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A decision science approach for integrating social science in climate and energy solutions

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The social and behavioural sciences are critical for informing climate- and energy-related policies. We describe a decision science approach to applying those sciences. It has three stages: formal analysis of decisions, characterizing how well-informed actors should view them; descriptive research, examining how people actually behave in such circumstances; and interventions, informed by formal analysis and descriptive research, designed to create attractive options and help decision-makers choose among them. Each stage requires collaboration with technical experts (for example, climate scientists, geologists, power systems engineers and regulatory analysts), as well as continuing engagement with decision-makers. We illustrate the approach with examples from our own research in three domains related to mitigating climate change or adapting to its effects: preparing for sea-level rise, adopting smart grid technologies in homes, and investing in energy efficiency for office buildings. The decision science approach can facilitate creating climate- and energy-related policies that are behaviourally informed, realistic and respectful of the people whom they seek to aid.

Policies for mitigating climate change or reducing the harm that it causes inevitably make assumptions about the behaviour of the people who must execute or respond to those policies. Unless those assumptions are realistic, the policies may fail. For example, wind farms have been rejected because planners failed to consider public opposition to changes in their view or the anticipated harm to birds or bats[1]; free weatherization programmes have failed because people do not want strangers coming into their homes[2]; and rebate programmes have experienced rebound effects whereby residential homeowners use more energy after buying more efficient appliances[3]. Even low-cost, high-benefit technological innovations may not gain acceptance unless consumers can see the benefits and feel able to take advantage of them. For example, many people cannot use information about energy consumption when expressed in unfamiliar units, such as kilowatt-hours[4–7]. Moreover, without behavioural evidence, one cannot know whether policies have failed because people did not understand them, did not want them, or could not execute them.

We outline a decision science approach for integrating the social and behavioural sciences into climate- and energy-related policy development, in order to realize the potential of natural science and engineering knowledge and thus address the challenges posed by climate change. Decision science involves the formal analysis of decisions, characterizing the choices that fully informed, rational actors would make; descriptive research, examining how people actually behave in those circumstances; and interventions designed to bridge the gap between the normative ideal and the descriptive reality[8–10]. Applying this approach requires continued collaboration between substantive experts, to ensure the accuracy of the analysis and the feasibility of the interventions, and social scientists, to create attractive interventions, secure them a fair hearing and assess their success[11,12]. It also requires continued interaction with decision-makers, so as to create options that they might find attractive[13–15]. The decision science approach seeks to facilitate informed decision-making so that people understand the risks, benefits and uncertainties well enough to make choices that reflect their values. Here, we illustrate how decision science has been applied in three domains related to mitigating climate change or adapting to its effects, with studies drawn from our own published research. Table 1 summarizes results from these studies.

Formal analysis

Decision science provides analytical frameworks that are general enough to accommodate decisions as diverse as those associated with climate and energy. Its first step is formal analysis: characterizing decisions in the structured form of choice options, valued outcomes and uncertainties regarding the outcomes that each option will produce[10,16,17]. In the USA, for example, a decision facing electric power generators is how (and how quickly) to reduce CO_2 emissions in the face of the US Environmental Protection Agency's Clean Power Plan[18]; a decision facing homeowners is how to prepare for flooding, given changes to the National Flood Insurance Program[19]. A formal analysis identifies the information that people need in order to make choices that are consistent with their values. To that end, it must include the relevant options (for example, affordable actions), valued outcomes (for example, personal safety and biodiversity) and uncertainties (for example, will insurance claims be honoured?). The evidence relevant to an analysis may come from the natural sciences (for example, the potency of greenhouse gases), engineering (for example, the cost and efficacy of control technologies), or the social sciences (for example, the willingness and ability of an individual to pay for emission reductions). The following three examples illustrate such analyses.

