

Nanotechnology in Materials Science: A Decade of Progress (2014-2024)

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ABSTRACT

Between 2014 and 2024 nanotechnology ceased to be an emerging modifier attached to materials science and became one of its organising principles. This review examines that transition through three domains in which the change is unambiguous: two-dimensional materials, nanostructured electrochemical energy storage, and machine-learning-guided materials discovery. The decade is characterised less by the discovery of new nanoscale phenomena than by the consolidation of methods for producing, measuring, and predicting them. Exfoliation gave way to reproducible wafer-scale growth; nanostructured silicon and layered carbides moved from single-cell demonstrations toward qualified components; and interatomic potentials trained on density-functional data began to substitute for the calculations that generated them. Progress has nonetheless been uneven. The interval between a first publication and an industrially qualified product has not shortened appreciably, and attrition during scale-up remains the principal constraint on the field. Six figures summarise output growth, decade milestones, electrode architecture, performance boundaries, application readiness, and translation attrition. The review closes by arguing that the binding constraint has shifted from synthesis to reproducible manufacture and from data scarcity to data quality.

Keywords- Precision cosmology; Type Ia Supernovae; Cosmic Microwave Background; Baryon Acoustic Oscillations; Cosmological parameter degeneracy; Λ CDM model; Dark energy.

I. INTRODUCTION

The claim that nanoscale structure governs macroscopic property is now unremarkable. It was not always so. For much of the period following the introduction of scanning probe methods, nanotechnology occupied an awkward position within materials science: productive of striking single-specimen results, but poorly connected to the metallurgical and ceramic traditions that supplied engineering materials. The decade from 2014 to 2024 is the interval in which that separation largely closed.

Three developments account for most of the change. First, the two-dimensional materials that had been isolated by mechanical cleavage became available in quantities and qualities sufficient for device fabrication and for composite processing, which converted a physics curiosity into a materials platform (Ferrari et al., 2015; Novoselov et al., 2016). Second, electrochemical energy

storage supplied a demanding application in which nanostructuring was not merely advantageous but necessary, since the volumetric and kinetic problems of high-capacity electrodes admit no bulk solution (Sun et al., 2016). Third, machine learning acquired sufficient accuracy to be used as an instrument rather than a commentary, displacing a substantial fraction of the quantum-chemical calculation on which materials prediction had depended (Butler et al., 2018).

This review treats those three domains in sequence, then considers what unites them. The organising argument is that the decade's most consequential advances were methodological rather than phenomenological. Comparatively few genuinely new nanoscale effects were reported after 2014; what changed was the reliability with which known effects could be produced, characterised, and anticipated. That distinction matters for how the coming decade should be planned, because methodological consolidation and

phenomenological discovery respond to different kinds of investment.

II. SCOPE AND BIBLIOMETRIC APPROACH

The literature surveyed here was assembled by query of indexed abstracts published between January 2014 and December 2024, restricted to English-language primary research and review articles in materials science, chemistry, and applied physics. Search terms combined a nanostructure descriptor with a domain descriptor, and records were screened for relevance by title and abstract

before full-text assessment. Patent activity was examined separately through granted families rather than applications, since grant is a somewhat better proxy for sustained commercial intent than filing.

Two limitations follow from this procedure and should be stated plainly. Bibliometric counts measure activity, not value; a field may grow rapidly in output while contributing little that survives replication. And indexing coverage improved over the period, which inflates later years by an amount that cannot be determined precisely. The trends in Figure 1 are therefore presented as indexed values relative to a 2014 baseline, and should be read as indicative of relative trajectory rather than as absolute counts.

