seen in Brabec et al.[38−40] and Ahmadi et al.[41−43] for solution-based processing of photovoltaic materials, Buonassisi et al. for high-throughput experimentation using machine learning (ML) and automated platforms to optimize solar energy efficiency,[44−46] Maruyama et al.,[33,45] and more.[47−50] Advanced robotic systems have been used to synthesize a variety of HP materials, including 2D, quasi-2D,[51] and nanocrystals[52] for optimization and explorations of the physio-chemistry, early stage crystallization, phase homogeneity, stability, and functionalities. Self-driving laboratories (SDLs)[50,53,54] including automated thin film robots[55,56] and free-roaming robots have been developed to automate research over the instruments themselves in what we can call a robotic chemist.[57,58] Utilizing a robot to perform repetitive and time-consuming tasks is beneficial, but many complex tasks still rely on human intervention and expertise such as decision-making, handling of materials, and adjustment of the experimental set up. Among the approaches that gained recent popularity are microfluidics,[59−63] which manipulate fluids at the microscale and have emerged as powerful tools for synthesizing new materials. Microfluidic devices allow precise control over reaction conditions, including mixing reactants, temperature, and flow rates, within tiny channels. This control is beneficial for synthesizing materials with uniform properties and creating gradient libraries with systematic composition

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Table 1. Overview of Various Automated Synthesis Methods Used for Material Discovery and Optimization

Reference	Method	Objective	Number of Samples	Pros	Cons
Ulrich W. Paetzold[68]	Automated spin-coating robot for handling sample positioning, pipetting, and antisolvent quenching	Improve reproducibility and reduce human error in perovskite solar cell fabrication	72 Thin films	High repeatability with consistent performance across nine batches, improved precision by eliminating surface defects, increased scalability while maintaining precision, reduced human error by removing operator variability	Initial setup of the robotic platform can be costly and complex, some steps in the process (like device assembly) still require manual intervention, there can be challenges in scaling the approach to large-scale industrial settings
Christoph J. Brabec[69]	Fully automated SPINBOT platform with Bayesian Optimization for spin-coating and optimizing perovskite thin-film fabrication	Accelerate the optimization of perovskite thin films for high efficiency and reproducibility in solar cells	96 Thin films	High reproducibility, precise control over synthesis parameters like pipet tip height (within 0.1 mm) for antisolvent injection, accelerated optimization through ML, automated substrate handling, scalability for larger runs	Initial setup of the automated system requires significant technical expertise and resources, some manual intervention still needed for device assembly, limited flexibility in adjusting non-automated layers, and high dependency on optimization algorithms that may not always converge to a global optimum
Christoph J. Brabec[70]	Robot-based high-throughput platform	Understand solvent-antisolvent crystallization and develop environmentally friendly solvent systems for perovskite fabrication	336 Compositions	Rapid screening of 336 samples in 2 days, comprehensive solvent-antisolvent database for lead halide perovskites, highly reproducible and unbiased experiments, environmentally friendly solvent system development, and potential scalability for industrial use	Initial setup and use of the robot system can be costly, high dependence on preselected solvent properties
Mahshid Ahmadi[71]	High-throughput automated workflow using robotic pipetting	Origin of the broadband emission in Pb−Sn 2D halide perovskites	96 Compositions	Robotic pipetting ensures precise mixing and reproducibility, knowledge transferability to thin film system, consuming small volume of materials (200−300 μL), system is capable of screening the evolution of phases through changes in time evolution of photoluminescence spectra in an accelerated fashion, screening combinatorial library of solid solutions	Limited access to high throughput characterization
Mahshid Ahmadi[51]	High-throughput automated synthesis-characterization workflow using pipetting robot, automated characterization by grazing-incidence wide-angle X-ray scattering (GIWAXS) and photoluminescence (PL) spectroscopy	Exploration of phase heterogeneities in quasi-2D perovskites. Identification of optimal 2D:3D compositional ratios for enhanced phase purity, stability and vertical charge transport	96 Compositions	Rapid exploration of 96 compositions, effective use of ML for analyzing massive data sets, comprehensive phase distribution insights through time-evolved PL and GIWAXS characterization, less materials waste, and improves scalability for industrial applications, knowledge transferability to thin films	Access to high throughput GIWAX is through synchrotron facility, costly and time-consuming
Milad Abolhasani[72]	Autonomous flow-based synthesis with ML for real-time optimization of perovskite quantum dots	Create an autonomous and scalable system for the optimization and continuous production of high-quality metal halide perovskite QDs	Over 1400 reactions (220 g QD solids per day)	Autonomous system with minimal human intervention, capable of producing over 1400 samples, rapid optimization through ML, highly precise control over quantum dot properties (PLQY, EFWHM, and EP), scalable for continuous production, and adaptable to various nanomaterial systems beyond quantum dots	The system's efficiency in some cases depends on pretrained models and prior data. If the data is unavailable, incomplete, or inconsistent across different laboratories, it can limit the system's initial performance
Milad Abolhasani[73]	Autonomous fluidic lab for optimization of lead-free nanocrystal synthesis	Investigate the effects of synthesis parameters (such as precursor concentration and reaction time) on the optical properties of $Cs_3Cu_2I_5$ NCs	Up to 100 experimental conditions	Integrate a Bayesian Optimization (BO) framework to map the synthesis-property space and build a predictive digital twin model, which serves both for mechanistic studies and closed-loop optimization of the synthesis process. Fast-track the discovery of high-performance NCs with minimal chemical consumption and waste (only 1 mL precursor per condition), contributing to the advancement of eco-friendly MHP NCs for clean energy technologies	High initial setup cost for autonomous experimentation, and significant computational resources needed to handle high-dimensional data sets during optimization
Berkeley Lab[74]	A fully autonomous laboratory designed to rapidly discover new materials using robots and AI	Accelerate the discovery of new materials for batteries and energy storage to meet global sustainability needs, while also supporting research in solar cells, fuel cells, and other clean energy technologies	Process 50 to 100 times as many samples as a human every day	24/7 autonomous operation with minimal human intervention, adaptable for solid-state synthesis, using AI and robotics to enhance efficiency	High setup and maintenance costs for the autonomous system, reliance on AI and robotics which need human oversight for complex tasks, limited flexibility for experiments not initially designed for the system

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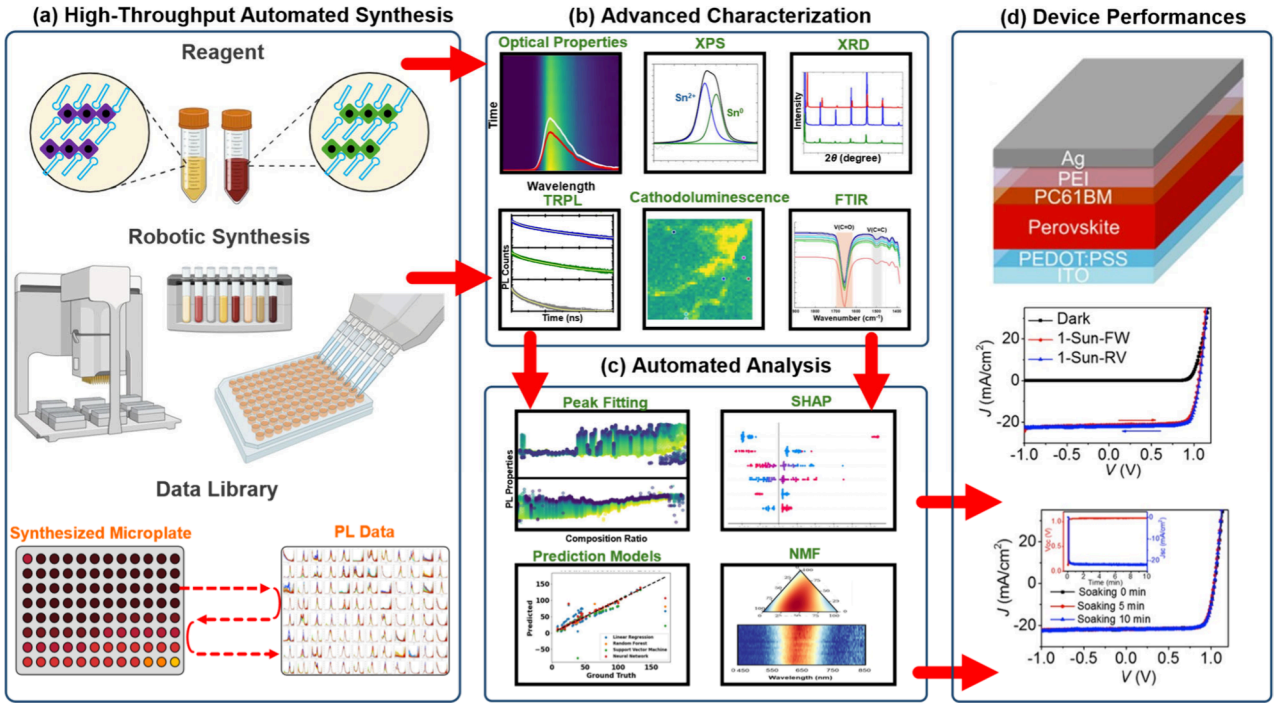

