Cell Reports
Physical Science

CellPress
OPEN ACCESS

Perspective

Potential to transform words to watts with large language models in battery research

Shuo Zhao,[1] Sihui Chen,[2] Jiayi Zhou,[3] Chao Li,[2] Tan Tang,[3] Stephen J. Harris,[4] Yang Liu,[1,*] Jiayu Wan,[2,*] and Xin Li[1,*]

SUMMARY

Conventional battery research often grapples with the challenge of accumulating scattered knowledge and information across countless academic resources, including papers, lectures, conferences, and more. This dispersed wealth of information spans a variety of modalities, further limiting the efficiency of literature review and methodology comparison, hindering the rapid advancement of energy storage technologies. In this perspective, we cover progress and introduce a paradigm shift catalyzed by large language models. The paradigm harnesses the power of natural language processing and artificial intelligence to enable rapid information synthesis and swift insight extraction. To illustrate the transformative potential, we present a practical demonstration of a comprehensive literature review in fast charging powered by ChatGPT, showcasing how the proposed paradigm can streamline the process of synthesizing information from a vast array of sources. This perspective underscores the profound impact of large language models on battery research, ushering in an era of efficiency and accelerated innovation in energy storage technologies.

INTRODUCTION

In the contemporary landscape of energy storage technologies, batteries assume a paramount role that transcends sectorial boundaries.[1] Their significance extends across various domains, from underpinning the proliferation of renewable energy sources[2,3] to powering the portable electronic devices that have become ubiquitous in modern society.[4,5] Nevertheless, as global energy demands continue their relentless ascent and environmental apprehensions intensify, the imperative for advancements in battery technology becomes increasingly pronounced.[6–8] This pressing need necessitates the development of a novel research paradigm that places paramount emphasis on achieving exceptionally high levels of efficiency.

In the conventional research paradigm for battery technologies, as shown on the left in Figure 1, researchers are required to navigate a vast and dispersed body of academic resources. These resources span multiple modalities, encompassing a myriad of articles, conferences, and lectures. Within this heterogeneous repository of information, researchers must undertake the challenging endeavor of identifying and synthesizing pertinent knowledge related to their research topics. Comprehensive literature reviews are essential not only to provide an in-depth understanding but also to stimulate innovative ideas and conceive pioneering methodologies. Afterward, the research process advances into the laboratory phase, involving experimental conduction, data collection, and result analysis.

[1]Data Science Research Center, Duke Kunshan University, No. 8 Duke Avenue, Kunshan, Jiangsu Province 215316, China

[2]Future Battery Research Center, Global Institute of Future Technology, Shanghai Jiao Tong University, Shanghai 200240, China

[3]Laboratory of Art and Archaeology Image, Zhejiang University, Hangzhou, Zhejiang 310028, China

[4]Energy Storage and Distributed Resources Division, Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA

*Correspondence:
yang.liu2@dukekunshan.edu.cn (Y.L.),
wanjy@sjtu.edu.cn (J.W.),
xinli.ece@duke.edu (X.L.)

https://doi.org/10.1016/j.xcrp.2024.101844

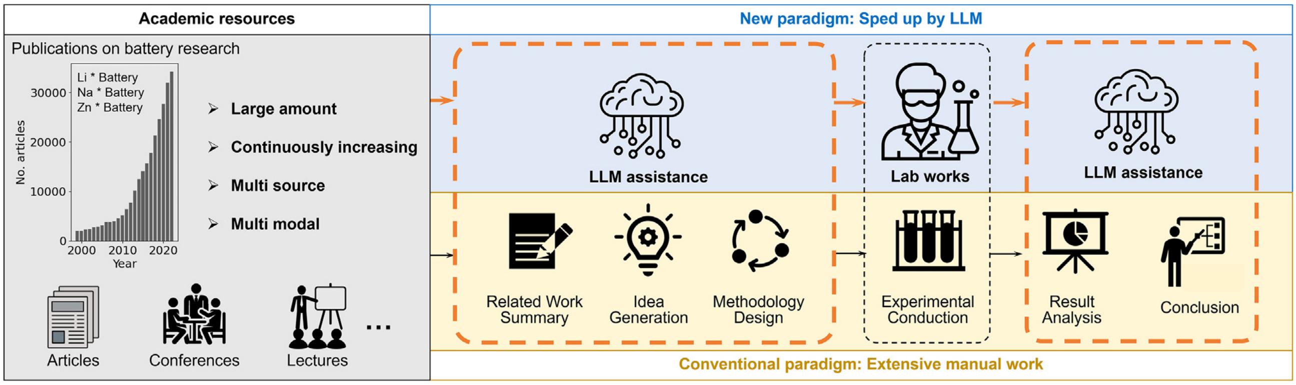

Figure 1. Comparative illustration of conventional and LLM-transformed research paradigms

In the conventional research paradigm shown in the yellow block, the time-consuming nature of critical processes—including incorporating related work, generating research idea, etc.—is primarily due to the vast volume of related academic resources that necessitate manual exploration. This abundance of resources poses a significant challenge to researchers, hampering the efficient development of new technologies. However, the LLM paradigm, shown in the blue block, can massively enhance the conventional search. It offers the potential to transform and optimize these fundamental components of the research process, promoting efficiency and enhancing research outcomes.

Despite its long-standing place in the scientific tradition, the conventional research paradigm presents inherent limitations. First and foremost, the dispersed nature of the literature, spanning a multitude of sources and formats, complicates the process of consolidating relevant insights. To illustrate, there are over 300,000 entries related to batteries in the Web of Science database, with this number continually on the rise. In fact, in 2022, this count surged to nearly 40,000, signifying the rapidly expanding body of knowledge in this field. Such a sheer volume of information necessitates significant time commitments and, even so, inevitably leads to the oversight of crucial findings. Moreover, identifying the most pertinent research in this vast sea of knowledge often requires extensive manual review and expert judgment. This human-intensive approach may inadvertently limit the scope and depth of the research exploration. Furthermore, the research endeavor typically entails repeated engagement with the literature, often through multiple iterations during both the idea generation and methodology design phases, resulting in a substantial investment of time and resources. This not only hampers the pace of scientific advancement but also poses a substantial obstacle in the face of pressing global challenges that demand swift solutions.