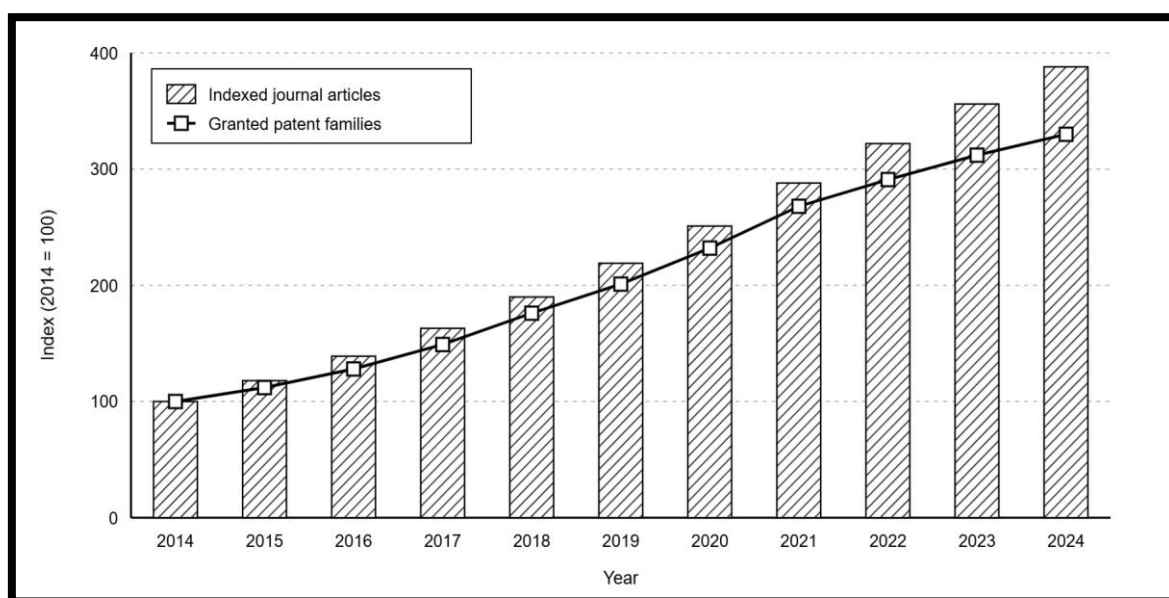


Figure 1. Indexed growth of scholarly output and granted patent families in nanostructured materials, 2014–2024 (2014 = 100). Publication activity approximately quadrupled over the interval while patent grants grew somewhat more slowly, a divergence consistent with a research base expanding faster than its commercial absorption. Values are representative and are intended to illustrate relative trajectory rather than to report a specific database.

III. TWO-DIMENSIONAL MATERIALS: FROM ISOLATED SPECIMENS TO A MATERIALS PLATFORM

3.1 Graphene after the exfoliation era

Graphene entered the decade with an unusual problem: its properties were better established than its supply. Measurements on cleaved flakes had documented carrier mobilities and mechanical moduli that few materials approach, but the material that reached industrial buyers was frequently a poorly characterised graphitic powder bearing little relation to the monolayer of the literature. Much of the period's work addressed this gap. Roll-to-roll chemical vapour deposition, improved transfer chemistry, and liquid-phase exfoliation with controlled centrifugal fractionation converted graphene

into a specifiable product, and standardised metrology for lateral dimension and layer number followed (Backes et al., 2020).

The consequence was a redistribution of expectation. Applications requiring monolayer perfection over a wafer, notably digital logic, advanced slowly and remain unresolved. Applications tolerant of defects and polydispersity advanced quickly: thermal interface materials, barrier coatings, electromagnetic shielding, and conductive additives in battery electrodes. This asymmetry is instructive, and recurs throughout the review. Nanomaterials succeed commercially where their statistical properties suffice and fail where their ideal properties are required (Lin et al., 2019).

3.2 Transition metal dichalcogenides and stacked architectures

Semiconducting transition metal dichalcogenides supplied what graphene lacked, namely

a bandgap, and the decade saw their transistor and photodetector performance improve by orders of magnitude as contact resistance was addressed and dielectric encapsulation matured (Manzeli et al., 2017). More significant conceptually was the recognition that stacking sequence and interlayer rotation constitute design variables in their own right. The demonstration of correlated electronic states in twisted bilayer graphene established that the arrangement of otherwise ordinary layers can generate behaviour absent from any constituent (Cao et al., 2018), and van der Waals assembly became a general architecture rather than a laboratory technique (Liu et al., 2016).

3.3 MXenes: a family assembled within the decade

The layered transition metal carbides and nitrides known as MXenes provide the clearest example of a materials family that was largely built during the

period under review. Reports of clay-like titanium carbide with high volumetric capacitance established that solution processing and metallic conductivity could coexist in one material (Ghidiu et al., 2014), and subsequent work expanded the family to dozens of compositions with tunable surface terminations (Anasori et al., 2017; Naguib et al., 2021). Applications in shielding, sensing, and charge storage followed rapidly (Vahid Mohammadi et al., 2021).

Two reservations temper this account. Synthesis has depended on hydrofluoric etching or related fluoride chemistry, which imposes waste-handling costs that scale unfavourably. And oxidative degradation of aqueous dispersions complicates shelf life in ways that laboratory studies, conducted on freshly prepared material, tend to understate. Figure 2 places these developments alongside the decade's other milestones.