Preparing for sea-level rise. Floods and storms are the most frequent and costly weather-related disasters in the USA, causing an estimated US$626.9 billion in losses between 1980 and 2011[19,20]. Climate models predict increased coastal flooding due to more frequent and intense high-impact storms[21,22] and rising sea levels[23,24], thereby affecting an increasing number of people living in flood-prone areas[25,26].

Individual actions designed to reduce vulnerability (for example, home retrofits, flood insurance and evacuation plans) are increasingly promoted as complements to large-scale public defences

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Table 1 | Decision science, with examples from applications to three domains of climate change mitigation and adaptation.

Case study	Preparing for sea level rise	Adopting residential smart grid technologies	Investing in energy efficiency in office buildings
Formal analysis	Feasible options (for example, retrofitting home) Valued outcomes (for example, peace of mind) Uncertainties (for example, government coverage of losses)	Feasible options (for example, feedback on consumption) Valued outcomes (for example, personal comfort) Uncertainties (for example, privacy of energy consumption data)	Feasible options (for example, efficient lighting) Valued outcomes (for example, transaction costs) Uncertainties (for example, promised savings)
Descriptive analysis	Think aloud use of decision aid Experiment assessing impact of contextual factors (evoking political beliefs, time horizon)	Mental models interviews, identifying user concerns Follow-up survey, assessing underlying dimensions (fear of being controlled, tangible benefits, accountability)	Mental model interviews, identifying concerns outside formal model Follow-up survey, assessing prevalence of beliefs
Intervention	Experimental evaluation of sea-level rise decision aid	Systematic review of field experiments Experimental evaluation of in-home display designs	Experimental evaluation of programmes addressing concerns (for example, contractors as change agents)

(for example, sea walls and levees)[27–30]. Nevertheless, few people adopt such measures voluntarily[31,32]. Although these low adoptions rates are frustrating to the authorities, they might still represent reasonable choices, depending on the residents' options, values and uncertainties.

Determining whether residents should want the options that programmes promote requires a formal analysis of the decisions facing them. That analysis must consider their feasible options (for example, retrofitting their home immediately or leaving it to the next owner), valued outcomes (for example, peace of mind and solidarity with neighbours) and uncertainties regarding which outcomes will follow the adoption of each option (for example, whether the government will pay for reconstruction and how climate change will affect storm surge risks). These analyses of individual decisions parallel those in the integrated assessments created for public decisions, which may include predictions of private choices (for example, settlement patterns on coastal plains)[33].

Adopting residential smart grid technologies. Smart grid technologies have been promoted as a way of reducing residential energy use by providing real-time consumption information to system operators (for example, to manage power quality and guide spot-market purchases) and to consumers (for example, to conserve energy based on appliance usage or participate in peak-shaving programmes)[34]. According to one estimate, global smart grid deployment could reduce annual greenhouse gas emissions by 0.9–2.2 × 10^9 tonnes of CO_2 (ref. 35). The USA has made major investments in these technologies[36], including the residential meters needed to implement demand-response programmes (for example, by setting higher prices during peak-use hours). If successful, such programmes could reduce reserve capacity costs[37], demand for new generation and system load, thereby making the service more reliable while reducing energy waste and carbon emissions[38].

Whether such programmes will indeed be attractive to consumers is a matter for analysis, by considering consumers' options (for example, ways to reduce consumption), valued outcomes (for example, comfort, cost, health and privacy) and uncertainties (for example, will the privacy of their consumption data be protected? Will savings plans be too complex to follow?). Prior experience provides one basis for assessing those uncertainties. However, its relevance always depends on conditioning factors, such as how rigorously the technology has been tested, how committed public utility commissioners are to defending consumer interests, and how well consumers can follow price signals[39,40]. As a result, expert judgment — interpreting the evidentiary record for specific circumstances — is part of any analysis[41,42].

Investing in energy efficiency in office buildings. Office buildings account for 16% of commercial-sector energy use in the USA[43]. Although the sector has great potential for cost-effective energy efficiency improvements (for example, occupancy sensors), adoption rates are low[43–45]. In attempts to speed the diffusion of these improvements, many US cities have established 2030 Districts, which are committed to reducing energy use by 50% for existing buildings by 2030 (www.2030districts.org).

