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Large-language-model-based white spot analysis of patent landscapes in emerging battery technologies

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Abstract

The rapid expansion of scientific publications and patent filings challenges conventional approaches for systematically assessing technological progress in emerging energy storage technologies. Here, we present an artificial intelligence-assisted patent analytics framework to identify technology-specific research gaps (“white spots”), using zinc-ion batteries (ZIBs) and organic electrode materials (OEMs) as representative case studies. Patents were classified across multiple analytical dimensions, including materials, battery chemistries, and key performance indicators (KPIs). Three analytically distinct types of white spots are identified: limited absolute patenting activity within a given category (activity white spots), insufficient quantitative performance disclosure despite active patenting (reporting white spots), and disproportionate reliance on knowledge transferred from adjacent battery fields (knowledge-flow white spots). The analysis reveals a strong dominance of aqueous electrolyte concepts in ZIBs, accounting for 1883 patents, while non-aqueous and solid electrolytes remain underrepresented. Citation network analysis further shows that innovation in these underexplored electrolyte classes relies disproportionately on knowledge originating from adjacent battery technologies. For OEMs, up to 93% of the 368 patents focus on lithium-based chemistries, which exhibit the most comprehensive quantitative reporting. In contrast, sodium-based and all-solid-state systems are characterized by substantial gaps in KPI disclosure, limiting cross-chemistry benchmarking. Overall, the results demonstrate that white spots in emerging battery technologies arise not only at the materials level, but also from asymmetric knowledge flows and incomplete performance reporting. The here proposed framework provides a scalable tool for mapping technological maturity and supporting research strategies in next-generation energy storage systems.

Keywords Patent analysis, Large language model, Artificial intelligence, Zinc-ion batteries, Organic electrodes, White spot analysis

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1 Introduction

The pace of innovation in energy storage technologies has accelerated markedly over the past decade, as reflected in the rapid growth of both scientific publications and patent filings. While this expansion signals intense research activity, it in turn introduces complexities in the systematic tracking of technological progress. Traditional bibliometric approaches, such as citation counts, keyword co-occurrence, or expert-driven reviews, are increasingly strained by the volume, heterogeneity, and technical depth of the available scientific literature and intellectual property (IP) [1, 2]. As a result, the comprehensive evaluation of technological advancements, the identification of emerging trends, and the detection of underexplored research gaps have become substantial challenges.

In response to these limitations, the integration of artificial intelligence (AI) and, more recently, large language models (LLMs) has emerged as a powerful and scalable approach for analyzing large volumes of unstructured textual information. This development builds upon earlier advances in text mining, bibliometrics, and knowledge flow analysis [3–5]. Specifically, LLMs enable semantic interpretation of complex technical documents at a level that surpasses the capabilities of keyword-based methods. Recent studies have demonstrated the efficacy of such models in extracting structured technological information from patents, tracing knowledge transfer across domains, and identifying dominant research themes with high efficiency [6, 7]. These capabilities position LLM-based analytics as a promising tool for mapping technological landscapes and uncovering breakthroughs and “white spots” that may be overlooked by conventional approaches.

Concurrently, the necessity for low-cost, safe, and sustainable energy storage technologies has become paramount [8]. The widespread deployment of lithium-ion batteries (LIBs) has raised concerns related to resource availability, supply chain concentration, and cost volatility, motivating intensified research into alternative battery chemistries [9–11]. However, many post-lithium-ion concepts remain at an early or intermediate stage of development and face persistent challenges related to materials and performance scalability, as well as manufacturability [12]. Consequently, the acceleration of research and development (R&D) in these domains warrants not only advancements at the materials and device level, but also systematic insight into innovation areas, critical gaps, and the distribution of innovation efforts.

In this context, zinc-ion batteries (ZIBs) and organic electrode materials (OEMs) constitute particularly relevant case studies. ZIBs have garnered substantial attention as a potentially low-cost and safe alternative for stationary energy storage, largely due to the abundance

of zinc and the inherent safety of aqueous electrolytes [13, 14]. Nevertheless, aqueous ZIB systems continue to exhibit limitations, including corrosion, dendrite formation, and a limited upper cell voltage imposed by the onset of oxygen evolution in water-based electrolytes (typically constraining practical cell voltages to around 2 V vs. Zn/Zn^{2+}) [15]. While non-aqueous and solid-electrolyte concepts have been proposed as potential pathways to mitigate water-related electrochemical constraints, the extent to which such alternatives are reflected in applied innovation remains unclear [16, 17]. This prompts further inquiry: to what extent are distinct electrolyte categories investigated within the ZIB patent landscape, and how do the scope and thematic emphasis of research differ across these electrolyte classifications?

OEMs represent a complementary and conceptually distinct innovation space. The replacement of inorganic electrode materials with redox-active organic compounds (e.g., OEMs) presents opportunities for enhanced sustainability, structural tunability, and potentially streamlined recycling processes [18, 19]. However, OEM performance is highly sensitive to the choice of battery chemistry, and reported results vary widely across lithium, sodium, multivalent ion, and solid-state systems [20]. Furthermore, the heterogeneity of material structures and application contexts exacerbates the complexity of cross-chemistry comparison and benchmarking using key performance indicators (KPIs) [21]. This prompts a secondary inquiry: which battery chemistries currently predominate in OEM-related innovation, and which KPIs are prioritized within and across these chemistries?

Here, we present an AI-assisted patent analytics framework that leverages LLM-based classification and citation network analysis to systematically map technological landscapes and identify white spots in emerging battery technologies. Utilizing ZIBs and OEMs as representative case studies, we illustrate how the proposed approach can adapt flexibly to different research questions and data scopes, yielding diverse and domain-specific insights contingent on the implemented search and classification strategy. By combining materials-centric analysis, performance-oriented KPI extraction, regional attribution, and knowledge flow mapping, this study illustrates the potential of LLM-based methods to support evidence-driven decision-making in battery research and innovation management. Throughout both case studies, we employ a consistent typological lens that distinguishes three analytically distinct but non-exclusive forms of white spots: activity white spots, defined as categories with limited absolute patenting volume relative to their technological potential; reporting white spots, arising where quantitative performance disclosure is systematically absent despite active patenting; and knowledge-flow white spots,

where a technology segment relies disproportionately on knowledge transferred from adjacent battery fields rather than having developed an internally consolidated innovation base.

2 Materials and methods

2.1 Data collection

In this study, international patent families (IPFs) related to ZIBs and OEMs were retrieved from the Derwent Innovation Index, a curated patent database providing harmonized patent family structures, standardized abstracts, citation information, and normalized assignee data. These features facilitate large-scale comparative patent analyses and ensure consistency across jurisdictions and publication formats. IPFs were selected as the unit of analysis to avoid geographic duplication and to ensure the consistent representation of inventive concepts across patent offices. The retrieval of patents was achieved through the implementation of a multifaceted search strategy, encompassing a synthesis of Cooperative Patent Classification (CPC) codes and keyword-based searches. These searches were meticulously executed on titles, abstracts, and claims, employing Boolean operators (AND, OR, NOT) to refine the search results. To this end, a series of technology-specific search queries were developed for ZIBs and OEMs, with the objective of reflecting their distinct technological scopes and material concepts. As with any keyword-based patent retrieval strategy, the dataset may not fully capture all relevant patents where conceptually related inventions are described using heterogeneous or non-standard terminology. This limitation is particularly relevant for emerging subfields such as dry solid state electrolytes (SSEs), where semantic inconsistency may lead to false negatives at the retrieval stage. In particular, the ZIB query required the term "zinc" to occur within close proximity (ADJ1) of "ion", "metal", or "air" (ADJn denotes the Derwent proximity operator requiring two terms to appear within *n* words of one another in the specified order), which excludes related but non-adjacent formulations such as "zinc anode" batteries; similarly, the OEM query applies a comparatively narrow combination of polymer/organic and electrode terms (Supplementary Table S 1). These design choices reflect a deliberate high-precision, low-recall search strategy intended to minimize the inclusion of irrelevant patent families, at the cost of potentially underestimating the absolute size of the underlying patent landscape. The reported counts and white spots should therefore be interpreted as conservative, lower-bound estimates, while relative comparisons across categories remain robust to this limitation. The temporal scope of the analysis spans priority years from 2000 to 2025, covering both early-stage and recent innovation activity. Given the

prevalence of delays between the filing and publication of patents, the standard 18-month publication lag was considered during the interpretation of recent patenting trends. Moreover, since the analysis was conducted during 2025, annual patenting metrics for the most recent years are likely to be incomplete and therefore not directly comparable to earlier years. The datasets were further enriched by retaining only those IPFs that were still alive, defined as those that had been granted or were pending. This approach centered the analysis on inventions that not only had ongoing legal protection, but also demonstrated a clear technological relevance. Of the 4257 ZIB IPFs initially retrieved (Supplementary Table S 1), 3641 were retained after excluding families identified as not related to zinc-based battery technology.

2.2 LLM implementation and validation

To capture the intrinsic complexity of battery materials systems and enable fine-grained, materials-centric analysis, we employed GPT-4o and GPT-4o-mini via the OpenAI API to classify IPFs across multiple analytical dimensions, including electrode and electrolyte materials, battery chemistries, and KPIs relevant to electrochemical energy storage.