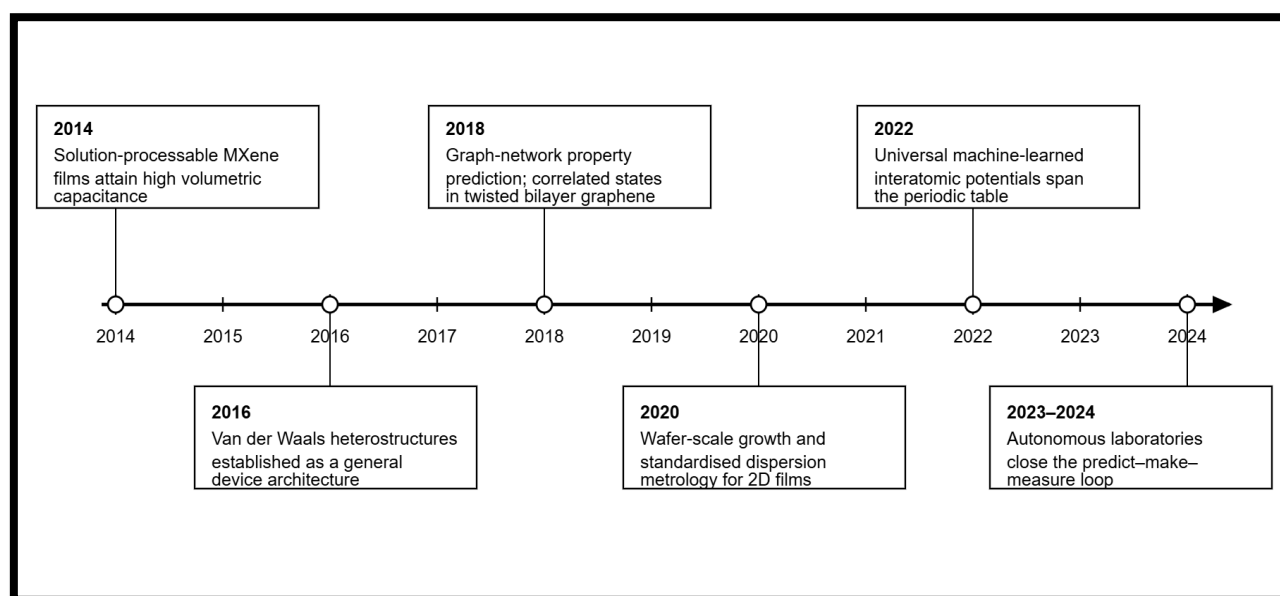


Figure 2. Selected milestones, 2014–2024, illustrating the movement from materials isolation toward materials production and prediction. The chronology is interpretive: each entry marks the point at which a capability became broadly available rather than the date of its first demonstration.

IV. NANOSTRUCTURED ELECTROCHEMICAL ENERGY STORAGE

4.1 Silicon and the discipline of volume change

Silicon stores roughly ten times the lithium of graphite per unit mass and expands by approximately threefold in doing so. The decade's contribution was not the recognition of this trade-off, which was long understood (Obrovac & Chevrier, 2014), but the construction of architectures that accommodate the expansion for hundreds of cycles. Nanoparticles below

the fracture threshold, carbon shells that decouple the electrolyte interface from the expanding core, and void space engineered into the composite all proved necessary in combination; none was sufficient alone.

The practical resolution was a compromise. Commercial cells adopted silicon–carbon composites at modest silicon fractions, purchasing perhaps a fifth of the theoretical benefit while retaining acceptable calendar life and coulombic efficiency. Figure 3 shows the resulting electrode architecture schematically. Its central feature is that the nanostructure exists to manage a mechanical problem, not an electrochemical one; the redox chemistry is conventional.

