Scholars Journal of Physics, Mathematics and Statistics
Abbreviated Key Title: Sch J Phys Math Stat
ISSN 2393-8056 (Print) | ISSN 2393-8064 (Online)
Journal homepage: https://saspublishers.com

Cross-Disciplinary Research Gaps in Physical, Chemical, and Environmental Sciences: An Integrative Review from Nanotechnology to Wastewater Treatment, Renewable Energy, Artificial Intelligence, and Biomedical Engineering

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DOI: https://doi.org/10.36347/sjpms.2025.v12i09.001 | **Received:** 04.09.2025 | **Accepted:** 21.10.2025 | **Published:** 07.11.2025

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Abstract

Review Article

The world of scientific development turns more and more towards solutions, connected with chemistry, physics, and the environmental science. This integrative review comprises evidence synthesis in the areas of nanotechnology and advanced materials, wastewater treatment and environmental chemistry, renewable energy and electrochemistry, photonics and sensors, artificial intelligence to science, and biomedical engineering. We chart gaps in research by recurring theme: understanding of mechanisms at interfaces and defects not yet understood, measuring and benchmarking against interoperable standards, scaling-up, manufacturing, and reliability under realistic load, data infrastructure, modeling, and uncertainty quantification, design-through-deployment sustainability, safety, and ethics. In each field, bottlenecks of limited characterization of operando operation linking nanoscale structure to device-level performance, lack of harmonized metrics that would allow cross-laboratory comparison, and the lack of validated multiscale models that would allow bridging electronic or molecular description with continuum behavior, are the most intractable. The main emerging opportunities in the field of physics-informed machine learning, closed-loop automated experimentation, and openly shared datasets with a sound metadata and provenance. Translators often have limited practice translation capacity due to weak process windows, sustained complex matrix permanence, and inadequate exposure, equity, and end-of-life route consideration. The review concludes with the cross-cutting roadmap, which underlines near-term interlaboratory studies and reference materials, medium term interoperable datasets and reliable surrogate models and long-term integrated pilot testbeds which links performance targets and techno-economic and life-cycle studies. The work will help align researchers, students, and sponsors with high-leverage problems and reproducible solutions that grow the scientific understanding and allow to have a sustainable and real-world impact.

Keywords: Nanotechnology; Wastewater treatment; Renewable energy; Electrochemistry; Photonics and sensors; Artificial intelligence; Machine learning; Biomedical engineering; Operando characterization; Uncertainty quantification; Reproducibility; Life-cycle assessment; Techno-economic analysis.

Citation: Nisha Jabeen *et al*. Cross-Disciplinary Research Gaps in Physical, Chemical, and Environmental Sciences: An Integrative Review from Nanotechnology to Wastewater Treatment, Renewable Energy, Artificial Intelligence, and Biomedical Engineering. Sch J Phys Math Stat, 2025 Nov 12(9): 369-388.

1. INTRODUCTION & METHODS

Scientific progress increasingly hinges on cross-domain integration: the ability to connect mechanistic understanding, comparable measurement, robust data/ML practice, reliable scale-up, and sustainability/ethics into one coherent workflow. Yet between 2018 and 2025, evidence across physical, life, and computational sciences shows recurring structural gaps that slow discovery and reduce proposal credibility—especially for students preparing theses and applicants competing for scholarships. This review synthesizes that evidence to provide a practical playbook for early-career researchers: how to state a mechanism-driven question, design standards-aligned methods, evaluate models under realistic shifts, plan for scale-up and reliability, and anticipate the sustainability and governance constraints that funders increasingly require (Khenkin *et al.*,2020; Page *et al.*,2021; Rethlefsen *et al.*,2021; Collins *et al.*,2024; Barker *et al.*,2022; Sansone *et al.*,2019; Ovadia *et al.*,2019; Schwartz *et al.*,2019, 2020; Cancela-Outeda *et al.*,2024; Antunes *et al.*,2024).

We organize the synthesis around five gap types. First are mechanism gaps, where elegant hypotheses lack decisive tests or neglect dominant cross-couplings under realistic operating conditions. A vivid case is photovoltaic stability: until the community consolidated ISOS-based procedures, mechanisms behind efficiency loss were confounded by incomparable stressors, uncontrolled ambient conditions, and the entanglement of ionic and electronic processes. The 2020 consensus statement reframed stability as a protocolized, reportable construct, turning anecdotal degradation into comparable evidence (Khenkin *et al.*,2020). The lesson generalizes: if mechanisms are not probed under standardized, documented conditions, cross-lab comparisons—and therefore cumulative progress—stall.

Second are measurement/standards gaps, when similar questions are pursued with incompatible protocols or partial reporting. At the review level, PRISMA 2020 modernized evidence reporting (eligibility criteria, study flow, risk of bias), while PRISMA-S specified how searches must be documented (databases, full strings, dates, filters, deduplication), enabling independent reproduction of the evidence base (Page *et al.*,2021; Rethlefsen *et al.*,2021). For prediction models, TRIPOD+AI raised the floor on transparency across regression and ML, emphasizing data provenance, handling of missingness, calibration, and decision-analytic evaluation (Collins *et al.*,2024). Together, these frameworks convert “methods” from narrative description to auditable record—a shift that selection panels explicitly reward.

Third are data/ML gaps, including dataset shift, leakage, and missing uncertainty quantification. Large comparative studies show that both accuracy and calibration degrade under corruptions and distribution shifts, and ad-hoc fixes often fail; better practices include explicit shift testing, uncertainty-aware modeling, and clear separation of development and evaluation data (Ovadia *et al.*,2019; Collins *et al.*,2024). For students, this translates into concrete actions: pre-register splits where appropriate, report calibration alongside accuracy/F1, and document data lineage and preprocessing so others can replicate or extend the work.

Fourth are scale-up/reliability gaps, where impressive lab-scale results fail in deployment or cannot be reproduced. Here, openness and artifact quality matter as much as experimental design. Extending FAIR principles from data to research software (FAIR4RS) treats code, workflows, and containers as first-class research outputs—findable, accessible, interoperable, and reusable—so that results can be reused and audited beyond a single machine or lab (Barker *et al.*,2022; Sansone *et al.*,2019). Surveys of computational research echo the same theme: reproducibility falters without environment capture and executable documentation; conversely, structured repositories and persistent identifiers measurably improve reliability and uptake (Antunes *et al.*,2024).

Fifth are sustainability/ethics gaps, which increasingly determine what projects are fundable and deployable. The Green AI agenda reframes efficiency—energy, time, and hardware—as a research dimension on par with accuracy, advocating transparent “price tags” for compute and efficiency-aware model choices (Schwartz *et al.*,2019, 2020). In parallel, risk-based regulation (for example, analyses of the EU AI Act) clarifies obligations for high-risk and general-purpose AI, making governance plans (dataset stewardship, documentation, impact/risk assessments) essential components of credible proposals (Cancela-Outeda *et al.*,2024). For students and scholarship applicants, integrating these considerations signals operational maturity and alignment with funder expectations.

Purpose and scope. Against this backdrop, the purpose of this review is to map where cross-domain gaps persist (2018–2025) and to translate community guidance into actionable steps for student projects and scholarship dossiers. The scope is deliberately integrative: rather than exhaust domain-specific minutiae, we foreground standards, protocols, and evaluation practices that generalize across fields and can be learned and applied in coursework, theses, and early publications (Page *et al.*,2021; Collins *et al.*,2024; Barker *et al.*,2022).

Framework. The five-gap scaffold functions as a concept map that links explanatory depth (mechanism) with comparability (measurement/standards), rigorous inference (data/ML), external validity (scale-up/reliability), and societal constraints (sustainability/ethics). Conceptually, this aligns with transdisciplinary models of research that cycle through co-learning, conceptualization, investigation, implementation, and reflection—ensuring that method choices in one box (e.g., ML evaluation) are consistent with realities in the others (e.g., field reliability or governance) (Pineo *et al.*,2021).

Evidence synthesis. We followed PRISMA 2020 for reporting and PRISMA-S for search transparency. Databases included Web of Science Core Collection, Scopus, PubMed/MEDLINE, IEEE Xplore, and ACM Digital Library, supplemented by official registries and networks (PRISMA/EQUATOR, FAIRsharing). The window was 2018–2025, English language, covering peer-reviewed studies, consensus/guideline documents, and major community frameworks. Search strings combined domain and gap constructs; examples include: (“mechanism*” OR stability OR degradation) AND (protocol* OR “real-world” OR field), (“reporting guideline*” OR PRISMA OR TRIPOD OR FAIR4RS) AND (standard* OR reproducib*), (“dataset shift” OR “uncertainty calibration”) AND (benchmark* OR evaluation), (scale-up OR reliability OR reproducib*) AND (survey OR guideline*), and (“Green AI” OR “carbon footprint”) OR (“AI Act” AND governance) (Page *et al.*,2021; Rethlefsen *et al.*,2021). Titles/abstracts were screened for relevance to at least one gap type and for transferability (methods, standards, evaluations with cross-domain utility). Exclusions were pre-2018 items unless directly cited within a post-2018 update, non-scholarly commentary lacking methodological content, and duplicates. For each inclusion, we extracted domain, study/guideline type, addressed gap(s), key contributions (checklists, protocol steps, benchmark findings), and adoption signals (citations, community endorsements). To mitigate selection bias, we anchored the corpus on consensus statements and comprehensive evaluations (Khenkin *et al.*,2020; Page *et al.*,2021; Rethlefsen *et al.*,2021; Collins *et al.*,2024; Sansone *et al.*,2019; Barker *et al.*,2022; Ovadia *et al.*,2019; Antunes *et al.*,2024).

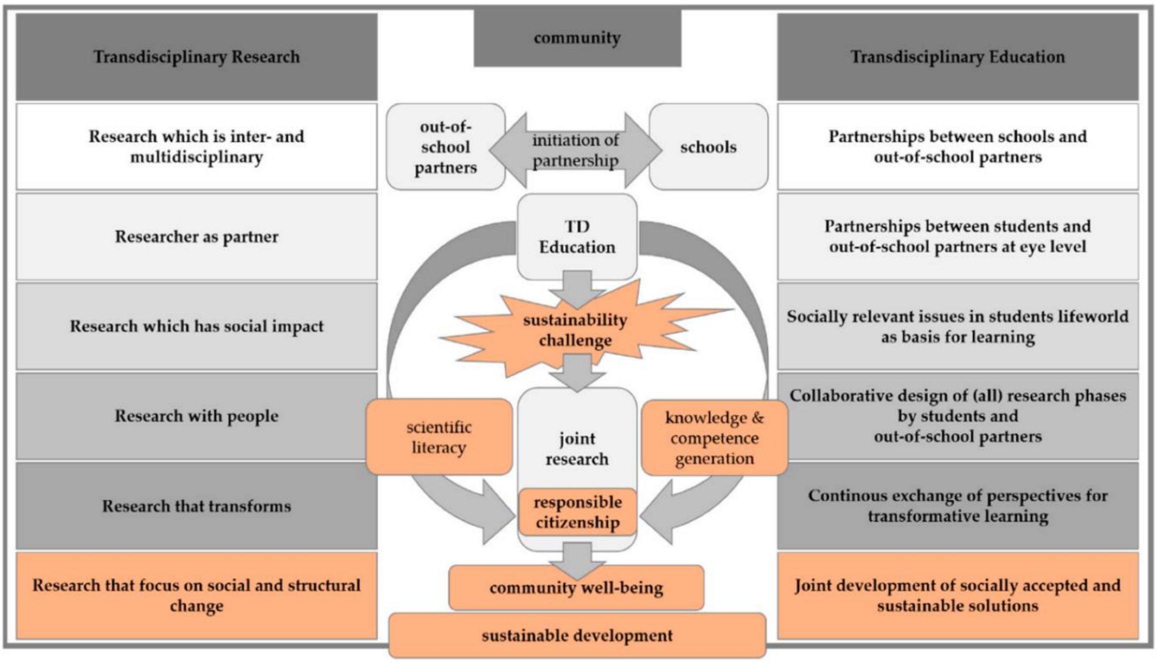

Figure1: Transdisciplinary Research–Education Framework for Sustainability

The diagram places community at the center, linking transdisciplinary research and education. A sustainability challenge triggers TD education and joint research between schools and out-of-school partners. These collaborations build scientific literacy and knowledge/competence, fostering responsible citizenship. The pathway aims for community well-being and sustainable development through socially accepted, transformative solutions.

