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Governments and companies face consequential decisions about allocating resources to the research, development, demonstration and deployment of energy technologies to meet environmental, economic and social goals. Here we discuss how research insights can inform and potentially improve these decisions to make effective use of limited resources and time in shaping the next-generation energy infrastructure. We outline three key research steps: forecasting technological change, relating investments to economic, social and environmental outcomes and informing decision-making processes. We recommend advances to address uncertainty as well as to make methods and results more practicable, emphasizing the importance of model validation, streamlining and interactivity. Progress has been made, yet further work is needed—for example, in the development of reduced-order, testable models and more comprehensive data collection. Overall, this research is beginning to inform decisions but could be adopted more widely by governments and the private sector to help support technological progress for energy affordability, equitable climate change mitigation, health benefits and other objectives.

While many low-carbon energy technologies have improved in cost and performance and grown in market share, further innovation is needed to reach global climate, health, security and energy access goals. Governments at national and subnational levels play essential roles in energy innovation by funding energy research, development, demonstration and deployment (RDD&D) directly or by incentivizing private investment. Governments' budgets generally include funding for public energy research, development and demonstration (RD&D), though this accounts for a small fraction of spending in defence and health, and in most Organisation for Economic Co-operation and Development (OECD) countries it accounts for less than 5% of total RD&D, apart from a few exceptions[1–4]. Additionally, while public and private investment in deploying clean energy has been increasing in recent years, amounts needed to address climate change far exceed current levels[5–7].

Because of the importance of developing solutions to global energy-related problems, the limited time left to avoid the worst effects of climate change and uncertain political commitments and

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noisy policy environments, there is a clear need for investment in energy RDD&D to make effective use of constrained resources. Here we describe how a growing understanding of processes of technology innovation and decision-making can support successful technology investment decisions. We emphasize government entities in our examples because of their central role in investing directly or nudging markets toward certain outcomes. Many of the points discussed here also apply to investments by for-profit companies in the private sector, as well as development banks and other intergovernmental entities and non-profit organizations.

This Perspective draws on past research on evidence-based methods to help make effective use of energy RDD&D investments to achieve long-term goals[8–10] and suggests a way to combine these insights to inform decisions. Research in past decades has developed an understanding of the drivers of energy technology innovation and their relationship to government policy and private investment. More specifically, research has focused on the rates of energy innovation and the underlying mechanisms of successes and failures (for example, [4,11–16]), models to examine the relationship between investment in energy technology and broader economic and environmental outcomes (for example, [5,6,8,10,17,18]) and means for research to inform decision-making in energy policy contexts (for example, [19–23]). This work has occurred in disparate research areas. Here we propose a conceptual framework for combining these areas, and we highlight priorities for future research drawing on the literature and our own research.

Research insights and methods are adopted in some energy investment contexts, but there is room for their further development and expanded use in government and private-sector decision-making[1,19,24–30]. One reason for the limited application of this research may be the resource intensiveness and lack of transparency of many existing methods and models. Although some progress in method usability has been made, these methods may still be too inconvenient for many to use, or too opaque[20,31]. Communication through intergovernmental organizations and think tanks that filter and distil research insights (for example, the Intergovernmental Panel on Climate Change, the International Energy Agency and the International Renewable Energy Agency) may help in some contexts. Yet further engagement with decision-makers is needed to understand context-specific barriers and solutions.

We discuss three research steps that form a cohesive framework to help inform investment in energy technologies, drawing on data analysis, concept and theory development, mathematical modelling, and engagement with stakeholders. These steps include forecasting technological change, relating investments in technology to broader technological, economic and environmental outcomes and informing decision-making processes (Fig. 1).

While there has been recent progress in research, advancements are still needed for each step ('Priority themes', Table 1) to improve forecasting and make research insights more usable by practitioners. How uncertainty is handled is central because advancing technological change requires experimentation at every stage of energy research, commercialization and deployment, and while some efforts will succeed others will fail.

A path forward for forecasting while managing uncertainty can be seen in the example of the theoretically grounded methods that have saved many billions of dollars in weather forecasting[32,33]. Technology forecasting differs from weather forecasting in its focus on human systems rather than purely natural systems, and thus introduces different challenges. Nonetheless, we posit that technology forecasting can be similarly valuable in informing decisions—for example, about the appropriate level of diversification or concentration across technologies in an investment portfolio.

More realistic forecasts of the costs and timing of energy technology development and deployment may help reduce budget and schedule overruns as observed in nuclear construction and carbon capture and storage (for example, refs. 34,35). Deployment and performance improvement rates for climate-mitigation technologies have been both underestimated (for example, renewables) and overestimated (for example, nuclear energy, bioenergy with carbon capture and storage), making a case for improved approaches[27,36,37]. The goal of this work is not to arrive at a perfect forecast but to improve on the outcomes as much as possible relative to a less deliberate approach. Models can also serve as tools for gaining insight into policy alternatives in the presence of uncertainties that preclude quantitative forecasts. In those cases, qualitative approaches are required.

The potential applicability of this research is far-reaching because technological innovation—which we define to include both improvement and adoption—is often a consequential lever for making a clean energy transition physically possible, affordable and widely beneficial. For this reason, stimulating technological innovation and adoption toward decarbonization features prominently in many countries' and companies' climate change mitigation goals, including nationally determined contributions to the Paris Agreement, state- and city-level net-zero plans and company sustainability targets.