The selection of materials, chemistries and KPIs was not heuristic but grounded in established experimental and review literature on ZIBs [13, 22] and OEMs [23], ensuring alignment with performance descriptors and degradation mechanisms commonly used in the scientific community. Each IPF was analyzed using a multi-assignment classification strategy, allowing a single IPF to be associated with multiple materials classes, chemistries, or performance categories when explicitly supported by the patent text. This approach reflects the multidimensional nature of battery inventions, which frequently span multiple material systems, performance targets, or application contexts.

As electrolyte innovation is of pivotal concern in ZIB systems, where electrochemical stability, dendrite formation, corrosion, and interfacial behavior are strongly governed by electrolyte properties, electrolyte classes were treated as the central analytical dimension [24, 25]. The extended analytical scope was deliberately centered on cathode materials, as these represent the principal loci of differentiated materials innovation in ZIB systems, whereas the anode is overwhelmingly based on metallic Zn across all electrolyte designs and therefore does not constitute a comparably differentiating analytical axis. Auxiliary cell components such as current collectors, membranes, and separators, while relevant to academic research and cell engineering, were outside the scope of the present classification scheme and were not separately tracked; their inclusion represents a possible extension of

the framework in future work. For LLM-based classification, electrolytes were defined as follows: aqueous electrolytes comprised water-based systems; non-aqueous/mixed electrolytes comprised organic solvent-based systems or explicit mixtures of water and organic solvents; hybrid solid-state electrolytes (SSEs) comprised polymer-based electrolytes containing solvent or plasticizer, including gel-type systems; and dry SSEs comprised ceramics, inorganic ionic conductors, dry polymers, and polymer composites without a liquid solvent phase.

We assessed regional patterns by extracting the organizational origin of the patent assignees. For this purpose, a dedicated variable (Assignee Country) was constructed for each IPF. The geographic origin was determined by mapping the ultimate parent organization of the assignee to its corresponding country of incorporation, thereby capturing the effective locus of inventive and strategic control rather than the filing jurisdiction alone. Subsequently, IPFs were aggregated into the following regional categories: China, United States, Europe, Japan, South Korea, and rest of the world (RoW). Europe comprises all countries that are members of the European Patent Office. IPFs associated with assignees based outside these regions were assigned to the RoW category.

To analyze performance-related information reported in patent documents, a structured workflow combining LLM-assisted screening and manual validation was implemented. KPI identification was performed exclusively on patent abstracts, as manual validation confirmed that relevant performance information is predominantly disclosed at this level. Initially, GPT-based classification was employed to ascertain whether patents quantitatively address specific KPIs, including discharge capacity, cycle life, and current density. This preliminary LLM-based filtration stage was implemented to methodically evaluate large patent datasets for performance relevance. Owing to the substantially larger size of the ZIB dataset relative to the OEM dataset, the subsequent manual extraction of quantitative KPI values was restricted to the OEM dataset, which served as a representative case to demonstrate the feasibility of fine-grained quantitative extraction within the proposed framework, given the associated cost and time requirements of manual value extraction at scale. For the ZIB dataset, the analysis was limited to LLM-based screening of KPI presence/absence. In a subsequent step, IPFs that were identified as KPI-relevant were subjected to manual expert analysis. During this process, quantitative performance values and contextual information were extracted where available. Extracted KPI values were standardized to consistent units (e.g., mAh g⁻¹ for capacity, mA g⁻¹ for current density) and manually screened for internal consistency. Values representing extreme outliers relative to

the broader reported distribution were excluded prior to analysis to avoid distortion by isolated, potentially atypical claims. In addition to the abstract text, supplementary information disclosed within the patent document, such as experimental descriptions or auxiliary performance spectra, was consulted to ensure accurate interpretation of reported KPIs.

The selection of GPT-4o and the overall classification methodology align with prior work by Hemmelder et al., who demonstrated that this model provides sufficient reasoning capabilities and robustness for patent analysis in highly technical domains [6]. In accordance with this prior validation, the temperature parameter was set to 0 to ensure deterministic and reproducible outputs, and the random seed was fixed to 42 across all API calls to enforce identical initial conditions for all classifications. The model configurations, analysis scopes, and LLM prompts employed for ZIB and OEM classification are documented in Supplementary Table S 13 and S 14, while the corresponding classification schemes are summarized in Supplementary Table S 2. Model selection reflected a deliberate trade-off between dataset scale and task complexity: GPT-4o-mini was employed across all ZIB-related classification tasks to enable cost-efficient processing of the substantially larger ZIB dataset, while GPT-4o was used for the smaller but chemically more heterogeneous OEM dataset, where fine-grained discrimination between closely related material classes benefits from the model's greater reasoning capability. Maximum output token limits were set according to the expected length of each task's output (e.g., 10 tokens for the binary OEM/Other pre-filter versus 1200 tokens for multi-label ZIB material assignment), and batch sizes were chosen empirically to balance throughput against context-length constraints and classification reliability, with smaller batches used for tasks requiring more extensive per-patent context (e.g., OEM-Chemistries) and larger batches for tasks with short, low-complexity outputs (e.g., OEM-General).

A manual validation procedure was conducted on a stratified subset of 100 IPFs per case study, annotated independently by two domain experts. Inter-rater agreement, quantified by Cohen's kappa (Supplementary Table S 6), yielded macro-averaged values of 0.89 (ZIB) and 0.88 (OEM), indicating near-perfect agreement across all classification dimensions (Table 1). Disagreements between annotators were resolved by consensus discussion, and the resulting gold-standard labels were used to evaluate LLM classification performance (Supplementary Table S 7). Macro-averaged F1 scores of 0.81 (ZIB) and 0.82 (OEM) demonstrate robust classification performance across materials, chemistries, and KPI categories. To contextualize these results, a rule-based keyword

Table 1 Classification performance of LLM-based and keyword-baseline approaches for ZIB and OEM patent datasets

	ZIB	OEM
Annotated subset	100 IPFs	100 IPFs
Macro-Kappa (Inter-Rater)	0.89	0.88
<i>Overall classification performance (all dimensions)</i>		
Macro-F1 (LLM)	0.81	0.82
Weakest class (LLM)	Dry solid state (0.71)	None (0.33)*
<i>Task-matched baseline comparison</i>		
Macro-F1 (LLM)	0.82	0.85
Macro-F1 (Keyword)	0.21	0.37
Relative improvement	3.9x	2.3x
Weakest class (Keyword)	Dry solid state (0.00)	Radical (0.00)

* The low F1 score for the "None" class reflects a systematic tendency of the LLM to assign at least one KPI label even under ambiguous conditions, rather than a general weakness in KPI classification; this implies that the reported extent of missing KPI disclosure is likely conservative. The overall macro-F1 values summarize performance across all analytical dimensions and are not directly comparable to the keyword baseline, which was implemented for a single dimension per case study. The task-matched block therefore restricts both classifiers to the same classification task, label set, and class count.

classifier was implemented as a baseline for one dimension per case. On these tasks the LLM achieves macro-F1 scores of 0.82 against 0.21 (ZIB) and 0.85 against 0.37 (OEM), a two- to four-fold improvement indicating that the gain over conventional keyword methods is substantial rather than incremental (Table 1, Supplementary Table S 7). Lower F1 scores were observed for structurally ambiguous or underrepresented categories, including dry SSEs in ZIBs (F1: 0.71) and the absence category "None" in OEM KPI classification (F1: 0.33), the latter reflecting a systematic tendency of the model to assign at least one KPI label under ambiguous conditions, which implies that the reported extent of missing KPI disclosure is likely conservative. Co-occurrence analysis of classification errors revealed that systematic misclassifications are confined to structurally adjacent category pairs: aqueous and hybrid SSE electrolytes in ZIBs, and carbonyl-based and N-heteroaromatic materials in OEMs, consistent with the inherent chemical overlap between these classes (Supplementary Table S 4 and S 5). The OEM chemistry prompt assigned "Lithium" by default where no battery chemistry was explicitly designated (Supplementary Table S 14). In the gold-standard subset, four of 100 IPFs carried no identifiable chemistry and were all assigned to lithium by the model. The reported lithium share is therefore an upper bound, consistent with the class-wise precision and recall for lithium in Supplementary Table S 7, while the relative ordering of chemistries is preserved when gold-standard labels are used.

To analyze temporal trends in material usage and KPI reporting, annual shares were normalized by the number

of patents per priority year. Specifically, for each year y and category k (material class or KPI), a normalized rate was calculated as:

$$Rate_{y,k} = \frac{Count_{y,k}}{N_y},$$

where $Count_{y,k}$ denotes the number of occurrences of category k in year y , and N_y the total number of IPFs in that year. This normalization reflects the average frequency with which a given material class or KPI is mentioned per patent in a given year, thereby controlling for fluctuations in annual patenting activity.

2.3 Citation network analysis

To assess cross-technology knowledge transfer and technological influence, a citation network analysis was conducted across multiple ZIB-related innovation dimensions, including electrolyte classes, material groups, and KPIs. Patent citations were used as proxies for technological knowledge flows, capturing how prior innovations associated with specific battery chemistries informed subsequent developments in these dimensions. Electrolyte classes were retained as one particularly important analytical lens, given the central role of electrolytes in governing stability, safety, and performance in ZIB systems; however, the analysis was not limited to electrolyte-related innovation alone. Both backward and forward citations were analyzed using distinct normalization schemes, each tailored to a specific analytical objective and designed to ensure comparability across technologies with substantially different patenting volumes.