2. Nanotechnology & Advanced Materials

2.1. Synthesis → Scale-up: From lab routes to continuous/green processes

Bench-top syntheses for nanocrystals, quantum dots, and 2D flakes achieve tight control over size, phase, and shape, but translation to kilogram-scale often fails because batch reactors obscure heat/mass-transfer limits, broaden residence-time distributions, and amplify impurity carryover. Continuous-flow platforms narrow those distributions, stabilize thermal profiles, and enable in-line monitoring/feedback—improving dispersity and run-to-run reproducibility compared with nominally identical batch recipes (Kusada & Kitagawa, 2022). In parallel, greener routes—biogenic reductants, lower-toxicity or bio-based solvents, low-temperature processing—reduce solvents and energy without sacrificing performance when paired with process analytical technology and design-of-experiments blocks that map the true process window (El-Seedi *et al.*,2024). Practically, students should (i) parameterize supersaturation/mixing/thermal ramps in small flow reactors, (ii) insert analytical checkpoints for residuals and unintended phases (e.g., ICP-MS, GC-MS, XRD/FTIR), and (iii) quantify lot-to-lot variability with replicated runs and statistical power.

Gaps: process windows; impurity control; reproducibility.

2.2. Interfaces & Ligands: Stability in air/water/biofluids

What sits on the surface governs performance and safety. Ligands that stabilize colloids in dry storage can desorb or exchange in humid air or aqueous/biofluid media, reshaping charge, corona composition, and reactivity. Operando probes—ambient-pressure XPS/XAS, liquid-cell TEM, bias-dependent optical/electrochemical spectroscopies—now track these transformations in real time, replacing post-mortem narratives with kinetic mechanisms (Wu *et al.*,2022; Bergmann *et al.*,2019). To make studies comparable, MIRIBEL provides minimum reporting for bio–nano experiments (size distributions from TEM/DLS; crystallinity; concentration units; media/buffer chemistry; dosing; zeta potential with pH/ionic strength; aging/storage conditions), while FAIR-aligned efforts encode such metadata for reuse across labs (Faria *et al.*,2018; Barker *et al.*,2022; Sansone *et al.*,2019). Treat zeta potential as a required stability readout (protocolized prep, triplicates, drift over days–weeks) and report explicit aging timelines with repeat sizing/charge.

Gaps: operando characterization; universal reporting (size, zeta, aging).

2.3. Defect Engineering: Defects → properties → device reliability

Across semiconductors, catalysts, and membranes, defects set non-radiative losses, ion migration, adsorption sites, and ultimately lifetime**.** The perovskite PV literature offers a template: map bulk/surface/interface defects to voltage loss, hysteresis, and stability; then passivate or exploit specific states to convert materials promise into reliable devices (Wang *et al.*,2024; Khenkin *et al.*,2020). A credible pipeline couples (i) multiscale models—DFT/MD for formation energies and barriers feeding drift-diffusion/device models under stress—with (ii) defect metrology standards—common excitation conditions for PL/TRPL, consistent trap-density extraction, and stability protocols aligned to realistic operation.

Gaps: multiscale models; defect metrology standards.

2.4. Safety-by-Design: Exposure, fate, and risk early in design

Safety and sustainability must be first-class objectives, not afterthoughts. The EU Safe-and-Sustainable-by-Design (SSbD) framework brings health, environment, and circularity criteria into materials R&D from the outset, while OECD work on nanomaterial test guidelines harmonizes characterization, dispersion protocols, dose metrics, and reporting so evidence travels across sectors (Caldeira *et al.*,2023; OECD, 2023). Predictive nano-QSAR/ML models are improving alongside curated datasets, enabling early hazard screening and prioritization of wet-lab tests; their credibility depends on clear descriptors, documented domain of applicability, and external validation under realistic exposure matrices (Ammar *et al.*,2024). In student projects, define plausible exposure routes (inhalation/dermal/aquatic), preselect harmonized test matrices (media, dose/time points), and log uncertainty just like any performance metric.

Gaps: predictive tox models; harmonized test matrices.

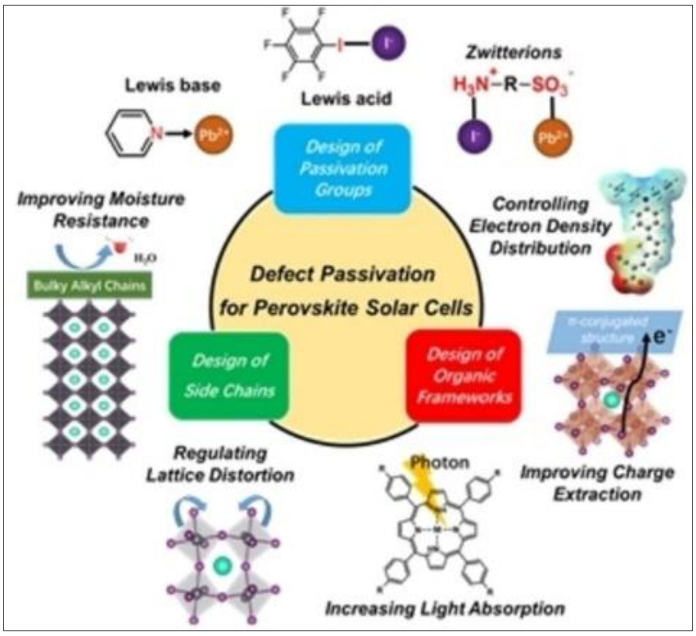

Figure 2. Defect-to-device pipeline — Defect passivation for perovskite solar cells: from molecule design to device performance

Figure 2. Defect-to-device pipeline. *Defect passivation for perovskite solar cells—from molecule design to device performance.* The schematic links chemical design (Lewis acid/base groups, zwitterions, side-chain engineering, frameworks) to targeted defect classes, showing how surface/bulk/interface passivation suppresses non-radiative recombination and improves device metrics (Wu, Li, Qi, Zhang, & Han, 2021).

Table 1: Cross-domain reporting checklist for nanomaterial studies (minimum to ensure comparability)

Category	Report this (minimum)	Notes/examples
Identity & composition	Precursor grades/purity; stoichiometry; phase (XRD/Raman); residuals/impurities (ICP-MS/GC-MS)	Include detection limits; note unintended phases
Size/shape/structure	Size distribution (TEM n≥200; DLS hydrodynamic size); morphology; crystallinity/defects (HRTEM/SAED; TRPL/EPR as relevant)	Provide raw images and analysis scripts
Surface & charge	Ligand identity and binding motif/coverage; zeta potential with pH/ionic strength and dispersant	Standardize sample prep; replicate across days
Environment & aging	Storage medium/temperature/light; aging timeline with periodic re-measures of size/charge/absorbance	Record precipitation, color/phase drift
Process conditions	Reactor type (batch/flow), temperature/pressure, mixing/residence time, atmosphere; yield and mass balance	For flow, include residence-time distribution
Reproducibility	Independent repeats (≥3), DoE/controls, lot-to-lot variability; statistical treatment	Share data and notebooks (FAIR/FAIR4RS)
Interactions & biointerface	Protein-corona protocol, media composition, endotoxin test; exposure route/scenario	Align to intended use and guideline where possible
Safety & sustainability	SSbD stage; solvent/energy footprint; waste handling; hazard screening (nano-QSAR + confirmatory tests)	Trace to OECD TGs or validated alternatives

3. Wastewater Treatment & Environmental Chemistry

3.1. Micropollutants/PFAS: Degradation pathways & by-products

Micropollutants—including pharmaceuticals, personal-care products, pesticides, endocrine disruptors, and industrial additives—persist in waters at ng L^{-1}–µg L^{-1} and frequently evade conventional treatment. Among these, per- and polyfluoroalkyl substances (PFAS) are outliers in persistence because the C–F bond (≈485 kJ mol^{-1}) resists electrophilic attack and most PFAS have surfactant-like mobility that frustrates capture. Modern destruction strategies therefore bifurcate into oxidative routes (•OH, $SO_4\bullet^-$, reactive halogen species, photolysis) and reductive routes (hydrated electrons e^-aq, strongly reducing cathodes/plasmas), with distinct intermediates and by-products. Advanced oxidation processes (AOPs) such as UV/H_2O_2, UV/persulfate, and ozone-based systems work well for many aromatic micropollutants by initiating hydroxylation, ring-opening, and carbonyl formation; however, for fully perfluorinated moieties these same conditions are inefficient and can even reveal hidden PFAS loads by converting precursors into terminal perfluoroalkyl acids (PFAAs). High-dose AOP studies report measurable increases in short-chain PFAAs (e.g., PFBA, PFPeA) despite apparent "removal" of unidentified PFAS, underscoring the need for fluorine mass balances rather than single-analyte removal (Ersan *et al.*,2024). For non-PFAS micropollutants, the same oxidation steps typically produce more polar fragments that a downstream bio-polishing step can mineralize; thus, for complex wastewaters, AOPs are most effective when they create biodegradability rather than attempting full mineralization in one unit.

The most compelling PFAS breakthroughs have come from reductive chemistry. Hydrated-electron systems (e.g., UV/sulfite) attack the α-C–F bond of perfluoroacyl groups, triggering stepwise defluorination and decarboxylation; carefully staged sequences achieve substantial fluoride release and measurable carbon mineralization in realistic matrices (Ren *et al.*,2021). A milestone demonstration showed low-temperature mineralization of perfluorocarboxylic acids by base-mediated activation in polar aprotic media, initiating cascades that ultimately yield fluoride and benign fragments—proof that PFAS defluorination can be chemically engineered without resorting to near-thermal-plasma extremes (Trang *et al.*,2022). Electrochemical routes now combine anodic oxidation (e.g., boron-doped diamond) for precursor destruction with cathodic or paired-cell reduction to accelerate defluorination; comprehensive surveys from 2018–2025 detail anode/cathode materials, cell hydraulics, faradaic efficiency, and durability constraints that still define scale-up feasibility (Xu *et al.*,2024).

Because by-products determine health risk and process credibility, monitoring must extend beyond the parent compound. For aromatic micropollutants, report aldehydes, carboxylates, and short diacids generated during partial oxidation, and couple these to biodegradability surrogates (BOD/COD, biodegradable DOC) to justify sequencing with biological steps. For PFAS, track short-chain and ultrashort species (e.g., trifluoroacetic acid) and close the fluorine balance via extractable organofluorine (EOF)**,** total organofluorine, and inorganic F^- so that mass is conserved even when transformation pathways split (Aro *et al.*,2022; Jiao *et al.*,2023; Ruyle *et al.*,2023). Nontarget high-resolution

MS adds an early-warning layer for unexpected transformation products and should be planned as a periodic check rather than an ad-hoc last step (Bugsel & von der Kammer, 2023).

Gaps—kinetics in real matrices; toxicity of intermediates. Rate constants measured in ultrapure water typically overpredict removal in natural waters. Natural organic matter (NOM), alkalinity (HCO_3^-/CO_3^{2-}), and halides (Cl^-/Br^-) scavenge radicals or re-route chemistry into less reactive carbonate/halogen radicals; turbidity and chromophores suppress UV fluence; metals and hardness create side reactions that impose hidden oxidant demand. Matrix-aware studies link these effects to energy demand (EE/O, kWh m^{-3}) and to by-product formation that can negate benefits (Li *et al.*,2022; Hübner *et al.*,2024). To convert this into practice, propose standard matrix panels—DOC/UV254 tiers, alkalinity tiers, halide tiers, and hardness tiers—and co-report intermediate toxicity using effect-based bioassays (e.g., oxidative stress, mutagenicity) so that "parent removal" does not mask risk transfer. In short, destruction chemistry is viable, but deployability hinges on kinetics and toxicology in the water you will actually treat.

3.2. *Hybrid Trains (AOP + Bio + Adsorption + Membranes): Design rules & control*

No single unit process is universally optimal for micropollutant control; hybrid trains that exploit complementary mechanisms routinely deliver higher resilience and lower life-cycle costs. The core principle is simple: use cheap, bulk steps to reduce UV shielding and oxidant/quenching demand; deploy AOPs to cut molecular "knots" that biology cannot; hand partially oxidized fragments to biological units for mineralization; polish with adsorption or membranes; and, for PFAS, pre-concentrate and destroy in small volumes rather than pushing raw flows through energy-intensive destructive units. In potable reuse, the canonical sequence—coagulation/filtration or biofiltration → UV-AOP (H_2O_2 or chlorine) → biological filtration or GAC—arose because DOC and UV-absorbing chromophores choke radical yield; reducing DOC upstream reduces EE/O and by-product risk downstream (Hübner *et al.*,2024). For halogenated precursors, it can be advantageous to place biological steps before oxidative units to limit halogenated by-products. For PFAS, adsorptive pre-concentration with GAC or ion-exchange followed by destruction in brines/RO concentrates (via electrochemical oxidation or advanced reduction) reliably lowers energy per m^3 treated while avoiding co-contaminant parasitics (Xu *et al.*,2024).