A simple, formal model of the decisions faced by building owners when investing in energy efficiency would compare the net economic benefit (from energy savings) of each option (for example, efficient lighting) with its costs (purchase, maintenance, disposal and backup). Options that pass such a cost–benefit test can be subjected to cost-effectiveness analysis, by identifying the best buys in energy saving (that is, those providing the greatest net savings for the least cost) and other investments (for example, new bathroom sinks). A more complete economic analysis could include the transaction costs of activities, such as investigating the options, securing trusted contractors and completing the associated paperwork (for example, documenting expenditures, occupancy and ownership). More complete analyses could include additional outcomes, such as the expected appeal of better facilities to prospective tenants, disruption to current tenants during renovations, and hassle of working with a programme's promoters. More complete still are analyses that consider uncertainties about promised savings, the ability of the owner to make payments, and occupancy rates. The usefulness of any analysis depends on how fully it includes the critical elements of a decision, without which its calculations represent misplaced precision (and its sensitivity analyses represent misplaced imprecision).

Descriptive research

Decision science proceeds from formal analysis to descriptive research by characterizing individuals' perceptions in comparable terms. Basic research has identified general ways in which the heuristics that guide lay judgments can produce both insight and bias[46]. Research focused on climate- and energy-related topics has examined how these processes play out in specific domains[47]. Our own work (illustrated below) has focused on how people think about specific decisions (rather than, say, on the general framing of climate issues). In that research, we typically elicit either summary judgments, paralleling the inputs for a formal analysis (for example, the probability of flooding in the next ten years)[15,41], or mental models of the processes that shape those outcomes (for example, how winds and tides affect storm surges)[48,49]. We typically begin with qualitative research, allowing participants to raise the issues on their minds in their natural language and formulation. We then proceed with structured surveys that assess the prevalence of key beliefs and values, sometimes supplemented with experiments that measure the influence of specific factors, such as how issues are framed or an individual's political identify is evoked.

Studies that elicit summary judgments draw on research whose roots lie in the dawn of scientific psychology (circa 1875), with