To address these formidable challenges, the advent of multimodal artificial intelligence (AI) emerges as a promising and transformative solution. Multimodal AI systems undergo training using a diverse array of data types, including video, audio, images, and text. This multifaceted training equips AI with the capability to understand content more comprehensively and to interpret context at greater depth. At the core of these advanced models, large language models (LLMs), such as OpenAI's ChatGPT,[9–13] play pivotal roles in bridging the human-machine gap. Initially, LLMs have been characterized by their remarkable ability to understand, generate, and manipulate human language at an unprecedented scale and accuracy.[9–13] These capabilities have subsequently been further extended to encompass the comprehension of various other formats of data.[14] Inspired by these remarkable capabilities, LLMs have found wide-ranging applications in various academic disciplines, providing assistance in fields such as medicine for clinical decision support[15]; biology, as exemplified by AlphaFold's ability to deduce protein structures from amino acid sequences[16]; mathematics involving discovering new solutions of complex algorithmic problems[17]; and chemistry, for the synthesis of new compounds.[18]

These applications shed light on the introduction of novel research paradigms transformed by LLMs in the field of battery research, offering the promise of overcoming long-standing challenges inherent in the traditional research approach.

Transitioning to this new paradigm (refer to Figure 1), LLMs are utilized to efficiently process vast quantities of research resources and, through their language comprehension and generation capabilities, extract insights from complex and multifaceted literature sources. This newfound capability is instrumental in addressing the challenges posed by the dispersed nature of battery research literature, the difficulty in identifying pertinent information, and the time-intensive iterations required in research design. As such, leveraging LLMs in battery research (or any other area of research) has the potential to streamline the process of information extraction, thereby enabling researchers to quickly access, analyze, and apply a wealth of knowledge. By efficiently consolidating relevant information from a wide array of sources, LLMs empower researchers to expedite idea generation and methodology design, bypassing the often time-consuming and repetitive stages traditionally associated with research. Furthermore, empowered by extensive access to a rich array of research resources and their evolving cognitive prowess, LLMs can help researchers distill insights from gathered experimental data and formulate well-supported conclusions. Essentially, beyond the experimental stage that necessitates manual intervention, the incorporation of LLMs streamlines facilitation throughout every phase of the research process.

Nonetheless, it is essential to recognize that while LLMs excel in information extraction, they may not possess domain-specific knowledge, such as the intricate details of battery technologies. This limitation can occasionally result in less-than-ideal responses to posed questions. To fully unlock the potential of this new paradigm in addressing the specific challenges of energy storage, a complementary approach is required to integrate information extraction capabilities of LLMs and the expertise of academic research resources. Such integration would create a synergistic partnership, harnessing the advantages of both LLMs and domain expertise, ultimately accelerating the advancement of innovative solutions in battery research.

To exemplify the transformative capabilities of incorporating LLMs into battery research, we demonstrate an approach in the realm of fast charging, referred to as "BatteryGPT." Fast charging serves as a compelling example for several reasons. Firstly, it has recently gained substantial attention, driven by the burgeoning marketing and adoption of electric vehicles (EVs). The widespread adoption of EVs is instrumental in mitigating greenhouse gas emissions and enhancing energy security for nations.[19] Fast-charging technology plays a pivotal role in alleviating the prevalent "range anxiety" associated with EVs. Consequently, numerous countries and regions, including the United States,[19] Europe,[20] and China,[21] have made significant commitments to the development of advanced electrification research aimed at enabling fast-charging solutions. As the demand for fast-charging solutions continues to escalate, the need for cutting-edge research becomes increasingly pronounced. Secondly, fast-charging technology is inherently intricate, comprising numerous technical details, intricate mechanisms, and evolving innovations.[22] This complexity positions it as a highly technological field where attention to detail is paramount, making it an ideal candidate for demonstrating how LLMs can effectively address the multifaceted aspects of advanced battery research.

BatteryGPT relies on a dedicated fast-charging database sourced from a large number of publications. When prompted with user input concerning their fast-charging

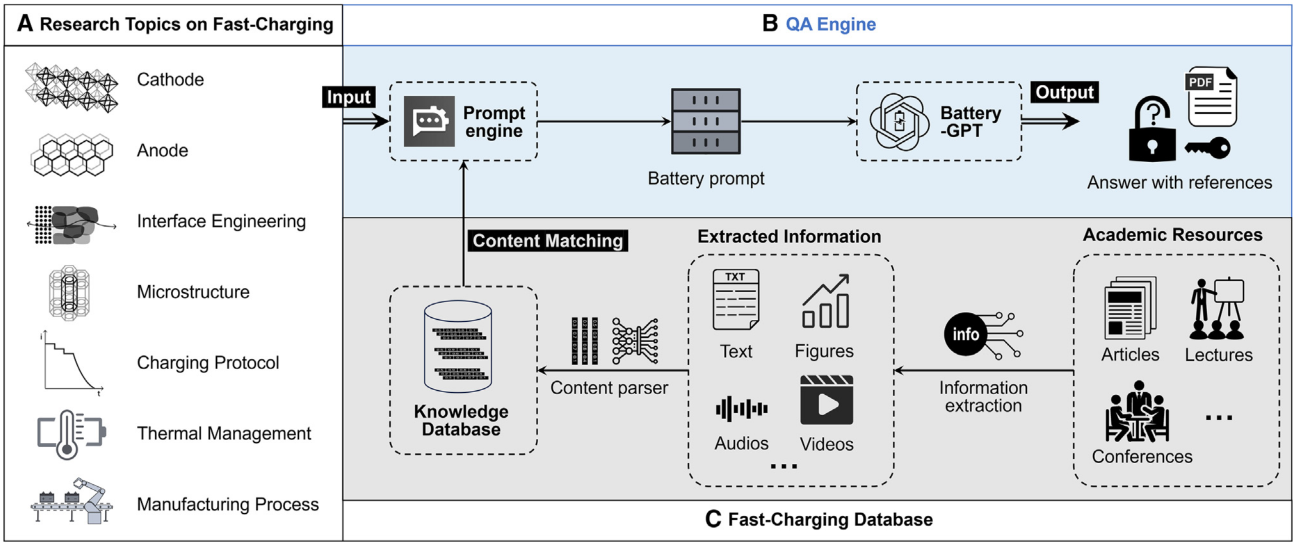

Figure 2. Application of LLMs to an expedited research review for fast-charging technologies

(A) Research topics of fast charging: an illustration of seven key research topics in the fast-charging domain, including anodes, cathodes, thermal management, etc., providing the foundational starting point to retrieve knowledge from BatteryGPT.