Sequence optimization hinges on (i) matrix-aware placement, (ii) controllability, and (iii) benchmarkability. UV/chlorine AOP (UV/Cl) illustrates all three. Radical speciation ($Cl\bullet$, $Cl_2\bullet^-$, $\bullet OH$) and quantum yields depend strongly on ammonia/chloramine chemistry, pH, and optical path; utilities that manage ammonia upstream or maintain chloramine steady state see more stable UV/Cl performance. A recent reuse-focused synthesis laid out implementer guidance (lamp selection, chlorine feed, ammonia management, by-product surveillance), emphasizing that UV/Cl is a train technology whose success depends on matrix conditioning and downstream biofiltration to scavenge oxidized fragments (Mackey, Hofmann, & Andrews, 2023; Chen, Mackey, & Andrews, 2024).

Design rules for control flow from a few measurable surrogates. Use UV254 and fluorescence EEMs to track aromaticity and adjust dose to a target EE/O; maintain oxidant residuals and monitor peroxydisulfate decay (if used) to infer radical availability; and couple finished-water analytics (target LC-MS/MS + periodic high-resolution nontarget) to confirm that "removal" does not merely reshuffle risk. For PFAS side loops, meter defluorination via F^- and report total/extractable organofluorine to capture transformation to ultrashort products. Control logic can be automated: if UVT drops below setpoints, divert to GAC or increase fluence; if oxidant residuals overshoot, trim dose; if brine PFAS exceeds a breakpoint, activate a destruction loop on regenerant streams. Photocatalytic membranes, ozonation-MBR synergies, and catalytic GAC show promise as reactive polishes, but gains shrink without real-time monitoring of membrane resistance growth and adsorber breakthrough.

Benchmarks—energy/chemicals per m^3. Report (i) EE/O for photochemical steps and kWh m^{-3} for electrochemical/plasma steps; (ii) oxidant dose (g m^{-3}); (iii) carbon cost (kg CO_2e m^{-3}) from electricity and chemicals; and (iv) finished-water outcomes: parent + sentinel transformation products (TPs), toxicity endpoints, and for PFAS, % defluorination and EOF. The IUPAC EE/O standard (Keen, Bolton, & Litter, 2018) remains the common currency for cross-reactor comparisons and should be cited with lamp type, path length, UVT, and reactor hydraulics.

Gaps—sequence optimization; energy/chemicals benchmarks. Most studies optimize within a unit process; few optimize the whole train against cost, energy, and carbon. Reported EE/O and kWh m^{-3} values often lack context (UVT, DOC, alkalinity, halides), making cross-study comparisons unfair. The field needs multi-site trials where identical trains are evaluated across standardized matrix panels, with co-reported EE/O, kWh m^{-3}, oxidant stoichiometry, and toxicity outcomes. Without that, utilities will continue to "locally" optimize and miss system-level minima.

3.3. *Membranes & Fouling: Materials, pretreatment, cleaning cycles*

Pressure-driven membranes (MF/UF/NF/RO) are the backbone of advanced trains because they offer deterministic separation and permit compact, modular design. Their Achilles' heel is fouling—a multi-mechanism phenomenon encompassing particulate/cake buildup, organic adsorption and pore blocking, inorganic scaling, and biofouling. Since 2018, material advances have targeted the first minutes of foulant–surface encounter (surface chemistry, charge, roughness) and the long tail of deposit maturation (hydrodynamics, pretreatment, cleaning). Zwitterionic and PEG-like coatings, nanocomposite skins (e.g., TiO_2, graphene oxide), and tailored polyamide chemistries can lower adhesion energies and water contact angles, delaying the onset of irreversible fouling. Ceramics offer higher chemical/thermal tolerance, enabling aggressive clean-in-place cycles. Yet field experience shows that operating conditions and pretreatment matter as much as surface science: inline coagulation, biofiltration, or powdered carbon upstream can transform a fragile system into a stable one by reducing foulant loading and shifting foulant character (Hübner *et al.*,2024).

Cleaning must match foulant type and membrane chemistry. For RO/NF, alkaline cleans target organic/biofouling; acid cleans remove carbonate/silica scalants; oxidants are potent but often incompatible with polyamide unless carefully controlled; ceramics tolerate harsher oxidants/temperatures. Good practice is to maintain normalized specific flux and salt passage within alarm bands and to blend scheduled cleans with condition-based triggers (ΔP, flux-decline rate). Plants increasingly deploy soft sensors and AI/ML predictors trained on SCADA telemetry (flow, pressure, conductivity, temperature, UV254) to forecast fouling and recommend setpoint changes (crossflow, flux, backwash/relax frequencies), but a common failing is non-transferability across sites due to unshared datasets and inconsistent influent reporting (Processes special issue reviews, 2024). When AOPs precede membranes, upstream radical chemistry can either help (depolymerize macromolecules) or hurt (create sticky fragments); sequence-specific pilot testing remains essential before lock-in.

Gaps—anti-fouling predictors; long-term field data. The literature is rich in lab-scale anti-fouling claims but thin on multi-year, multi-site demonstrations. Progress requires three things: (i) standardized challenge panels that vary NOM (DOC/SUVA), divalent cations (Ca^{2+}/Mg^{2+}), silica, particulates, and biogrowth potential to fairly rank membranes/coatings; (ii) open telemetry corpora to benchmark ML predictors with agreed inputs/targets (e.g., days-ahead TMP rise); and (iii) harmonized cleaning taxonomies (chemistry, dose, contact time, recovery) tied to material compatibility and life-cycle impacts. Absent these, "anti-fouling" remains a lab-specific label rather than a guarantee of stable energy per m^3 over years.

3.4. Real-World Variability: NOM/ions/co-contaminants

Whether a promising bench recipe becomes a reliable plant process is decided by the matrix**:** natural organic matter (NOM), alkalinity, halides, hardness, metals, particulates, and co-contaminants such as ammonia or nitrite. Between 2018 and 2025, a consistent picture emerged. NOM competes for photons, scavenges radicals, and forms coronas on adsorbents and membranes; alkalinity shifts radical equilibria, forming carbonate radicals ($CO_3{\bullet}^-$) with different selectivity; halides (Cl^-/Br^-) steer photo-halogen chemistry toward reactive halogen species or brominated organics; hardness/silica drives scaling; and co-contaminants rewire oxidant demand and by-product spectra. Multi-matrix AOP studies show order-of-magnitude swings in apparent kinetics and EE/O across matrices that would be indistinguishable by target load alone (Li *et al.*,2022). UV/Cl specifically is matrix-sensitive**:** chloramine photolysis pathways, ammonia/chloramine equilibria, and pH all modulate radical speciation and therefore energy demand and by-product risk; guidance for potable reuse now treats ammonia management as a prerequisite to stable UV/Cl operation (Mackey *et al.*,2023; Chen *et al.*,2024). Persulfate-based AOPs show a dual role for NOM: at low concentrations, NOM can mediate electron transfer or act as a photosensitizer; at typical watersheds' DOC, NOM is an efficient radical scavenger (Luo *et al.*,2024). Carbonate species can either buffer pH and stabilize reactive oxygen species or divert •OH to less reactive $CO_3{\bullet}^-$, depending on contaminant functionality and dose (Rayaroth *et al.*,2023).

To make results transferable, embed Standard Influent Panels into methods: at minimum, DOC/UV254 tiers (e.g., 1/3/6/10 mg L^{-1} with SUVA bands), alkalinity tiers (e.g., 50/150/300 mg L^{-1} as $CaCO_3$), halide tiers (Cl^- 0–250 mg L^{-1}; Br^- 0–0.5 mg L^{-1}), and hardness tiers (Ca^{2+}/Mg^{2+} 50–300 mg L^{-1}). For UV-based steps, report path length and UVT at the operating wavelength (including 222 nm if far-UVC is used). Couple performance to finished-water outcomes: parent + sentinel TPs, effect-based bioassays for oxidative stress and mutagenicity, and for PFAS, defluorination and organofluorine balances. Finally, replicate a subset of tests with reference NOMs (e.g., IHSS standards) so that other labs can reproduce your "matrix corners." Treating the matrix as a design variable rather than a nuisance is what enables generalizable design rules.

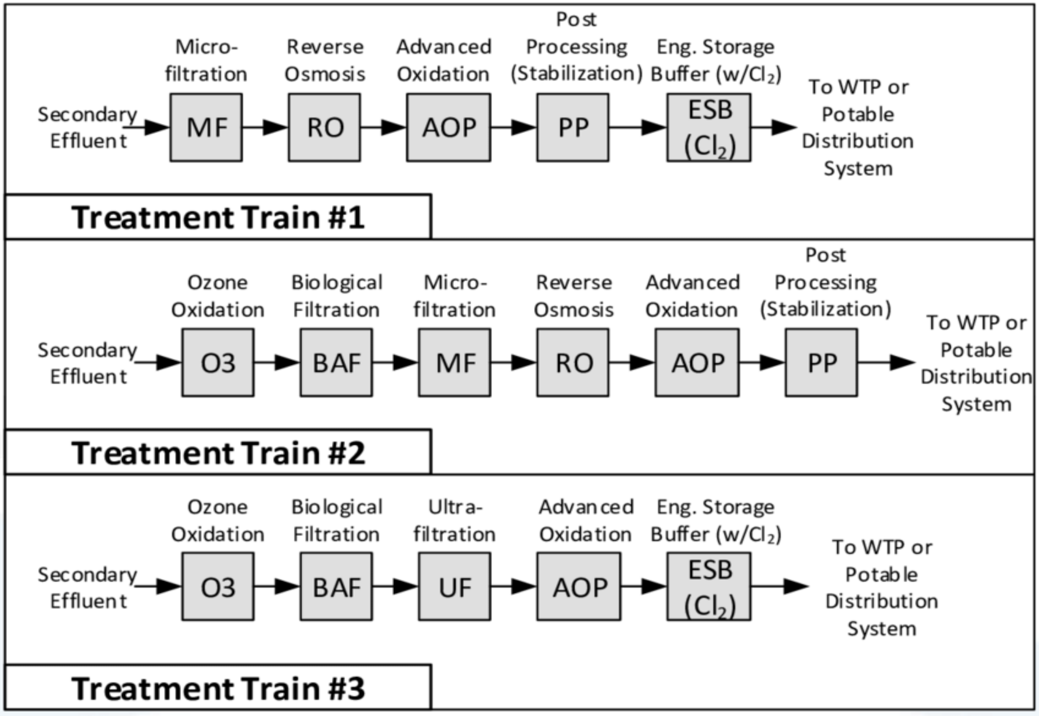

Figure 3: Process-train decision tree (reference trains for potable reuse).

Representative treatment trains used in direct potable reuse programs—e.g., (1) MF→RO→AOP and (2) O_3→BAF→MF/UF→RO→AOP—provide a backbone for decision-tree sequencing across AOP, bio, adsorption, and membranes. Use this as the template for branch choices driven by matrix tiers (UVT/DOC, alkalinity, halides, hardness), target classes (aromatic vs. PFAS), and energy/chemical benchmarks.

4. Renewable Energy & Electrochemistry

4.1. Batteries (Liquid & Solid): SEI/CEI chemistry; chemomechanics

Electrochemical performance and safety in both liquid-electrolyte Li-ion/Li-metal cells and solid-state batteries are governed by the structure, chemistry, and mechanics of interphases at anode (SEI) and cathode (CEI). From 2018–2025, three converging insights shape today's design rules. First, solvation and reduction pathways in the primary electrolyte determine SEI composition and morphology; high-donor, fluorinated, and localized-high-concentration electrolytes (LHCEs) bias reduction toward inorganic-rich, mechanically robust SEIs that suppress parasitic reactions and improve Coulombic efficiency. Second, cathode–electrolyte interphases form from oxidative electrolyte decomposition and salt anion participation, particularly at high-Ni layered oxides and high upper-cutoff voltages; CEI chemistry (e.g., M–F, oxyfluorides, sulfonates) governs impedance growth, oxygen release, and transition-metal dissolution. Third, chemomechanics—volume change, stress generation, fracture of active particles and interphases—co-drives aging, linking reaction heterogeneity to crack networks that expose fresh surfaces and accelerate SEI/CEI growth.

For solid-state batteries (SSBs)**,** Li penetration is now recognized as a mechanics-and-defects problem coupled to electrochemistry. Above a critical current density (CCD)**,** Li can thread along grain boundaries, pores, or mechanically weak interphases, even in "stiff" ceramics; local stress concentrators, electronic leakage, and void formation during stripping create conditions for filament nucleation. Practical stability therefore depends on (i) interphase engineering (lithiophilic interlayers; halide/oxide buffers; reactive wetting to reduce voids), (ii) microstructure control (dense electrolytes with low porosity and benign grain-boundary chemistry), and (iii) stack pressure and temperature that keep contact stable without crushing brittle ceramics. In liquid cells, analogous principles apply at softer length scales: SEI elasticity and yielding modulate how Li plates/strips and whether dendritic features are blunted or sharpened by the interphase.