Figure 3. Experimental workflow of HPs exploration. (a) High-throughput automated synthesis of materials using a pipetting robot platform generates a combinatorial library of the compositions, followed by the high-throughput automated characterization (Photoluminescence spectroscopy) of the synthesized compositions. (b) Advanced characterizations of the samples. (c) Automated data analysis of data, enabling thorough tracking of materials properties. (d) Fabrication and performance evaluation of devices using the target compositions discovered and optimized in the previous steps. Reproduced from *ACS Nano*,[79] Copyright [2017] American Chemical Society.

variations. Systems such as Artificial chemist and smart dope developed by Abolhasani et al.[64,65] are able to accelerate synthesis space exploration and optimization of lead halide perovskite quantum dots (LHPs) (QDs). deMello et al.[66] was able to successfully synthesize Pt and Pd single atoms stabilized on graphitic carbon nitride utilizing a microfluidic system. Utilizing this microfluidic system, they were able to conduct a systematic study on the effect of metal on the final loading of single atom catalysis. Wang et al.[67] was able to utilize ML-assisted synthesis of perovskite quantum dots to elucidate the nucleation growth-ripening mechanisms but was also able to guide the synthesis of the QDs with precise wavelength conditions by combining gradient boosting (GB) and random forest (RF) to make predictions of the photoluminescence (PL).

While automated laboratories have significantly advanced synthesis workflows, challenges remain. Currently, we can scale synthesis processes effectively; for instance, combining droplet synthesis and robotics can produce thousands of compositions per day or explore multiple processing pathways for a single composition, as well as various additives.[75−77] However, this acceleration in the synthesis of individual materials is insufficient. The key challenges ahead lie in characterization and particularly in closing the loop—using the results of characterization to inform the selection of subsequent materials composition and processing conditions autonomously. Achieving this will require sophisticated integration of automated characterization techniques and real-time data analysis to efficiently guide the next steps in materials exploration efficiently. As explained in Table 1, these automated systems significantly enhance the efficiency and accuracy of material synthesis, emerging as powerful tools for precise control over reaction conditions, including mixing, temperature, and flow rates within tiny channels. This allows for the synthesis of materials with uniform properties and the creation of gradient or combinatorial libraries with systematic composition variations. While the estimates in the table are approximate, they provide a useful comparison of how these techniques stack up against state-of-the-art (SoTA) methods. The table highlights the key aspects of each methodology, including how automated systems enhance the efficiency and accuracy of the material synthesis. However, speeding up synthesis in isolation does not inherently bring value, unless there is concurrent progress in characterizing the materials produced. For example, more advanced characterization methods, such as X-ray diffraction and hyperspectral optical microscopy, are necessary to verify the structural properties and microstructural optical homogeneity of the synthesized materials, as were crucial in the development of high-efficiency solar cells. Furthermore, the accelerating one stage of the process, such as synthesis, does not lead to meaningful advancements unless it is paired with high-fidelity characterization that confirms the material's functional properties. In this regard, we developed a high-throughput automated workflow combining pipetting robots with advanced characterization techniques like grazing-incidence wide-angle X-ray scattering (GIWAXS) and photoluminescence (PL) spectroscopy.[51,71] This approach allowed for rapid exploration of 96 compositions and provided comprehensive phase distribution insights, illustrating how high throughput structural and optical characterization can accelerate material discovery. Figure 3 illustrates how a fully integrated workflow can address these challenges. It highlights the progression from high-throughput synthesis of HP compositions, where robotic platforms rapidly generate combinatorial libraries, to advanced characterization of the materials. Automated data analysis then extracts key

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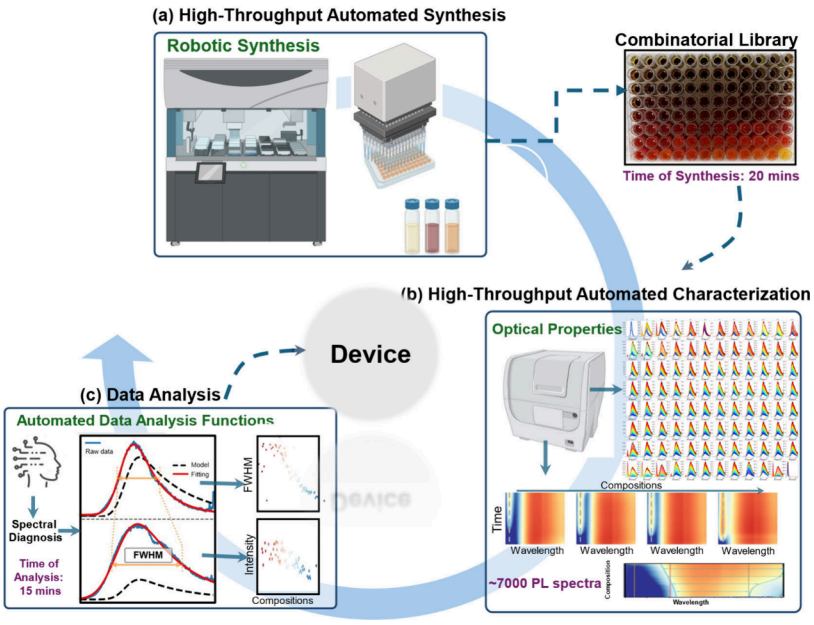

Figure 4. Automated experimental workflow of HP exploration. (a) High-throughput automated synthesis using a pipetting robot, (b) high-throughput automated PL characterizations of the 96 different compositions over time using a multimodal optical reader, and (c) automated data analysis of the PL spectra, enabling thorough tracking of PL properties over time, analyzing composition-property relationship targeting solar cell application. Part of (b) and (c) Reproduced with permission from *Advanced Functional Materials*,[71] Copyright [2024] John Wiley and Sons.

insights from this characterization, which can be used to systematically track and correlate the material properties.

Abolhasani et al. showcases autonomous flow-based synthesis systems augmented with ML for real-time optimization of perovskite quantum dots.[72,73] Their system integrated Bayesian Optimization frameworks and predictive digital twin models to map the synthesis-property space and optimize the synthesis process in real-time. This allowed for the autonomous production of over 1,400 samples with precise control over quantum dot properties, illustrating a successful integration of real-time data analysis within an automated characterization loop. In addition, coordination of multiple characterization techniques has proven to be a critical factor for success. For example, Slautin et al.[78] demonstrated a dynamic decision-making framework where ML was used to decide, in real-time, when to deploy techniques like Raman or scanning probe microscopy (SPM), that can potentially be extended to X-ray diffraction, optical spectroscopy, or electron microscopy. This iterative process, guided by real-time data, optimized the experimental pathway, ensuring that each technique was deployed at the most effective time. While this coordinated optimization highlights the potential of multiple characterization techniques working together, fully autonomous decision-making frameworks are still under development. Future advancements should focus on dynamically adjusting the sequence and depth of characterization to optimize the overall experimental process.

The workflow concludes with device fabrication and performance evaluation, all while the data are fed back into the system. This closed-loop system represents necessary advancement toward more efficient, autonomous materials discovery processes.

CLOSING THE CHARACTERIZATION LOOP

Characterization is crucial in materials science. We seek to understand specific properties or the underlying physics and chemistry of materials, which inform hypotheses for new material synthesis and optimization. Even for simple crystalline materials, properties can deviate significantly from theoretical predictions due to defects and structural variability. For real-world materials, complexities, such as microstructures and defective phases, add further challenges.