(B) Knowledge retrieval and answer generation: research questions are combined with relevant information retrieved from the knowledge database to form a prompt. The BatteryGPT model then utilizes this prompt to generate the desired answers, enhancing the speed and accuracy of research review for fast-charging technologies.

(C) Knowledge database construction: a broad range of multimodal academic resources, such as articles and lectures, are tapped to extract knowledge about fast-charging technology. This knowledge comprises various types, including text, audio, and more. Subsequently, it is transformed into vector representations, a crucial process that enables efficient knowledge retrieval.

objectives, the BatteryGPT system seamlessly embarks on a comprehensive exploration of the expansive landscape of battery research literature. It efficiently extracts the most pertinent and current information related to fast-charging technologies. Following this information retrieval process, the LLM expertly organizes and synthesizes the wealth of knowledge, furnishing the user with a coherent and insightful summary. This summary encapsulates key findings, recent advancements, and potential methodologies pertinent to fast charging within the realm of battery technology. The concise yet powerful flow of BatteryGPT is demonstrated in Figure 2 and will be discussed in the next section.

BatteryGPT AND FAST CHARGING

Fast charging stands as a pivotal requirement in battery technology that would enable a transformative leap forward with profound implications.[19] Its significance lies in its ability to dramatically reduce the time required to replenish the energy stored within batteries (perhaps down to 5–10 min to go from 20% to 80% state of charge), making it an essential component of our increasingly electrified world. In the context of EVs, fast charging addresses a key concern for consumers by alleviating range anxiety, thereby accelerating the broader adoption of electric mobility.[23–25] This, in turn, contributes to a significant reduction in greenhouse gas emissions and a reduced dependence on fossil fuels, fostering a more sustainable and environmentally conscious future. Beyond EVs, fast charging is pivotal for the integration of renewable energy sources into our power grids, enhancing grid stability, promoting energy sustainability, and offering a practical solution for emergency situations.[26,27] As battery technology continues to advance, fast charging is a linchpin in ushering in a new era of convenience, environmental responsibility, and energy efficiency.

In the realm of fast-charging research, several key areas are of paramount importance.

(1) Anode and cathode materials: the materials for both the anode and cathode impact the rate at which energy can be stored and released, directly influencing the charging speed of batteries.[28–34]
(2) Interface engineering: interface engineering ensures efficient electron and ion transport during rapid charging, reducing degradation and heat generation.[35,36]
(3) Microstructure optimization: fine-tuning the microstructure can improve mass transfer and overall efficiency.[37–48]
(4) Charging protocol design: intelligent charging protocols that take into account the specific needs and limitations of fast-charging batteries can help balance speed and battery longevity.[49,50]
(5) Thermal management: maintaining appropriate temperature levels during fast charging is vital to prevent overheating and thermal-induced degradation. Effective thermal management strategies are fundamental for safe and efficient fast-charging.[51–55]
(6) Manufacturing processes: developing efficient and scalable manufacturing processes is essential to bring fast-charging batteries to mass production. Ensuring consistency and quality during production is a critical research aspect.[56,57]

FROM WORDS TO WATTS

Limited by their training corpus, general-purpose LLMs usually lack specialized knowledge required for answering professional inquiries about fast-charging technology, leading to potential inaccuracies and factual errors, commonly referred to as "hallucination."[13] To address this issue, one promising approach is incorporating external knowledge into prompts, a technique known as retrieval-augmented generation (RAG).[58] In essence, given a specific query, RAG first retrieves a collection of relevant knowledge from a designated source. This retrieved knowledge is then amalgamated as contextual information alongside the original query, subsequently provided to the LLM as prompt input to trigger the generation of corresponding responses. In this process, the interaction with the LLM is implemented using prompt only, and no training or fine-tuning is involved.

In fact, the RAG paradigm leverages the zero-shot learning capability of the LLM, which presents remarkable advantages in the considered scenario. Taking advantage of this framework, the integration of most up-to-date knowledge can be enabled by simply updating the knowledge database. This effectively avoids the massive computational cost for fine-tuning the LLM and mitigates the risk for retrieving irrelevant information.

Inspired by the principles of RAG, BatteryGPT is proposed to utilize LLMs to transform the landscape of fast-charging technology investigation. As depicted in Figure 2, this innovative framework consists of two integral components: (1) the fast-charging database and (2) the question-answer (QA) engine.

Fast-charging database

The core of the fast-charging database is a central repository of knowledge extracted from an extensive collection of research articles. These articles are initially sourced through a search on the Web of Science using the keyword "fast-charging," yielding a pool of approximately 2,200 articles. However, due to the diverse origins of these publications, web scraping techniques, conducted with proper authorization, allow for the automated gathering of only around 1,000 articles from this pool.

To enhance the resources available for BatteryGPT, this article database is further enriched by integrating the insights and expertise of researchers, leading to the inclusion of approximately 50 high-quality articles obtained through manual collection. The selection of these manually acquired articles adheres to specific criteria, including (1) the timeliness of the papers, (2) the scholarly standing of the publishers, (3) the academic reputation of authors, and (4) the quality of the literature reflected through citation metrics. A detailed list of these articles is provided in an Excel spreadsheet of fast-charging papers extracted from literature (see Data S1), with a dedicated column indicating whether the articles were downloaded automatically or manually.