Testing gaps remain. Despite progress, we lack standardized dendrite-onset descriptors that transfer across chemistries and formats. CCD is helpful but test-condition-sensitive (electrolyte thickness, temperature, pressure, areal capacity, pulse shape). Imaging-backed descriptors that report effective current density at constrictions, interphase fracture energy, and void evolution would translate better to pack-level risk. Likewise, calendar vs. cycle aging is frequently conflated. Calendar aging (open-circuit or low-rate storage at set SOC/temperature) follows Arrhenius-type kinetics dominated by SEI/CEI growth and transition-metal dissolution; cycle aging superposes mechanical stressors (lithiation-induced strain, shoulder reactions at high cutoff) and electrochemical stressors (plating/stripping, oxygen redox). Harmonized protocols should therefore separate these modes (fixed SOC ladders and temperatures for calendar; controlled depth-of-discharge, C-rate, and rest profiles for cycling) and report both with identical analytics (e.g., incremental capacity/voltage analysis, gas evolution, impedance spectroscopy) so models can disentangle mechanisms instead of fitting lumped fade.

4.2. Electrolyzers & Fuel Cells: Catalysts–membrane compatibility

Durability in PEM and AEM water electrolyzers and PEM/alkaline fuel cells hinges on chemical/thermal compatibility between catalysts, ionomers, and membranes under realistic load cycles. In PEM electrolyzers, OER catalysts (IrO_2, doped oxides) must resist transient high potentials, oxygen-rich environments, and acidic attack; dissolution/redistribution roughen catalyst layers and thin electronic pathways. At the same time, perfluorosulfonic acid (PFSA) ionomers and membranes face radical-driven scission (•OH, •OOH) and dehydration–rehydration cycles that embrittle backbones. Catalyst layers must therefore be co-designed with ionomer chemistry (side-chain length, acid capacity, radical scavengers) and pore architecture to sustain triple-phase boundaries without starving reactants or trapping O_2. In AEM electrolyzers, the durability bottleneck shifts to alkaline stability of cationic headgroups (e.g., quaternary ammonium β-elimination), carbonate management, and transition-metal dissolution/precipitation; matching catalyst supports and membranes (e.g., corrosion-resistant Ni/Fe/Co phases with stable poly(aryl piperidinium) or spirocyclic AEMs) is central to lifetime.

For PEM fuel cells, start–stop and load-cycling drive Pt and Pt-alloy dissolution, Ostwald ripening, and carbon support corrosion, while ionomer/membrane thinning accelerates peroxide/radical formation and pinhole growth. Impurity tolerance—NH_3, H_2S, SO_2, Cl^-, trace metals—remains a practical constraint; even ppb–ppm levels can poison active sites or shift reaction selectivity, so pre-treatment**,** filters, and operating windows (humidity/temperature) must be codified alongside catalyst choices. Emerging ultra-low-Ir PEM electrolyzers and PGM-free fuel-cell cathodes amplify compatibility stakes: supports, binders, and membranes must share electrochemical stability windows, gas/water transport characteristics, and interfacial adhesion across thermal and hydration cycles.

Gaps: (i) Durability under realistic load cycles (start-stop, ramping, dynamic electrolyzer operation with curtailed renewables) still lags steady-state tests; protocols need drive-cycle profiles (potential, current, RH, temperature) and synchronized analytics (dissolution via ICP-MS, EIS impedance mapping, tomography). (ii) Impurity tolerance libraries are incomplete; systematic challenge matrices (ammonia, sulfides, chlorides, silica, and transition metals at technology-relevant ppb–ppm) tied to recoverability (air/voltage hold, potential cycling) would convert one-off poisoning studies into engineering rules. (iii) Membrane–catalyst co-aging is under-reported; shared tests that capture mutual degradation (radicals from one layer attacking the other) will prevent incompatible pairings from entering pilots.

4.3. PV & PEC Stability: Light/heat/humidity/bias synergy

Device stability in photovoltaics (PV) and photoelectrochemical (PEC) systems emerges from the coupled action of light intensity/spectrum, temperature, humidity/water, and electrochemical bias. In perovskite PV, ion migration, interfacial reactions, and phase segregation are accelerated by electric fields and thermal stress; in Si and thin-film PV, metallization corrosion, encapsulant browning, and potential-induced degradation (PID) dominate. PEC devices layer additional stressors: electrocatalyst corrosion, gas-bubble management, and electrolyte reactivity at photoelectrode surfaces. The 2018–2025 period delivered two standardization thrusts. First, consensus protocols for perovskite stability (ISOS) formalized illumination, temperature, humidity, and maximum-power-point tracking (MPPT) testing so results are comparable beyond single-lab anecdotes. Second, PV standards (e.g., IEC 61215-2) tightened damp-heat, thermal-cycling, and UV exposure criteria, while PEC best-practice papers stressed reporting of stability metrics (e.g., time to 80% of initial photocurrent at 1-sun, electrolyte composition, pH, bias, and gas analysis).

The central message is synergy: stressing one axis at a time misleads. Elevated temperature often stabilizes perovskite ion transport (reducing hysteresis) yet accelerates decomposition and metallization diffusion; humidity may passivate certain surfaces at low levels but drives hydrolysis at high RH; bias stabilizes MPPT performance in some architectures yet triggers interfacial reactions elsewhere. Therefore, stability plans should reflect operational ensembles (e.g., outdoor diurnal cycling with irradiance/temperature/humidity histograms), not single-point soaks. A credible outdoor ↔ accelerated correlation requires matched spectra (AM1.5G or measured site spectra), temperature cycling, and encapsulation realism (glass/barrier choices, edge seals). For PEC, stability must couple photocurrent retention with Faradaic efficiency and gas crossover; catalysts and protective layers must be compatible with both electrolyte and illumination.

Gaps: (i) Cross-lab stability metrics remain heterogeneous. Report PCE retention curves under MPPT with identical binning (e.g., T, RH, irradiance), plus activation/conditioning histories; harmonize failure definitions (T_{80}, slope to knee point). (ii) Outdoor vs accelerated correlations are under-documented: many accelerated tests fail to replicate moisture/oxygen ingress pathways or realistic UV/thermal cycles; structured round-robin campaigns with identical samples across climates are needed. (iii) Bias-coupled stress (e.g., PEC under load, PV under reverse bias hot-spots) lacks standard recipes; include bias windows, duty cycles, and current set-points in every stability report.

4.4. Thermal Management & Efficiency: Interfaces, thermoelectrics

Across battery packs, power electronics, electrolyzers, fuel cells, and PV/PEC balance-of-system, thermal bottlenecks often set reliability and efficiency. Two fronts dominate: thermal interfaces and phonon engineering in disordered solids/complex alloys. On interfaces, performance is governed by contact resistance—a convolution of bulk TIM conductivity, bond-line thickness, wetting, roughness, and clamping pressure. Since 2018, high-conductivity fillers (graphene/graphite, hexagonal BN, metal nanowires) in compliant matrices have pushed through-plane conductivities upward while maintaining low modulus to conform to roughness; sintered metal TIMs and phase-change TIMs reduce bond-line thickness further. Yet metrology variance obscures fair comparison. Re-adoption of ASTM D5470 (reapproved within 2018–2025) and guarded-hot-plate variants—together with reporting of pressure–thickness–temperature maps—is restoring comparability. For field reliability, the key is aging under compression/thermal cycling (pump-out, dry-out, binder oxidation) and electrical properties (leakage, dielectric strength) for packs and inverters; reporting should couple thermal figures to creep/relaxation and dielectric metrics.

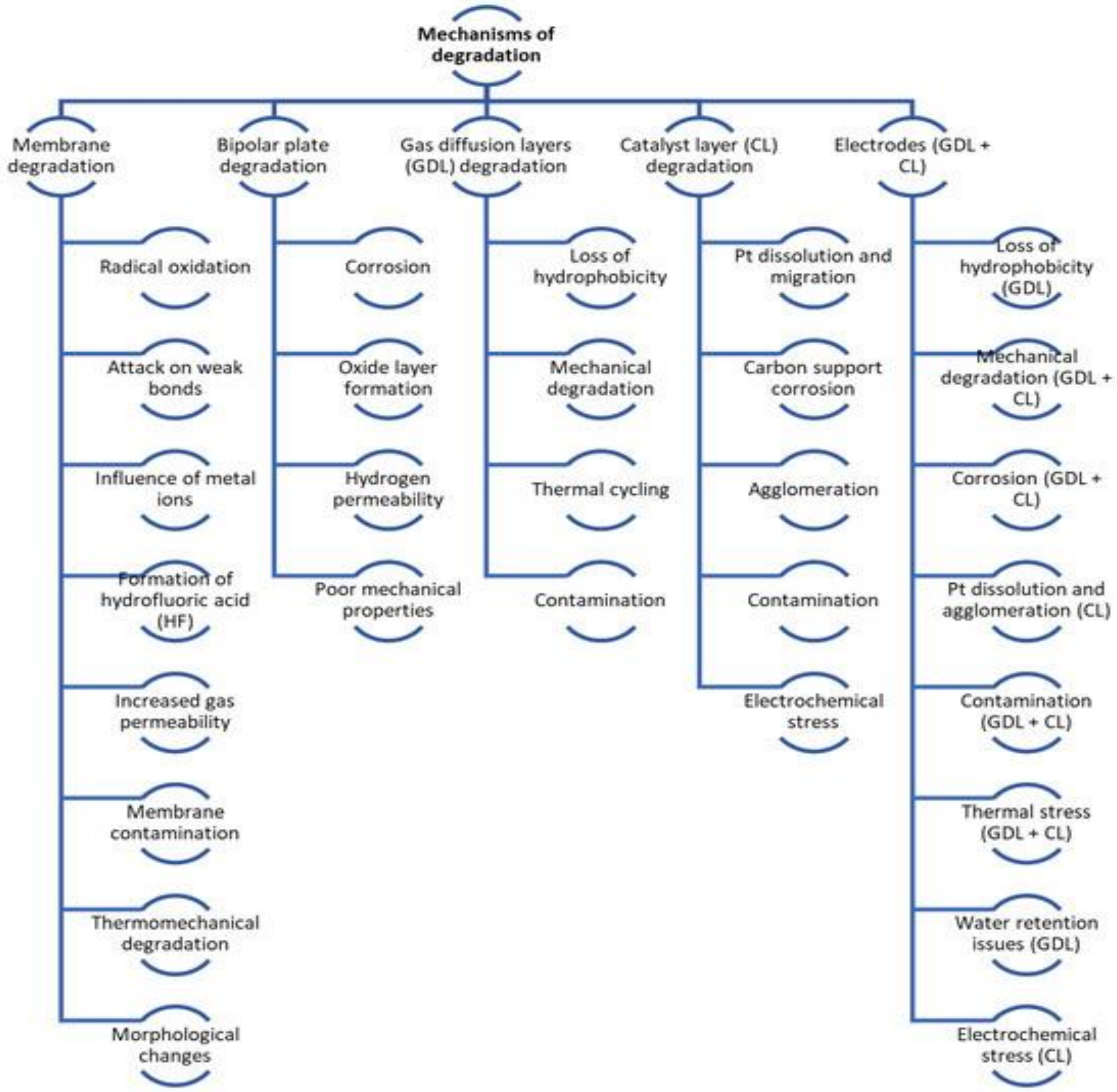

Figure 4: Degradation/failure tree across electrochemical energy devices

In phonon engineering, the focus has shifted from perfect crystals to disordered crystals, complex alloys, and amorphous networks where heat is carried by a mix of propagons (wave-like phonons), diffusons (diffusive vibrations), and locons (localized modes). 2018–2025 work leveraged alloy disorder, hierarchical nanostructuring, and rattler modes to depress lattice thermal conductivity without catastrophically scattering charge carriers—central for thermoelectrics. In parallel, amorphous and hybrid materials for encapsulation and membranes benefit from vibrational-mode engineering that lowers κ while preserving mechanical robustness and barrier properties. For systems engineering, the themes rhyme: (i) pursue low-κ where heat needs to be trapped (thermoelectric legs, thermal barriers), (ii) pursue ultra-low contact resistance where heat must be extracted (stacks, modules), and (iii) measure both with traceable, standardized methods.

Gaps: (i) Contact-resistance standards must be enforced in publications: specify test fixtures, clamping pressure, surface finishes, bond-line thickness, temperature, and aging, all per a recognized standard (e.g., ASTM D5470-17(2022)). (ii) Phonon engineering in disordered solids needs shared datasets linking structure (pair distribution functions, vibrational densities of states) to κ and mechanical/dielectric properties, enabling inverse design. (iii) System-level metrics—°C/W at interface + module thermal budget + control policy—should accompany material data so thermal upgrades translate to installed efficiency and lifetime.