For backward citation analysis, a battery-type-centered normalization was applied to trace cross-chemistry knowledge flows and quantify the relative influence of diverse battery chemistries on ZIB-related innovation dimensions, including electrolyte classes, material groups, and KPIs. For each battery chemistry, IPFs assigned to that battery type were treated as the knowledge source. Citation shares were calculated as the proportion of backward citations originating from these IPFs that referenced patents associated with a given analytical category within the respective innovation dimension. Accordingly, the normalization base consisted of all backward citations made by IPFs of a given battery type, and the resulting shares express how strongly each battery chemistry contributed to the knowledge base underlying specific electrolyte classes, material groups, or KPI-related patenting activity. This formulation enables direct comparison of the relative technological influence of ZIBs, LIBs, and other battery systems, independent of absolute patent portfolio sizes.

For forward citation analysis, a class-based normalization was applied to quantify the subsequent technological relevance of specific innovation categories across battery chemistries. Citation shares were calculated as the proportion of forward citations received by IPFs associated with a given electrolyte class, material group, or KPI that originated from patents assigned to different battery types, normalized to the total number of forward citations received by that category. This approach captures which battery chemistries most strongly drew on, and thereby amplified, knowledge associated with specific ZIB-related innovation dimensions, providing a complementary perspective on technological influence.

Only IPFs with at least one valid citation were included in the citation network. Citations occurring within the same IPF were excluded to prevent artificial inflation of knowledge flows. Self-citations do not affect the analysis, as knowledge flows are evaluated between battery chemistries and electrolyte designs rather than within identical categories. Patent citations do not unambiguously reflect intentional knowledge transfer. Citations may be added by patent examiners during prosecution, included for legal or strategic reasons, or shaped by jurisdiction-specific citation practices, rather than reflecting the inventors' own assessment of relevant prior art. Furthermore, given the pronounced concentration of Chinese assignees within the ZIB patent landscape, citation patterns may additionally be shaped by region-specific citation practices, including a tendency toward higher domestic citation rates and potential language-related barriers to citing non-domestic prior art. Citation-based knowledge flows reported here should therefore be interpreted as indicative of technological proximity and prior-art linkage, which may reflect but do not unambiguously establish intentional knowledge transfer.

To assess whether the inclusion of pending patent applications introduces systematic bias into the citation network results, a sensitivity analysis was performed by restricting the dataset to granted patent families. Backward citation shares across all electrolyte classes, material groups, and KPI categories remained stable within ± 0.04 , confirming the robustness of the reported cross-domain knowledge flow patterns (Supplementary Table S 10 and S 11). Forward citation shares were uniformly higher in the granted-only analysis (Supplementary Table S 12), consistent with the higher average citation frequency of examined patents, but the relative ordering of electrolyte classes by knowledge flow directionality was fully preserved. The main conclusions regarding the self-referential character of aqueous ZIB innovation and the disproportionate cross-domain dependence of SSE concepts are therefore robust to this methodological choice.

3 Results

3.1 ZIB patent landscape white spots by electrolyte

The following results apply the three-part white-spot framework to the ZIB patent landscape. The analysis identifies activity white spots in underrepresented non-aqueous and solid-state electrolyte segments, and knowledge-flow white spots in the asymmetric cross-domain citation dependence of these emerging configurations. Reporting-related patterns are noted where relevant in the KPI discussion but are analyzed more systematically in the OEM case study. The ZIB and OEM case studies should be understood as complementary applications of the same transferable framework rather than as independent analyses, each illustrating a different analytical capability enabled by the underlying methodology.

ZIBs are attracting increasing attention as candidates for low-cost and inherently safer energy storage, particularly for stationary applications, owing to the abundance of zinc, the prospect of scalable cell designs and the favorable safety profile of water-based systems relative to incumbent battery technologies [26]. Concurrently, research is progressing beyond conventional aqueous configurations, with a shift toward higher-voltage intercalation chemistries and Zn–air concepts. Furthermore, in order to suppress parasitic processes such as the hydrogen evolution reaction (HER) and the oxygen evolution reaction (OER), which remain central constraints on reversibility and accessible operating voltage, different materials and electrolyte strategies are employed [27, 28]. Against this backdrop, patent data provide insight into which of these technological directions are beginning to translate into applied innovation.

The present patent landscape of ZIBs remains strongly dominated by aqueous electrolyte systems, which account for 1883 of the analyzed IPFs with priority years between 2017 and 2025, the largest share across all electrolyte classes (55%; Fig. 1). This concentration indicates that applied innovation in ZIBs still follows predominantly an aqueous development trajectory. By contrast, non-aqueous/mixed and SSE concepts each remain below 8% of total ZIB-related patenting activity, suggesting that these alternative electrolyte approaches have not yet diffused into application-oriented innovation at comparable scale.

Recent growth can be attributed to Chinese IPFs, which have a majority share of annual filings extending it to almost 98% in 2024. This trend is consistent with growing industrial and policy interest in safe and cost-effective stationary energy storage [22, 29]. The apparent decline in patent counts in 2025 should not be interpreted substantively, however, because patent data are subject to the standard 18-month publication delay. Moreover, as the analysis was conducted during 2025, the most recent

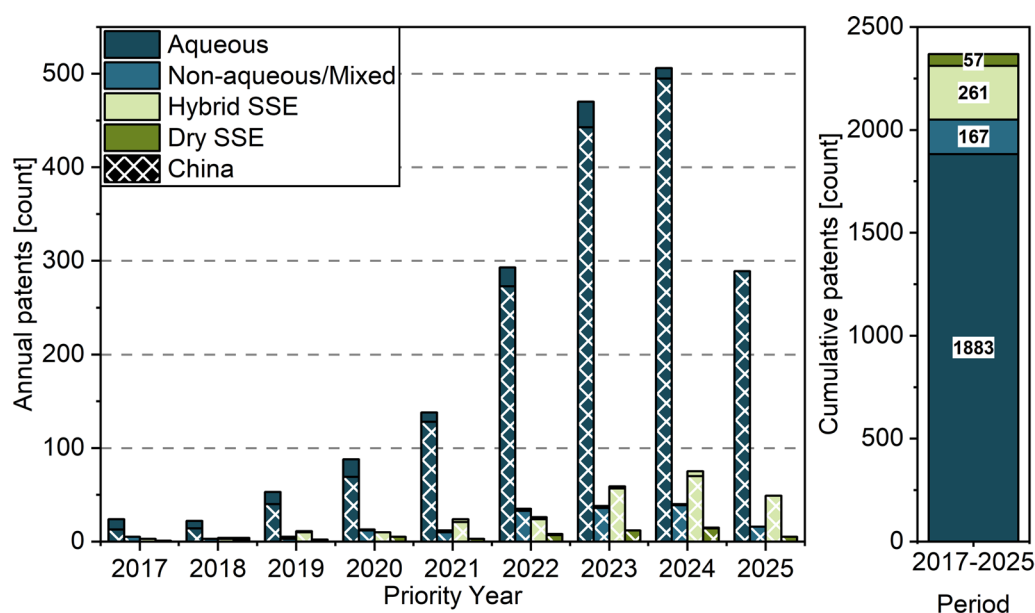


Fig. 1 Annual and cumulative patenting activity across ZIB electrolyte classes from 2017 to 2025, hatched segments denote patent families assigned to China

annual counts are necessarily incomplete and will likely rise as additional filings become publicly available.

Despite the presence of SSE-related patents within the ZIB landscape, these patents are predominantly concentrated in the domain of hybrid SSEs as opposed to dry SSEs. This distribution indicates that much of the innovation currently associated with solid-state ZIB electrolytes remains focused on solvent-assisted architectures that combine liquid-like ion transport with partial mechanical stabilization. By contrast, structurally self-supporting dry SSE concepts remain a comparatively small niche, consistent with persistent challenges in achieving sufficient Zn^{2+} conductivity, stable electrode–electrolyte interfaces and controlled Zn deposition under all-solid-state conditions [30].

A more fine-grained view of recent patenting shows that each electrolyte class is characterized by distinct dominant innovation strategy. In aqueous ZIBs, recent patenting is centered primarily on suppressing parasitic HER and OER through electrolyte additives, protective interphases, and related stabilization measures (e.g., US20230282806A1, CN113161631B, and CN114039109B). A second major trajectory is the development of highly concentrated or water-in-salt-type electrolytes, which aim to reduce water activity and expand the practical electrochemical stability window (e.g., US12100803B2, US20240339671A1, and CN112886004B). Taken together, these patterns indicate that aqueous ZIB innovation is focused less on replacing the electrolyte platform itself than on stabilizing

water-based Zn electrochemistry through local solvation control and mitigation of water-induced side reactions.

In non-aqueous/mixed ZIBs, the dominant strategy is the enhancement of Zn-salt solubility and ion transport in non-aqueous environments (e.g., US20230018070A1, and CN118507859A). By contrast, co-solvent approaches and SEI-focused stabilization strategies appear much less frequently. This distribution suggests that the central challenge in non-aqueous/mixed ZIB development is still to establish chemically viable and sufficiently conductive Zn-ion environments before more advanced interface-engineering strategies can scale.