This amalgamated repository, comprised of a substantial number of articles, forms the cornerstone of this research paradigm. As these articles are originally in PDF format, a subsequent step involves text parsing to extract and process the text from these documents using Python. Each paragraph within the PDF documents is parsed into text snippets, thereby ensuring that the knowledge contained within them is accessible for analysis and retrieval.

To further enhance the efficiency of knowledge retrieval, the textual data are converted into vector representations using the text embedding technique. This conversion into numerical vectors is a pivotal step, streamlining the data for computational analysis and enabling the system to rapidly retrieve and process information.

It is essential to note that, in addition to research articles, the database has the potential to incorporate a diverse array of multimodal academic resources, such as lectures and contributions from academic conferences. This expansion encompasses a variety of data formats, including traditional text, figures, audio, video, and potentially more. This broader inclusion of data modalities offers a comprehensive and holistic perspective of the fast-charging field, ensuring that a wide spectrum of knowledge is readily available for research and analysis.

QA engine

The QA engine is crafted to interpret and respond to user-generated questions related to fast-charging technology. These posed questions are converted into vectors using the same technology as that used to construct the fast-charging database. Leveraging the vector representations of textual content, the QA engine searches the vast expanse of the fast-charging database to extract pertinent information, insights, or answers from the wealth of data stored within based on the embedding cosine similarities. Once this information is retrieved, it is amalgamated with specific formatting requirements, shaping it into a prompt for BatteryGPT. This prompt guides BatteryGPT to generate the final output, delivering concise, contextually accurate, and user-friendly answers or insights that directly address the user's questions and providing reliable references for further exploration. The algorithmic flow, along with an illustrative example, is detailed in Figure S1.

One significant challenge in this approach is the limitation of prompt length, constraining the volume of domain-specific knowledge accessible to LLMs for a given query. This limitation necessitates condensing the most pertinent and high-quality textual content within a confined input space to attain optimal output, thereby intensifying the demand for superior information retrieval. Enhancing the quality of

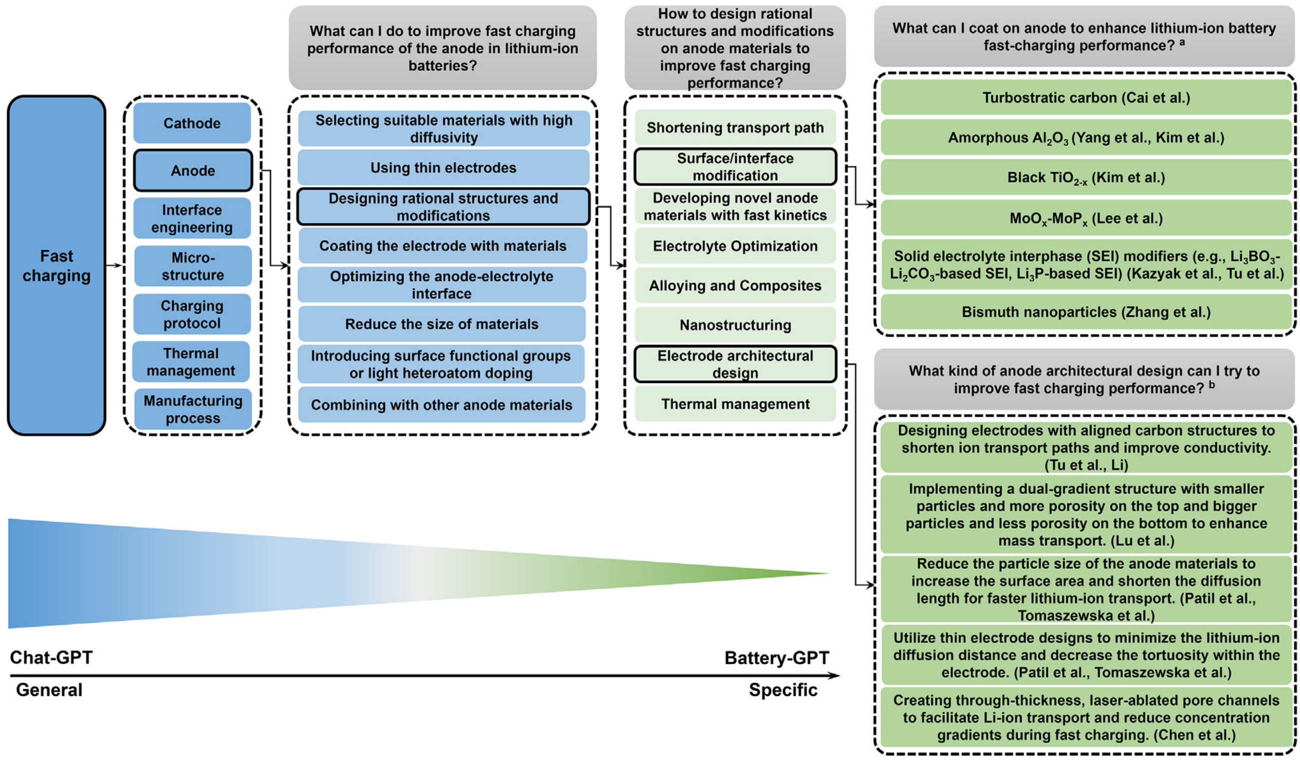

Figure 3. Demonstration of generated answers using ChatGPT and BatteryGPT for various research questions

To assess the performance of ChatGPT and BatteryGPT regarding fast-charging knowledge, a hierarchical sequence of questions is devised. The sequence begins with a question regarding anode technology, which is selected from the broader research topics related to fast charging. The answer to this question is then condensed into different items. Among these items, a specific one related to structure modification is chosen, highlighted with a black border, leading to more detailed and specific questions. As such, four questions are posed, indicating three levels of inquiry that transition from general to more specific aspects. These questions are shown in gray, and the answers obtained from ChatGPT and BatteryGPT are summarized in blue and green, respectively.