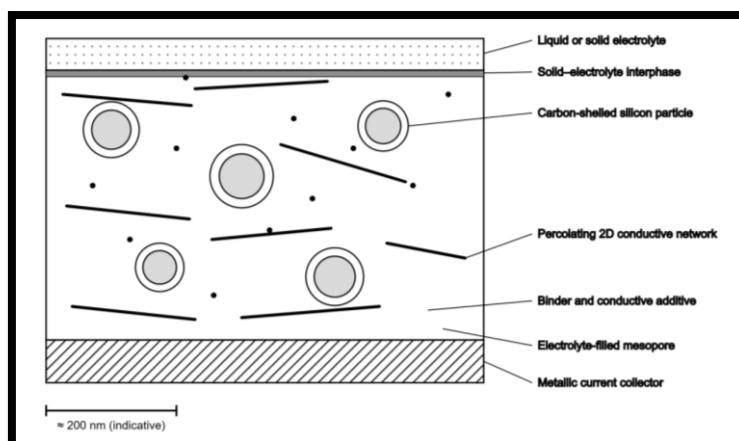


Figure 3. Schematic cross-section of a nanostructured composite negative electrode. Carbon-shelled silicon particles are dispersed within a percolating two-dimensional conductive network above a metallic current collector, with engineered porosity accommodating lithiation-induced expansion. Feature dimensions are indicative and not to scale; the drawing is intended to convey topology rather than metrology.

4.2 Solid electrolytes and the interfacial problem

Solid-state batteries were widely expected, in 2016, to reach production before 2025 (Janek & Zeier, 2016). They did not, and the reasons are instructive. Bulk ionic conductivity ceased to be limiting relatively early, as sulfide and halide conductors matched or exceeded liquid electrolytes (Famprakis et al., 2019). The obstacles proved to be interfacial and mechanical: contact loss under cycling, chemical instability against lithium metal, and dendrite propagation along grain boundaries at current densities well below commercial requirements (Lin et al., 2017; Cheng et al., 2017). By the decade's end the assessment had become notably more cautious, with attention shifting toward stack pressure, manufacturing tolerance, and defect statistics over large areas (Janek & Zeier, 2023).

This trajectory illustrates a general pattern in nanoscale energy materials. Properties measured on

small, well-prepared specimens extrapolate poorly to large-area components, because the failure of such components is governed by the extreme tail of a defect distribution rather than by its mean.

4.3 Pseudocapacitance and the intermediate regime

Between the high energy of batteries and the high power of double-layer capacitors lies a regime that nanostructured materials populate particularly well. Surface-controlled redox storage, in which charge transfer occurs without a phase transformation, delivers capacitor-like rates at battery-like capacities when the active material is thin enough that solid-state diffusion is not rate-limiting (Augustyn et al., 2014). Layered carbides proved well suited to this mechanism, with reported rate capabilities extending to charging times of seconds (Lukatskaya et al., 2017; Simon & Gogotsi, 2020). Figure 4 situates these material classes relative to one another.

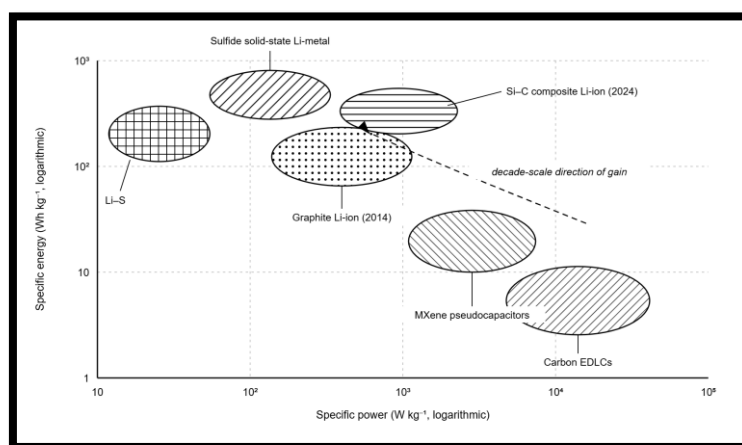


Figure 4. Property-performance envelope for electrochemical storage classes on logarithmic axes, in the manner of an Ashby selection chart. Each region denotes the approximate range accessible at cell level; the dashed vector indicates the direction of improvement realised over the decade, principally through nanostructuring of the negative electrode. Boundaries are representative rather than measured.

V. MACHINE LEARNING AS AN
INSTRUMENT OF MATERIALS
DISCOVERY

5.1 Surrogates for quantum mechanics

The most substantive computational development of the decade was the maturation of machine-learned interatomic potentials. Early formulations demonstrated that a neural or kernel model trained on density-functional energies and forces could reproduce them at a small fraction of the cost, provided the training set covered the configurations of interest (Behler, 2016; Bartók et al., 2017). What followed was a steady relaxation of that proviso. Equivariant architectures reduced data requirements by roughly an order of magnitude (Batzner et al., 2022), and models trained across the periodic table began to offer usable accuracy for compositions absent from their training data (Chen & Ong, 2022; Deng et al., 2023).