Tree-style breakdown of operating stressors propagating to component-level mechanisms and observable performance loss. Branches illustrate how chemical/thermal/electrical stress drives interfacial reactions (e.g., ionomer or membrane attack, catalyst dissolution/redistribution), transport losses (gas/mass transport limits, contact resistance), and mechanical failure (cracks, agglomeration), culminating in symptoms such as impedance rise, voltage decay, and efficiency loss. Although drawn for a PEM fuel cell, this hierarchy maps directly to batteries (SEI/CEI growth, Li penetration, contact aging), electrolyzers (membrane/ionomer scission, catalyst shedding), and PV/PEC devices (encapsulant/catalyst degradation, series-R growth). *Source (APA, no link):* Foniok, K., *et al.*, (2025).

5. Photonics, Sensors & Optoelectronics

5.1. Perovskite LEDs/Detectors: Ion migration, blue/UV stability

Metal–halide perovskites have transformed visible-light emitters and detectors, but device ceilings are still set by ionic motion and interfacial reactivity under coupled bias–light–heat stress. In LEDs, halide-vacancy hopping and mobile A-site ions ($MA^+/FA^+/Cs^+$) distort the internal field, induce spectral drift, and catalyze interfacial decomposition of transport layers; the effect intensifies for blue/near-UV devices because higher photon energy, Cl/Br-rich alloys, and quasi-2D phase distributions amplify non-radiative pathways and phase segregation (Li *et al.*,2022; Zhao *et al.*,2024). Stabilizing the electric double layer using robust 2D/3D heterostructures, halide-binding ligands, and low-polarity, oxidation-resistant transport layers extends T_{50}, yet deep-blue PeLEDs still exhibit luminance-dependent drift (Li *et al.*,2022; Zhao *et al.*,2024).

Perovskite photodetectors show parallel physics: high-field operation promotes ion migration, dark-current growth, and interfacial redox, whereas photovoltaic/zero-bias architectures using thick single crystals or 2D perovskites suppress ion-migration-driven instabilities and reduce noise, enabling long-term imaging (Sakhatskyi *et al.*,2023; Liu *et al.*,2024).

Gaps—operando bias-light maps; encapsulation chemistries. The field would benefit from standardized operando maps that sweep bias, photon flux/spectrum, temperature, and humidity while tracking EL/PL spectra, EQE, dark current, and impedance to decouple ionic from electronic dynamics (Li *et al.*,2022). Encapsulation remains chemistry-limited: barriers must block H_2O/O_2 and acidic volatiles while remaining ion-inert under blue/UV; UV-hard silicones/urethanes, stack-compatible getters, and low-ionic-content adhesives are promising but under-reported for PeLEDs and detectors (Zhao *et al.*,2024).

5.2. Silicon Photonics & Packaging: Co-packaged optics, reliability

At 51.2–102.4 Tb/s switch generations, co-packaged optics (CPO) reduces electrical I/O loss and energy/bit by co-locating photonics with the ASIC, shifting reliability to a multi-material stack (PICs, III–V gain, micro-bumps, underfills/adhesives, LTCC/organic interposers, TIMs, fiber attach). Primary risks mirror advanced electronics packaging: CTE mismatch concentrates strain at underfill and bump interfaces; underfill chemistry and cure history govern moisture uptake, modulus growth, and adhesion; and adhesive bonds at fiber, microlens, and lid joints age via thermo-oxidation, plasticization, and moisture-assisted hydrolysis (Bender *et al.*,2024; Gao *et al.*,2025). Device-level constraints compound these risks—laser temperature windows, adhesive wicking near facets, and 3D-package warpage that perturbs fiber–waveguide alignment—so cooling design (liquid cold plates; high-κ TIMs) must be co-optimized with alignment stability and material selection (Herrick, 2025; Gao *et al.*,2025).

Gaps—high-heat-flux materials; bond/adhesive aging. Local heat fluxes near 1 kW cm^{-2} demand TIMs combining sub-100-µm bond-lines, high through-plane κ, dielectric strength, and creep resistance—traits rarely co-optimized in optical-grade materials (Gao *et al.*,2025; Wu *et al.*,2025). Long-horizon aging datasets for epoxies/silicones/hybrids under combined temperature–humidity–optical flux are sparse, and "photonic contamination" (outgassing, refractive-index drift, fluorescence) lacks shared test recipes (Plachý *et al.*,2025; Bender *et al.*,2024).

5.3. Sensors (Electrochemical/Optical/Bio): Selectivity & drift

Selectivity and drift are the twin constraints for long-lived chemical and biosensors in real matrices (biofluids, food, wastewater, air). Electrochemical sensors encounter non-specific adsorption, redox interferents, and biofouling; optical sensors contend with background fluorescence, scattering, and photobleaching. Two design philosophies have matured. First, antifouling interfaces—zwitterionic brushes, peptide/saccharide coatings, slippery composites, hydrogels—sustain sensitivity by resisting protein and cell adhesion without blocking transport (Kourti *et al.*,2024). Second, calibration-free/self-calibrating readouts convert environmental fluctuation into common-mode noise: ratiometric signals, dual-frequency or kinetic interrogation of electron-transfer rates, and internal standards reduce apparent drift (Yang *et al.*,2018; Abeykoon *et al.*,2024). ML-assisted filtering and transfer learning now track drift, compensate matrix shifts, and output uncertainty bands, pushing sensors from one-off demos to deployable networks with declared error bars (Zhao *et al.*,2025; Yan *et al.*,2024).

Gaps—antifouling surfaces; calibration-free methods & UQ. Field-ready antifouling requires standardized fouling challenges (protein panels, whole blood/serum, wastewater fractions) and long-horizon soaks with cyclic temperature and flow; many coatings succeed in single-protein assays but fail against mixed biofilms (Kourti *et al.*,2024). For calibration-free sensing, pair ratiometric/kinetic readouts with formal uncertainty quantification—e.g., hierarchical Bayesian models or bootstrap confidence intervals that ingest raw voltammograms or spectra, propagate drift-compensation steps, and report credible intervals rather than point estimates (Abeykoon *et al.*,2024; Zhao *et al.*,2025).

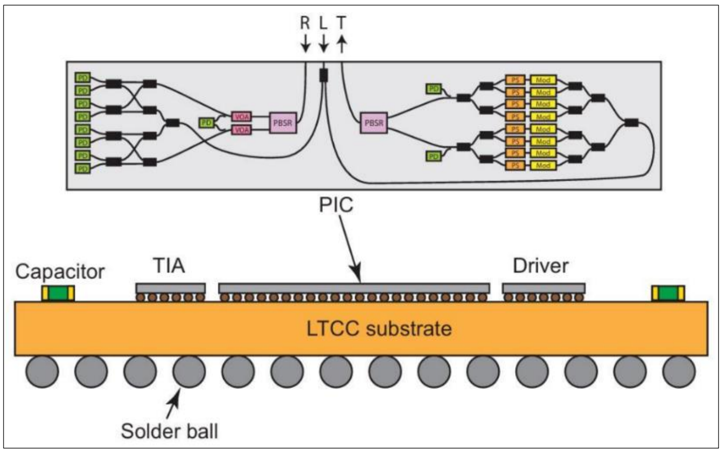

Figure 5. Packaging stack reliability map (co-packaged optics cross-section as a reliability template)

Cross-sectional schematics of hybrid optical packages on fan-out wafer-level platforms illustrate the stacked materials and interfaces—PIC, driver/TIA, LTCC/organic substrates, micro-bumps, underfill/adhesives, and optical attach—where thermomechanical, moisture, and chemical stress concentrate. Use this anatomy to map failure risks (CTE mismatch, bond-line aging, delamination, and fiber/connector creep) and to place sensors/controls for prognostics.

AI FOR SCIENCE & DATA INFRASTRUCTURE

PHYSICS-INFORMED ML: CONSERVATION/CAUSALITY CONSTRAINTS

Physics-informed machine learning (PIML) blends mechanistic priors with statistical learning so models respect what we already know about nature while still fitting complex data. The most common route imposes soft constraints by adding PDE residuals, boundary/initial conditions, or conservation penalties to the loss; this is the logic behind physics-informed neural networks (PINNs) and many of their successors. Because the residual term couples predictions to differential operators, the network "pays" for violating mass, momentum, charge, or energy budgets, making it a better citizen under sparse supervision and enabling inverse problems (parameter identification, hidden forcing) as naturally as forward simulation (Raissi, Perdikaris, & Karniadakis, 2019; Karniadakis *et al.*,2021; Wu, Yu, & Huang, 2024). A complementary route uses hard constraints: architectures that are *born* conservative—Hamiltonian/Lagrangian networks preserve symplectic structure; divergence-free layers restrict flows; and equivariant networks encode symmetries (translations/rotations/parity) so small datasets are amplified by group structure (Ma & Ma, 2023; Sánchez Cruz *et al.*,2024).

Beyond state prediction, many scientific tasks learn operators—maps from functions to functions (e.g., forcing → solution). Neural operators such as the Fourier Neural Operator (FNO) and DeepONet learn these maps directly and generalize across meshes, parameters, and boundary conditions, providing orders-of-magnitude speedups for surrogate modeling and design loops (Li *et al.*,2021; Kovachki, Lanthaler, & Mishra, 2021; Lu *et* *al.*,2021). Operator learning also creates a natural place to encode **causal constraints:** if we treat interventions (boundary changes, source terms) as inputs, the learned operator can be stress-tested with do-like perturbations and penalized when it breaks invariants or yields non-physical counterfactuals.

Small-data robustness hinges on three levers. First, structure priors—symmetry/equivariance; conservative layers; admissibility regions—shrink hypothesis space so we need fewer labels. Second, multi-fidelity training couples high-accuracy but scarce simulations/experiments to coarse or inexpensive models; consistency losses tie the scales together. Third, active sampling targets the most informative experiments or simulations using acquisition functions that explicitly value physics residuals, uncertainty, or controllability. When data are truly scarce, Gaussian processes with physics-aware kernels or low-rank/Koopman models still set strong baselines; their calibrated uncertainties often outperform deep nets for extrapolation.

OOD detection is not optional in science. Distribution shift appears whenever we change operating conditions or apply a surrogate outside its training envelope. Add runtime sentinels**:** (i) statistical detectors (energy-based scores, feature-space distances, density models), (ii) conformal prediction to produce calibrated prediction sets/intervals with finite-sample error guarantees, and (iii) physics monitors (PDE residuals, conservation gaps, monotonicity and positivity checks). The best practice is to fuse them: gate decisions on both uncertainty and residual; when either is high, fall back to a slower but trusted solver or trigger a new experiment (Angelopoulos & Bates, 2023; Theunissen *et al.*,2025; Zhao, Xu, & Wang, 2025).

Gaps—robust small-data learning; OOD detection. Benchmarks still favor abundant labels or synthetic data that share the generator with the test set. We need small-N, non-i.i.d. benchmarks with *documented physics* and held-out regimes to stress causal and OOD claims. And we need reporting standards that always ship uncertainty, residual diagnostics, and decision rules, not just point accuracy (Wu *et al.*,2024).

5.4. Data Standards (FAIR): Schemas, metadata, provenance

The FAIR principles—Findable, Accessible, Interoperable, Reusable—now extend beyond datasets to research software and entire workflows. FAIR4RS reframes software as a first-class research object, emphasizing persistent identifiers (DOIs, ORCID), explicit licensing, machine-readable metadata, and versioned provenance so computational results can be reproduced and cited with the same rigor as samples or spectra (Barker *et al.*,2022). On the data side, cross-domain practice is coalescing around a few pillars:

- Community catalogs + schemas. For bioimaging, OME-NGFF/OME-Zarr delivers cloud-native chunked storage and common metadata that keep 3D/5D images FAIR at scale (Moore *et al.*,2021, 2023). In photon/neutron science, NeXus defines a shared HDF5-based schema for instruments, events, units, and experimental state, easing multi-facility analysis. In materials science, NOMAD Metainfo provides an extensible schema that harmonizes computational and experimental records; FAIRmat tutorials show how to author custom sections and parsers so lab-native formats map to open representations (Sbailò *et al.*,2022).
- Provenance. The W3C PROV family (PROV-DM/PROV-O) gives a standard vocabulary—entities, activities, agents—to link raw inputs, processing steps, and outputs. Recent "Common Provenance Model" work demonstrates PROV-aligned patterns that stitch together wet-lab, simulation, and analysis steps so you can audit a figure or a trained model end-to-end (Moreau & Groth, 2013; Wittner *et al.*,2023).
- Packaging & exchange. RO-Crate wraps datasets, software, and workflows into a machine-actionable "crate" with JSON-LD metadata, making it trivial to ship complete, citable research objects between repos, HPC, and cloud (Soiland-Reyes *et al.*,2022).
- Open benchmarks. Discipline-specific, open testbeds are the fastest path to shared progress: Matbench curates 13 materials tasks with a public leaderboard; the Open Catalyst datasets (OC20/OC22) provide massive DFT relaxations and energies for catalysis; and MLCommons Science is pushing for standardized, FAIR benchmarks and metadata across experimental sciences (Dunn *et al.*,2020; Tran *et al.*,2023; MLCommons, 2024–2025).