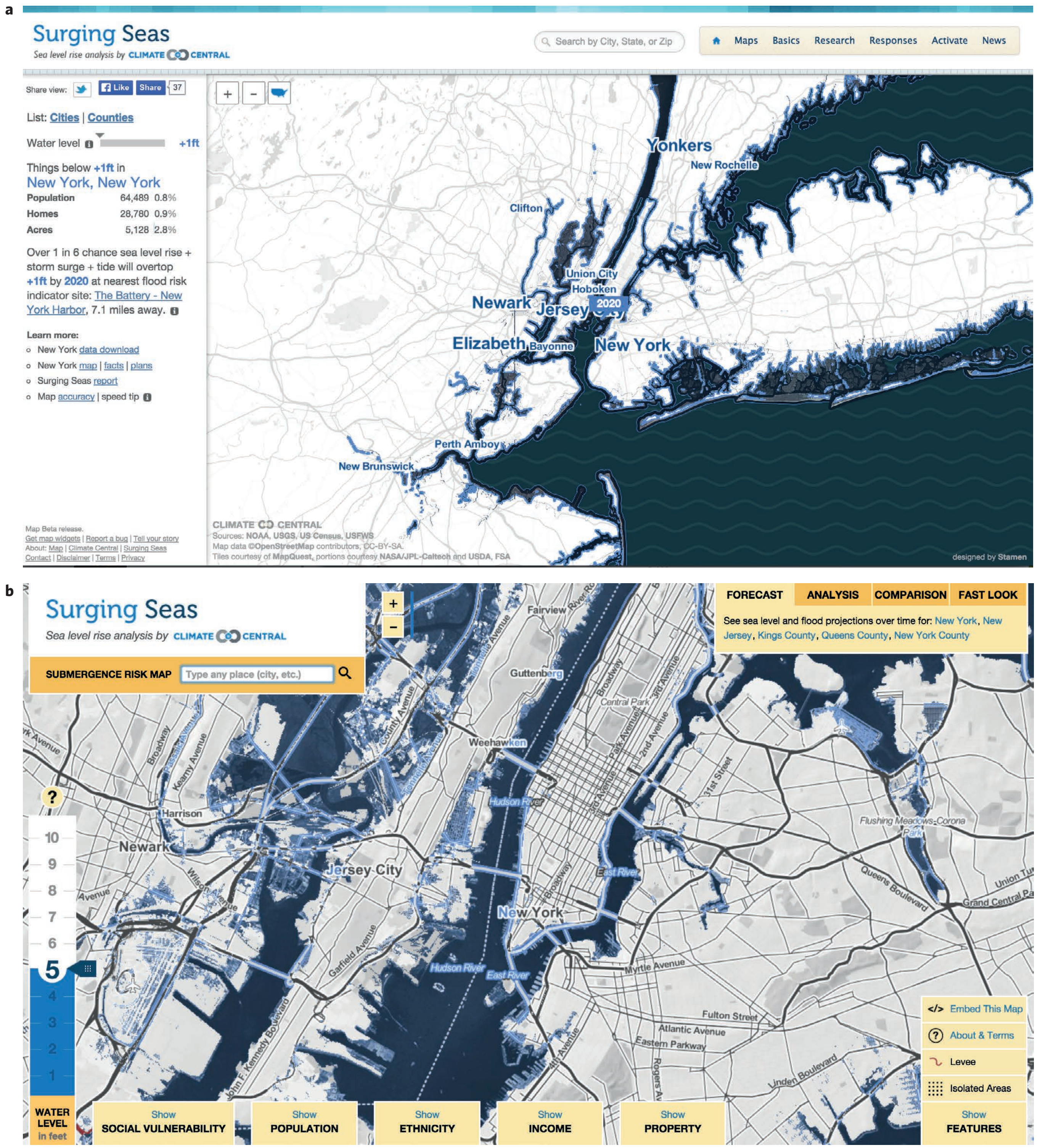

Figure 1 | Climate Central's Surging Seas Risk Finder for New York City. a, Initial design. **b**, Design after iterative testing. Reproduced with permission from ref. 12, © 2014 PNAS.

tasks assessing the psychological equivalent of physical stimuli (for example, brightness and heaviness). Researchers found that such 'psychophysical' judgments can depend on seemingly subtle aspects of how stimuli are presented, such as where the first two stimuli lie in the overall set and whether whole or fractional numbers are used[50–52]. Studies that extended these methods to the judgments of risks and benefits highlighted additional concerns, such as the importance of clear, consensual definitions[15,41,42,53,54]. For example, judgments of 'risk' may be misinterpreted if the term means different things to technical experts (fatalities in an average year) and laypeople (adding a measure of catastrophic potential, for non-average years)[55]. Judgments of the 'probability of rain' may be misinterpreted unless laypeople know what forecasters mean by 'rain' (the chance of a particular measurable amount, the percentage of the area covered, or the fraction of the day)[56].

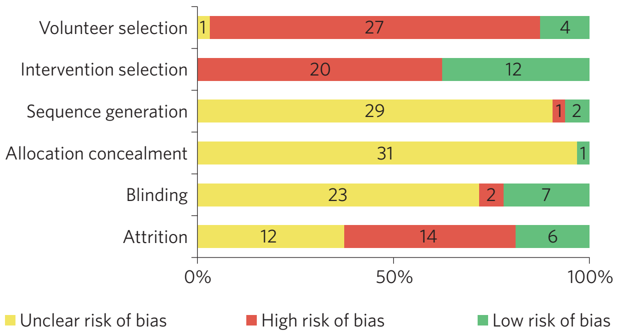

Figure 2 | Risk-of-bias assessment for 32 studies of in-home displays, dynamic pricing and home automation systems. Most studies were at high risk of bias from participant selection (volunteers), intervention selection (non-random assignment) and attrition (leaving some conditions at a high or disproportionate rate). Reporting was insufficient to allow determining risk-of-bias for most studies with respect to sequence generation (the order of assignment to conditions), allocation concealment (whether hidden from participants) and blinding (whether hidden from researchers). Reproduced with permission from ref. 91, © 2013 Elsevier.