[a]Sources are as follows: Cai et al.,[41] Yang et al.,[52] Kim et al.,[42] Kim et al.,[43] Lee et al.,[39] Kazyak et al.,[38] Tu et al.,[59] Zhang et al,[44]

[b]Sources are as follows: Tu et al.,[45] Li,[46] Lu et al.,[40] Patil et al.,[47] Tomaszewska et al.,[48] Chen et al.[60]

information retrieval involves integrating various criteria such as citation analysis and author reputation into the evaluation of content quality. By incorporating these additional metrics alongside cosine similarity, the ranking of relevant content could be refined, thereby potentially enhancing Battery-GPT's output. This targeted enhancement forms a central focus for our future research endeavors.

RESULTS OF BatteryGPT

The outcomes of this transformative research paradigm for fast-charging technology, as portrayed in Figure 3, underscore its remarkable efficacy in addressing research questions and facilitating in-depth exploration of this field. This example focuses on a series of hierarchical questions that delve into various aspects of anode technology. It begins with a broad question and then follows up with more specific inquiries about structure modifications, surface modification, and electrode architecture. Each subsequent question builds upon the previous answer, leading to a progression from broad to specific aspects. Figure 3 provides a summary of the main points for each answer for demonstration purposes. The complete and detailed answers can be found in Note S1.

One of the salient results is the system's ability to provide answers to research questions effectively. The vast expanse of data stored within the fast-charging database, coupled with the natural language understanding capabilities of ChatGPT, equips the system to deliver broad insights and responses to a wide array of queries, offering a comprehensive understanding of fast-charging technology.

To delve into further detail, this paradigm excels in providing precise and domain-specific responses to highly specific questions. By tapping into the domain knowledge embedded in the database, BatteryGPT demonstrates its capacity to offer detailed and contextually relevant answers that are rooted in the literature of fast-charging technology. For example, consider the question regarding surface modification technology. BatteryGPT not only lists various materials for coating but also provides specific compounds along with relevant references, rendering the answer credible and facilitating further investigation.

Moreover, BatteryGPT excels in providing answers with a remarkable degree of timeliness and precision. A noteworthy illustration is its recommendation of Li_3P for enhancing the solid-electrolyte interphase (SEI).[59] During the initial cycling of the battery, a continuous crystalline Li_3P-based SEI was spontaneously generated *in situ*. This process involves the precise construction of an extremely thin P nanolayer on the graphite surface, achieved through the strategic interaction of S molecules. This innovative approach involving Li_3P induces a low-solvent-coordination Li+ solvation structure near the inner Helmholtz plane, reducing Li+ desolvation barriers and enhancing SEI Li+ diffusion. Pouch cells equipped with this modified graphite anode achieve remarkably fast charging times of 10 and 6 min for 91.2% and 80% capacities, respectively. Notably, this represents a very recent and promising development in anode materials for fast-charging Li-ion batteries.

Another example of the prowess of BatteryGPT is its recommendation of laser-patterning technology for electrode architecture design.[60] Conventionally, the use of thick electrodes has posed challenges related to ion transport, resulting in a trade-off between power and energy density. However, by employing a laser-patterning process, it becomes possible to craft a three-dimensional graphite anode architecture characterized by vertical pore channels that serve as efficient pathways for rapid ionic transport. Such an architecture exhibits remarkable capacity retention even after numerous fast-charge cycles, significantly outperforming unpatterned electrodes. This achievement positions laser patterning as a promising avenue for the development of safe and fast-charging solutions for high-energy-density batteries.

In summary, the results underscore the versatility and proficiency of this research paradigm. While ChatGPT excels at addressing general inquiries, BatteryGPT goes a step further by drawing from domain knowledge to offer specific and expert-level responses, ultimately enriching the knowledge exploration and research experience in the realm of fast-charging technology. In comparison to traditional literature search engines like Google Scholar, the incorporation of LLMs offers significant advantages. Unlike those traditional tools that solely provide a list of related articles, LLMs can comprehend and summarize the content into insightful categories, thus enabling more organized and hierarchical research.

OUTLOOK AND PERSPECTIVES

As exemplified by the capabilities of BatteryGPT, this innovative research paradigm powered by LLMs offers a profound transformation in the domain of fast-charging technology research. The results we have witnessed underscore the paradigm's exceptional proficiency in enabling rapid information synthesis and swift insight extraction. These insights can be retrieved in an organized manner, making the research process more efficient and streamlined. Another key strength of this paradigm is its adaptability and capacity for continuous growth. The fast-charging database can be dynamically updated with new literature, ensuring that the generated information remains current and aligned with the latest research. Furthermore, the system not only provides answers but also furnishes reliable references for further exploration, enriching the user experience and promoting in-depth research. This feature can be further enhanced by ranking the reliability of references using meta information, such as the number of citations and the reputation of publishers. This will be the focus of our future work.

In a broader perspective, this innovative research paradigm, transformed by LLMs, holds the potential to propel innovation across a spectrum of new energy research domains. Its efficiency in knowledge retrieval and the generation of contextually accurate responses transcends the confines of fast-charging technology, serving as a template for reshaping the research landscape in various disciplines.

Furthermore, with the rapid advancements in transformative technologies, including LLMs and other AI tools, the application scope of these evolved paradigms extends well beyond traditional text-based outputs. Their inherent adaptability empowers them to produce outputs in diverse formats, spanning from code scripts to audio narrations and even video presentations. This adaptability caters to a wide array of research scenarios and diverse research needs.

Figure 4 outlines some of the promising perspectives where LLM-transformed paradigms can be leveraged, marking a pivotal shift in the way we approach research in an ever-evolving landscape.

Research review

(1) Content comprehension: LLMs can be employed to swiftly comprehend extensive volumes of research resources, assisting in the synthesis of complex content.
(2) Related work summary: with unrestricted access to a vast repository of research resources, these systems possess the capability to autonomously produce comprehensive summaries of related work. This approach not only expedites the literature review process but also offers a more holistic and insightful perspective.
(3) Research trend analysis: LLMs are invaluable for identifying emerging trends in research topics, offering researchers insights into the evolving landscape of their field.