Hybrid SSE patenting is even more strongly concentrated in gel-polymer electrolytes (e.g., CN113416273B, CN113782844B and CN113429616B), whereas interface-engineering concepts form only a much smaller secondary group. This imbalance indicates that most hybrid SSE innovation continues to rely on solvent-containing polymer matrices as the dominant route to combine ionic transport with partial mechanical stabilization.

Dry SSE patents follow a different, albeit still highly concentrated, pattern. Ceramic and composite solid electrolytes dominate this category (e.g., CN118610610A, CN118610611A and CN116826156A). Despite the retrieval of a dataset that may be considered incomplete due to the heterogeneity of patent terminology, including the US11749825B2 as a pertinent exemplar of an inorganic solid-state Zn conductor, the broader observation that dry SSE patenting remains limited in absolute terms remains valid. Taken together, these patterns

suggest that genuinely dry SSE innovation is beginning to explore ceramic and composite conductors but has not yet achieved the breadth or momentum observed for gel-assisted hybrid architectures.

Overall, these strategies indicate that recent ZIB electrolyte innovation remains strongly path dependent. Aqueous systems are dominated by stabilization strategies that suppress water-induced parasitic reactions, non-aqueous/mixed systems focus primarily on establishing viable Zn-ion solvation environments, hybrid SSEs are driven overwhelmingly by gel-polymer concepts, and dry SSEs remain confined to a small number of ceramic- and composite-oriented approaches. The field therefore still appears to be occupied largely with overcoming class-specific enabling constraints, whereas more disruptive electrolyte concepts remain comparatively rare in applied innovation.

The materials and KPI analysis depicted in Fig. 2 reveal that metallic Zn remains the universal anode material across all electrolyte designs, underscoring that innovation efforts in ZIBs are directed primarily toward electrolyte formulation and interfacial engineering rather than anode replacement. This configuration is technologically sound, as the utilization of metallic Zn maintains the fundamental energetic logic of ZIBs. Substituting Zn with alternative anode materials would elevate the anode potential, consequently decreasing cell voltage in a battery class that currently lags behind Li- and Na-based incumbents in gravimetric and volumetric energy density. Recent work on next-generation ZIB design correspondingly places the central materials challenge on the cathode side, where higher-voltage intercalation hosts and improved Zn-ion mobility are required to increase practical energy density [31].

This broader technological context is reflected clearly in the patent landscape. The prominence of Mn- and V-based cathode classes reflects their continued role as the most technologically actionable host families in ZIB development. Mn-based cathodes are attractive because of their abundance and favorable sustainability profile, whereas V-based materials remain important because their layered or tunnel-type oxides can enable comparatively high reversible Zn storage and good cycling stability. At the same time, both classes face persistent limitations that help explain the continued search for improved cathodes, including Mn dissolution, structural degradation, and voltage hysteresis in Mn-based systems, as well as dissolution, low operating voltage and sustainability concerns in V-based systems [32–35].

A more differentiated view across electrolyte classes reveals clear differences in cathode prioritization. In aqueous ZIB patents, cathode-related activity remains concentrated in Mn- and V-based materials, whereas

C-based and Zn–air cathodes occupy a more marginal role. Accordingly, aqueous innovation continues to follow established cathode trajectories, with limited evidence for a broader shift toward high-voltage cathode innovation. Non-aqueous/mixed electrolytes show a broader cathode profile, in which Mn- and V-based materials remain important but C-based and Zn–air-related concepts account for a comparatively larger share around 20%. The strongest shift is observed in hybrid and dry SSEs, where Zn–air concepts account for a markedly larger share than in aqueous systems. This likely reflects the much higher energy-density potential of air cathodes relative to intercalation-type transition-metal hosts. Once innovation moves beyond the safety and cost logic of conventional aqueous ZIBs, the rationale for retaining low-voltage Zn-ion intercalation chemistries become less compelling relative to Li- and Na-based incumbents. By contrast, Zn–air-type conversion cathodes offer a more plausible route toward competitive energy density. Even so, Mn- and V-based cathodes remain present, indicating that no clearly dominant new cathode regime has yet emerged.

The broader cathode landscape also extends beyond the dominant classes shown in Fig. 2. As summarized in Supplementary Table S 3, Fe-based cathodes represent the most visible alternative class across all electrolyte designs, with shares generally ranging from around 9% to 14%. By contrast, Cr-based cathodes remain less frequent, and OEMs play only a minor role throughout. These patterns indicate that alternative cathode chemistries have entered the patent landscape, but thus far mainly as secondary trajectories rather than as leading directions of applied innovation. In particular, the comparatively consistent presence of Fe-based systems suggests that more earth-abundant cathode chemistries are already being explored across multiple electrolyte environments, even though they have not yet displaced Mn- and V-based host materials as the central focus of ZIB patenting.

The KPIs reinforce this interpretation. In aqueous systems, patent activity is dominated by cycle life, dendrite inhibition and corrosion, indicating that stability-related bottlenecks continue to define the applied innovation agenda. Capacity- and energy-density-related metrics are less prominent, suggesting that performance scaling remains secondary to stabilizing the basic electrochemical system. Non-aqueous/mixed systems show a distinct but internally consistent KPI profile. Cycle life remains the leading priority, but capacity and dendrite inhibition are both comparatively prominent. Rather than being contradictory, this combination points to a dual design logic: moving beyond aqueous electrolytes makes higher-capacity operation

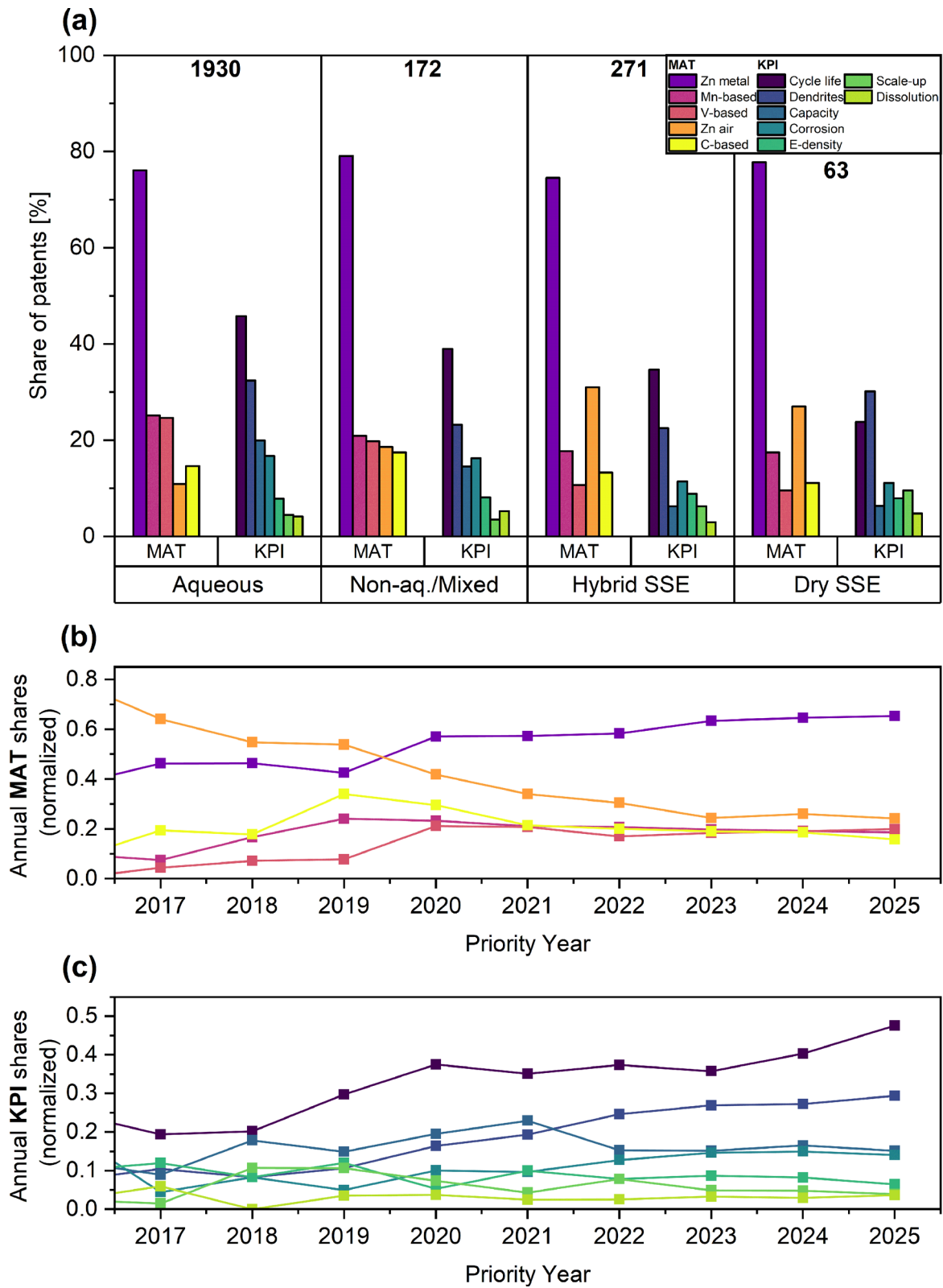


Fig. 2 Material (MAT) and KPI profiles of ZIB patents across electrolyte classes. **a** Patent shares assigned to MATs and KPIs for aqueous, non-aqueous/ mixed, and dry SSE designs; numbers denote total IPFs per class. **b** Normalized annual MAT shares and **c** normalized annual KPI shares by priority year, reported as per-patent assignment frequencies

more attractive by relaxing some of the electrochemical limitations of water-based systems, yet it does not eliminate Zn plating instability or interfacial degradation. Hybrid and dry SSEs shift the emphasis further toward interfacial control. Although cycle life remains important, dry SSEs in particular show a comparatively strong focus on dendrites, whereas capacity becomes less prominent than in non-aqueous/mixed systems. This suggests that once liquid-assisted transport is reduced or removed, the central bottlenecks shift from performance scaling toward maintaining stable contact, sufficient Zn^{2+} transport through the electrolyte phase and controlled Zn deposition under mechanically constrained conditions.