Gaps—cross-domain ontologies; open benchmarks. Most schemas are domain-siloed**;** cross-walks between, say, NeXus beamline logs and NOMAD materials workflows, or OME metadata and reaction notebooks, are ad hoc. We need cross-domain ontologies (units, sample provenance, instrument states) and profiles that pin down ambiguous fields (concentration units; temperature ramps; uncertainty). On benchmarks, communities like catalysis and materials have strong public suites; others (electrochemistry, soft matter, bioassay kinetics) need open, license-clean datasets with defined splits, uncertainty labels, and reproducible baselines.

5.5. Closed-Loop Labs & Automation: Active learning in wet/dry labs

A closed-loop lab (a.k.a. self-driving lab) links experiment, simulation, and ML into a continuous cycle: plan → make → measure → learn → plan. In chemistry and materials, modern platforms combine automated synthesis/processing with active learning**—**most often Bayesian optimization (BO)**—**to explore high-dimensional recipes with far fewer trials than grid search, while respecting safety and resource constraints (Tom *et* *al.*,2024; Di Fiore *et al.*,2024). BO's surrogate models (Gaussian processes, ensembles, neural operators) provide posterior means and uncertainty, and acquisition rules (expected improvement, UCB, knowledge gradient) trade off exploitation vs. exploration. For discovery problems, generative models can propose candidates that BO then prioritizes for synthesis, closing the loop between generative design and physical validation (Loeffler *et al.*,2024).

In practice, durable closed loops depend on two under-appreciated layers. First is instrument interoperability**.** Orchestrating pumps, robots, sensors, and analyzers across vendors requires standard vocabularies and protocols. SiLA 2 (HTTP/2-based) exposes device capabilities as services, enabling discovery, control, and monitoring with consistent semantics; the SiLA 2 Manager demonstrates multi-device integration in real labs (Bromig *et al.*,2022). At the protocol level, Autoprotocol and the newer Laboratory Automation Protocol (LAP) specify steps in a machine-readable way so recipes can be executed, versioned, and audited across sites (Anhel *et al.*,2023). Without these, active learners stall on glue code rather than science. Second is data plumbing**:** results must be written in FAIR formats with PROV-compatible provenance and RO-Crates so experiments can be replayed, branched, and peer-reviewed.

Uncertainty-aware optimization is the other pillar. Scientific objectives are noisy, heteroscedastic, and sometimes censored (e.g., failed synthesis, no signal). Good loops (i) model measurement noise explicitly; (ii) replicate adaptively where uncertainty is high; (iii) incorporate constraints (toxicity, cost, process limits) via probabilistic feasibility models; and (iv) use robust BO to optimize worst-case or risk-aware objectives across environmental variability (Foldager *et al.*,2023). For hybrid wet/dry programs, multi-fidelity BO fuses fast simulations (coarse DFT, empirical models) with slower experiments and penalizes simulation bias using learned discrepancy terms. Finally, stopping rules should be statistical (credible gap to the incumbent, expected regret thresholds), not ad hoc.

Gaps—instrument interoperability; uncertainty-aware optimization. Vendor ecosystems still fragment interfaces; even with SiLA 2 or Autoprotocol/LAP, coverage is partial and feature models diverge. Communities should publish capability profiles (what verbs a device must speak), plus reference implementations and conformance tests. On optimization, we lack benchmarks with real-world noise and ground-truth optima where algorithms can be compared fairly; many studies report one-off case studies without uncertainty or feasibility accounting. The way forward is shared open loops**:** simulated "digital twins" with tunable noise + a few physical tasks anyone can run (microfluidic synthesis, simple electrochemistry), all shipped with schemas, provenance, and leaderboards.

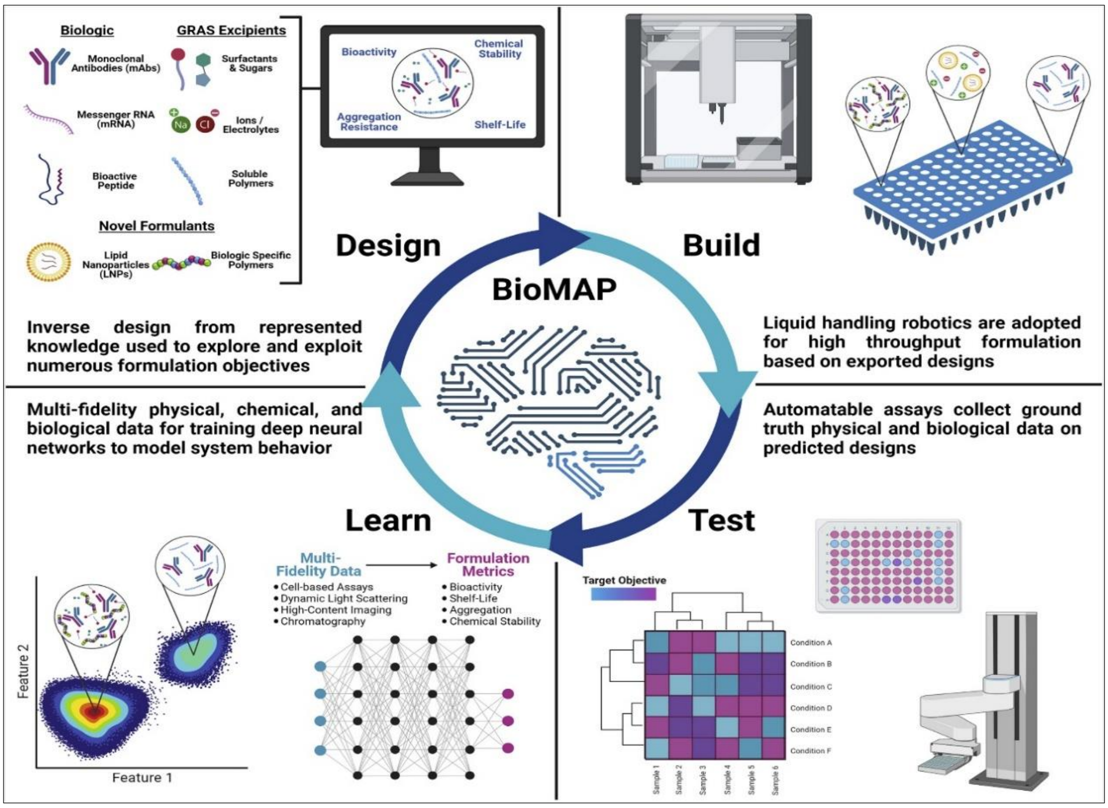

Figure 6: Experiment ↔ simulation ↔ ML loop (self-driving lab template)

A closed-loop Design–Build–Test–Learn schematic showing ML proposing candidates with uncertainty, automated instruments executing experiments, and results feeding back to update models—exactly the flow for experiment ↔ simulation ↔ ML with active-learning acquisition. Use this anatomy to annotate your stack (e.g., SiLA 2/Autoprotocol/LAP control; FAIR metadata with PROV/RO-Crate; multi-fidelity simulators providing priors). Source (APA): Tamasi, M. J., & Gormley, A. J. (2022). *Biologic formulation in a self-driving biomaterials lab*. *Cell Reports Physical Science, 3*(9), 101041.

6. Biomedical Engineering & Biophysics

6.1. Biomaterial–Immune Interface: Long-term integration

Long-term integration of implants, scaffolds, and wearable/ingestible sensors is governed by the biomaterial–immune interface. Within minutes, a dynamic protein corona forms and reorganizes; within hours to days, neutrophils and monocyte-derived macrophages interrogate the surface; over weeks to months, fibroblasts and myofibroblasts can encapsulate the device and throttle mass transfer—or, if properly guided, promote constructive remodeling. Recent work shows that immuno-instructive surfaces bias macrophage phenotypes and limit fibrosis using chemistry (e.g., zwitterions, catechols), topography (nanoscale roughness), and controlled release of pro-resolving mediators (Amani *et al.*,2024). Equally important, mechanobiology shapes fate: macrophages and fibroblasts sense stiffness and strain; stiffer or constrained interfaces favor pro-fibrotic activation and persistent foreign-body response (Ni *et al.*,2023). The design rule is therefore twofold: tune both chemical cues and mechanical boundary conditions to achieve durable integration.

Scale and loading amplify failure modes. Micromotion, curvature, and contact forces focus stresses that recruit myofibroblasts and thicken capsules; allometric analyses suggest that small-animal successes may overestimate human performance unless loads and geometry are matched (Padmanabhan *et al.*,2023). Interface-focused solutions—such as adhesive anti-fibrotic interlayers that conform to wet tissue and deliver local cues—have reduced capsule formation across multiple organs in vivo, pointing to interface engineering rather than wholesale bulk-material swaps as a pragmatic path to longevity (Wu *et al.*,2024).

The persistent challenge is predictive in vitro ↔ in vivo correlation (IVIVC)**.** Classical monoculture assays on static plastic poorly capture opsonization dynamics, cytokine crosstalk, and tissue mechanics. Organ-on-chip and organoid systems that integrate immune trafficking (endothelium → interstitium), pulsatile flow, and tunable stiffness/strain yield richer IVIVC for adsorption, macrophage polarization, and fibrotic signaling (Van Os *et al.*,2023). For comparability, reports should specify corona protocols, flow/shear, ECM composition and stiffness, cyclic strain, co-culture timing, and, when possible, paired in vivo readouts (capsule thickness, cell composition, cytokines) gathered under matched mechanics and surface chemistry.

Gaps. (i) Validated IVIVC panels that map chip/organoid outputs to long-term human outcomes remain scarce; multi-site ring trials bridging standardized chips, animal models, and explant histology are overdue. (ii) Mechanobiology in design control is under-reported; submissions should include in situ stiffness, expected micromotion, and mitigation strategies (compliant interlayers, soft-hard transitions) that keep cells in pro-resolving regimes.

6.2. Targeted Delivery & Nanocarriers: Transport in heterogeneous tissues

“Targeting” fails when transport fails. Heterogeneous interstitial flow, elevated interstitial fluid pressure (IFP), abnormal vasculature, and dense extracellular matrix (ECM) create spatially variable drug exposure, even for carriers that bind the right receptors. Tumor and inflamed-tissue mechanics—solid stress, matrix crosslinking, vessel compression—limit convection and flatten gradients (Stylianopoulos *et al.*,2018). Critically, patient-to-patient variability in microvascular density, IFP, and ECM architecture dominates outcomes; a carrier that excels in one lesion can underperform in another despite identical dosing (Tehrani *et al.*,2024). Multiscale models that couple blood flow, vessel leakiness, interstitial transport, and binding kinetics, seeded by imaging (DCE-MRI, CT, ultrasound elastography) and biopsy-derived ECM metrics, now support patient-specific strategies and are beginning to show clinical promise (Salavati *et al.*,2025).

For nanocarriers and depots, spatiotemporal release must be co-designed with transport. Responsive chemistries (pH, redox, enzymes, hypoxia) can synchronize payload release to local cues, but only if access and residence are adequate. Modeling has matured from polymer-network diffusion to tissue-scale convection–diffusion–reaction and organ-scale PBPK frameworks; paired with uncertainty-aware inference (Bayesian calibration; discrepancy terms), these tools identify when to favor rapidly diffusing small molecules, ECM-penetrating soft nanoparticles, or pre-treatments (e.g., hyaluronidase, angiotensin-pathway drugs) that lower IFP and open transport pathways (Yoon *et al.*,2020).

What to report for transferability: (i) Tissue mechanics (IFP, elastic modulus proxies), (ii) vascular metrics (perfusion, microvessel density), (iii) ECM descriptors (collagen/HA content and alignment), and (iv) single-cell exposure where feasible (mass-spectrometry imaging, single-cell PK). With these, investigators can distinguish chemistry-limited from transport-limited failure and quantify patient variability rather than treating it as noise.

Gaps. (i) Widely adopted spatiotemporal release models that couple realistic tissue mechanics and binding are still rare in preclinical packages; open datasets with paired imaging and outcomes would accelerate convergence on credible models. (ii) Prospective handling of patient variability is uncommon; adaptive dosing and stratified trials guided by imaging surrogates of IFP/ECM are natural next steps.