Studies of lay mental models have almost as long a history[58–60]. They compare intuitive representations of how a process works to a formal one, with topics as diverse as syllogistic reasoning, the circulatory system and climate dynamics[61]. In our studies, formal analyses are the standard of comparison. However, unlike studies in other domains, which assume the validity of the formal model, in our research the model can change, particularly if people identify options, values, outcomes or uncertainties that it has missed.

Mental models interviews begin with general questions (for example, "what comes to mind when you think about wind power?"), so as to avoid presuming that the researchers have identified all relevant elements. In that spirit, interviewees are encouraged to expand on each topic that they address, so as to hear out their views and the language expressing them. The interview proceeds with questions that focus increasingly on topics in the formal analysis. This reduces the risk of missing topics because the interview happened to go in other directions, while increasing the risk of suggesting topics that are not naturally part of participants' mental models.

Follow-up surveys can estimate the prevalence of views heard in such interviews. Follow-up experiments can assess the role of specific factors, such as the impact of context (for example, cues evoking political identity) on expressed beliefs. As with all social and behavioural science research, the development of those instruments requires iterative pretesting, typically with individuals drawn from the target population thinking aloud as they perform a task, with researchers alert to cases where it was not interpreted as intended. Manipulation checks ask respondents in the actual studies to report on how they interpreted questions[53,62–64].

Preparing for sea-level rise. Our descriptive research began with structured interviews in which participants were asked to think aloud while using the Surging Seas decision aid (http://sealevel.climatecentral.org) (Fig. 1). Those interviews allowed us to capture many aspects of their thinking, such as their intuitive conceptualization of the probability and impact of flooding events. However, they left us uncertain as to how people thought about one key factor in the formal analysis of decisions involving coastal flooding exacerbated by sea-level rise: the time horizon. Their natural perspective could depend on both pragmatic concerns (for example, how long they expect to live in an area) and subjective feelings of psychological distance[65–67]. For example, one study found greater concern about climate change when people had shorter time horizons (and less psychological distance)[68]. On the other hand, with shorter time horizons, there is also less chance of bad events occurring, which could reduce willingness to translate concern into action.

To investigate how such processes play out in one specific context, we randomly assigned people to one of three time frames (2020, 2050 or 2100) when making judgments using the Surging Seas decision aid. For example: "keeping what [I] learned about coastal floods in [county] in mind… I would still move with my family to [county] (if I was planning on doing that already)"; "Now, please set the highest expected flood height that you and your family would be willing to live with, at some point between today and [2020/2050/2100], before deciding not to move to [county]. What height did you pick?" We found similar responses for all three time horizons[66]. One possible explanation of that seeming insensitivity to time horizon is that immersion in the decision aid overwhelmed any effects of manipulating the time period. A second possible explanation is that changing the time period had cancelling effects, with longer periods showing greater risks while also increasing participants' psychological distance from them.

In another experiment, we examined the effect of evoking respondents' political identity on their judgments[69]. The politically polarized debate over climate change[70,71] has raised the prospect of personal values acting as 'perceptual screens' so that people interpret (and perhaps misinterpret) messages in ways that reinforce their existing views and allegiances[72–74] — as special cases of general psychological processes, such as confirmation bias[75] and motivated reasoning[46,76–79]. Our study manipulated political identity on climate change in the context of decisions about buying a home in an area subject to sea-level rise. In order to make the task more realistic (while still hypothetical), participants used the real estate search website Zillow together with the Surging Seas decision aid. We found that, once immersed in that decision, participants with different political views responded similarly, except when a strong appeal to their political identity was embedded in the task. However, even that difference vanished when participants stated their position on climate change beforehand, which seemingly allowed them to focus on the practical decision. Political positions have, however, been found to affect behaviour for less-involving tasks[79–81].