The aggregated temporal trends in Fig. 2 (b) and (c) indicate a broader shift in innovation priorities across the ZIB field. Over time, the normalized share of Zn–metal assignments increases further, reinforcing the consolidation of metallic Zn as the universal anode design. On the cathode side, Zn–air declines most, whereas Mn-, V- and C-based cathodes remain present throughout and converge toward a more even distribution in recent years. This does not point to the emergence of a single dominant next-generation cathode family, but rather to a broader exploration of competing cathode strategies as the field moves away from an earlier relative emphasis on Zn–air-related concepts. On the performance side, cycle life becomes increasingly dominant, capacity gains relevance, and dendrite inhibition remains consistently important, whereas energy-density-related claims remain comparatively limited throughout. Taken together, these temporal trends suggest that ZIB patenting continues to prioritize durable operability and stabilization over more aggressive performance targets, even as the cathode materials landscape becomes more differentiated.

Overall, these results identify several persistent white spots in the ZIB patent landscape. As activity white spots, non-aqueous/mixed and especially dry SSE electrolyte segments remain markedly underrepresented: despite their potential to extend operating voltage and suppress water-related degradation, they collectively account for fewer than 15% of ZIB filings. The translation of cathodes capable of enabling meaningfully higher operating voltage and practical energy density is similarly limited, with applied innovation still centered predominantly on established Mn- and V-based host chemistries and only partial diversification toward alternatives. From a reporting perspective, energy-density-related KPI metrics remain consistently underrepresented relative to stability-oriented indicators such as cycle life and dendrite inhibition, suggesting that performance scaling is not yet the central applied focus even as the cathode landscape diversifies. The knowledge-flow dimension of these white

spots is traced in the following section through citation network analysis.

The citation network analysis provides additional context for these white spots by showing that ZIB electrolyte innovation is embedded in markedly asymmetric cross-chemistry knowledge flows (Fig. 3). Here, backward citations capture the prior patent knowledge on which a given ZIB electrolyte concept draws, whereas forward citations indicate the battery chemistries that subsequently cite patents associated with that electrolyte concept. Viewed at the electrolyte level, aqueous ZIB patents occupy the central position in the network. They draw on a broad prior knowledge base spanning multiple battery fields, yet their downstream influence remains concentrated predominantly within subsequent ZIB patenting. This pattern suggests that aqueous ZIB innovation has developed into a comparatively self-referential and application-specific trajectory, consistent with its dominant share and greater technological maturity in the overall patent landscape. This interpretation should, however, be considered alongside the pronounced regional concentration of the ZIB landscape. Given that Chinese assignees account for nearly 98% of recent ZIB filings, elevated within-jurisdiction citation tendencies may partly contribute to the self-referential character of aqueous ZIB patenting rather than this exclusively reflecting technological consolidation. The converse applies to non-aqueous/mixed and SSE concepts: because domestic prior art in these smaller subfields is sparse, Chinese applicants may be structurally constrained to cite cross-domain references, which could inflate the apparent outward-facing character of their citation base beyond what technological dependence alone would predict.

By contrast, non-aqueous/mixed electrolytes and SSEs exhibit a more heterogeneous and outward-facing knowledge base, consistent with the pattern of knowledge-flow white spots. Their backward citation profiles show comparatively stronger links to metal–air and lead–acid batteries, indicating that these less mature ZIB embodiments rely more heavily on cross-domain strategies. Importantly, this should not be interpreted as evidence that SSE development is absent from Li- and Na-based systems. Rather, such contributions are likely absorbed into the broader LIB and sodium-ion battery (SIB) clusters used here, such that knowledge originating from all-solid-state Li- or Na-based research enters the network through those parent categories rather than through a separate solid-state label. The overall picture is therefore one of emerging ZIB electrolytes being assembled from multiple established technology lineages rather than evolving primarily within a closed ZIB-specific knowledge base—a defining characteristic of knowledge-flow white spots.

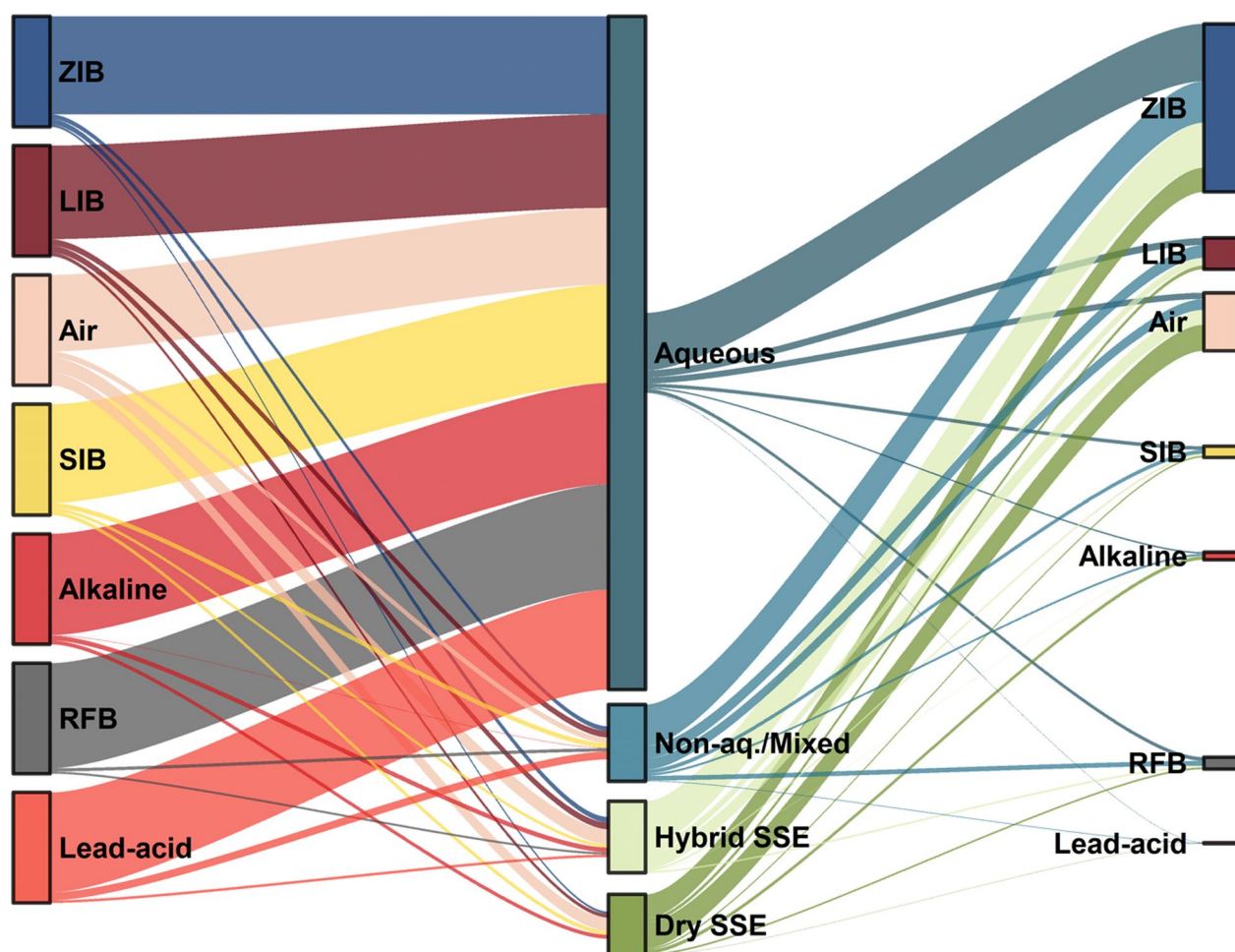


Fig. 3 Knowledge flows between battery types and ZIB electrolyte designs. Electrolyte designs act both as knowledge recipients and as sources of subsequent technological influence. Battery types connected through backward citations represent antecedent knowledge sources, whereas those connected through forward citations represent downstream knowledge recipients. Flow thickness indicates the share of total citation-based knowledge flow from the respective battery type or electrolyte design to the corresponding receiving categories. (RFB: redox-flow batteries)

The material- and KPI-resolved citation networks (Supplementary Figure S 1 and S 2) further refine this picture by showing that these cross-domain linkages are not uniform across subtopics. Different ZIB materials draw on distinct prior-art constellations, indicating that the knowledge base of, for example, Zn–air-related concepts differs substantially from that of Mn-, V- or C-based embodiments. This heterogeneity is important as it suggests that the most promising transfer pathways are subtopic-specific rather than generic. In particular, Zn–air concepts appear structurally closer to metal–air battery innovation streams, whereas more conventional host-material strategies remain more strongly coupled to the broader intercalation-battery knowledge base. Likewise, the KPI-level network shows that performance targets such as cycle life, dendrite suppression, capacity and corrosion mitigation are informed by different upstream

chemistry mixes, implying that distinct external technology domains may be relevant depending on whether the developmental bottleneck is primarily electrochemical stability, interfacial control or practical energy density.