The influence of research is sometimes limited even if the insights are widely considered, because investment decisions are made on the basis of not only economic, climate or other goals but also other stakeholder interests. However, for governments and companies that seek to lead in developing the next-generation energy system and to succeed in rapidly evolving energy markets, research insights can play an essential role.

Forecasting technological change

Anticipating how clean energy technologies may respond to funding levels and policy design is critical for informing investments (step 1, Fig. 1). Technologies include various forms of hardware and soft technology. By 'soft technology' we mean non-physical forms of codified knowledge defining processes[38]. Examples of soft technology include design and site assessment software for energy projects, installation checklists, best practices in construction and permitting, interconnection standards and other means of defining processes involved in the design, permitting, installation, operation and end-of-life management of energy projects, facilities and systems[38].

One approach to forecasting technological change is to apply data-informed mathematical models. The term 'data-informed models' used here includes both 'data-driven models' that represent correlations in data and 'mechanistic models' of the underlying drivers.

Wright's law is the most widely used data-driven model for characterizing energy technology cost evolution. It is also known as a learning curve or experience curve and uses historical data to correlate technological performance with cumulative production[11,39]. An alternative is Moore's law, which considers time as the key independent variable[11]. Other multifactor models aim to incorporate the effects of additional drivers of change such as research and development (R&D) investments[40,41] but may be prone to overfitting given current data limitations[11]. These and other performance curves can be used to forecast future performance changes[42], preferably with estimates of uncertainty[11], and can be used in portfolio analysis to inform deployment policy (step 2, Fig. 1)[36,43].

Mechanistic models, in contrast to data-driven models, aim to directly represent the drivers of technological change. Recent advances in mechanistic models have related energy RDD&D to past technological innovation, and linked future investments to potential further progress[12,13,34,44,45]. Mechanistic approaches often begin with modelling the engineering features of hardware or soft technology and relating these to cost and other aspects of performance[12,38]. Changes in cost and performance over time are then related to changes in engineering features. These changes are attributed to higher-level mechanisms such as economies of scale, learning by doing and R&D, and to policy instruments[12]. Validation is performed by comparing observed changes in

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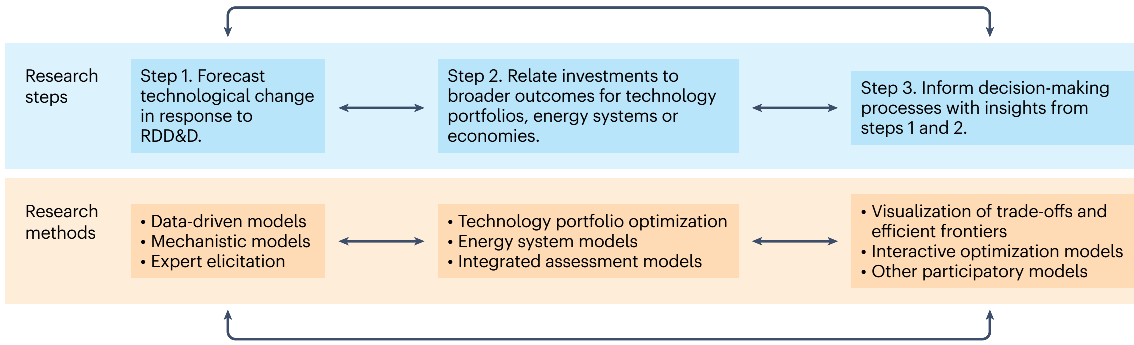

Fig. 1 | Three steps in research to inform energy RDD&D decision-making. In step 1, forecasts are made of how investments may lead to technology improvements. Step 2 translates these forecasts into outcomes such as the performance of a portfolio of investments or a set of impacts on an energy system or the broader economy. In step 3, these outcomes are considered in a structured way with decision-makers, with the potential to incorporate a diversity of preferences for outcomes among users. Each research step (or pair of steps) can be used alone to provide useful insight for decision-making, or the steps can be used in sequence with each step informing the subsequent one, and feedback loops informing the next iteration. For example, better forecasts for individual technologies enable more reliable estimates of the broader outcomes of RDD&D investments, and can help build trust in the research insights on the part of decision-makers. This can in turn help research to inform RDD&D decision-making, completing a feedback loop.

Table 1 | Priority research themes across the three steps are focused on validation, streamlining and enhancing interactivity

		Step 1. Forecast technological change	Step 2. Relate investments to broader outcomes	Step 3. Inform decision-making processes
Priority themes		Streamlining and validating data collection and models	Streamlining and validating models	Enhancing interactive methods
Research advances	Recent	• Mechanistic models • Hybrid of learning curves & expert elicitation • Expanded and harmonized data from expert elicitations	• Open-source modular frameworks • Reduced-order integrated assessment models	• Many-objective non-probabilistic exploratory methods • Robust portfolio decision analysis • Visualization tools for transparency
	Potential	• Investigation of pessimism bias • Hybrid of mechanistic models & expert elicitation • Online expert elicitation • Shared data repository • Automated data collection	• Machine learning for fast-running, portable, approximate models • Theoretically grounded integration of disparate models	• Combination of non-probabilistic approaches • Solutions co-designed with practitioners

Some of the research advances listed represent 'recent' progress and others are 'potential' future advances. This is not an exhaustive list of advances.

cost or performance with the sum of changes predicted from individual engineering variables. The insights can inform prospective analyses of promising R&D investments[34,12] for specific technologies, especially if component-level estimates of future improvement potential can be obtained in consultation with technology experts.