Adopting residential smart grid technologies. The response of some customers to smart grid technologies reflect issues that are seemingly missing from the formal models of those technologies' advocates, such as concern over privacy, health effects and unfair electricity bills[82,83]. To create a comprehensive picture of such concerns, we conducted mental models interviews, followed by a survey that examined the prevalence of decision-relevant beliefs expressed in those interviews, using the language revealed there[84]. Principal components analysis found that customer concerns covered three primary factors: (1) fear of being controlled, including concerns about privacy and utility company control over electricity use (for example, switching off air conditioning during peak demand); (2) tangible benefits, including expectations for financial savings and reduced blackout risk; and (3) accountability of the utility company, including perceived opportunities to check the accuracy of electricity bills and receive appliance-specific usage information. Logistic regression models found more positive attitudes toward smart meters among those who believed them to bring tangible benefits and those who had less fear of being controlled. Those attitudes were, however, unrelated to accountability — perhaps a fortunate result for smart meter advocates, as the interviews found that consumers expected much better feedback than the meters can provide.

Investing in energy efficiency in office buildings. Motivated by the puzzlingly low rates of investment in energy efficiency technologies for offices, we conducted mental model interviews and a follow-up survey with owners of class B and C (that is, non-premier) office buildings (A.D., G.W.-P. and T.K., manuscript in preparation). Both the interviews and the survey were structured around a formal model of the owners' energy efficiency decisions, which included both economic and non-economic concerns. Respondents' perspectives were elicited with sufficient detail to evaluate the attractiveness of both currently available options and potentially better ones. When estimates were provided for the expected costs and benefits of energy efficient lighting systems, survey respondents demonstrated a surprising willingness to invest (given the lack of actual adoption). However, when asked about financing programmes to help pay for those investments, many owners expressed a principled objection to incurring debt, with some even rejecting loans at zero per cent interest. For those individuals, the net present value calculation of a simple economic model is irrelevant. Rather, they need an analysis that evaluates energy-efficient options without assuming a positive discount rate. Many respondents expressed scepticism about the claims made for energy savings and about the motives of the people making them — all concerns that are missing from promoters' analyses of owner decisions.

Interventions

Disparities between formal models and descriptive realities offer opportunities for interventions designed to improve the models (so that they capture the concerns of decision-makers), the options (so that they address decision-makers' needs) or communications with decision-makers (so that the options are understood and those offering them are trusted). Basic research should inform the programme-design process to suggest potential directions, and then be followed by vigorous pre-testing of successive designs and rigorous evaluation of the one that is eventually deployed. Sound design has many facets (for example, tone, wording, aesthetics and organization), hence can draw on inputs from many research areas[85,86]. Evaluation similarly draws on the research areas needed to measure a programme's success in achieving goals, such as how well people understand the programme, how attractive they find it and how well they can implement their choices.

Preparing for sea-level rise. In our evaluation of Climate Central's Surging Seas Risk Finder decision aid (Fig. 1)[66,69], we sought to draw on these diverse research literatures, guided by empirical assessment of the aid's success in meeting three evaluative criteria: users' (1) knowledge, measured by their ability to recall decision-relevant facts; (2) preferences, measured by the consistency of their judgments with alternative displays (for example, with different time horizons); and (3) active mastery, measured by their ability to make sound inferences based on the presented material. Changes prompted by that testing included introducing bright colours to highlight important features, reorienting a bar showing water level from horizontal to vertical (in order to match intuitive notions of depth), and making the initial screen more welcoming by reducing clutter (for example, moving detailed information to secondary screens accessed by advanced tabs). Surging Seas was, we believe, the only website on the initial rollout of www.data.gov/climate to have undergone such user testing.