Taken together, these results suggest that the white spots identified in the ZIB patent landscape are shaped not only by intrinsic materials limitations but also by uneven access to transferable knowledge from adjacent battery fields. The key implication is therefore not simply that non-aqueous/mixed electrolytes and SSEs remain immature, but that different ZIB embodiments appear to have different external knowledge reservoirs on which future progress may draw. Aqueous ZIBs already follow a relatively consolidated internal trajectory, whereas hybrid and dry SSE as well as Zn–air batteries appear more dependent on knowledge translated from established domains such as metal–air, lead–acid, LIB and

SIB technologies. These cross-domain interfaces may therefore represent potentially promising entry points for targeted innovation, although whether sparse patenting in these areas reflects genuine opportunity or persistent technical and commercial barriers cannot be determined from patent activity alone.

3.2 OEM patent landscape white spots by chemistry

Beyond the search for improved cathodes in ZIBs, OEMs provide a broader design space for next-generation batteries and a complementary case study for the analytical framework developed here. Due to the tunable redox chemistry at the molecular level, enhanced sustainability and mitigated supply vulnerability, OEMs resemble promising electrode materials. However, their practical deployment remains limited by persistent challenges, including dissolution, low intrinsic conductivity, and the difficulty of translating promising half-cell behavior into robust full-cell performance [23, 36, 37]. In this study, OEM-related patents were defined strictly as patents on organic or polymeric electrode materials, excluding inorganic electrodes, electrolytes, separators, binders, coatings, and broader battery-system claims. The LLM-based approach is therefore extended beyond the ZIB domain to a smaller but chemically more heterogeneous dataset, demonstrating how the same methodology can resolve fine-grained material classes and extract quantitative performance metrics—capabilities that are particularly valuable for identifying reporting white spots alongside activity white spots [36, 37].

In this area, lithium-based battery chemistries account for up to 93% of analyzed IPFs while maintaining the highest growth rate (Fig. 4), underscoring the dominant role as the primary application field for OEMs. By contrast, the comparatively smaller shares of sodium-based batteries and all-solid-state batteries (ASSBs) indicate that the transfer of OEM innovation into these emerging application spaces remains uneven. This distribution highlights the broader dependence on established battery ecosystems in which performance evaluation, materials integration and commercialization pathways are already more clearly defined [6, 38, 39].

Across all investigated battery chemistries, OEM patenting is dominated by Chinese IPFs, with smaller contributions from South Korea, the United States and Europe (Fig. 5a). This regional concentration is particularly pronounced in lithium-, sodium- and multivalent systems, whereas the ASSB-related OEM landscape remains small overall. The broader pattern suggests that applied OEM innovation is currently driven primarily by Asian patenting activity, especially in battery domains that already offer stronger industrial development and integration pathways.

The material-class distributions reveal pronounced chemistry-dependent design preferences across the six-category taxonomy. Lithium- and multivalent-based systems share a common structural logic: in both chemistries, N-heteroaromatic materials and carbonyl-based compounds emerge as the two dominant classes, together accounting for roughly half of lithium-based and nearly three-quarters of multivalent-based patents. This

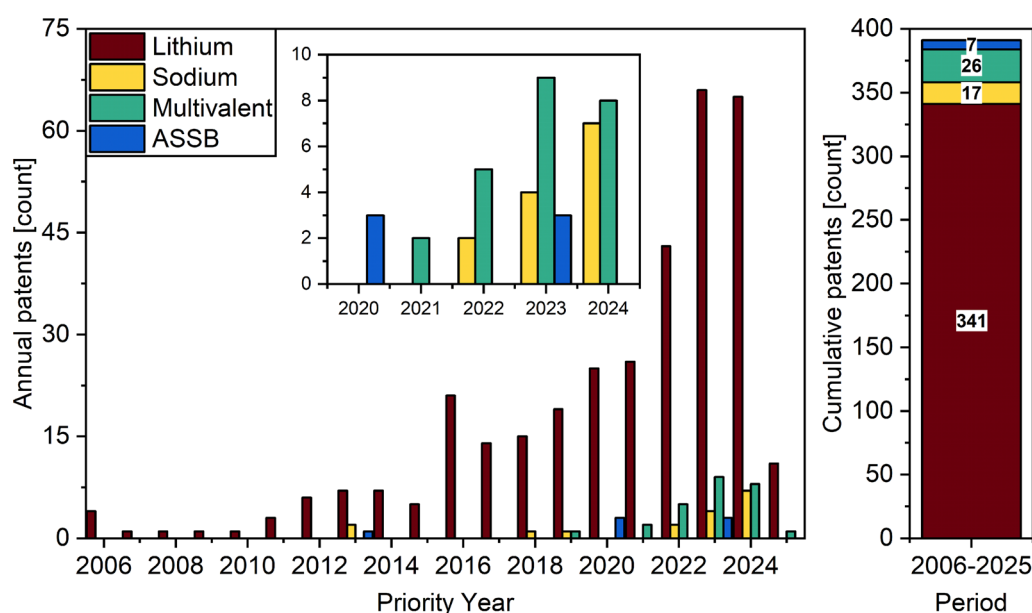


Fig. 4 Annual and cumulative OEM patent counts divided by battery chemistry

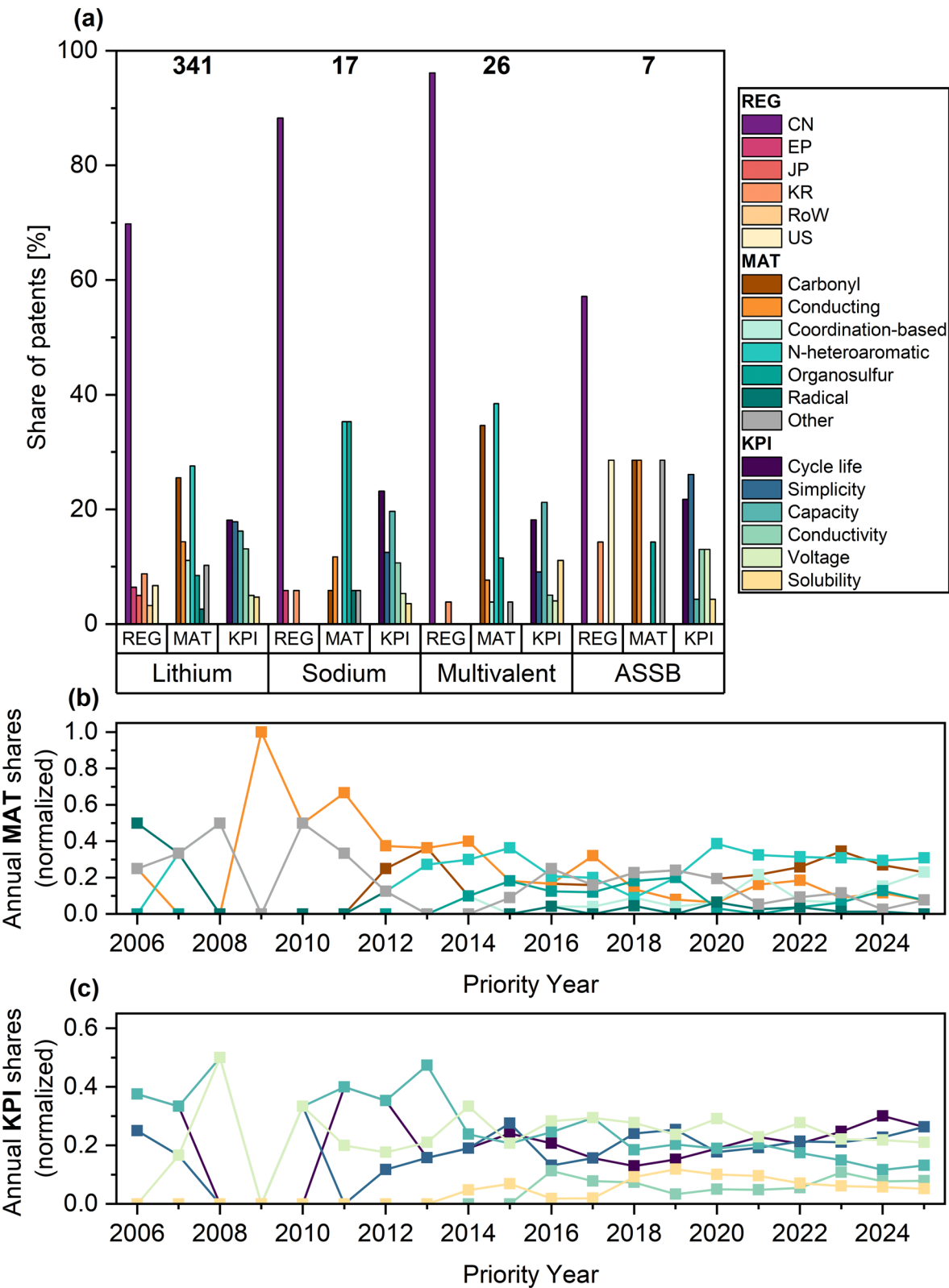


Fig. 5 **a** Share of patents by region (REG), material class (MAT), and key performance indicator (KPI) for four battery chemistries; numbers above each chemistry indicate the total patent count. **b** Normalized annual material shares and **c** normalized annual KPI shares plotted over the priority year, where values represent the average number of occurrences per patent in a given year (counts normalized by the total number of patents in that year)

convergence reflects the broad applicability of quinone- and imide-type carbonyl redox chemistry alongside nitrogen-rich aromatic systems—including phenazine-, phenoxazine-, acridine-, and quinoxaline-based compounds—across both single- and multi-electron-transfer chemistries. The relative dominance of N-heteroaromatic materials is more pronounced in multivalent systems, consistent with the higher charge-carrier valency placing greater demands on structural stability and redox-site density. Coordination-based organic materials and conducting polymers constitute secondary groups in lithium-based systems, while their presence in multivalent patents is markedly smaller.