'Expert elicitation', in contrast to data-informed mathematical models, relies on inputs from experts about how technologies may respond to investment[46]. This method gathers subjective probability distributions from experts about future changes conditional on levels of RDD&D funding. Elicitations characterize a range of outcomes, including low-probability events. One recent advance was to harmonize a large set of expert elicitations on climate and energy technologies[14]. Other work compared expert-elicitation-based predictions with observed trends and forecasts based on data-driven models[15,47,48]. These initial comparisons found that data-driven models outperformed those based on expert elicitations and called for further examination with an expanded dataset[15,47,48].

We emphasize, however, that neither certainty nor a full understanding of uncertainty are reasonable to expect[49–52]. Substantial uncertainty or even ambiguity—which refers to uncertainty that cannot be quantified—should be expected[49,50,52]. Rather, the goal is to do as well as possible. Importantly, no forecasting model should be considered complete without a careful treatment of uncertainty, including in some cases the explicit recognition that quantitative uncertainty estimates cannot be reliably obtained and that, therefore, quantitative forecasts of technological change cannot be made. In those cases, fully diversifying investments across the complete set of energy technology options is often appropriate until further information becomes available.

Additional progress on validating forecasts and streamlining data collection can improve forecasts using data-informed, mathematical models and expert elicitations. Streamlining data collection, which means making the process less complex and less resource intensive, allows for datasets covering longer periods and more technologies, which will help validate models. Validating forecasts against data through hindcasting enhances understanding of their uncertainty and helps improve forecasting methods[11]. Hindcasting refers to testing models calibrated on an earlier portion of the time-series data on a separate, more recent portion of the data. We discuss three important research areas, which all require engagement with decision-makers who are the users of the research.

First, identifying and correcting biases in expert elicitations is a priority for validation, including investigation of the pessimism hypothesis[14,53]. Unlike the expected motivational bias in which experts promote their technology, the hypothesized pessimism bias suggests that experts overemphasize barriers or overlook possibilities for improvement[54]. Human psychology may not be well suited to predicting cumulative changes, leading experts to underestimate cumulative experience and resulting technological change[55]. Overall, systematically collecting data on past energy RDD&D investments and outcomes will help investigate biases[54]. Bias correction should also be considered for data-driven and mechanistic mathematical models in the collection of data where samples may favour certain companies or technology variants.

A second area for future research is to investigate 'hybrid approaches' to expert elicitations that aim to correct biases by visualizing possible nonlinear relationships between time, experience and technological change. Providing this context to experts could help them produce better estimates.

Another promising hybrid approach is to combine mechanistic models with expert elicitations. Mechanistic models can be designed to match experts' level of energy engineering, investment and manufacturing expertise. The models can then help link experts' responses to cost and performance change[12,34,38,56]. For example, scientists who study adsorption can provide forecasts of the energy penalty for carbon capture systems, and a mechanistic model can then be used to identify how these affect costs[16].

A third priority is to streamline data collection methods. This is important for mathematical models (data driven and mechanistic) and expert elicitations alike, since eliciting inputs from experts and updating data are often time consuming and expensive. Online methods may reduce the costs and time required for expert elicitation[57]. The greater upfront investment in designing the protocol and user interface is recouped if data collection campaigns can reuse this infrastructure several times. Combined approaches are also possible—for example, using an online platform for information-sharing, initial elicitations or discussions, and then pursuing more intensive interactions with a subset of experts. A related option involves developing a shared repository of elicitation results and data on technological change that can be vetted and updated by multiple users, as currently exists for economic and energy inputs to integrated assessment models[58].

Streamlining data collection through automation may allow for continuous monitoring of technology performance changes. Such data are needed to inform and test mathematical models of technological change (data driven and mechanistic) and experts' predictions. Expanded data collection may be especially important to track progress in technology deployment processes, where the availability of empirical data (for example, on installation productivity and business process features across locations and suppliers) is limited. Understanding the change in profit margins as technology markets mature requires accurate information on costs and prices of technology components over time.

It will be important to monitor and improve data quality for all methods, as data uncertainty due to measurement uncertainty and sample-size limitations remains a challenge. Data accessibility is also important and can be challenging when firms claim data as proprietary. Requirements for public disclosure can help, for example, in government-funded energy projects.

Relating investments to broader outcomes

In addition to forecasting technological change, it is important to anticipate the effects of technologies on the energy system and the economy[59]. This research step (step 2, Fig. 1) involves identifying which distribution of investments across different technologies may achieve desired outcomes. There are many possible approaches to addressing this question, but they all typically involve examining technologies in a modelled context and exploring optimal investments under uncertainty. A modelled solution may maximize estimated social welfare or minimize costs under emissions or other climate change constraints, or it may consider multiple objectives aligned with the United Nations Sustainable Development Goals or other environmental, social or governance criteria[60].