6.3. Point-of-Care Diagnostics: Stability, user variability, real-world performance

Point-of-care (POC) diagnostics succeed only when analytical design and deployment realities co-evolve. Shelf stability hinges on reagent formulation (lyophilization, excipients), membrane/microfluidic materials, and temperature/humidity robustness**;** in the field, user variability—sample collection, timing, interpretation—often dominates analytical differences. The REASSURED framework (Real-time connectivity, Ease of specimen collection, Affordable, Sensitive, Specific, User-friendly, Rapid/robust, Equipment-free, Delivered) reframed success metrics for low-resource settings (Land *et al.,*2019). Complementing this, WHO Target Product Profiles (TPPs) specify minimal/optimal performance and operational requirements for priority tests (e.g., TB), providing procurement-grade targets rather than lab-bench aspirations (World Health Organization, 2024).

To advance from prototypes to regulatory-grade validation**,** follow CLSI methods: EP05 (precision across days/operators), EP07 (interference—hemolysis, lipemia, bilirubin, common drugs), EP09 (method comparison/bias to a reference), and EP17 (limits of blank/detection/quantitation). Field performance should then be established with prospective, consecutive-enrollment studies that capture ambient extremes (heat/humidity), user training levels, and lot-to-lot variation. For low-resource deployments, pair clinical accuracy with operational metrics—failure rates, time-to-result, connectivity uptime, and total cost per test (Wang *et al.*,2021).

User variability deserves dedicated engineering. Build calibration-free readouts (ratiometric/internal controls) and error-proofing (sample adequacy indicators; lockouts when timing/temperature windows are violated). Smartphone readers can standardize timing, temperature logging, and interpretation, but must be validated against lighting/camera differences. For low-resource field trials, use REASSURED-aligned protocols with environmental soaks (e.g., 40–45 °C, 75–85% RH), dust/light exposure, transport vibration, and usability studies that track error modes and mitigation rates. Reviews from 2021–2025 emphasize that this deployment-centric testing often determines public-health impact more than marginal gains in analytical sensitivity (Wang *et al.*,2021).

Gaps. **(i)** Regulatory-grade validation beyond emergency use remains rare; many POC papers stop at accuracy against a lab assay under ideal handling. Full CLSI panels and TPP-anchored field studies are needed for credibility and procurement. (ii) Field trials in low-resource settings that integrate environmental stress, user diversity, and connectivity are scarce; funders should require REASSURED/TPP-aligned designs and open reporting (protocols, de-identified datasets) to enable meta-analysis.

7. Cross-Cutting Challenges, Policy & Roadmap

7.1. Standards & Reproducibility: Interlab studies; reference materials

Across all six domains in this review, reproducibility rises or falls on three pillars: (i) clear methods and metadata, (ii) traceable measurements**,** and (iii) interlaboratory verification**.** Methods are now scaffolded by community guidance—PRISMA 2020 for transparent evidence synthesis (Page *et al.*,2021), TRIPOD+AI for prediction models (Collins *et al.*,2024), and FAIR/FAIR4RS to treat datasets and research software as first-class, citable research objects with persistent identifiers, machine-readable metadata, and explicit licensing (Sansone *et al.*,2019; Barker *et al.*,2022). Traceability requires calibrations and reference materials; here, certified standards (e.g., NIST SRMs, European RMs) and ring-test materials for environmental chemistry, electrochemistry, and biomaterials anchor instrument bias and enable quantified measurement uncertainty to travel with results. Interlab reproducibility hinges on round-robins and proficiency testing: photovoltaic stability (ISOS) has shown how shared stress protocols transform anecdotal claims into comparable data (Khenkin *et al.*,2020), and similar exercises are feasible for membranes/fouling, PeLED stability, or closed-loop AOP trains.

Minimum cross-domain expectations follow naturally: preregistered or version-controlled protocols**,** RO-Crate or PROV-O provenance that captures who/what/when for each transformation, and artifact release (code, data, CAD) under FAIR/FAIR4RS so others can re-run—not just re-read—your work (Soiland-Reyes *et al.*,2022; Moreau & Groth, 2013). Two cultural gaps remain: (1) studies still under-report uncertainty (calibration curves, repeatability, intermediate precision), and (2) “methods” are treated as narrative rather than auditable process. Our recommendation is simple: choose the guideline that fits your study (PRISMA/TRIPOD/ISOS/IEC), pair it with FAIR+PROV, and insist on at least one interlab checkpoint before making performance claims.

7.2. Scale-Up & Reliability: TRL→MRL pathways; accelerated testing

Promising lab results rarely fail for lack of cleverness—they fail at interfaces between readiness levels. Technology Readiness Levels (TRLs) describe function in relevant environments; Manufacturing Readiness Levels (MRLs) describe whether you can make it repeatably and affordably at volume (GAO, 2020). Most academic programs stop at TRL 3–4 and never gate to MRL-aware plans. A practical bridge is to define joint exit criteria**:** every TRL gate must declare the specific design, metrology, supply chain, and quality controls required to achieve the corresponding MRL gate (GAO, 2020).

Reliability evidence must also move from ad hoc stress to standards-anchored testing with documented correlations to field behavior. Photovoltaics rely on IEC 61215-2 (damp heat, thermal cycling, UV); perovskites add ISOS bias-light-temperature profiles (IEC, 2021; Khenkin *et al.*,2020). Batteries mix calendar and cycle-life protocols and shipping safety (UN 38.3), while electronics lean on JEDEC/IEC environmental sequences. Two rules of thumb generalize: (i) use multi-axis stress that matches the operational ensemble (temperature, humidity/water, light, potential/current, mechanical load, impurities) rather than single-factor soaks; and (ii) co-report degradation signatures (impedance growth, defluorination, PCE retention under MPPT, catalyst ECSA loss, contact resistance drift) with uncertainty so models can learn mechanistic fingerprints instead of lumped fade. When accelerated testing is unavoidable, publish the outdoor/field ↔ accelerated mapping (activation energies, acceleration factors, failure modes) so others can reuse—not repeat—your work (Wheeler *et al.*,2022).

7.3. Sustainability & Ethics: LCA/TEA integration; equity in deployment

Performance claims are insufficient without context. Life-Cycle Assessment (LCA) and Techno-Economic Analysis (TEA) must appear alongside efficacy—not as afterthoughts—using ISO-aligned practice for goal/scope, system boundaries, inventory, and impact assessment (ISO 14040/44). That applies from AOP trains (energy per m³, oxidant grams per m³, carbon cost) to perovskite PV (energy payback, lead stewardship), batteries (pack cradle-to-grave including recycling), PeLEDs (encapsulation and rare-metal footprints), and closed-loop labs (instrument energy, consumables). On the computing side, Green AI reframes efficiency (energy, time, hardware) as a research metric, asking authors to publish resource “price tags” alongside accuracy (Schwartz *et al.*,2019; Schwartz *et al.*,2020). For materials/chemistry R&D, Safe-and-Sustainable-by-Design provides a governance scaffold that blends hazard, exposure, circularity, and performance from the start (Caldeira *et al.*,2023).

Equity is part of rigor, not a slogan. Water technologies should report performance in low-resource conditions (intermittent power, hot/humid environments) and price per m³ at realistic volumes; POC diagnostics should conform to REASSURED and WHO TPPs; AI-enabled automation must address workforce impacts and access (Land *et al.*,2019; World Health Organization, 2024). Ethical deployment demands data governance (consent, privacy, data sovereignty), community engagement, and explicit plans for affordability and serviceability—particularly when a device depends on consumables, cold chain, or proprietary software.

7.4. Policy & Certification: Bench-to-policy translation; incentives

Bench-to-policy translation works when evidence is decision-readable**.** That means: (i) tests performed in accredited labs (ISO/IEC 17025) or under Good Laboratory Practice when appropriate; (ii) conformity assessment against recognized standards (e.g., IEC 61215/61730 for PV; CLSI EP series for diagnostics; NSF/ANSI standards for drinking-water components; ISO 13485 for medical-device QMS; EU AI Act risk-based conformity for high-risk ML); and (iii) registries where results can be discovered and compared. Incentives matter: performance-based procurement, milestone-based grants that tie funding to TRL→MRL gates, and extended producer responsibility for end-of-life recovery create pull for reliable, sustainable products. Finally, regulators and funders can accelerate uptake by endorsing open testbeds and benchmarks (e.g., Matbench; Open Catalyst) and by recognizing FAIR/FAIR4RS compliance in review criteria (Dunn *et al.*,2020; Tran *et al.*,2023; Barker *et al.*,2022).

REFERENCES

- Abeykoon, S. W., Salim, P., Halford, A., Arroyo, A. F., & Plaxco, K. W. (2024). Calibration-free, single-sweep voltammetric quantitation with electrochemical aptamer-based sensors. *Analytical Chemistry*, *96*(48), 17845–17854.
- Amani, H., *et al.*, (2024). Immunomodulatory biomaterials: Tailoring surface chemistry and topography. *Advanced Healthcare Materials*, *13*(20), 2401253.
- Ammar, A., *et al.*, (2024). FAIR assessment of nanosafety data reusability with community standards. *Frontiers in Toxicology*, *2*, 1388982.
- Angelopoulos, A. N., & Bates, S. (2023). *Conformal prediction: A gentle introduction*. Now Publishers.
- Anhel, A. M., *et al.*,,(2023). The Laboratory Automation Protocol (LAP) format and repository. *ACS Synthetic Biology*, *12*(10), 2644–2651.
- Antunes, B., *et al.*,, (2024). A survey of reproducible research with a focus on high-performance computing. *Journal of Computational Science*.
- Aro, R., Kärrman, A., Weiss, J. M., Gyllenhammar, I., & Wang, T. (2022). Extractable organofluorine

analysis: A way to screen for elevated PFAS levels. *Environment International, 165*, 107322.

- ASTM. (2022). *ASTM D5470-17(2022): Standard test method for thermal transmission properties of thermally conductive electrical insulation materials*. ASTM International.
- Barker, M., *et al.*,, (2022). Introducing the FAIR Principles for research software (FAIR4RS). *Scientific Data, 9*, 622.
- Bender, E., Park, S., & Kim, H. (2024). Modern trends in microelectronics packaging reliability. *Micromachines, 15*, 170.
- Bergmann, A., *et al.*,, (2019). Operando insights into nanoparticle transformations during catalysis. *ACS Catalysis, 9*(7), 6711–6723.
- Borup, R. L., *et al.*,,(2020). PEM fuel cell durability and degradation under automotive cycles. *Journal of Power Sources, 479*, 228806.
- Bromig, L., Gemünd, D., & Kritikaki, A. (2022). The SiLA 2 Manager for rapid device integration. *SoftwareX*, *18*, 101176.
- Bugsel, B., & von der Kammer, F. (2023). Nontarget screening strategies for PFAS prioritization and identification by high-resolution mass spectrometry. *TrAC Trends in Analytical Chemistry, 164*, 117069.
- Cahill, D. G., *et al.*,,(2019). Nanoscale thermal transport—II: 2019 roadmap. *Journal of Applied Physics*.
- Caldeira, C., *et al.*,,(2023). *Safe and Sustainable by Design: Application of the SSbD framework to case studies*. Joint Research Centre Technical Report.
- Cancela-Outeda, C., Rodríguez-González, R., & Vázquez, X. H. (2024). The EU's AI Act: A framework for collaborative governance. *Patterns, 5*(10), 100982.
- Chen, T., Mackey, E., & Andrews, S. (2024). Kinetics of chlorine and chloramine reactions in RO permeate and their impact on radical formation during UV/chlorine AOP. *Water Research, 254*, 121433.
- CLSI. (2018–2020). *EP05/EP07/EP09/EP17—Precision, interference testing, method comparison/bias, and detection capability*. Clinical and Laboratory Standards Institute.
- Collins, G. S., *et al.*,,(2024). TRIPOD+AI: Updated guidance for reporting prediction model studies using regression or machine learning. *BMJ, 385*, e078378.
- Di Fiore, F., *et al.*,,(2024). Active learning and Bayesian optimization: A unified perspective. *Archives of Computational Methods in Engineering, 31*, 3021–3048.
- Dunn, A., Wang, Q., Ganose, A., Dopp, D., & Jain, A. (2020). Matbench test set and Automatminer reference algorithm. *npj Computational Materials, 6*, 138.
- El-Seedi, H. R., *et al.*,,(2024). Updated review of metal nanoparticles fabricated by green synthesis. *Biotechnology Reports, 41*, e00865.
- Ersan, M. S., *et al.*,,(2024). Advanced oxidation may transform unknown PFAS into detectable shorter-chain species. *Chemosphere, 352*, 150076.
- Fan, X., *et al.*,,(2018). Fluorinated electrolytes for high-voltage and lithium-metal batteries. *Nature Energy*.
- Faria, M., Björnmalm, M., Thurecht, K. J., *et al.*,,(2018). Minimum information reporting in bio–nano experimental literature (MIRIBEL). *Nature Nanotechnology, 13*, 777–785.
- Foldager, J., *et al.*,,(2023). On the role of model uncertainties in Bayesian optimization. In *Proceedings of UAI 2023* (pp. 592–601).
- GAO. (2020). *Technology Readiness Assessment Guide*. U.S. Government Accountability Office.
- Gao, H., Xu, T., Wang, Y., & Li, J. (2025). Progress in research on co-packaged optics. *Micromachines, 16*(9), 1037.
- Gao, Z., *et al.*,,(2022). Graphene/BN-based thermal interface materials: Progress and prospects. *Nano Energy*.
- He, Y., *et al.*,,(2022). Heat conduction in disordered solids: From propagons to diffusons. *Nature Materials*.
- Herrick, R. W. (2025). Laser reliability constraints for silicon-photonics packaging. In *Proceedings of SPIE* (Vol. 13370).
- Hübner, U., *et al.*,,(2024). Advanced oxidation processes for water and wastewater: A tutorial review. *Heliyon, 10*(4), e25678.
- IEC. (2021). *IEC 61215-2: Terrestrial photovoltaic modules—Design qualification and type approval—Part 2: Test procedures*. International Electrotechnical Commission.
- Jiao, E., *et al.*,,(2023). Further insight into extractable (organo)fluorine mass balance in drinking water. *Environmental Science & Technology, 57*(40), 14667–14676.
- Karniadakis, G. E., Kevrekidis, I., Lu, L., Perdikaris, P., Wang, S., & Yang, L. (2021). Physics-informed machine learning. *Nature Reviews Physics, 3*(6), 422–440.
- Kasemchainan, P., *et al.*,,(2019). Critical currents in solid-state lithium metal batteries. *Nature Materials*.
- Kazyak, E., *et al.*,,(2020). Li penetration in ceramic solid electrolytes: Operando visualization and mechanisms. *Joule*.
- Keen, O., Bolton, J. R., & Litter, M. I. (2018). Standard reporting of electrical energy per order (EE/O) for UV/H_2O_2 reactors (IUPAC Technical Report). *Pure and Applied Chemistry, 90*(9), 1487–1499.
- Khenkin, M. V., *et al.*,,(2020). Consensus statement for stability assessment and reporting for perovskite photovoltaics based on ISOS procedures. *Nature Energy, 5*(1), 35–49.
- Kovachki, N., Lanthaler, S., & Mishra, S. (2021). On universal approximation and error bounds for