Sodium-based IPFs show a distinct distribution in which N-heteroaromatic materials and organosulfur compounds are co-equal in prominence, while carbonyl contributions are comparatively minor—a pattern suggesting that sodium electrochemistry may benefit particularly from the coordinating capabilities and higher redox potentials of these systems, though the small absolute sample size ($n = 17$) warrants interpretive caution. ASSB concepts are notably absent of any N-heteroaromatic contributions and instead distribute across carbonyl, conducting polymer, and the residual ‘Other’ category in roughly equal shares, indicating that mixed-conducting and structurally compliant materials remain the primary focus in solid-state-oriented OEM architectures. A representative example is KR102173238B1, which illustrates that organic active materials have already begun to enter ASSB-related patenting, even if this field remains highly exploratory. The residual ‘Other’ category represents the remaining structural heterogeneity not captured by the six defined classes.

Similar to ZIBs, cycle life and capacity emerge as the dominant KPIs, indicating that OEM patenting is still centered primarily on demonstrating reversible energy storage with practically relevant output. Conductivity, solubility, and simplicity—the latter capturing explicit statements regarding straightforward synthesis routes or ease of scale-up, as defined in the corresponding LLM prompt (Supplementary Table S 14) and treated as a qualitative presence/absence indicator rather than a quantifiable performance metric—also appear repeatedly, showing that OEM innovation is shaped not only by electrochemical targets but also by persistent materials-integration constraints. This is particularly important because OEMs compete with incumbent inorganic cathode technologies in lithium- and sodium-based batteries. The realization of practical relevance therefore requires not only promising redox chemistry but also feasible processing, scalable production, and acceptable electrode-level performance. In this context, the recurring emphasis on simplicity is revealing, as it indicates that ease of synthesis and

scale-up are already treated as key translational criteria rather than secondary considerations.

The aggregated temporal trends in Fig. 5 (b) and (c) suggest that these chemistry-specific patterns are accompanied by a broader shift in innovation priorities across the OEM field. N-heteroaromatic materials show the most pronounced growth, consolidating as the largest material class in recent years, while carbonyl-based compounds also gain in relative prominence. Conducting polymers exhibit the most substantial decline, consistent with a transition from early-stage exploration toward more structurally specialized, high-redox-density molecular systems. Coordination-based materials increase modestly, whereas organosulfur materials decline in relative importance. On the performance side, cycle life and capacity become increasingly prominent over time, while solubility, conductivity, and simplicity persist as background constraints throughout. Taken together, these trends suggest that OEM patenting is moving from early materials exploration toward questions of practical durability and scalable implementation.

Given their cross-chemistry prevalence and their role as the most consistently reported performance outcomes, cycle life and discharge capacity provide the most robust basis for a more detailed quantitative analysis. Voltage was tracked as an initial KPI category (Supplementary Table S 2) but was excluded from detailed quantitative analysis due to its comparatively infrequent and inconsistent reporting across chemistries, consistent with its minor role in the temporal KPI trends. Current density was extracted not as an independent performance target but as a contextual parameter necessary for interpreting reported capacity and cycle-life values, given that both metrics are strongly dependent on the applied testing conditions. The next step therefore examines not only whether patents report numerical performance data at all, but also how these data are distributed across battery chemistries and where reporting remains too sparse for meaningful benchmarking.

The quantitative performance reporting shown in Fig. 6 reveals pronounced chemistry-dependent differences in both the availability and the character of reported KPI data, and in doing so directly illustrates the concept of reporting white spots within the OEM landscape. Panel a indicates that only 7% of lithium-based OEM patents disclose numerical values at the abstract level. This figure should not be interpreted as the absolute absence of quantitative reporting within the patent document: a spot-check of 30 randomly selected patents classified as disclosing no KPI values in their abstracts revealed that 63% contained numerical performance data within the full patent text, primarily in figures and experimental descriptions (Supplementary Table S 8).

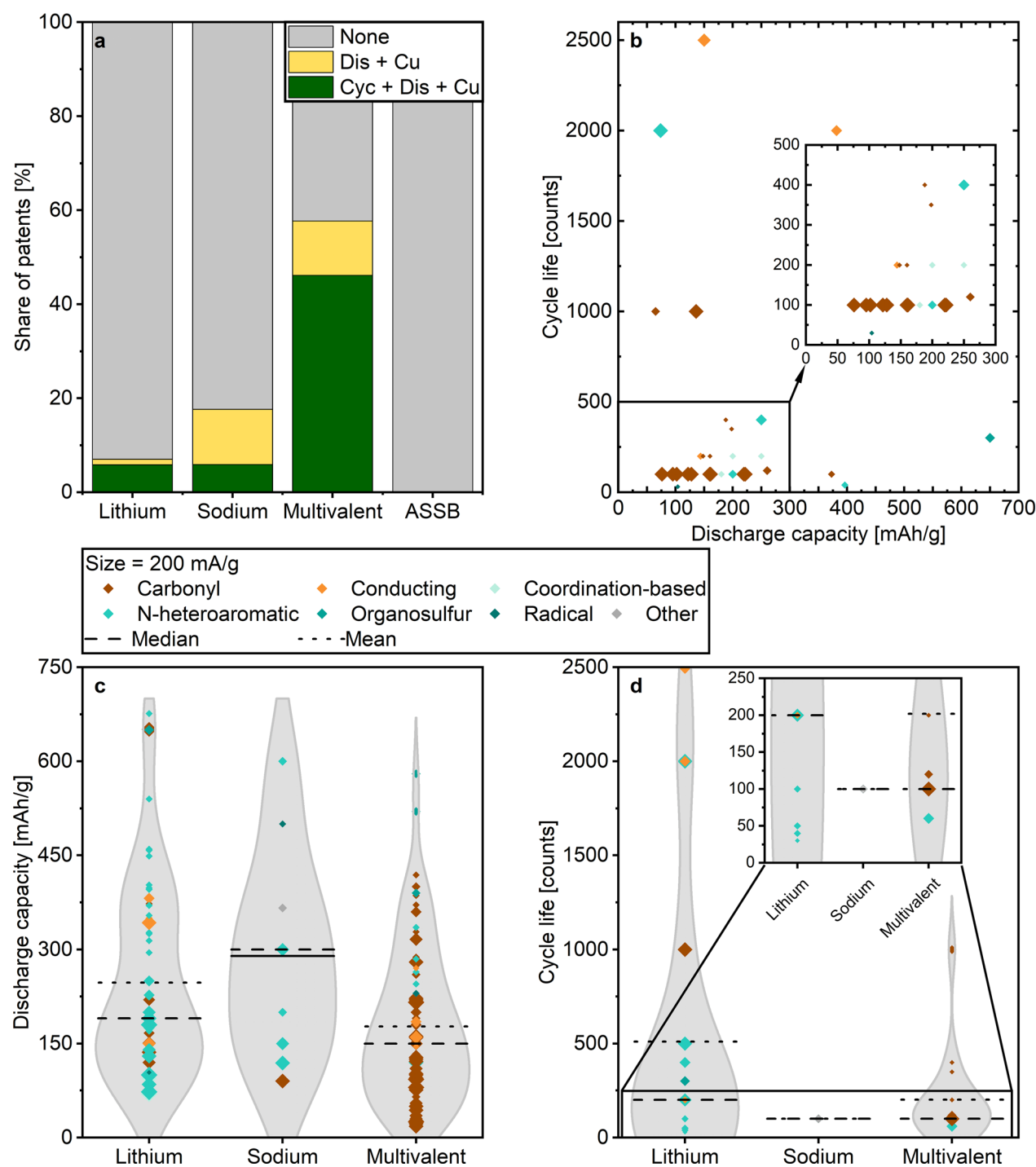


Fig. 6 Quantitative KPI reporting in OEM patent families across battery chemistries. **a** Share of patents reporting discharge capacity and current density (“Dis + Cu”), cycle life together with discharge capacity and current density (“Cyc + Dis + Cu”), or none. **b** Relationship between reported cycle life, discharge capacity and current density at the patent level. Violin plots of the reported **c** discharge capacity and **d** cycle life in OEM patent families, grouped by battery chemistry. Color coding denotes the respective material group, while marker size corresponds to the applied current density

This discrepancy reflects the structure of patent drafting, in which abstracts are intentionally concise and legally hedged while detailed performance claims are embedded in experimental embodiments; the disclosed KPI rates therefore characterize the accessibility of performance data to automated abstract-level analysis rather than the true prevalence of quantitative reporting. The reported disclosure rate accordingly represents a conservative lower-bound estimate of actual quantitative reporting, whereas the reported extent of missing disclosure correspondingly constitutes an upper-bound estimate. Among the investigated chemistries, multivalent OEM patents were found to be the most quantitatively documented subset (58%), with a markedly larger share of filings reporting both capacity- and cycling-related metrics. Conversely, ASSB-related OEM patents provide no sufficiently robust quantitative basis for further analysis, representing a pronounced activity white spot within the OEM landscape.