The system boundaries of these models vary in size. They may analyse investments in a portfolio of technologies for a particular energy service—for example, emission-free vehicles—or they may consider the cost or performance of an entire energy system, or the effect of a carbon constraint on the larger economy. These models range from analytically tractable energy portfolio optimization problems to detailed simulations of the energy systems or economy. Here we find it useful to present them as a single broad category of models to discuss the advantages and drawbacks of different approaches.

The models can be more abstract or more detailed. For example, an economy-wide model may be highly abstracted[61,62] or more detailed[63], and the same is true of a model with a more limited scope—for example, a power system model[64], or a model of investments in a portfolio of technologies serving a particular end-use (for example, vehicle technologies). In general, across these models, there is a tension between realism and the ability to interpret and test (or validate) models against data. Validation is important for better understanding parametric uncertainties and structural uncertainties. More model detail generally limits the validation that is practical because of constraints on the quantity of data available. Data may not be available to test the significance of all of the different variables considered and the interactions between them.

Models with a wider scope and substantial detail can be used to study a greater number of factors affecting investment and policy outcomes, including institutional and policy conditions, economic and environmental feedback and international and sectoral spillovers, as well as societal preferences and behaviours. Such analyses seek to understand how policy instruments can be combined to increase energy RDD&D investment effectiveness while minimizing negative effects on competitiveness or distributional outcomes—for example, ref. 65.

A broader scope with less detail often abstracts away the technology-related decision variables that are the focus of this Perspective. These variables are often the ones that society has the greatest ability to change through innovation. Smaller boundaries, for example around a particular technology end-use such as light-duty vehicles, miss interactions across end-uses and sectors of the economy, but can take a closer look at specific technology-related decision variables while remaining less complex and more testable.

Across all of these cases, validation is important for understanding how well models perform in terms of their explanatory and predictive power, and for improving them. Streamlining models reduces the detail and model complexity as much as possible while capturing the most important features of a system, and can support validation. In step 2, as in step 1, validation and streamlining are priority areas for future research advances, particularly for models with larger system boundaries and high model complexity.

Streamlining models is also important from an operational perspective, as complex models are slower and more expensive to run. This is especially true when the modelled system boundary expands from solving for an optimal investment portfolio in a set of substitutable technologies (that is, energy technologies with similar functionality) to solving for a least-cost energy system, considering market participant-specific responses (for example, Nash–Cournot game theoretic approaches)[17], or identifying guidelines for a decarbonization transition that support objectives beyond cost considerations. Streamlined models will cost less, be more efficient and easier to use, and enable the interactions discussed in step 3 (Fig. 1 and Table 1).

Examples of recent advances in streamlining models include reduced-form methods for stochastic portfolio optimization[66,67] and open-source modular frameworks with reduced computational processing times that enable comparisons among models[68], or implementation of adaptive actions as the future unfolds[69]. Another fruitful direction for developing fast-running, portable, approximate models for decision support is applying machine learning techniques[70]. Multimodel studies of low-carbon energy R&D scenarios[18] allows for the collection of large ensembles of data, which can serve as inputs to models using machine learning[22].

Streamlining models can also support validation against measured data (for example, hindcasting or out-of-sample testing more generally). Determining the best levels of energy RDD&D funding across technologies or projects typically involves combinatorial alternatives and uncertainties in problem structure and parameterization. More parsimonious models allow for global sensitivity analysis to identify the interactions that determine observed outcomes, thus making them more transparent. Tracing the key determinants in simpler models can allow for testing models against data using various forms of hindcasting[11]. Validation of this kind can support model improvements. Validation may also lead to a more theoretically grounded methodology for integrating models and addressing bias propagation.

It can be challenging to retain enough detail in models to make them realistic enough to inform real-life decision-making processes, while also streamlining them to run faster, enable interaction with decision-makers and support model validation[71]. Reduced-order models require simplifying assumptions that may miss important interactions and details of real systems. The complexities of the energy system can make simplification challenging, and informing RDD&D investments often requires considering bottom-up detail on individual technologies alongside market-level technology competition and broader societal impacts.

One way to address this tension is to clearly articulate the purpose of the model and include just enough but no more detail than is needed to answer specific questions (for example, budget allocations across technology areas versus informing funding priorities within technology areas). The resulting models would effectively balance the trade-off between realism and streamlining. They could also serve well in informing step 3 processes of policy exploration, with higher-resolution models then brought in when needed to consider possible policy outcomes in greater detail.

Informing decision-making processes

An important goal of this research is to inform decisions about energy RDD&D investments. Yet many research insights never reach decision-makers. Enhancing interaction can help address this challenge.

Allowing decision-makers to interact directly with research results from steps 1 and 2 can help generate useful insights and build familiarity. Exchanges with decision-makers that are structured around interactive models can also help inform decision-making processes where likelihoods cannot be easily quantified and probabilistic methods are therefore challenging to deploy. Such 'deep uncertainty' can come in many forms, including disagreement over parameters or relationships assumed in the models discussed in the first two sections[72]. Deep uncertainty can also result from differing stakeholder preferences over the eventual outcomes of decision-making processes.