Basic characterization of materials is typically performed by using multiple complementary methods. For example, scanning transmission electron microscopy (STEM) provides structural information with atomic precision,[80,81] Raman spectroscopy reveals molecular vibrations,[82,83] X-ray diffraction (XRD) gives average structural data,[84,85] scanning probe microscopy (SPM) assesses local functionalities,[86−88] cathodoluminescence (CL) examines emission properties,[77,89] and time-of-flight secondary ion mass spectrometry (ToF-SIMS) maps chemical compositions.[90,91] Integrating data from these diverse techniques to construct a comprehensive model of the material is a significant challenge.

This integration is difficult because each method provides different types of information on varying scales and resolutions. For many of these characterization methods, the resultant data are obtained in the form of complex large dimensional data sets. As such, the applications of classical ML methods to these systems becomes a challenge.[92−95] Indeed, the paradigmatic approach for material property optimization is based on classical Bayesian Optimization. In this, the synthesis is performed over several regions within the parameter space, whether concentration, chemical space of spacer molecules, or processing histories. Based on measured functionalities, a surrogate model capable of predicting properties and their uncertainties over the whole parameter space is built. The predicted properties and uncertainties are combined using a preselected policy into the acquisition function, and the location in the parameter space corresponding to the maximum of the acquisition function is chosen as the next

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experiment. This approach is now foundational for automated experiments.

Figure 4 demonstrates the integration of automated synthesis, characterization, and data analysis as essential components in HP exploration. It shows how high-throughput robotic synthesis can rapidly produce a large library of material compositions. These compositions are then subjected to high-throughput PL characterizations, capturing thousands of spectra over time. Automated data analysis processes this vast amount of spectral data, tracking critical properties and preparing the materials for device applications. This loop exemplifies the fast-paced, automated workflow required to bridge the gap between fundamental discovery and real-world applications, ensuring that each step—synthesis, characterization, and analysis—feeds efficiently into the next step, enabling more streamlined materials exploration and device integration.

However, the obvious limitation of this approach is that optimization is possible if the reward function (or several reward functions) is well-defined. Depending on how the reward function is defined based on the multidimensional data set, optimization can follow different pathways. For example, even for simple emission (PL) measurements, exploration of composition space will be strongly dependent on whether we optimize peak intensity (i.e., quantum efficiency), peak width (phase purity), peak position (bandgap), or peak change with time (stability). These considerations become particularly relevant if we consider characterization using multiple tools. In this case, co-orchestration of multiple scientific tools requires developing the common reward functions that quantify the benefit of characterization by multiple methods.[96−98]

The discovery of effective reward functions remains a critical challenge on the path to fully automated laboratories. Defining optimal reward functions in multidimensional characterization involves translating complex experimental objectives—such as stability, efficiency, or material performance—into quantifiable metrics that can be optimized in real-time. These reward functions must balance short-term improvements with long-term experimental goals, ensuring that the system does not overfit to intermediate successes at the expense of broader objectives. For example, even in material science optimization, trade-offs among phase purity, energy efficiency, and environmental sustainability must often be captured within a single reward function. The real challenge lies in determining how to weigh these different parameters in a way that reflects the desired outcome of the research.

These reward functions can be based on understanding the mechanisms that form structures, which requires correlating these data to uncover relationships between structures, defects, and properties. Alternatively, the low cost and fast proxies can be constructed based on correlative studies and human heuristics. The selection process often involves iterative refinement, where preliminary reward functions are tested and their outputs evaluated for alignment with experimental results. ML and statistical techniques, such as Bayesian Optimization or Gaussian Processes, can assist in discovering these reward functions, but human input is crucial to guide and adjust based on domain expertise. Additionally, as new data are collected, reward functions may need to be updated to better align with evolving experimental priorities, making the process dynamic rather than static. Achieving this level of integration demands advanced data analysis techniques, robust computational models, and seamless communication between different characterization tools. It is also important to note that, for automated laboratories to be viable, this characterization must be performed at small volumes and at a fast pace, matching the synthesis time scale to avoid bottlenecks and keeping fabrication costs manageable. Lastly, discoverability is essential. A reward function must be designed in such a way that it allows for real-time feedback loops within the automated optimization framework. Balancing the complexity of multi-dimensional data with real-time optimization constraints remains an ongoing research challenge. The reward function itself is any measurable outcome that can be optimized during an experiment. While long-term objectives like addressing global warming exist, more immediate reward functions, such as optimizing the band gap of a material, help direct the process. Designing these reward functions requires human intuition because, while we can solve optimization problems, we can only hypothesize about what constitutes a good reward function. For instance, it is challenging to predict how today's optical spectrum might translate into photovoltaic performance or material stability in the future.

Similar problems emerge in transitions from fundamental discovery to manufacturing along the commercialization path. The fundamental knowledge is created at the lab level, working with relatively simple systems. Transition from materials synthesis to making prototype devices to real world deployment is associated with the transitions to progressively high dimensional parameter spaces and larger feedback times. At the same time, real-world value is created only at the stage of manufacturing and deployment. This propagation of basic knowledge from fundamental discovery to manufacturing and value from manufacturing to basic science is the next frontier for ML development.

Figure 5 illustrates the intricate integration of various stages of material development, emphasizing the synergy between

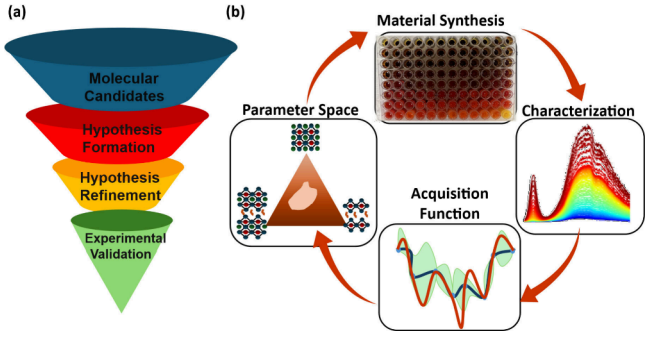

Figure 5. (a) Theoretical funnel and (b) experimental optimization loop across scales and times.

theoretical insights and experimental validation. The funnel in Figure 5a represents the paradigmatic theoretical workflow, where large spaces of molecular candidates (or theories) are gradually distilled into more specific hypotheses. This process involves applying computational techniques that range from high-throughput screening to more detailed, resource-intensive simulations as the candidate pool narrows. As hypotheses are refined, they undergo a critical phase where initial ideas are honed, inconsistencies are resolved, and predictions become more precise before being tested experimentally.

The experimental counterpart in Figure 5b is the optimization loop, a dynamic and iterative process that spans material synthesis, characterization, and data analysis. In this

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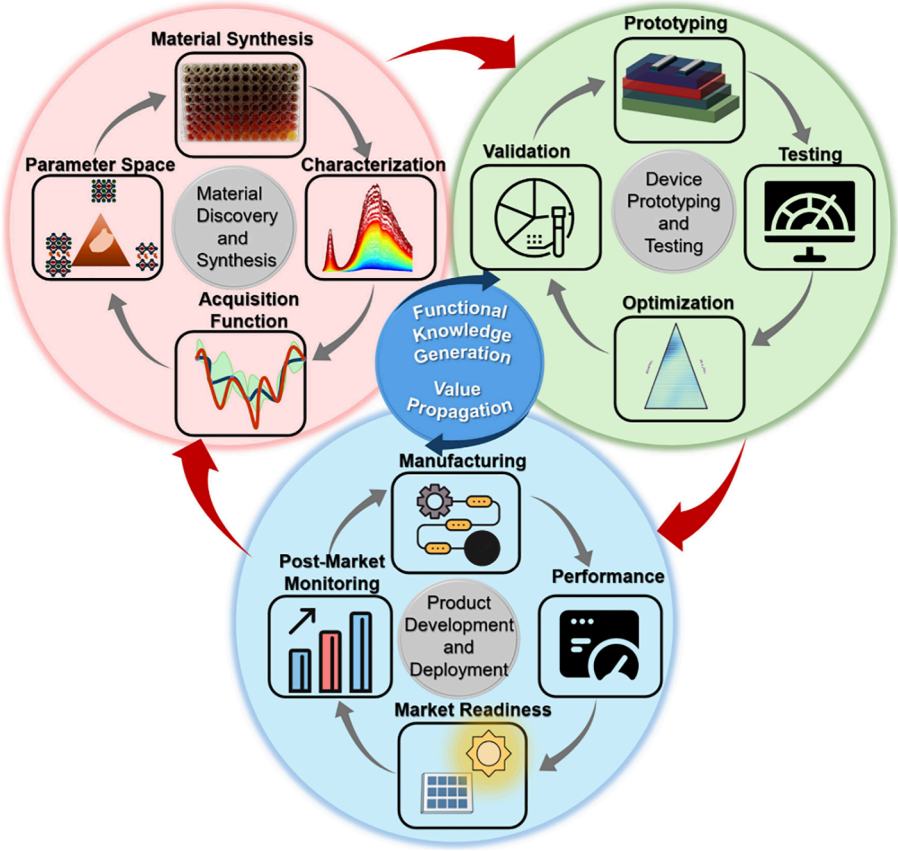