Methodology design

(1) Method recommendation: leveraging the wealth of expertise within research resources, LLMs can offer guidance on the most relevant, effective, or commonly employed research approaches within a given field or topic.
(2) Troubleshooting current methods: these paradigms are adept at diagnosing issues in current research methods and providing solutions to overcome them.
(3) Method optimization: after troubleshooting, LLMs can offer relevant solutions by drawing upon similar knowledge from their database, thereby enhancing overall efficiency and effectiveness.

Scenario		Texts	Chart &Tables	Flow	Codes	Slides	Audios	Videos
Research Review	Content Comprehension	✓						
	Related Work Summary	✓	✓					
	Research Trend Analysis	✓	✓					
Methodology Design	Method Recommendation	✓		✓				
	Method Optimization	✓		✓				
	Trouble Shooting	✓						
Result Analysis	Data Interpretation & Summarization	✓						
	Comparative Analysis	✓	✓					
	Data Visualization		✓		✓			
Academic Communication	Presentation	✓				✓		
	Lectures & Tutorials	✓				✓	✓	✓
	Interactive Report	✓					✓	✓

Figure 4. Perspective of LLMs in battery research

LLMs find applications across a multitude of scenarios within the field of battery research. In each of these scenarios, LLMs provide a wide array of functions that yield diverse multimodal results, ultimately enhancing research efficiency.

Result analysis

(1) Data interpretation and summarization: LLMs can aid in the interpretation of complex research data, offering valuable insights and facilitating meaningful conclusions.
(2) Comparative analysis: researchers can employ these systems to conduct comparative analyses, assisting in drawing comparisons between research outcomes.
(3) Data visualization: LLMs have the capability to generate code snippets to assist in crafting data visualizations, enabling the presentation of research outcomes in a clear, visually engaging, and comprehensible manner.

Academic communication

(1) Presentation assistance: LLMs can assist in creating compelling presentations, ensuring clear and impactful communication of research findings.
(2) Lectures and interactive reports: these paradigms can be harnessed to generate lecture materials and interactive reports, fostering engaging and informative academic communication.

In essence, the adaptability and transformative potential of LLM-transformed paradigms are not limited to any single field but extend across a wide spectrum of research scenarios and formats. As these systems continue to evolve, they hold the promise of streamlining research, enhancing innovation, and facilitating effective communication within the academic and research communities.

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.xcrp.2024.101844.

AUTHOR CONTRIBUTIONS

Conceptualization, Y.L., J.W., and X.L.; methodology, S.Z., Y.L., J.W., and X.L.; investigation, S.C., C.L., and S.J.H.; data curation, S.Z., J.W., S.C., and C.L.; writing – original draft, S.Z.; writing – review & editing, all authors; visualization, J.Z. and T.T.; supervision, Y.L., J.W., and X.L.

DECLARATION OF INTERESTS

The authors declare no competing interests.

DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the authors used ChatGPT in order to polish the draft. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

REFERENCES

1. Manthiram, A. (2017). An outlook on lithium-ion battery technology. ACS Cent. Sci. *3*, 1063–1069.
2. Wali, S.B., Hannan, M.A., Reza, M.S., Ker, P.J., Begum, R.A., Rahman, M.A., and Mansor, M. (2021). Battery storage systems integrated renewable energy sources: A biblio metric analysis towards future directions. J. Energy Storage *35*, 102296.
3. Bagheri, M., Nurmanova, V., Abedinia, O., Salay Naderi, M., Ghadimi, N., and Salay Naderi, M. (2019). Renewable energy sources and battery forecasting effects in smart power system performance. Energies *12*, 373.
4. Liang, Y., Zhao, C.Z., Yuan, H., Chen, Y., Zhang, W., Huang, J.Q., Yu, D., Liu, Y., Titirici, M., Chueh, Y., et al. (2019). A review of rechargeable batteries for portable electronic devices. InfoMat *1*, 6–32.
5. Saxena, S., Sanchez, G., and Pecht, M. (2017). Batteries in portable electronic devices: A user's perspective. EEE. Ind. Electron. Mag. *11*, 35–44.
6. Placke, T., Heckmann, A., Schmuch, R., Meister, P., Beltrop, K., and Winter, M. (2018). Perspective on performance, cost, and technical challenges for practical dual-ion batteries. Joule *2*, 2528–2550.
7. Gurung, A., and Qiao, Q. (2018). Solar charging batteries: advances, challenges, and opportunities. Joule *2*, 1217–1230.
8. Chao, D., and Qiao, S.Z. (2020). Toward high-voltage aqueous batteries: super-or low-concentrated electrolyte? Joule *4*, 1846–1851.
9. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., et al. (2017). Attention is all you need. Adv. Neural Inf. Process. Syst. *30*, 6000–6010.
10. Radford, A., Narasimhan, K., Salimans, T., and Sutskever, I. (2018). Improving Language Understanding by Generative Pre-training (OpenAI). https://cdn.openai.com/research-covers/languageunsupervised/language_understanding_paper.pdf.
11. Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., and Sutskever, I. (2019). Language models are unsupervised multitask learners. OpenAI blog *1*, 9.
12. Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J.D., Dhariwal, P., et al. (2020). Language models are few-shot learners. Adv. Neural Inf. Process. Syst. *33*, 1877–1901.
13. Ouyang, L., Wu, J., Jiang, X., Almeida, D., Wainwright, C., Mishkin, P., et al. (2022). Training language models to follow instructions with human feedback. Adv. Neural Inf. Process. Syst. *35*, 27730–27744.
14. (2023). GPT-4 Technical Report. Preprint at arXiv. OpenAI,. https://doi.org/10.48550/arXiv.2303.08774.
15. Thirunavukarasu, A.J., Ting, D.S.J., Elangovan, K., Gutierrez, L., Tan, T.F., and Ting, D.S.W. (2023). Large language models in medicine. Nat. Med. *29*, 1930–1940.
16. Jumper, J., Evans, R., Pritzel, A., Green, T., Figurnov, M., Ronneberger, O., Tunyasuvunakool, K., Bates, R., Žídek, A., Potapenko, A., et al. (2021). Highly accurate protein structure prediction with AlphaFold. Nat *596*, 583–589.
17. Romera-Paredes, B., Barekatain, M., Novikov, A., et al. (2024). Mathematical discoveries from program search with large language models. Nature *625*, 468–475.
18. Zheng, Z., Zhang, O., Borgs, C., Chayes, J.T., and Yaghi, O.M. (2023). Chat-GPT chemistry assistant for text mining and prediction of MOF synthesis. J. Am. Chem. Soc. *145*, 18048–18062.
19. Liu, Y., Zhu, Y., and Cui, Y. (2019). Challenges and opportunities towards fast-charging battery materials. Nat. Energy *4*, 540–550.
20. Jochem, P., Szimba, E., and Reuter-Oppermann, M. (2019). How many fast-charging stations do we need along European highways? Transport. Res. Transport Environ. *73*, 120–129.
21. Zhu, G.L., Zhao, C.Z., Huang, J.Q., He, C., Zhang, J., Chen, S., Xu, L., Yuan, H., and Zhang, Q. (2019). Fast-charging lithium batteries: recent progress and future prospects. Small *15*, 1805389.
22. Ahmed, S., Bloom, I., Jansen, A.N., Tanim, T., Dufek, E.J., Pesaran, A., Burnham, A., Carlson, R.B., Dias, F., Hardy, K., et al. (2017). Enabling fast-charging–A battery technology gap assessment. J. Power Sources *367*, 250–262.
23. Collin, R., Miao, Y., Yokochi, A., Enjeti, P., and Von Jouanne, A. (2019). Advanced electric vehicle fast-charging technologies. Energies *12*, 1839.
24. shafiei, M., and Ghasemi-Marzbali, A. (2022). Fast-charging station for electric vehicles, challenges and issues: A comprehensive review. J. Energy Storage *49*, 104136.
25. Wassiliadis, N., Schneider, J., Frank, A., Wildfeuer, L., Lin, X., Jossen, A., and Lienkamp, M. (2021). Review of fast-charging strategies for lithium-ion battery systems and their applicability for battery electric vehicles. J. Energy Storage *44*, 103306.
26. Srdic, S., and Lukic, S. (2019). Toward extreme fast-charging: Challenges and opportunities in directly connecting to medium-voltage line. IEEE Electrific. Mag. *7*, 22–31.
27. Xie, W., Liu, X., He, R., Li, Y., Gao, X., Li, X., Peng, Z., Feng, S., Feng, X., and Yang, S. (2020). Challenges and opportunities toward