Interactive decision models can engage decision-makers and other civil society participants in various ways. Modelling for insight provides decision-makers with a better understanding of interactions and how systems work, while modelling to generate specific actionable solutions can directly inform levels of investment in energy technology portfolios or policies. In some circumstances, qualitative insights may prove most useful, while in others quantitative insights may be preferred. An interactive 'deliberation-with-analysis' process can be created to help with difficult and consequential technology and policy decisions[73].

One specific approach is to apply exploratory methods[74] such as robust decision-making (RDM), which iteratively engages decision-makers to select strategies that balance trade-offs[75]. RDM uses models as tools for exploration instead of forecasting when there is deep uncertainty[21]. Uncertainties are characterized by how they affect perceptions of alternative choices, and analyses aim to gain agreement on which courses of action are robust to several potential futures, rather than focusing on improving forecasts. Foregoing the need for consensus over input assumptions helps address disagreement over beliefs about model specifications, the likelihood of different outcomes and data adequacy. Working backwards from the policy deliberation to be informed, RDM can identify energy technology portfolios that produce desired results despite uncertainty and in that way can help users arrive at a consensus over a course of action.

Another approach to modelling for insight is robust portfolio decision analysis[23], which uses a dominance method focusing on disagreement about likely outcomes of different actions. This method identifies a set of reasonable RDD&D portfolios by eliminating any portfolio that performs worse than another portfolio across all plausible probability distributions. The results may reveal that, for example, some energy technologies are present in all non-dominated portfolios (that is, those that were not outperformed). For example, in ref. 23 expert elicitations were used to probe how R&D might impact the costs and efficiencies of energy technologies, a model translated these technological impacts into potential societal impacts, and robust portfolio decision analysis was used to identify which technologies appeared across several investment portfolios. By identifying common ground[76] while leaving flexibility by avoiding a single 'optimal' solution, this process can form the basis of an iterative process to explore the range of non-dominated portfolios.

Understanding the mechanisms underlying technological change can also be useful in this context. While there may be differences in beliefs about the rates at which energy technologies may respond to an investment, a common understanding of the underlying drivers of improvement may allow for consensus building and action. The relevant drivers may be at the level of the engineering design of a technology or process, or at a higher level including various scale economies, types of research or demonstration activity, and deployment strategies. Overall, focusing on a few key insights from models (a few 'big messages') may allow difficult decision-making processes to move forward.

These methods can be extended further to address disagreement over objectives (outcomes of the decision-making process), as is done in multiple objective RDM[77]. Multiple objective RDM uses evolutionary search algorithms to generate a set of near-Pareto efficient alternatives that do not prioritize any single objective and then uses RDM to iterate for robustness.

Implementing interactive approaches will require model transparency and clear communication. Explaining models to potential users, demonstrating their benefits and drawbacks, and building interest are all important. Showing users the full extent of probabilistic data might be counterproductive but showing only a subset of possible solutions may embed analysts' potential biases in the information provided[22]. As one potential solution, visualization tools[78] can use preprocessed data to allow decision-makers to choose the extent of probabilistic data and other information they are provided, and to navigate freely across modelling assumptions and solutions.

Overall, further experimentation is needed to arrive at tools that can fulfil their promise of informing decisions[79]. Research on co-designing solutions with practitioners will be important. Users of the research can inform model formulation, streamlining, interactivity, storytelling and visualization. Behavioural studies of model-enhanced decision-making processes in action can point to promising approaches.

It is important to note that research insights are one input to a decision-making process that is often less structured than outlined in Fig. 1 and Table 1. Research can provide information to decision-makers, especially if the exchange of information happens in both directions throughout all stages of research design and execution. Ultimately, though, decisions will be made on the basis of a range of stakeholders' interests, often extending beyond achieving environmentally, socially and economically effective energy solutions. However, the approaches we discuss could better align research outputs with decision-making processes.

Conclusions and future outlook

Decision-making processes concerning public energy RDD&D must confront the challenge of making consequential choices under uncertainty. These decisions will affect the global population's access to high-quality energy services, the human health impacts of energy-related pollutants and the risks to human and natural systems from climate change. The private sector faces similar challenges though with a different scope, often focused on individual industries and not the entire economy, and often with a shorter-term focus compared with the longer time horizons traditionally considered by governments.

Research on the outcomes of RDD&D policy decisions can help inform policy-making. Technology forecasts, methods to optimize investments in technology portfolios, and models to help inform decision-making processes can all help. While no amount of research will remove uncertainty about the future, it can potentially increase the chances of a successful policy. Research to understand how to better support technology innovation is as critical as research to develop individual technologies.

Validating models, streamlining models and enhancing interactivity are future research priorities. These three advances all support one another. Streamlining models can reveal consequential assumptions that should be the focus of validation efforts. Validation can point to where models can and cannot generate useful insight, thus informing how decision-makers use models. Streamlining will allow some models to run in real time (or near real time), enabling interaction with users. Recent advances have been made but more work is needed in these areas, in collaboration with practitioners (that is, users of the research).

Much past research has focused on wealthy nations. It is essential that future research also considers other parts of the world. While there are conclusions that can be generalized across locations, specifically for technologies that are purchased and sold in globally integrated markets, there are also many insights that must be tailored to particular contexts. When forecasting technology change, deployment processes (a kind of soft technology) and related costs are often highly variable across locations[38]. Desired outcomes of investments in energy processes are also location dependent across and within nations.