Figure 6. A workflow that illustrates the transition from fast, iterative learning in fundamental research to slower, more deliberate processes involved in manufacturing and market adoption.

loop, materials are synthesized according to the refined hypotheses, characterized to assess their properties, and analyzed to determine how well they meet the desired criteria. This process leverages high-throughput experimental techniques that can quickly generate and assess a large number of compositions, providing the data necessary to validate or refine theoretical predictions. The outcomes of this characterization and analysis are then fed back into the hypothesis refinement stage, allowing for continuous improvement of both the hypotheses and the materials themselves. This cyclical process underscores the importance of maintaining a close feedback loop between theory and experiment, enabling researchers to refine their understanding and optimize their material properties progressively. This approach is crucial in materials science, where the complexity of material behaviors, including defect chemistry, phase stability, and interfacial interactions, often necessitates multiple iterations to achieve the desired outcomes. At the frontier of ML development, this integration offers opportunities for accelerating the discovery process. ML models, particularly those capable of active learning and Bayesian Optimization, can guide the exploration of large compositional spaces by prioritizing experimental directions that are most likely to yield promising results. As the funnel narrows and the experimental data accumulate, ML models can transition from simpler models used in the initial screening to more sophisticated models that can handle the increased complexity of smaller, refined candidate sets. This shift allows researchers to use computational resources more efficiently and to explore both known and novel material spaces systematically. The experimental loop thus becomes not only a means of validating theoretical predictions but also a key component in training and refining ML models, enabling them to predict properties more accurately and explore unexplored regions of material space. This synergy between automated experiments and ML-driven insights can significantly reduce the time and cost associated with material discovery, making it possible to tackle complex challenges such as designing materials for specific environmental conditions or optimizing stability for real-world applications. The continued development of these ML approaches, with a focus on integrating them seamlessly into experimental workflows, represents a critical frontier for advancing materials science and bridging the gap between laboratory-scale discovery and practical deployment.

However, these are only elements that build the realistic workflow from fundamental research to practical application. Figure 6 expands on this by detailing the entire workflow, illustrating how fast, iterative learning in fundamental research transitions to slower, more deliberate processes in manufacturing and market adoption. The red and green loops in Figure 6 represent the early stages of material development, where rapid iterations in the synthesis, characterization, and optimization drive the discovery of new materials and the refinement of their properties. These stages are characterized by a focus on exploration and innovation, with researchers continually pushing the boundaries of what is possible.

As the process moves toward manufacturing and market adoption, depicted in the blue loop, the pace slows and the focus shifts from exploration to optimization and validation. Here, the insights gained from the earlier stages are applied to

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scale up production, ensure consistency and reliability, and meet the stringent requirements of real-world applications. The workflow in Figure 6 emphasizes the necessity of coupling multiple loops across scales and times. This coupling ensures that the rapid, iterative learning that drives fundamental research can be effectively integrated into the more deliberate processes required for successful commercialization.

The transition from fundamental research to manufacturing is not a one-way street. As materials move through the stages of prototyping, testing, and market deployment, new challenges and opportunities arise, which can feed back into the earlier stages of the workflow. For example, issues encountered during manufacturing might prompt new lines of inquiry in fundamental research, leading to further refinement of the theoretical models or development of new materials with enhanced properties. This bidirectional flow of knowledge and value is critical for sustaining innovation and ensuring that the entire process, from discovery to deployment, remains adaptive and responsive to emerging needs and challenges.

Ultimately, the connections on this development path not only accelerate the transition from laboratory discoveries to real-world impact but also ensure that the knowledge and value generated at each stage are propagated throughout the entire cycle. This propagation of insights and innovations is essential for driving continuous improvement in material performance and for ensuring that scientific advances translate into tangible benefits in real-world applications. By effectively coupling the fast-paced, exploratory stages of material development with the slower, more methodical processes of commercialization, this workflow represents a powerful model for accelerating the development and deployment of advanced materials.

These connections are particularly relevant in the context of HPs, where rapid advancements in synthesis and characterization techniques have opened new possibilities for their use in a wide range of applications, from photovoltaics to optoelectronics. However, realizing the full potential of these materials requires not only a deep understanding of their fundamental properties but also the ability to translate this understanding into practical and scalable solutions. The workflow depicted in Figure 6 provides a roadmap for achieving this translation, guiding researchers through the complex and often nonlinear journey from discovery to deployment and ensuring that each stage contributes to the overall goal of creating materials that are not only scientifically interesting but also commercially viable and societally beneficial.

As an example, the workflows outlined in Figures 5 and 6 were implemented by combining high-throughput synthesis and characterization with the Gated Gaussian Process Bayesian Optimization (Gated-GPBO) algorithm by Yang et al.[99] This enabled the exploration of 480 quasi-2D Cs-based HP compositions using 5 different spacer molecules and the rapid screening of over 20,000 PL spectra. Promising quasi 2D HPs were identified via unsupervised ML and validated through high-fidelity characterization techniques, such as hyperspectral cathodoluminescence (CL) imaging, GIWAXS, and nuclear magnetic resonance (NMR) spectroscopy. Then, two optimized spacers were selected to make a ternary quasi 2D Cs-based HP compositional system using dual or Gated-GPBO active learning, yielding materials with ideal band gap energy and stability. The thin films of optimized composition achieved solar cell power conversion efficiencies (PCE) of up to 11.16%, representing an ∼60% improvement over manually selected compositions, with results confirmed across 20 devices.

GOING INTO THE UNKNOWN

Classical physics methods and ML excel in interpolation tasks. For example, Gaussian processes can model complex functions and predict outcomes based on existing data,[85,100−103] while structured Gaussian processes combine physics-based models with data-driven approaches, enhancing predictive power.[25,104] These methods effectively interpolate data to identify trends and optimal compositions. However, the far more complex problem is extrapolation to new compositions, conditions, molecules, and processing parameters. ML struggles with extrapolation, because it relies heavily on the data on which it was trained. Without adequate data covering the new regions of parameter space, predictions can be highly uncertain. Human hypothesis-making plays a crucial role in addressing this challenge. Researchers' expertise and intuition can guide the selection of promising new areas to explore, which ML models can then analyze. Humans and ML can work together by leveraging human creativity and domain knowledge to generate hypotheses and using ML to test and refine these hypotheses efficiently.[105] This synergy can accelerate the discovery process by combining the strengths of human insight with the computational power of ML, ensuring robust predictions and innovative breakthroughs in materials science.

SUMMARY

Looking ahead, achieving direct solar to climate impact requires the capability to tie the beneficial physical and chemical functionalities in a single material. While theoretical approaches have now advanced to the point where they can swiftly explore vast chemical and molecular spaces, they are often constrained by supply chain limitations—whether in terms of material delivery or synthesis capabilities. On the other hand, while solid solution spaces are theoretically challenging to navigate, they can be explored much more rapidly through experimental methods.