fast-charging of lithium-ion batteries. J. Energy Storage *32*, 101837.

28. Sun, C., Ji, X., Weng, S., Li, R., Huang, X., Zhu, C., Xiao, X., Deng, T., Fan, L., Chen, L., et al. (2022). 50C fast-charge li-ion batteries using a graphite anode. Adv. Mater. *34*, 2206020.

29. Paul, P.P., McShane, E.J., Colclasure, A.M., Balsara, N., Brown, D.E., Cao, C., Chen, B., Chinnam, P.R., Cui, Y., Dufek, E.J., et al. (2021). A review of existing and emerging methods for lithium detection and characterization in Li-ion and Li-metal batteries. Adv. Energy Mater. *11*, 2100372.

30. Tanim, T.R., Weddle, P.J., Yang, Z., Colclasure, A.M., Charalambous, H., Finegan, D.P., Lu, Y., Preefer, M., Kim, S., Allen, J.M., et al. (2022). Enabling extreme fast-charging: Challenges at the cathode and mitigation strategies. Adv. Energy Mater. *12*, 2202795.

31. Qian, J., Zhu, T., Huang, D., Liu, G., and Tong, W. (2022). Insights into the enhanced reversibility of graphite anode upon fast-charging through Li reservoir. ACS Nano *16*, 20197–20205.

32. Wang, C.Y., Liu, T., Yang, X.G., Ge, S., Stanley, N.V., Rountree, E.S., Leng, Y., and McCarthy, B.D. (2022). Fast-charging of energy-dense lithium-ion batteries. Nat *611*, 485–490.

33. Liu, Y., Gong, X., Podder, C., Wang, F., Li, Z., Liu, J., Fu, J., Ma, X., Vanaphuti, P., Wang, R., et al. (2023). Roll-to-roll solvent-free manufactured electrodes for fast-charging batteries. Joule *7*, 952–970.

34. Lee, M.J., Lho, E., Bai, P., Chae, S., Li, J., and Cho, J. (2017). Low-temperature carbon coating of nanosized Li1. 015Al0. 06Mn1. 925O4 and high-density electrode for high-power Li-ion batteries. Nano Lett. *17*, 3744–3751.

35. Gao, H., Yan, Q., Holoubek, J., Yin, Y., Bao, W., Liu, H., Baskin, A., Li, M., Cai, G., Li, W., et al. (2023). Enhanced electrolyte transport and kinetics mitigate graphite exfoliation and Li plating in fast-charging Li-ion batteries. Adv. Energy Mater. *13*, 2202906.

36. Xia, D., Kamphaus, E.P., Hu, A., Hwang, S., Tao, L., Sainio, S., Nordlund, D., Fu, Y., Huang, H., Cheng, L., and Lin, F. (2023). Design criteria of dilute ether electrolytes toward reversible and fast intercalation chemistry of graphite anode in Li-ion batteries. ACS Energy Lett. *8*, 1379–1389.

37. Xu, H., Zhu, J., Finegan, D.P., Zhao, H., Lu, X., Li, W., Hoffman, N., Bertei, A., Shearing, P., and Bazant, M.Z. (2021). Guiding the design of heterogeneous electrode microstructures for Li-ion batteries: Microscopic imaging, predictive modeling, and machine learning. Adv. Energy Mater. *11*, 2003908.

38. Kazyak, E., Chen, K.H., Chen, Y., Cho, T.H., and Dasgupta, N.P. (2022). Enabling 4C fast-charging of lithium-ion batteries by coating graphite with a solid-state electrolyte. Adv. Energy Mater. *12*, 2102618.