All of the different stages of RDD&D are important and can lead to innovation. It is important not to overlook the important innovation that has resulted from deployment policies in the past, and which could occur in the future. The innovation resulting from research and development has received more attention, but innovation through demonstration and deployment policies is equally important.

Both early-stage and mature technologies are important to study. Although many more mature decarbonization technologies are cost competitive and scalable, they are not yet being adopted at the level required to substantially reduce global emissions, and enhancing their attractiveness could speed their adoption. Newer, earlier stage technologies may also be needed, especially for energy services that are currently more difficult to decarbonize[80].

Further development of these research areas in collaboration with practitioners holds promise for expediting progress towards improved energy affordability, equity, climate protection and improved health. While the approaches and insights outlined here are specific to technology innovation in energy systems, the overall framework could potentially also be productively applied to other societally relevant areas of technological advancement.

References

1. IEA *Energy Technology Perspectives 2020* Special Report on Clean Energy Innovation (OECD Publishing, 2020).
2. *Energy Technology RD&D Budgets* (IEA) (accessed 31 May 2024); https://www.iea.org/data-and-statistics/data-product/energy-technology-rd-and-d-budget-database-2
3. *OECD Data Explorer* (OECD) (accessed 31 May 2024); https://stats.oecd.org/index.aspx?r=814876
4. Hourihan, M. *A Primer on Federal R&D Budget Trends* (AAAS, 2021).
5. Bertram, C. et al. Energy system developments and investments in the decisive decade for the Paris Agreement goals. *Environ. Res. Lett.* **16**, 074020 (2021).
6. Kreibiehl, S. et al. in *Climate Change 2022: Mitigation of Climate Change* (eds Shukla, P. R. et al.) 1547–1640 (Cambridge Univ. Press, 2022).
7. *World Energy Investment 2024* https://www.iea.org/reports/world-energy-investment-2024 (IEA, 2024).
8. Pugh, G. et al. Energy R&D portfolio analysis based on climate change mitigation. *Energy Econ.* **33**, 634–643 (2011).
9. Kurth, M. et al. A portfolio decision analysis approach to support energy research and development resource allocation. *Energy Policy* **105**, 128–135 (2017).
10. Olaleye, O. & Baker, E. Large scale scenario analysis of future low carbon energy options. *Energy Econ.* **49**, 203–216 (2015).
11. Nagy, B., Farmer, J. D., Bui, Q. M. & Trancik, J. E. Statistical basis for predicting technological progress. *PLoS ONE* **8**, e52669 (2013).
12. Kavlak, G., McNerney, J. & Trancik, J. E. Evaluating the causes of cost reduction in photovoltaics modules. *Energy Policy* **123**, 700–710 (2018).
13. Gambhir, A., et al. How are future energy technology costs estimated? Can we do better? *Int. Rev. Environ. Resour. Econ.* **15**, 271–318 (2021).
14. Verdolini, E., Anadón, L. D., Baker, E., Bosetti, V. & Aleluia Reis, L. Future prospects for energy technologies: insights from expert elicitations. *Rev. Environ. Econ. Policy* **12**, 133–153 (2018).
15. Nemet, G. F. Improving the crystal ball. *Nat. Energy* **6**, 860–861 (2021).
16. Nemet, G. F., Baker, E. & Jenni, K. E. Modeling the future costs of carbon capture using experts' elicited probabilities under policy scenarios. *Energy* **56**, 218–228 (2013).
17. Gabriel, S. A., Conejo, A. J., Fuller, J. D., Hobbs, B. F. & Ruiz, C. *Complementarity Modeling in Energy Markets* (Springer, 2013).
18. Bosetti, V. et al. Sensitivity to energy technology costs: a multi-model comparison analysis. *Energy Policy* **80**, 244–263 (2015).
19. Pless, J., Hepburn, C. & Farrell, N. Bringing rigour to energy innovation policy evaluation. *Nat. Energy* **5**, 284–290 (2020).
20. Morgan, M. G. Our knowledge of the world is often not simple: policymakers should not duck that fact, but should deal with it. *Risk Anal.* **35**, 19–20 (2015).
21. Popper, S. W., et al. *Natural Gas and Israel's Energy Future: Near-Term Decisions from a Strategic Perspective* (RAND Corporation, 2009).
22. Guivarch, C. et al. Using large ensembles of climate change mitigation scenarios for robust insights. *Nat. Clim. Change* **12**, 428–435 (2022).
23. Baker, E., Bosetti, V. and Salo, A. Robust portfolio decision analysis: an application to the energy research and development portfolio problem. *Eur. J. Oper. Res.* **284**, 1107–1120 (2020).
24. Sivaram, V., Cunliff, C., Hart, D., Friedmann, J.& Sandalow, D. *Energizing America* (Columbia University SIPA Center on Global Energy Policy, 2020).
25. Chong, H. *Closing the Gap: Priorities for the U.S. Department of Energy's Building RD&D Portfolio* (Information Technology and Innovation Foundation Center for Clean Energy Innovation, 2022).
26. *IEA Energy Innovation Forum 2024* https://www.iea.org/events/iea-energy-innovation-forum-2024 (IEA, 2024).
27. Trancik J. E. et al. *Technology Improvement and Emissions Reductions as Mutually Reinforcing Efforts: Observations from the Global Development of Solar and Wind Energy* (Institute for Data, Systems and Society, Massachusetts Institute of Technology, 2015).