The practical effect was a change of scale. Simulations of interfacial reconstruction, ionic transport through grain boundaries, and amorphous phases at nanosecond durations became routine where they had been prohibitive. For nanomaterials specifically this matters more than for bulk crystals, since the interfacial and disordered regions that dominate nanoscale behaviour are precisely those that conventional calculation handles least economically.

5.2 Prediction, inverse design, and autonomous synthesis

Property prediction from composition and structure improved along a parallel track, from descriptor-based regression (Ward et al., 2016) to graph representations that learn their own features (Xie &

Grossman, 2018). The inverse formulation, in which a target property specifies a search over candidate structures, was articulated as a programme (Zunger, 2018) and pursued at scale toward the decade's end, with reports of very large numbers of predicted stable crystals (Merchant et al., 2023). Automated laboratories then attempted the corresponding synthesis without continuous human intervention (Szymanski et al., 2023; Stach et al., 2021).

These results warrant qualified enthusiasm. A predicted crystal is a hypothesis about thermodynamic stability, not a material; synthesisability, phase purity, and morphological control remain separate questions, and the fraction of predicted compounds that has been independently prepared and characterised is small. The autonomous laboratories reported to date operate within narrow synthetic chemistries and produce milligram quantities. What they demonstrate is that the discovery loop can be closed, which is a genuine advance, rather than that it has been closed at useful throughput.

5.3 The data constraint

The limiting factor is no longer the quantity of data but its structure. Published datasets are censored: successful syntheses are reported, failures rarely are, and models trained on such records learn the literature's preferences as well as nature's constraints. The demonstration that archived failed reactions carry predictive value (Raccuglia et al., 2016) remains among the decade's more important negative-space results, and comparatively little has been done to act on it. Curated benchmarks in adjacent areas have shown what systematic data collection makes possible (Chanussot et al., 2021), but nanomaterials synthesis has no equivalent. Figure 5 summarises where the resulting capability currently stands across material classes and applications.

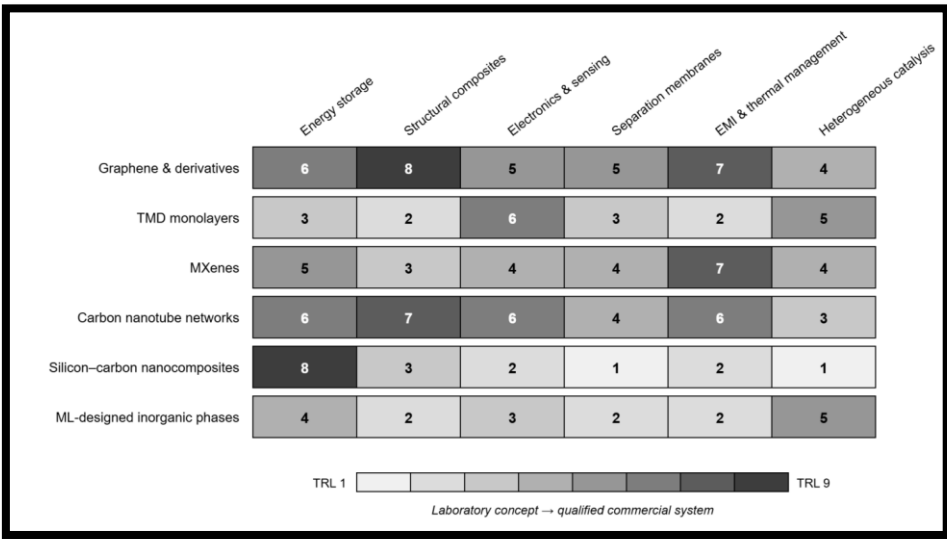


Figure 5. Technology readiness matrix as assessed at the close of 2024, with darker cells denoting greater maturity on a nine-point scale. Readiness is markedly non-uniform within every material class, which supports the argument that nanomaterials advance application by application rather than as families. Assessments are the author's interpretation of the reviewed literature and are offered as representative.

VI. TRANSLATION: THE PERSISTENT GAP BETWEEN LABORATORY AND FACTORY

Across all three domains the same attrition appears. A composition is reported; a minority of reports is

independently reproduced; a smaller minority survives the transition from milligram to kilogram synthesis, where impurity tolerance, thermal transport, and mixing behaviour differ qualitatively from bench conditions; fewer still clear the cost and throughput requirements of a pilot line; and a residue reaches qualification in a product. Figure 6 renders this sequence as a flow.