Fourier Neural Operators. *Journal of Machine Learning Research, 22*, 1–76.

- Kourti, D., Nikoleli, G.-P., & Nikolelis, D. (2024). Antifouling label-free electrochemical aptasensors: Materials and strategies. *Biosensors, 14*(6), 214.
- Kusada, K., & Kitagawa, H. (2022). Continuous-flow syntheses of alloy nanoparticles. *Materials Horizons, 9*, 547–558.
- Land, K. J., *et al.*,,(2019). REASSURED diagnostics to inform disease control. *Nature Microbiology, 4*(1), 46–54.
- Li, D., *et al.*,,(2022). Impact of water matrices on oxidation effects and energy demand during UV-based AOPs. *Science of the Total Environment, 838*, 156035.
- Li, N., Niu, X., Gao, M., & Zhang, X. (2022). Ion migration and interfacial degradation in perovskite LEDs: Mechanisms and mitigation. *Advanced Materials, 34*(19), 2105550.
- Li, Z., Kovachki, N., Azizzadenesheli, K., *et al.*,,(2021). Fourier Neural Operator for parametric PDEs. *arXiv:2010.08895*.
- Liu, R., Chen, Q., & Sun, X. (2024). Halide perovskite X-ray detectors: Fundamentals, device physics, and stability. *APL Reviews, 11*(2), 021327.
- Loeffler, H. H., *et al.*,,(2024). Generative active learning for optimal molecular design. *Journal of Chemical Theory and Computation, 20*(22), 9153–9166.
- Lu, L., Jin, P., Pang, G., Zhang, Z., & Karniadakis, G. E. (2021). Learning nonlinear operators via DeepONet. *Nature Machine Intelligence, 3*(3), 218–229.
- Luo, D., Wang, H., Li, X., & Wang, Y. (2024). The dual role of natural organic matter in persulfate-based AOPs: A mini-review. *Environmental Science and Pollution Research, 31*(22), 47754–47768.
- Ma, P., & Ma, W. (2023). A feedforward unitary-equivariant neural network. *Neural Networks, 163*, 118–129.
- Mackey, E., Hofmann, R., & Andrews, S. (2023). UV-chlorine advanced oxidation for potable water reuse: State of the art and research needs. *Water Research, 254*, 121433.
- MLCommons. (2024–2025). *Science Working Group and datasets*. MLCommons Reports.
- Moore, J., *et al.*,,(2021). OME-NGFF: A next-generation file format for bioimaging. *Nature Methods, 18*, 1496–1498.
- Moore, J., *et al.*,,(2023). OME-Zarr: Cloud-optimized bioimaging with NGFF. *bioRxiv*, 2023.02.17.528834.
- Moreau, L., & Groth, P. (2013). PROV-DM: The PROV data model. *W3C Recommendation*.
- Ni, Y., *et al.*,,(2023). Macrophage mechanosensing in stiffness-related foreign body responses. *Advanced Science, 10*(5), 2204973.
- Nong, H. N., *et al.*,,(2020). A unique oxygen evolution catalyst for PEM electrolyzers. *Nature*.
- OECD. (2023). *Programme on safety of manufactured nanomaterials: Test guidelines and guidance documents*. Organisation for Economic Co-operation and Development.
- Ovadia, Y., *et al.*,,(2019). Can you trust your model's uncertainty? Evaluating predictive uncertainty under dataset shift. In *Advances in Neural Information Processing Systems (NeurIPS)*.
- Padmanabhan, J., *et al.*,,(2023). Allometric scaling of tissue forces drives pathological foreign-body reactions. *Nature Biomedical Engineering, 7*, 1589–1602.
- Page, M. J., *et al.*,,(2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, n71.
- Park, J., *et al.*,,(2023). Stability metrics and reporting for photoelectrochemical water splitting. *ACS Energy Letters*.
- Pineo, H., Turnbull, E. R., Davies, M., *et al.*,,(2021). A new model for transdisciplinary research to improve health outcomes. *Health Promotion International, 36*(2), 481–492.
- Plachý, Z., Němec, M., & Vojtěch, D. (2025). Reliability evaluation of underfill systems in electronics production. *Polymers, 17*(16), 2206.
- Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks. *Journal of Computational Physics, 378*, 686–707.
- Rahman, M. M., *et al.*,,(2024). Advanced control strategies of membrane fouling in wastewater treatment: A review. *Processes, 12*(12), 2681.
- Rauh, R., *et al.*,,(2022). Potential-induced degradation and mitigation in PV modules. *Progress in Photovoltaics*.
- Ren, Z., *et al.*,,(2021). Reductive degradation of PFOA by UV/sulfite in complex matrices. *Water Research, 205*, 117669.
- Rethlefsen, M. L., *et al.*,,(2021). PRISMA-S: An extension to PRISMA for reporting literature searches in systematic reviews. *Systematic Reviews, 10*, 39.
- Ruyle, B. J., *et al.*,,(2023). Interlaboratory comparison of extractable organofluorine in environmental samples. *Environmental Science & Technology, 57*(48), 17431–17441.
- Sakhatskyi, K., Voronov, O., & Yakunin, S. (2023). Long-term stable perovskite X-ray detectors operated at zero bias. *Nature Photonics, 17*, 1171–1178.
- Salavati, H., *et al.*,,(2025). Image-guided patient-specific prediction of interstitial flow and drug transport. *IEEE Transactions on Medical Imaging*.
- Sánchez Cruz, S., *et al.*,,(2024). Equivariant neural networks for robust CP-odd observables. *Physical Review D, 110*, 096023.
- Sansone, S.-A., *et al.*,,(2019). FAIRsharing as a community approach to standards, repositories and policies. *Nature Biotechnology, 37*(4), 358–367.

- Sbailò, L., *et al.,*,(2022). The NOMAD AI Toolkit. *npj Computational Materials, 8*, 111.
- Schwartz, R., Dodge, J., Smith, N. A., & Etzioni, O. (2019). Green AI. *arXiv:1907.10597*.
- Schwartz, R., *et al.,*,(2020). Green AI. *Communications of the ACM, 63*(12), 54–63.
- Soiland-Reyes, S., *et al.,*,(2022). Packaging research artefacts with RO-Crate. *Data Science, 5*(2), 97–138.
- Stylianopoulos, T., *et al.,*,(2018). Re-engineering tumor microenvironments to improve transport. *Trends in Cancer, 4*(9), 653–665.
- Tehrani, M. H. H., *et al.,*,(2024). Effect of tumor heterogeneity on enhancing drug delivery: A modeling study. *Computers in Biology and Medicine*, *178*, 108574.
- Theunissen, L., *et al.,*,(2025). Evaluation of OOD detection methods for single-cell omics. *Briefings in Bioinformatics*.
- Tom, G., *et al.,*,(2024). Self-driving laboratories for chemistry and materials. *Chemical Reviews, 124*(17), 11035–11088.
- Tran, R., *et al.,*,(2023). The Open Catalyst 2022 dataset. *ACS Catalysis*, *13*(9), 6223–6240.
- Trang, B., *et al.,*,(2022). Low-temperature mineralization of perfluorocarboxylic acids via base-mediated defluorination. *Science, 377*(6608), 839–845.
- Van Os, L., *et al.,*,(2023). Integrating immune cells in organs-on-chips: A tutorial. *Cell Reports Methods, 3*(7), 100489.
- Varcoe, J. R., *et al.,*,(2020). Anion-exchange membranes in electrochemical energy systems. *Energy & Environmental Science*.
- Wang, A., Kadam, S., Li, H., Shi, S., & Qi, Y. (2018). Interfacial phenomena in cathode–electrolyte interphases. *Materials Today*.
- Wang, C., *et al.,*,(2021). Point-of-care diagnostics for infectious diseases. *Biosensors and Bioelectronics, 166*, 112455.
- Wang, Z., *et al.,*,(2024). Defects and defect passivation in perovskite solar cells. *Molecules, 29*(9), 2104.
- Wheeler, D., *et al.,*,(2022). Outdoor/accelerated correlations in PV reliability: A DuraMAT perspective. *Joule*, *6*(6), 1180–1205.
- World Health Organization. (2024). *Target product profile for tuberculosis diagnosis and drug-resistance tests at peripheral settings*. WHO.
- Wu, J., *et al.,*,(2024). Adhesive anti-fibrotic interfaces reduce capsule formation across organs. *Nature, 629*, 92–99.
- Wu, R., *et al.,*,(2022). Operando characterization of organic mixed ionic/electronic conductors. *Chemical Reviews, 122*(16), 14487–14545.
- Wu, T., Li, X., Qi, Y., Zhang, Y., & Han, L. (2021). Defect passivation for perovskite solar cells: From molecule design to device performance. *ChemSusChem*, *14*(24), 5442–5467.
- Xia, Z., *et al.,*,(2022). Alkaline-stable cationic polymers for AEM electrolyzers. *Nature Energy*.
- Xu, R., Sun, H., Xu, K., & Wang, C. (2021). Interphases in high-energy batteries: Structure, chemistry, and control. *Nature Energy*.
- Xu, X., *et al.,*,(2024). Electrochemical advanced oxidation of PFAS: Anode materials, mechanisms, and scale-up challenges. *Chemical Engineering Journal, 494*, 147672.
- Yan, J., Xu, H., & Wang, J. (2024). Molecularly imprinted ratiometric fluorescent sensors: Toward calibration-free analysis. *Sensors, 24*(12), 4977.
- Yoon, M. S., *et al.,*,(2020). Spatiotemporal drug release from nanocarriers. *Advanced Drug Delivery Reviews*, *156*, 2–19.
- Zebarjadi, M., *et al.,*,(2021). Strategies for low lattice thermal conductivity in thermoelectrics. *Advanced Materials*.
- Zhao, B., Zhou, Y., & Song, J. (2024). Strategies for highly stable blue perovskite LEDs. *Materials Today Energy, 35*, 101307.
- Zhao, Y., Li, D., & Chen, Z. (2025). AI-enhanced electrochemical sensing systems: Drift tracking and uncertainty reporting. *Biosensors, 15*(8), 487.
- Zhao, Z., Xu, M., & Wang, S. (2025). Out-of-distribution detection by regaining lost clues. *Artificial Intelligence, 332*, 104085.
- Zheng, X., *et al.,*,(2023). Ionomer–catalyst interactions and durability in PEM devices. *Chemical Reviews*.