28. *U.S. Leadership and the Historic Paris Agreement to Combat Climate Change* https://obamawhitehouse.archives.gov/the-press-office/2015/12/12/us-leadership-and-historic-paris-agreement-combat-climate-change (Obama White House Archives, 2015).
29. *Multi-Year Program Plan* https://www.energy.gov/oced/office-clean-energy-demonstrations (US Office of Clean Energy Demonstrations (OCED), 2023).
30. *Innovation Fund Progress Report* https://climate.ec.europa.eu/eu-action/eu-funding-climate-action/innovation-fund/what-innovation-fund_en#what-is-being-funded-and-how (European Union, 2023).
31. Clarke, L. & Baker, E. *Workshop Report: RD&D Portfolio Analysis Tools and Methodologies* (Joint Global Change Research Institute, 2011).
32. Allen, A. et al. End-to-end data-driven weather prediction. *Nature* **641**, 1172–1179 (2025).
33. Shrader, J. G., Bakkensen, L. & Lemoine, D. *Fatal Errors: the Mortality Value of Accurate Weather Forecasts* Working Paper 31361 (National Bureau of Economic Research, 2023).
34. Eash-Gates, P. et al. Sources of cost overrun in nuclear power plant construction call for a new approach to engineering design. *Joule* **4**, 2348–2373 (2020).
35. Wang, N., Akimoto, K. & Nemet, G. F. What went wrong? Learning from three decades of carbon capture, utilization and sequestration (CCUS) pilot and demonstration projects. *Energy Policy* **158**, 112546 (2021).
36. Way, R., Ives, M. C., Mealy, P. & Farmer, J. D. Empirically grounded technology forecasts and the energy transition. *Joule* **6**, 2057–2082 (2022).
37. Grant, N., Hawkes, A., Mittal, S. & Gambhir, A. The policy implications of an uncertain carbon dioxide removal potential. *Joule* **5**, 2593–2605 (2021).
38. Klemun, M. M., Kavlak, G., McNerney, J. & Trancik, J. E. Mechanisms of hardware and soft technology evolution and the implications for solar energy cost trends. *Nat. Energy* **8**, 827–838 (2023).
39. Lafond, F. et al. How well do experience curves predict technological progress? A method for making distributional forecasts. *Technol. Forecast. Soc. Change* **128**, 104–117 (2018).
40. Shayegh, S., Sanchez, D. L. & Caldeira, K. Evaluating relative benefits of different types of R&D for clean energy technologies. *Energy Policy* **107**, 532–538 (2017).
41. Santhakumar, S., Meerman, H. & Faaij, A. Improving the analytical framework for quantifying technological progress in energy technologies. *Renew. Sustain. Energy Rev.* **145**, 111084 (2021).
42. Tsai, P. H. et al. Quantitative technology forecasting: a review of trend extrapolation methods. *Int. J. Innov. Technol. Manag.* **20**, 2330002 (2023).
43. Way, R., Lafond, F., Lillo, F., Panchenko, V. & Farmer, J. D. Wright meets Markowitz: how standard portfolio theory changes when assets are technologies following experience curves. *J. Econ. Dyn. Control* **101**, 211–238 (2019).
44. Nuñez-Jimenez, A., Knoeri, C., Hoppmann, J. & Hoffmann, V. H. Beyond innovation and deployment: modeling the impact of technology-push and demand-pull policies in Germany's solar policy mix. *Res. Policy* **51**, 104585 (2022).
45. McNerney, J., Farmer, J. D., Redner, S. & Trancik, J. E. Role of design complexity in technology improvement. *Proc. Natl Acad. Sci. USA* **108**, 9008–9013 (2011).
46. Morgan, G. Use (and abuse) of expert elicitation in support of decision-making for public policy. *Proc. Natl Acad. Sci. USA* **111**, 7176–7184 (2014).
47. Meng, J., Way, R., Verdolini, E. & Anadon, L. D. Comparing expert elicitation and model-based probabilistic technology cost forecasts for the energy transition. *Proc. Natl Acad. Sci. USA* **118**, e1917165118 (2021).
48. Trancik, J. E. Testing and improving technology forecasts for better climate policy. *Proc. Natl Acad. Sci. USA* **118**, e2109417118 (2021).
49. Albright, R. What can past technology forecasts tell us about the future? *Technol. Forecast. Soc. Change* **69**, 443–464 (2002).
50. Apreda, R., Bonaccorsi, A., dell'Orletta, F. & Fantoni, G. Expert forecast and realized outcomes in technology foresight. *Technol. Forecast. Soc. Change* **141**, 277–288 (2019).
51. Kott, A. & Perconti, P. Long-term forecasts of military technologies for a 20–30 year horizon: an empirical assessment of accuracy. *Technol. Forecast. Soc. Change* **137**, 272–279 (2018).
52. Fye, S., Charbonneau, S., Hay, J. & Mullins, C. An examination of factors affecting accuracy in technology forecasts. *Technol. Forecast. Soc. Change* **80**, 1222–1231 (2013).
53. Bonaccorsi, A., Apreda, R. & Fantoni, G. Expert biases in technology foresight. Why they are a problem and how to mitigate them. *Technol. Forecast. Soc. Change* **151**, 119855 (2020).
54. O'Hagan, A., et al. *Uncertain Judgements: Eliciting Experts' Probabilities* (Wiley, 2006).
55. Gonzalez, C., Sanchez-Segura, M. I., Dugarte-Peña, G. L. & Medina-Dominguez, F. Valence matters in judgments of stock accumulation in blood glucose control and other global problems. *J. Dyn. Decis. Mak.* **4**, 3 (2018).
56. Ziegler, M. S., Song, J. & Trancik, J. E. Determinants of lithium-ion battery technology cost decline. *Energy Environ. Sci.* **14**, 6074–6098 (2021).
57. Wiser, R. et al. Expert elicitation survey on future wind energy costs. *Nat. Energy* **1**, 16135 (2016).
58. Shiraki, H. & Sugiyama, M. Back to the basic: toward improvement of technoeconomic representation in integrated assessment models. *Clim. Change* **162**, 13–24 (2020).
59. Ruegg, R., O'Connor, A. C. & Loomis, R. J. *Evaluating Realized Impacts of DOE/EERE R&D Programs. Standard Impact Evaluation Method* Report DOE/EE-1117 (Lawrence Berkeley National Lab. (LBNL), 2014).
60. *Transforming Our World: the 2030 Agenda for Sustainable Development* A/RES/70/1 (UN General Assembly, 2015).
61. Barrage, L. & Nordhaus, W. Policies, projections, and the social cost of carbon: results from the DICE-2023 model. *Proc. Natl Acad. Sci. USA* **121**, e2312030121 (2024).
62. Weitzman, A. Prices vs. quantities. *Rev. Econ. Stud.* **41**, 477–491 (1974).
63. Krey, V. et al. *MESSAGEix-GLOBIOM Documentation* https://doi.org/10.22022/IACC/03-2021.17115 (International Institute for Applied Systems Analysis, 2020).
64. Sepulveda, N. A., Jenkins, J. D., de Sisternes, F. J. & Lester, R. K. The role of firm low-carbon electricity resources in deep decarbonization of power generation. *Joule* **2**, 2403–2420 (2018).
65. Peñasco, C., Anadón, L. D. & Verdolini, E. Systematic review of the outcomes and trade-offs of ten types of decarbonization policy instruments. *Nat. Clim. Change* **11**, 257–265 (2021).
66. Salo, A., Keisler, J & Morton, A. (eds) *Portfolio Decision Analysis: Improved Methods for Resource Allocation* International Series in Operations Research & Management Science Vol. 162 (Springer, 2011).
67. Anadon, L. D., Baker, E. & Bosetti, V. Integrating uncertainty into public energy research and development decisions. *Nat. Energy* **2**, 17071 (2017).
68. Moore, F. C. et al. Mini-PAGE, an open-source implementation of the PAGE09 integrated assessment model. *Sci. Data* **5**, 180187 (2018).