The key to unlocking the full potential of this combined approach lies in the ability to conavigate these complex spaces by effectively integrating theory and experiment. However, the central challenge will be to identify fast proxy signals that can guide us toward the optimal material compositions for real-world uses. This is achievable only by closing the characterization loop, where each method provides high-dimensional data that together offer a comprehensive understanding of the material's functionality. Automated laboratories offer a transformative opportunity to meet this challenge. By integrating robotics, high-throughput screening, and ML, these laboratories can rapidly conduct experiments that significantly accelerate material discovery and optimization. However, this shift also requires a workforce skilled in both ML and experimental design. Bridging this gap will necessitate educational initiatives and professional development programs aimed at equipping domain experts with the necessary ML expertise.

Materials with individually tunable chemical and physical functionalities are uniquely suited to address pressing environmental challenges such as methane and CO_2 conversion. By focusing on the development and deployment of such advanced materials, we have the chance to make a significant

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and tangible impact on climate change, driving innovation that not only mitigates environmental harm but also paves the way for sustainable industrial applications.

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Notes

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REFERENCES

(1) Weiss, D. S.; Saffman, M. Quantum computing with neutral atoms. *Phys. Today* **2017**, *70* (7), 44−50.

(2) Hofer, M. P.; Jakobsson, C.; Zafiropoulos, N.; Vamvakas, S.; Vetter, T.; Regnstrom, J.; Hemmings, R. J. Regulatory watch: Impact of scientific advice from the European Medicines Agency. *Nat. Rev. Drug Discovery* **2015**, *14* (5), 302.

(3) Alper, K.; Tekin, K.; Karagöz, S.; Ragauskas, A. J. Sustainable energy and fuels from biomass: a review focusing on hydrothermal biomass processing. *Sustainable Energy & Fuels* **2020**, *4* (9), 4390−4414.

(4) Roy, A.; Sharma, A.; Yadav, S.; Jule, L. T.; Krishnaraj, R. Nanomaterials for remediation of environmental pollutants. *Bioinorganic Chemistry and Applications* **2021**, *2021* (1), 1764647.

(5) Schäppi, R.; Rutz, D.; Dähler, F.; Muroyama, A.; Haueter, P.; Lilliestam, J.; Patt, A.; Furler, P.; Steinfeld, A. Drop-in fuels from sunlight and air. *Nature* **2022**, *601* (7891), 63−68.

(6) Fawzy, S.; Osman, A. I.; Doran, J.; Rooney, D. W. Strategies for mitigation of climate change: a review. *Environmental Chemistry Letters* **2020**, *18*, 2069−2094.

(7) Nisbet, E.; Fisher, R.; Lowry, D.; France, J.; Allen, G.; Bakkaloglu, S.; Broderick, T.; Cain, M.; Coleman, M.; Fernandez, J. Methane mitigation: methods to reduce emissions, on the path to the Paris agreement. *Reviews of Geophysics* **2020**, *58* (1), No. e2019RG000675.

(8) Manzari, M. T.; Shamay, Y.; Kiguchi, H.; Rosen, N.; Scaltriti, M.; Heller, D. A. Targeted drug delivery strategies for precision medicines. *Nat. Rev. Mater.* **2021**, *6* (4), 351−370.

(9) Smith, P.; Soussana, J. F.; Angers, D.; Schipper, L.; Chenu, C.; Rasse, D. P.; Batjes, N. H.; Van Egmond, F.; McNeill, S.; Kuhnert, M. How to measure, report and verify soil carbon change to realize the potential of soil carbon sequestration for atmospheric greenhouse gas removal. *Global Change Biology* **2020**, *26* (1), 219−241.

(10) Victoria, M.; Haegel, N.; Peters, I. M.; Sinton, R.; Jäger-Waldau, A.; del Canizo, C.; Breyer, C.; Stocks, M.; Blakers, A.; Kaizuka, I. Solar photovoltaics is ready to power a sustainable future. *Joule* **2021**, *5* (5), 1041−1056.

(11) Dambhare, M. V.; Butey, B.; Moharil, S. Solar photovoltaic technology: A review of different types of solar cells and its future trends. *Journal of Physics: Conference Series* **2021**, *1913*, 012053.

(12) Kumar, K. R.; Chaitanya, N. K.; Kumar, N. S. Solar thermal energy technologies and its applications for process heating and power generation-A review. *Journal of Cleaner Production* **2021**, *282*, 125296.

(13) Yu, J.; Tang, Y. M.; Chau, K. Y.; Nazar, R.; Ali, S.; Iqbal, W. Role of solar-based renewable energy in mitigating CO2 emissions: evidence from quantile-on-quantile estimation. *Renewable Energy* **2022**, *182*, 216−226.

(14) Ming, T.; Gui, H.; Shi, T.; Xiong, H.; Wu, Y.; Shao, Y.; Li, W.; Lu, X.; de Richter, R. Solar chimney power plant integrated with a photocatalytic reactor to remove atmospheric methane: A numerical analysis. *Sol. Energy* **2021**, *226*, 101−111.

(15) Jena, A. K.; Kulkarni, A.; Miyasaka, T. Halide perovskite photovoltaics: background, status, and future prospects. *Chem. Rev.* **2019**, *119* (5), 3036−3103.

(16) Yin, W.-J.; Yang, J.-H.; Kang, J.; Yan, Y.; Wei, S.-H. Halide perovskite materials for solar cells: a theoretical review. *Journal of Materials Chemistry A* **2015**, *3* (17), 8926−8942.

(17) D'Innocenzo, V.; Srimath Kandada, A. R.; De Bastiani, M.; Gandini, M.; Petrozza, A. Tuning the light emission properties by band gap engineering in hybrid lead halide perovskite. *J. Am. Chem. Soc.* **2014**, *136* (51), 17730−17733.

(18) Wu, X.; Li, B.; Zhu, Z.; Chueh, C.-C.; Jen, A. K.-Y. Designs from single junctions, heterojunctions to multijunctions for high-performance perovskite solar cells. *Chem. Soc. Rev.* **2021**, *50* (23), 13090−13128.

(19) Motta, C.; El-Mellouhi, F.; Sanvito, S. Charge carrier mobility in hybrid halide perovskites. *Sci. Rep.* **2015**, *5* (1), 12746.

(20) Li, F.; Ma, C.; Wang, H.; Hu, W.; Yu, W.; Sheikh, A. D.; Wu, T. Ambipolar solution-processed hybrid perovskite phototransistors. *Nat. Commun.* **2015**, *6* (1), 8238.

(21) Zhang, F.; Lu, H.; Tong, J.; Berry, J. J.; Beard, M. C.; Zhu, K. Advances in two-dimensional organic-inorganic hybrid perovskites. *Energy Environ. Sci.* **2020**, *13* (4), 1154−1186.

(22) Yang, J.; Kalinin, S. V.; Cubuk, E. D.; Ziatdinov, M.; Ahmadi, M. Toward self-organizing low-dimensional organic-inorganic hybrid perovskites: Machine learning-driven co-navigation of chemical and compositional spaces. *MRS Bull.* **2023**, *48* (2), 164−172.