In instances where numerical data are reported, the resulting capacity-cycle-life landscape remains broad but interpretable (Fig. 6c, d). Lithium-based OEMs span the widest discharge-capacity range and contain the highest upper-end values. Multivalent systems appear to be more strongly oriented toward durable operation under reported test conditions than toward maximizing specific capacity alone. Sodium-based OEMs remain comparatively sparse in this regard, such that their apparent central tendencies should be interpreted cautiously. Because the most extreme outliers were excluded from the analysis, the plotted distributions reflect the more representative body of reported performance values rather than isolated exceptional claims.

At the same time, the correlation space in Fig. 6b highlights an important limitation of the current patent data. Reported high-capacity values are not embedded in a standardized electrode-level context, and high-capacity claims without current-density context that is systematically comparable across patents remain of limited interpretability. More broadly, critical parameters for practical benchmarking—especially areal capacity, mass loading and other electrode-level metrics—were not available with sufficient consistency to support a structured analysis. As a result, the reported values capture material-level claims more readily than practically comparable electrode-level performance. In this sense, the current patent literature still provides only a partial view of the true trade-off between capacity, durability, and rate conditions.

These reporting gaps constitute a systematic reporting white spot rather than a minor formal limitation. Meaningful comparison of OEM concepts across chemistries would require, at minimum, the more consistent

disclosure of discharge capacity, current density, cycle life, and basic electrode-level information—especially areal capacity, mass loading, and electrolyte-to-capacity ratio—parameters that were not available with sufficient consistency to support a structured cross-chemistry analysis in the present dataset. Without such context, even numerically explicit patents remain only partially benchmarkable. Taken together, the data identify an additional dimension of the OEM innovation landscape that requires further investigation: beyond the domains of chemistry and material selection, the transparency of performance reporting is itself unevenly developed. Notably, this reporting white spot persists even within lithium-based systems—the most active and mature OEM chemistry—suggesting that incomplete KPI disclosure reflects structural features of patent drafting practice rather than simply technological immaturity.

3.3 White spot typology and strategic implications

Across both case studies, the three white-spot types recur as analytically distinct but frequently co-occurring phenomena. Activity white spots are most clearly exemplified by dry SSEs in ZIBs and ASSB-related OEM concepts. Reporting white spots are most pronounced in lithium-based OEM patents, which exhibit the lowest rate of abstract-level KPI disclosure despite representing the dominant activity category. Knowledge-flow white spots characterize non-aqueous/mixed and SSE-related ZIB innovation. These categories are not mutually exclusive; a given technological direction may simultaneously exhibit several of these characteristics. Table 2 summarizes the white spots identified in this study according to this typology, together with their supporting evidence, indicative confidence levels, and possible strategic implications. The strategic implications listed in Table 2 describe the current structure of applied innovation and are not validated predictors of future technological opportunity.

4 Conclusion

This study introduces a scalable framework for identifying technological white spots in emerging battery fields by combining large-scale patent analysis with LLM-based materials classification, KPI extraction, and knowledge-flow analysis. The two application areas examined here should therefore be understood as case studies for method development rather than as exhaustive domain reviews. Taken together, they demonstrate how patent data can be interrogated not only for chemistry-level innovation patterns, but also for differences in technological maturity, reporting transparency, and cross-domain knowledge sourcing—three dimensions corresponding to

Table 2 Summary of identified white spots, supporting evidence, confidence, and strategic implications

White spot	Type	Supporting evidence	Confidence level	Strategic implications
Dry SSEs	Activity	Below 8% of all ZIB IPFs; concentrated in ceramic/composite concepts	Medium (small category; F1 0.71)	High technical entry barrier; potential high-risk/high-reward direction rather than simple neglect
Hybrid SSE to Dry SSE transition	Activity	Hybrid SSEs dominated by gel-polymer concepts; interface-engineering approaches comparatively rare	Medium	May reflect a technological maturity barrier rather than a lack of research interest
Quantitative KPI disclosure	Reporting	Only 7% of lithium-based OEM patents disclose numerical KPI values	High (large sample), but constrained by abstract-only extraction (see Methods)	Improved disclosure could facilitate cross-chemistry benchmarking and investment decisions
ASSB-related OEMs	Activity + Reporting	Smallest chemistry class; no sufficiently robust quantitative basis; class-recall 0.70	Low (sample too small for robust conclusions)	Early-stage exploratory field; currently too immature for a clear strategic recommendation
Aqueous ZIBs	Reference	<i>Dominant, self-referential category</i>	<i>High</i>	<i>Mature field; innovation potential likely incremental rather than structurally open</i>

the activity, reporting, and knowledge-flow white spots that serve as the structuring analytical lens of this study.

In the ZIB case study, activity white spots are most apparent in non-aqueous/mixed electrolytes and especially dry SSE segments, which collectively account for fewer than 15% of filings despite their potential to overcome the electrochemical constraints of water-based systems. Alongside these, knowledge-flow white spots characterize the same emerging segments: the citation network analysis reveals that these less mature ZIB configurations draw disproportionately on prior art from adjacent domains such as metal–air and lead–acid batteries, rather than from a consolidated ZIB-specific knowledge base. Aqueous ZIB innovation, by contrast, exhibits a more self-referential citation structure consistent with its greater technological maturity, though this pattern is also shaped by the pronounced concentration of Chinese assignees and associated regional citation tendencies. In this sense, the ZIB case study shows that white spots can arise not only from intrinsic materials limitations, but also from the structure of knowledge flows and the availability of external innovation resources.

The OEM case study serves a complementary role within the framework. Rather than focusing on knowledge flows, it demonstrates how LLM-assisted patent analysis can resolve fine-grained material classes and extract quantitative performance metrics from a chemically heterogeneous dataset, revealing reporting white spots that are not visible from activity counts alone. Lithium-based OEM systems dominate in volume and exhibit the most established ecosystem, yet they

simultaneously represent the most pronounced reporting white spot: despite accounting for 93% of OEM filings, only 7% of these patents disclose numerical KPI values at the abstract level. ASSB-related OEM concepts represent a pronounced activity white spot, with a patent base insufficient to support quantitative benchmarking. These patterns together indicate that white spots in OEM innovation are multidimensional: sodium-, multi-valent-, and ASSB-related concepts are sparse in activity, while lithium-based concepts are extensive in activity but systematically underreported in performance. In both dimensions, incomplete access to structured performance data limits the ability to draw rigorous, cross-chemistry conclusions.

A key implication across both case studies is that the ability to identify where quantitative reporting is robust and where it is persistently absent adds an analytically informative layer beyond conventional activity mapping. Rather than treating reporting gaps solely as data limitations, the present study demonstrates that patterns of missingness are themselves meaningful signals of which innovation domains remain poorly benchmarked, and where standardization of disclosure practices would most improve the tractability of evidence-based technological foresight. Critical parameters for practical benchmarking, especially areal capacity, mass loading, and electrode-level metrics, were absent with sufficient consistency to prevent structured cross-chemistry analysis; their more systematic inclusion in patent documents would substantially enhance the analytical value of future patent-based performance assessments.

Taken together, the two case studies highlight complementary strengths of the methodological approach and demonstrate that white spots in emerging battery technologies arise not only at the materials level, but also from asymmetric knowledge flows and incomplete performance reporting. The strategic implications of each identified white spot, including supporting evidence, indicative confidence levels, and possible actionable directions for R&D strategy, IP positioning, and funding decisions, are synthesized in Table 2. The adaptability of the framework to different chemistries, material classes, and reporting patterns suggests its potential for application in other energy-storage domains characterized by heterogeneous terminology and rapidly growing patent activity.

In a broader context, the results indicate that a structured patent analysis can offer an early perspective on the development of emerging battery technologies, allowing patent data to be utilized not only to monitor activity, but also to identify areas of technological consolidation, persistent bottlenecks, and limited evidence of practical progress. It should be emphasized that the white spots identified in this study reflect the current state and structure of applied innovation rather than validated predictors of future technological opportunity. Sparse patenting in a given direction may equally indicate genuine, underexploited potential or persistent technical and commercial barriers that limit its practical viability; the present framework does not distinguish between these possibilities. A natural extension of this work would be a temporal validation, in which white spots are defined using patents up to a historical cutoff year and subsequently assessed against later patent growth or citation impact within the same categories. Such an approach would provide a rigorous, retrospectively testable foundation for validating white-spot analysis as a potential predictive signal for technology foresight, establishing the present framework as a scalable, evidence-based tool for examining structural shifts in emerging battery innovation landscapes.

Supplementary Information

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Supplementary Material 1.

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Data availability

No datasets were generated or analyzed during the current study.

Declarations

Competing interests

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