39. Lee, S.M., Kim, J., Moon, J., Jung, K.N., Kim, J.H., Park, G.J., Choi, J.H., Rhee, D.Y., Kim, J.S., Lee, J.W., and Park, M.S. (2021). A cooperative biphasic MoOx–MoPx promoter enables a fast-charging lithium-ion battery. Nat. Commun. *12*, 39.

40. Lu, L.L., Lu, Y.Y., Zhu, Z.X., Shao, J.X., Yao, H.B., Wang, S., Zhang, T.W., Ni, Y., Wang, X.X., and Yu, S.H. (2022). Extremely fast-charging lithium ion battery enabled by dual-gradient structure design. Sci. Adv. *8*, eabm6624.

41. Cai, W., Yan, C., Yao, Y.X., Xu, L., Xu, R., Jiang, L.L., Huang, J.Q., and Zhang, Q. (2020). Rapid lithium diffusion in order@ disorder pathways for fast-charging graphite anodes. Small Struct. *1*, 2000010.

42. Kim, D.S., Kim, Y.E., and Kim, H. (2019). Improved fast-charging capability of graphite anodes via amorphous Al2O3 coating for high power lithium-ion batteries. J. Power Sources *422*, 18–24.

43. Kim, D.S., Chung, D.J., Bae, J., Jeong, G., and Kim, H. (2017). Surface engineering of graphite anode material with black TiO2-x for fast chargeable lithium-ion battery. Electrochim. Acta *258*, 336–342.

44. Zhang, S., Zhang, Y., Zhang, Z., Wang, H., Cao, Y., Zhang, B., Liu, X., Mao, C., Han, X., Gong, H., et al. (2022). Bi works as a Li reservoir for promoting the fast-charging performance of phosphorus anode for Li-ion batteries. Adv. Energy Mater. *12*, 2103888.

45. Tu, S., Lu, Z., Zheng, M., Chen, Z., Wang, X., Cai, Z., Chen, C., Wang, L., Li, C., Seh, Z.W., et al. (2022). Single-layer-particle electrode design for practical fast-charging lithium-ion batteries. Adv. Mater. *34*, 2202892.

46. Li, G. (2021). Regulating mass transport behavior for high-performance lithium metal batteries and fast-charging lithium-ion batteries. Adv. Energy Mater. *11*, 2002891.

47. Patil, R.S., Khandelwal, A., Kim, K.Y., Hariharan, K.S., and Kolake, S.M. (2019). Model based design of composite carbonaceous anode for li-ion battery for fast-charging applications. J. Electrochem. Soc. *166*, A1185–A1196.

48. Tomaszewska, A., Chu, Z., Feng, X., O'kane, S., Liu, X., Chen, J., Ji, C., Endler, E., Li, R., Liu, L., et al. (2019). Lithium-ion battery fast-charging: A review. eTransportation *1*, 100011.

49. Dufek, E.J., Abraham, D.P., Bloom, I., Chen, B.R., Chinnam, P.R., Colclasure, A.M., Gering, K.L., Keyser, M., Kim, S., Mai, W., et al. (2022). Developing extreme fast charge battery protocols–A review spanning materials to systems. J. Power Sources *526*, 231129.

50. Mathieu, R., Briat, O., Gyan, P., and Vinassa, J.M. (2021). Comparison of the impact of fast-charging on the cycle life of three lithium-ion cells under several parameters of charge protocol and temperatures. Appl. Energy *283*, 116344.

51. Zeng, Y., Zhang, B., Fu, Y., Shen, F., Zheng, Q., Chalise, D., Miao, R., Kaur, S., Lubner, S.D., Tucker, M.C., et al. (2023). Extreme fast-charging of commercial Li-ion batteries via combined thermal switching and self-heating approaches. Nat. Commun. *14*, 3229.

52. Yang, X.G., Liu, T., Gao, Y., Ge, S., Leng, Y., Wang, D., and Wang, C.Y. (2019). Asymmetric temperature modulation for extreme fast-charging of lithium-ion batteries. Joule *3*, 3002–3019.

53. Keyser, M., Pesaran, A., Li, Q., Santhanagopalan, S., Smith, K., Wood, E., Ahmed, S., Bloom, I., Dufek, E., Shirk, M., et al. (2017). Enabling fast-charging–Battery thermal considerations. J. Power Sources *367*, 228–236.

54. Liu, T., Ge, S., Yang, X.G., and Wang, C.Y. (2021). Effect of thermal environments on fast-charging Li-ion batteries. J. Power Sources *511*, 230466.

55. Carter, R., and Love, C.T. (2022). Using thermal energy to enable fast-charging of energy-dense batteries. Joule *6*, 2447–2449.

56. Yang, X.G., Vishnugopi, B.S., Mukherjee, P.P., Wang, W., Sun, F., and Wang, C.Y. (2022). Advancements in extreme fast-charging to foster sustainable electrification. One Earth *5*, 216–219.

57. Lee, S., and Cho, J. (2015). Critical requirements for rapid charging of rechargeable Al-and Li-ion batteries. Angew. Chem. Int. Ed. *54*, 9452–9455.

58. Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., Goyal, et al.. (2020). Retrieval-augmented generation for knowledge-intensive NLP tasks. Adv. Neural Inf. Process. Syst. *33*, 9459–9474.

59. Tu, S., Zhang, B., Zhang, Y., Chen, Z., Wang, X., Zhan, R., Ou, Y., Wang, W., Liu, X., Duan, X., et al. (2023). Fast-charging capability of graphite-based lithium-ion batteries enabled by Li3P-based crystalline solid–electrolyte interphase. Nat. Energy *8*, 1365–1374.

60. Chen, K.H., Namkoong, M.J., Goel, V., Yang, C., Kazemiabnavi, S., Mortuza, S., Kazyak, E., Mazumder, J., Thornton, K., Sakamoto, J., and Dasgupta, N.P. (2020). Efficient fast-charging of lithium-ion batteries enabled by laser-patterned three-dimensional graphite anode architectures. J. Power Sources *471*, 228475.