(23) Mao, L.; Stoumpos, C. C.; Kanatzidis, M. G. Two-dimensional hybrid halide perovskites: principles and promises. *J. Am. Chem. Soc.* **2019**, *141* (3), 1171−1190.
(24) Ahmadi, M.; Ziatdinov, M.; Zhou, Y.; Lass, E. A.; Kalinin, S. V. Machine learning for high-throughput experimental exploration of metal halide perovskites. *Joule* **2021**, *5* (11), 2797−2822.
(25) Sanchez, S. L.; Foadian, E.; Ziatdinov, M.; Yang, J.; Kalinin, S. V.; Liu, Y.; Ahmadi, M. Physics-driven discovery and bandgap engineering of hybrid perovskites. *Digital Discovery* **2024**, *3*, 1577.
(26) Zhou, Y.; Zhao, Y. Chemical stability and instability of inorganic halide perovskites. *Energy Environ. Sci.* **2019**, *12* (5), 1495−1511.
(27) Jain, A.; Persson, K. A.; Ceder, G. Research Update: The materials genome initiative: Data sharing and the impact of collaborative ab initio databases. *APL Materials* **2016**, *4* (5), 053102.
(28) Merchant, A.; Batzner, S.; Schoenholz, S. S.; Aykol, M.; Cheon, G.; Cubuk, E. D. Scaling deep learning for materials discovery. *Nature* **2023**, *624* (7990), 80−85.
(29) Curtarolo, S.; Setyawan, W.; Hart, G. L. W.; Jahnatek, M.; Chepulskii, R. V.; Taylor, R. H.; Wang, S.; Xue, J.; Yang, K.; Levy, O.; et al. AFLOW: An automatic framework for high-throughput materials discovery. *Comput. Mater. Sci.* **2012**, *58*, 218−226.
(30) Mennen, S. M.; Alhambra, C.; Allen, C. L.; Barberis, M.; Berritt, S.; Brandt, T. A.; Campbell, A. D.; Castañón, J.; Cherney, A. H.; Christensen, M. The evolution of high-throughput experimentation in pharmaceutical development and perspectives on the future. *Org. Process Res. Dev.* **2019**, *23* (6), 1213−1242.
(31) Lippi, G.; Da Rin, G. Advantages and limitations of total laboratory automation: a personal overview. *Clinical Chemistry and Laboratory Medicine (CCLM)* **2019**, *57* (6), 802−811.
(32) Tom, G.; Schmid, S. P.; Baird, S. G.; Cao, Y.; Darvish, K.; Hao, H.; Lo, S.; Pablo-García, S.; Rajaonson, E. M.; Skreta, M. Self-driving laboratories for chemistry and materials science. *Chem. Rev.* **2024**, *124* (16), 9633−9732.
(33) Tabor, D. P.; Roch, L. M.; Saikin, S. K.; Kreisbeck, C.; Sheberla, D.; Montoya, J. H.; Dwaraknath, S.; Aykol, M.; Ortiz, C.; Tribukait, H.; et al. Accelerating the discovery of materials for clean energy in the era of smart automation. *Nature reviews materials* **2018**, *3* (5), 5−20.
(34) Sadeghi, S.; Canty, R. B.; Mukhin, N.; Xu, J.; Delgado-Licona, F.; Abolhasani, M. Engineering a Sustainable Future: Harnessing Automation, Robotics, and Artificial Intelligence with Self-Driving Laboratories. *ACS Sustainable Chem. Eng.* **2024**, *12* (34), 12695−12707.
(35) Abolhasani, M.; Kumacheva, E. The rise of self-driving labs in chemical and materials sciences. *Nature Synthesis* **2023**, *2* (6), 483−492.
(36) Volk, A. A.; Abolhasani, M. Performance metrics to unleash the power of self-driving labs in chemistry and materials science. *Nat. Commun.* **2024**, *15* (1), 1378.
(37) Seifrid, M.; Pollice, R.; Aguilar-Granda, A.; Morgan Chan, Z.; Hotta, K.; Ser, C. T.; Vestfrid, J.; Wu, T. C.; Aspuru-Guzik, A. Autonomous chemical experiments: Challenges and perspectives on establishing a self-driving lab. *Acc. Chem. Res.* **2022**, *55* (17), 2454−2466.
(38) Hu, H.; Shi, H.; Zhang, J.; Hauch, J. A.; Osvet, A.; Brabec, C. J. Automated Synthesis of 1-Tetradecylphosphonic Acid-Capped FAPbBr3 Nanocrystals for Light Conversion in Display Applications. *ACS Appl. Nano Mater.* **2024**, *7* (8), 8823−8829.
(39) Langner, S.; Häse, F.; Perea, J. D.; Stubhan, T.; Hauch, J.; Roch, L. M.; Heumueller, T.; Aspuru-Guzik, A.; Brabec, C. J. Beyond Ternary OPV: High-Throughput Experimentation and Self-Driving Laboratories Optimize Multicomponent Systems. *Adv. Mater.* **2020**, *32* (14), 1907801.
(40) Gu, E.; Tang, X.; Langner, S.; Duchstein, P.; Zhao, Y.; Levchuk, I.; Kalancha, V.; Stubhan, T.; Hauch, J.; Egelhaaf, H. J.; et al. Robot-Based High-Throughput Screening of Antisolvents for Lead Halide Perovskites. *Joule* **2020**, *4* (8), 1806−1822.
(41) Sanchez, S. L.; Tang, Y.; Hu, B.; Yang, J.; Ahmadi, M. Understanding the ligand-assisted reprecipitation of CsPbBr3 nanocrystals via high-throughput robotic synthesis approach. *Matter* **2023**, *6* (9), 2900.
(42) Yang, J.; Lawrie, B. J.; Kalinin, S. V.; Ahmadi, M. High-Throughput Automated Exploration of Phase Growth Behaviors in Quasi-2D Formamidinium Metal Halide Perovskites. *Adv. Energy Mater.* **2023**, *13* (43), 2302337.
(43) Higgins, K.; Ziatdinov, M.; Kalinin, S. V.; Ahmadi, M. High-Throughput Study of Antisolvents on the Stability of Multicomponent Metal Halide Perovskites through Robotics-Based Synthesis and Machine Learning Approaches. *J. Am. Chem. Soc.* **2021**, *143* (47), 19945−19955.
(44) Hippalgaonkar, K.; Li, Q.; Wang, X.; Fisher, J. W., III; Kirkpatrick, J.; Buonassisi, T. Knowledge-integrated machine learning for materials: lessons from gameplaying and robotics. *Nat. Rev. Mater.* **2023**, *8* (4), 241−260.
(45) Stach, E.; DeCost, B.; Kusne, A. G.; Hattrick-Simpers, J.; Brown, K. A.; Reyes, K. G.; Schrier, J.; Billinge, S.; Buonassisi, T.; Foster, I.; et al. Autonomous experimentation systems for materials development: A community perspective. *Matter* **2021**, *4* (9), 2702−2726.
(46) Correa-Baena, J.-P.; Hippalgaonkar, K.; van Duren, J.; Jaffer, S.; Chandrasekhar, V. R.; Stevanovic, V.; Wadia, C.; Guha, S.; Buonassisi, T. Accelerating materials development via automation, machine learning, and high-performance computing. *Joule* **2018**, *2* (8), 1410−1420.
(47) Shimizu, R.; Kobayashi, S.; Watanabe, Y.; Ando, Y.; Hitosugi, T. Autonomous materials synthesis by machine learning and robotics. *APL Materials* **2020**, *8* (11), 111110.
(48) Li, Z.; Najeeb, M. A.; Alves, L.; Sherman, A. Z.; Shekar, V.; Cruz Parrilla, P.; Pendleton, I. M.; Wang, W.; Nega, P. W.; Zeller, M.; et al. Robot-Accelerated Perovskite Investigation and Discovery. *Chem. Mater.* **2020**, *32* (13), 5650−5663.
(49) Chan, E. M.; Xu, C.; Mao, A. W.; Han, G.; Owen, J. S.; Cohen, B. E.; Milliron, D. J. Reproducible, High-Throughput Synthesis of Colloidal Nanocrystals for Optimization in Multidimensional Parameter Space. *Nano Lett.* **2010**, *10* (5), 1874−1885.
(50) Li, J.; Wang, H.; Lin, L.; Fang, Q.; Peng, X. Quantitative Identification of Basic Growth Channels for Formation of Monodisperse Nanocrystals. *J. Am. Chem. Soc.* **2018**, *140* (16), 5474−5484.
(51) Yang, J.; Hidalgo, J.; Song, D.; Kalinin, S. V.; Correa-Baena, J. P.; Ahmadi, M. Accelerating Materials Discovery by High-Throughput GIWAXS Characterization of Quasi-2D Formamidinium Metal Halide Perovskites. *Adv. Funct. Mater.* **2024**, 2409293.
(52) Sanchez, S. L.; Tang, Y.; Hu, B.; Yang, J.; Ahmadi, M. Understanding the ligand-assisted reprecipitation of CsPbBr3 nanocrystals via high-throughput robotic synthesis approach. *Matter* **2023**, *6* (9), 2900−2918.
(53) Häse, F.; Roch, L. M.; Aspuru-Guzik, A. Next-Generation Experimentation with Self-Driving Laboratories. *Trends in Chemistry* **2019**, *1* (3), 282−291.
(54) Li, J.; Li, J.; Liu, R.; Tu, Y.; Li, Y.; Cheng, J.; He, T.; Zhu, X. Autonomous discovery of optically active chiral inorganic perovskite nanocrystals through an intelligent cloud lab. *Nat. Commun.* **2020**, *11* (1), 2046.
(55) MacLeod, B. P.; Parlane, F. G. L.; Morrissey, T. D.; Häse, F.; Roch, L. M.; Dettelbach, K. E.; Moreira, R.; Yunker, L. P. E.; Rooney, M. B.; Deeth, J. R.; et al. Self-driving laboratory for accelerated discovery of thin-film materials. *Science Advances* **2020**, *6* (20), No. eaaz8867.
(56) MacLeod, B. P.; Parlane, F. G. L.; Rupnow, C. C.; Dettelbach, K. E.; Elliott, M. S.; Morrissey, T. D.; Haley, T. H.; Proskurin, O.; Rooney, M. B.; Taherimakhsousi, N.; et al. A self-driving laboratory advances the Pareto front for material properties. *Nat. Commun.* **2022**, *13* (1), 995.
(57) Zhu, Q.; Huang, Y.; Zhou, D.; Zhao, L.; Guo, L.; Yang, R.; Sun, Z.; Luo, M.; Zhang, F.; Xiao, H.; et al. Automated synthesis of