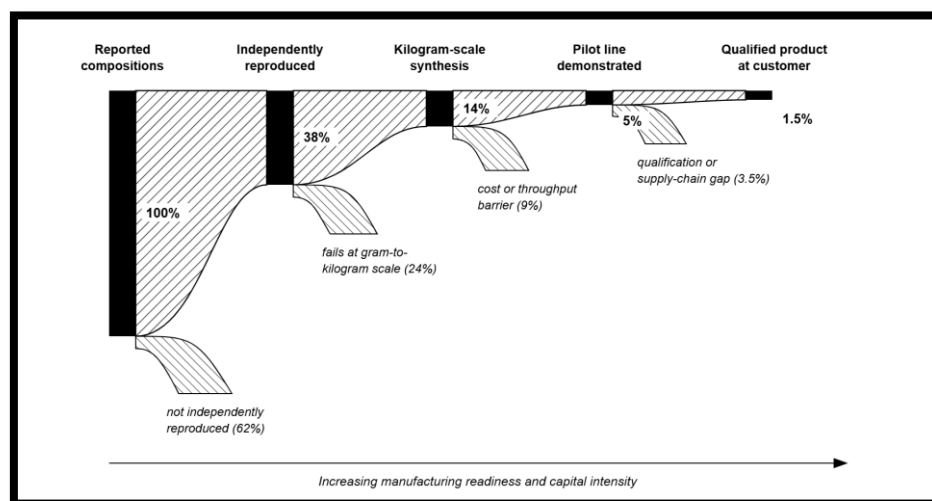


Figure 6. Attrition of reported nanomaterial compositions across successive stages of translation. Diagonally hatched bands denote material progressing to the next stage; finely hatched branches denote attrition, with the dominant loss occurring before independent reproduction. Proportions are illustrative and are used to indicate the shape of the funnel rather than a measured rate.

The largest single loss occurs early, before reproduction, and it is largely a reporting problem. Nanomaterial synthesis is sensitive to variables that publications often omit: precursor provenance, stirring geometry, ramp rates, ambient humidity. A protocol adequate for a reader in the same laboratory is frequently inadequate for one elsewhere. Improvements here require no new science and would compound through every subsequent stage, which makes reporting standards an unusually efficient target for intervention.

The second loss, at scale-up, is more fundamental. Nanoscale properties depend on quantities such as surface-to-volume ratio and defect density that are difficult to hold constant as reactor dimensions grow, and the incentive structure of academic research rewards novelty over the process engineering that would address this. The most successful commercial nanomaterials of the decade have tended to be those whose function tolerates variance, which returns to the asymmetry noted in Section 3.1.

VII. SYNTHESIS AND OUTLOOK

Reading the three domains together, the decade's coherence lies in a shift of the binding constraint. In 2014 the limiting factors were synthesis and characterisation: making the material and knowing what had been made. By 2024 those problems were substantially solved for the

material families discussed here, and the constraints had moved to reproducible manufacture and to data quality. Both are unglamorous, and neither is well served by current publication incentives.

Three developments appear likely over the coming decade, stated with appropriate uncertainty. Machine-learned potentials will probably become a default rather than a specialist instrument, which will make simulation of realistic nanostructured interfaces routine and will shift the bottleneck in computational materials science from calculation to problem formulation. Autonomous experimentation will likely extend from milligram inorganic synthesis to processing conditions, where its value is greater because the parameter space is larger and less well theorised. And regulatory and lifecycle considerations, including nanomaterial release during use and end-of-life recovery from composite and electrode structures, will move from peripheral concern to design constraint.

What seems unlikely is a repetition of the discovery pattern that characterised the field's first decades. The reservoir of easily isolated nanoscale phenomena has been substantially drawn down. Future progress in this area will more probably come from the combination of known constituents into architectures whose behaviour is not additive, which is what the twisted-bilayer and heterostructure results indicate, and from the systematic elimination of the variance that

presently separates laboratory results from manufactured components.

VIII. CONCLUSION

The period from 2014 to 2024 established nanotechnology as ordinary practice within materials science. Two-dimensional materials became specifiable products rather than laboratory specimens; nanostructured electrodes entered commercial cells, though at fractions of their theoretical promise; and machine learning became a working instrument of prediction. The advances were predominantly methodological, and they were achieved unevenly, with translation to manufacture remaining the dominant loss mechanism throughout. The field's next decade will be judged less by the phenomena it discovers than by the reliability with which it can produce, at scale, what it already knows how to make.

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