69. Marangoni, G., Lamontagne, J. R., Quinn, J. D., Reed, P. M. & Keller, K. Adaptive mitigation strategies hedge against extreme climate futures. *Clim. Change* **166**, 37 (2021).
70. Strnad, F. M., Barfuss, W., Donges, J. F. & Heitzig, J. Deep reinforcement learning in World-Earth system models to discover sustainable management strategies. *Chaos* **29**, 123122 (2019).
71. Saltelli, A. A short comment on statistical versus mathematical modelling. *Nat. Commun.* **10**, 3870 (2019).
72. Lempert, R. J., Popper, S. & Bankes, S. *Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis* (RAND Corporation, 2003).
73. National Research Council *Understanding Risk: Informing Decisions in a Democratic Society* (National Academies Press, 1996).
74. Herman, J. D., Reed, P. M., Zeff, H. B. & Characklis, G. W. How should robustness be defined for water systems planning under change? *J. Water Resour. Plan. Manag.* **141**, 04015012 (2015).
75. Marchau, V. A., Walker, W. E., Bloemen, P. J. & Popper, S. W. *Decision Making under Deep Uncertainty: from Theory to Practice* (Springer, 2019).
76. Martin, C. J. in *Negotiating Agreement in Politics* (eds Mansbridge, J. & Martin, C. J.) (American Political Science Association, 2013).
77. Kasprzyk, J. R., Nataraj, S., Reed, P. M. & Lempert, R. J. Many objective robust decision-making for complex environmental systems undergoing change. *Environ. Model. Softw.* **42**, 55–71 (2013).
78. Brunhart-Lupo, N., Bush B., Gruchalla, K., Potter, K. & Smith, S. *Collaborative Exploration of Scientific Datasets Using Immersive and Statistical Visualization* Report NREL/PR-2C00-79574 (National Renewable Energy Lab. (NREL), 2021).
79. Overpeck, J. T., Meehl, G. A., Bony, S. & Easterling, D. R. Climate data challenges in the 21st century. *Science* **331**, 700–702 (2011).
80. Davis, S. J. et al. Net-zero emissions energy systems. *Science* **360**, eaas9793 (2018).

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