oxygen-producing catalysts from Martian meteorites by a robotic AI chemist. *Nature Synthesis* **2024**, *3* (3), 319−328.
(58) Burger, B.; Maffettone, P. M.; Gusev, V. V.; Aitchison, C. M.; Bai, Y.; Wang, X.; Li, X.; Alston, B. M.; Li, B.; Clowes, R.; et al. A mobile robotic chemist. *Nature* **2020**, *583* (7815), 237−241.
(59) Steiner, S.; Wolf, J.; Glatzel, S.; Andreou, A.; Granda, J. M.; Keenan, G.; Hinkley, T.; Aragon-Camarasa, G.; Kitson, P. J.; Angelone, D.; Cronin, L. Organic synthesis in a modular robotic system driven by a chemical programming language. *Science* **2019**, *363* (6423), No. eaav2211.
(60) Abdel-Latif, K.; Epps, R. W.; Bateni, F.; Han, S.; Reyes, K. G.; Abolhasani, M. Self-Driven Multistep Quantum Dot Synthesis Enabled by Autonomous Robotic Experimentation in Flow. *Advanced Intelligent Systems* **2021**, *3* (2), 2000245.
(61) Wu, J.; He, Z.; Chen, Q.; Lin, J.-M. Biochemical analysis on microfluidic chips. *TrAC Trends in Analytical Chemistry* **2016**, *80*, 213−231.
(62) Yang, C.-G.; Xu, Z.-R.; Lee, A. P.; Wang, J.-H. A microfluidic concentration-gradient droplet array generator for the production of multi-color nanoparticles. *Lab Chip* **2013**, *13* (14), 2815−2820.
(63) Niu, G.; Zhang, L.; Ruditskiy, A.; Wang, L.; Xia, Y. A Droplet-Reactor System Capable of Automation for the Continuous and Scalable Production of Noble-Metal Nanocrystals. *Nano Lett.* **2018**, *18* (6), 3879−3884.
(64) Bateni, F.; Sadeghi, S.; Orouji, N.; Bennett, J. A.; Punati, V. S.; Stark, C.; Wang, J.; Rosko, M. C.; Chen, O.; Castellano, F. N.; et al. Smart Dope: A Self-Driving Fluidic Lab for Accelerated Development of Doped Perovskite Quantum Dots. *Adv. Energy Mater.* **2024**, *14* (1), 2302303.
(65) Epps, R. W.; Felton, K. C.; Coley, C. W.; Abolhasani, M. Automated microfluidic platform for systematic studies of colloidal perovskite nanocrystals: towards continuous nano-manufacturing. *Lab Chip* **2017**, *17* (23), 4040−4047.
(66) Moragues, T.; Mitchell, S.; Faust Akl, D.; Pérez-Ramírez, J.; deMello, A. Droplet-Based Microfluidics Platform for the Synthesis of Single-Atom Heterogeneous Catalysts. *Small Structures* **2023**, *4* (4), 2200284.
(67) Chen, G.; Zhu, X.; Xing, C.; Wang, Y.; Xu, X.; Bao, J.; Huang, J.; Zhao, Y.; Wang, X.; Zhou, X.; et al. Machine Learning-Assisted Microfluidic Synthesis of Perovskite Quantum Dots. *Advanced Photonics Research* **2023**, *4* (1), 2200230.
(68) Baumann, D. O.; Laufer, F.; Roger, J.; Singh, R.; Gholipoor, M.; Paetzold, U. W. Repeatable Perovskite Solar Cells through Fully Automated Spin-Coating and Quenching. *ACS Appl. Mater. Interfaces* **2024**, *16* (40), 54007−54016.
(69) Zhang, J.; Liu, B.; Liu, Z.; Wu, J.; Arnold, S.; Shi, H.; Osterrieder, T.; Hauch, J. A.; Wu, Z.; Luo, J.; et al. Optimizing Perovskite Thin-Film Parameter Spaces with Machine Learning-Guided Robotic Platform for High-Performance Perovskite Solar Cells. *Adv. Energy Mater.* **2023**, *13* (48), 2302594.
(70) Gu, E.; Tang, X.; Langner, S.; Duchstein, P.; Zhao, Y.; Levchuk, I.; Kalancha, V.; Stubhan, T.; Hauch, J.; Egelhaaf, H. J.; et al. Robot-based high-throughput screening of antisolvents for lead halide perovskites. *Joule* **2020**, *4* (8), 1806−1822.
(71) Foadian, E.; Yang, J.; Harris, S. B.; Tang, Y.; Rouleau, C. M.; Joy, S.; Graham, K. R.; Lawrie, B. J.; Hu, B.; Ahmadi, M. Decoding the Broadband Emission of 2D Pb-Sn Halide Perovskites through High-Throughput Exploration. *Adv. Funct. Mater.* **2024**, 2411164.
(72) Epps, R. W.; Bowen, M. S.; Volk, A. A.; Abdel-Latif, K.; Han, S.; Reyes, K. G.; Amassian, A.; Abolhasani, M. Artificial chemist: an autonomous quantum dot synthesis bot. *Adv. Mater.* **2020**, *32* (30), 2001626.
(73) Sadeghi, S.; Bateni, F.; Kim, T.; Son, D. Y.; Bennett, J. A.; Orouji, N.; Punati, V. S.; Stark, C.; Cerra, T. D.; Awad, R.; et al. Autonomous nanomanufacturing of lead-free metal halide perovskite nanocrystals using a self-driving fluidic lab. *Nanoscale* **2024**, *16* (2), 580−591.
(74) Biron, L. *Meet the Autonomous Lab of the Future*; 2023; newscenter.lbl.gov/2023/04/17/meet-the-autonomous-lab-of-the-future/.
(75) Hoogenboom, R.; Meier, M. A.; Schubert, U. S. Combinatorial methods, automated synthesis and high-throughput screening in polymer research: past and present. *Macromol. Rapid Commun.* **2003**, *24* (1), 15−32.
(76) Takeuchi, I.; Lauterbach, J.; Fasolka, M. J. Combinatorial materials synthesis. *Mater. Today* **2005**, *8* (10), 18−26.
(77) Yang, J.; Lawrie, B. J.; Kalinin, S. V.; Ahmadi, M. High-Throughput Automated Exploration of Phase Growth Behaviors in Quasi-2D Formamidinium Metal Halide Perovskites. *Adv. Energy Mater.* **2023**, *13* (43), 2302337.
(78) Slautin, B. N.; Liu, Y.; Funakubo, H.; Vasudevan, R. K.; Ziatdinov, M.; Kalinin, S. V. Bayesian Conavigation: Dynamic Designing of the Material Digital Twins via Active Learning. *ACS Nano* **2024**, *18* (36), 24898−24908.
(79) Wu, T.; Collins, L.; Zhang, J.; Lin, P.-Y.; Ahmadi, M.; Jesse, S.; Hu, B. Photoinduced bulk polarization and its effects on photovoltaic actions in perovskite solar cells. *ACS Nano* **2017**, *11* (11), 11542−11549.
(80) Liu, Y.; Kelley, K. P.; Vasudevan, R. K.; Ziatdinov, M.; Kalinin, S. V. Machine Learning-driven Autonomous Microscopy for Materials and Physics Discovery. *Microscopy and Microanalysis* **2023**, *29*, 1866−1867.
(81) Dang, Z.; Shamsi, J.; Palazon, F.; Imran, M.; Akkerman, Q. A.; Park, S.; Bertoni, G.; Prato, M.; Brescia, R.; Manna, L. In situ transmission electron microscopy study of electron beam-induced transformations in colloidal cesium lead halide perovskite nanocrystals. *ACS Nano* **2017**, *11* (2), 2124−2132.
(82) Musiienko, A.; Cizek, J.; Elhadidy, H.; Praus, P.; Higgins, K.; Dryzhakov, B.; Kanak, A.; Sureau, F.; Pipek, J.; Belas, E. Origin of defects and positron annihilation in hybrid and all-inorganic perovskites. *Chem. Mater.* **2022**, *34* (1), 297−306.
(83) Ledinský, M.; Löper, P.; Niesen, B.; Holovský, J.; Moon, S.-J.; Yum, J.-H.; De Wolf, S.; Fejfar, A.; Ballif, C. Raman spectroscopy of organic-inorganic halide perovskites. *journal of physical chemistry letters* **2015**, *6* (3), 401−406.
(84) Pool, V. L.; Dou, B.; Van Campen, D. G.; Klein-Stockert, T. R.; Barnes, F. S.; Shaheen, S. E.; Ahmad, M. I.; Van Hest, M. F.; Toney, M. F. Thermal engineering of FAPbI3 perovskite material via radiative thermal annealing and in situ XRD. *Nat. Commun.* **2017**, *8* (1), 14075.
(85) Higgins, K.; Valleti, S. M.; Ziatdinov, M.; Kalinin, S. V.; Ahmadi, M. Chemical robotics enabled exploration of stability in multicomponent lead halide perovskites via machine learning. *ACS Energy Lett.* **2020**, *5* (11), 3426−3436.
(86) Liu, Y.; Yang, J.; Vasudevan, R. K.; Kelley, K. P.; Ziatdinov, M.; Kalinin, S. V.; Ahmadi, M. Exploring the relationship of microstructure and conductivity in metal halide perovskites via active learning-driven automated scanning probe microscopy. *J. Phys. Chem. Lett.* **2023**, *14* (13), 3352−3359.
(87) Kalinin, S. V.; Ziatdinov, M.; Hinkle, J.; Jesse, S.; Ghosh, A.; Kelley, K. P.; Lupini, A. R.; Sumpter, B. G.; Vasudevan, R. K. Automated and autonomous experiments in electron and scanning probe microscopy. *ACS Nano* **2021**, *15* (8), 12604−12627.
(88) Liu, Y.; Yang, J.; Lawrie, B. J.; Kelley, K. P.; Ziatdinov, M.; Kalinin, S. V.; Ahmadi, M. Disentangling electronic transport and hysteresis at individual grain boundaries in hybrid perovskites via automated scanning probe microscopy. *ACS Nano* **2023**, *17* (10), 9647−9657.
(89) Yang, J.; LaFollette, D. K.; Lawrie, B. J.; Ievlev, A. V.; Liu, Y.; Kelley, K. P.; Kalinin, S. V.; Correa-Baena, J. P.; Ahmadi, M. Understanding the Role of Cesium on Chemical Complexity in Methylammonium-Free Metal Halide Perovskites. *Adv. Energy Mater.* **2023**, *13* (33), 2202880.
(90) Higgins, K.; Lorenz, M.; Ziatdinov, M.; Vasudevan, R. K.; Ievlev, A. V.; Lukosi, E. D.; Ovchinnikova, O. S.; Kalinin, S. V.; Ahmadi, M. Exploration of electrochemical reactions at organic-

inorganic halide perovskite interfaces via machine learning in in situ time-of-flight secondary ion mass spectrometry. *Adv. Funct. Mater.* **2020**, *30* (36), 2001995.
(91) Harvey, S. P.; Li, Z.; Christians, J. A.; Zhu, K.; Luther, J. M.; Berry, J. J. Probing perovskite inhomogeneity beyond the surface: TOF-SIMS analysis of halide perovskite photovoltaic devices. *ACS Appl. Mater. Interfaces* **2018**, *10* (34), 28541−28552.
(92) Van Der Maaten, L.; Postma, E.; Van Den Herik, J. Dimensionality reduction: A comparative review. *Journal of machine learning research* **2009**, *10* (13), 66−71.
(93) Lusher, S. J.; McGuire, R.; van Schaik, R. C.; Nicholson, C. D.; de Vlieg, J. Data-driven medicinal chemistry in the era of big data. *Drug Discovery Today* **2014**, *19* (7), 859−868.
(94) Chong, S. S.; Ng, Y. S.; Wang, H.-Q.; Zheng, J.-C. Advances of machine learning in materials science: Ideas and techniques. *Frontiers of Physics* **2024**, *19* (1), 13501.
(95) Rodrigues, J. F.; Florea, L.; de Oliveira, M. C. F.; Diamond, D.; Oliveira, O. N. Big data and machine learning for materials science. *Discover Materials* **2021**, *1* (1), 12.
(96) Slautin, B. N.; Liu, Y.; Funakubo, H.; Vasudevan, R. K.; Ziatdinov, M. A.; Kalinin, S. V. Bayesian Co-navigation: Dynamic Designing of the Materials Digital Twins via Active Learning. *ACS Nano* **2024**, *18*, 24898.
(97) Slautin, B. N; Pratiush, U.; Ivanov, I. N; Liu, Y.; Pant, R.; Zhang, X.; Takeuchi, I.; Ziatdinov, M. A; Kalinin, S. V Multimodal co-orchestration for exploring structure-property relationships in combinatorial libraries via multi-task Bayesian optimization. *arXiv* **2024**, arXiv:2402.02198.
(98) Kalinin, S. V.; Slautin, B. N.; Pratiush, U.; Ivanov, I. N.; Liu, Y.; Pant, R.; Zhang, X.; Takeuchi, I.; Ziatdinov, M. A. Multimodal Co-orchestration for Exploring Structure-Property Relationships in Combinatorial Libraries via Multi-Task Bayesian Optimization. *Microscopy and Microanalysis* **2024**, *30* (1), 344−346.
(99) Um, M.; Sanchez, S. L.; Song, H.; Lawrie, B. J.; Ahn, H.; Kalinin, S. V.; Liu, Y.; Choi, H.; Yang, J.; Ahmadi, M. Tailoring Molecular Space to Navigate Phase Complexity in Cs-based Quasi-2D Perovskites via Gated-Gaussian-Driven High-Throughput Discovery. *chemrxiv* **2024**, chemrxiv-2024-8qtk2.
(100) Tao, Q.; Xu, P.; Li, M.; Lu, W. Machine learning for perovskite materials design and discovery. *Npj computational materials* **2021**, *7* (1), 23.
(101) Deringer, V. L.; Bartók, A. P.; Bernstein, N.; Wilkins, D. M.; Ceriotti, M.; Csányi, G. Gaussian process regression for materials and molecules. *Chem. Rev.* **2021**, *121* (16), 10073−10141.
(102) Kalinin, S. V.; Lupini, A. R.; Vasudevan, R. K.; Ziatdinov, M. Gaussian process analysis of electron energy loss spectroscopy data: multivariate reconstruction and kernel control. *npj Computational Materials* **2021**, *7* (1), 154.
(103) Kanno, S.; Imamura, Y.; Hada, M. Alternative materials for perovskite solar cells from materials informatics. *Phys. Rev. Mater.* **2019**, *3* (7), 075403.
(104) Ziatdinov, M.; Liu, Y.; Kelley, K.; Vasudevan, R.; Kalinin, S. V. Bayesian active learning for scanning probe microscopy: From Gaussian processes to hypothesis learning. *ACS Nano* **2022**, *16* (9), 13492−13512.
(105) Hysmith, H.; Foadian, E.; Padhy, S. P.; Kalinin, S. V.; Moore, R. G.; Ovchinnikova, O. S.; Ahmadi, M. The future of self-driving laboratories: from human in the loop interactive AI to gamification. *Digital Discovery* **2024**, *3* (4), 621−636.

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