Adopting residential smart grid technologies. Smart-grid-enabled technologies can provide real-time feedback to customers about their energy consumption, through devices such as in-home displays (IHDs). Promoters of this technology postulate that such feedback will improve consumers' mental models of their home energy use[87–89], so that they use existing appliances more effectively and thus allow the introduction of more attractive products (for example, home automation systems) or programmes (for example, dynamic pricing)[90]. Many studies have examined how well that potential has been achieved.

In a systematic review, Davis *et al.*[91] evaluated the methodological soundness of all accessible studies examining the impacts

Figure 3 | A screenshot showing simulated appliances with specific feedback. Reproduced with permission from ref. 93, © 2013 Elsevier.

of programmes offering IHDs or demand pricing. Their evaluation asked whether those studies had methodological flaws identified by medical researchers as biasing the conclusions of clinical trials[92]. As seen in Fig. 2, the risk of such biases often could not be estimated because critical details were missing in the research summaries (often found in the grey literature of technical reports issued without independent peer review). When risk of bias could be assessed, it was often high because participants in these experiments were volunteers, selected their treatment group, or dropped out at high overall rates or disproportionate rates across treatment groups. After applying a correction factor estimated from medical clinical trials, there was only weak evidence that IHDs helped homeowners to reduce their energy use and no evidence of reducing peak energy use or enhancing the effectiveness of dynamic pricing programmes.

As an input to designing more effective IHDs, we had consumers create their own displays by selecting the information features that they wanted, from among ones offered on commercially available IHDs[93]. Most participants wanted only a few key features, most commonly information on their overall bill and electricity usage of specific appliances[94]. Participants reported a strong dislike of features such as comparisons with their neighbour's usage, a popular intervention[95]. However, a follow-up study[93], with a display that included the desired features (Fig. 3), found that people often could not use the information provided by the desired features. For example, although people preferred receiving appliance-specific feedback in dollar units, they actually learned more about how to rank the relative consumption of various appliances from simply being told how much electricity those appliances used.

Investing in energy efficiency in office buildings. Each result from study of owners of class B and C commercial office buildings suggests a direction for designing interventions. For example, owner scepticism about the motives and claims of the promoters of energy efficiency interventions suggests enlisting trusted contractors as change agents, thereby enabling them to provide information and implement improvements, as part of their ongoing work on a building's energy systems. The unwillingness of owners to take on debt, even with subsidized interest rates, suggests emphasizing programmes that address their uncertainty about their ability to make payments, such as installing occupancy sensors, which require modest capital costs and provide relatively predictable energy savings.

For field trials of any intervention, one methodological concern is the Hawthorne effect (named after the Western Electric factory where it was first described in the 1920s), whereby knowledge of being in a study affects participant behaviour, independent of any effects of the intervention. As a result, a Hawthorne condition is a natural part of any field trial. Schwartz *et al.*[96] estimated the size of such an effect by performing an experiment in which postcards were sent to randomly selected residential customers, stating that they had been enrolled in a one-month study of their 'electricity consumption', followed by weekly reminders. Over the month, participants reduced their consumption by 2.7% — an effect comparable to actual interventions. A second methodological concern with field trial data is that performing many statistical analyses sometimes causes spurious relationships to emerge by chance[97]. We controlled for this possibility by specifying the analyses in advance and checking their robustness by evaluating different model specifications (for example, using a two- or four-year baseline for estimating consumption without the postcards) blind to their identity.

Discussion and conclusion

Facilitating informed decisions about climate- and energy-related policies requires us to understand the facts of those choices (for example, the relevant climate science and technological realities), their structure (that is, the relevant options, valued outcomes and uncertainties) and the individuals who bear the consequences. Decision science offers a systematic approach for recruiting and integrating the relevant evidence. It entails an iterative process involving subject matter experts, to identify potentially relevant issues; social scientists, to characterize the perspectives and options of decision-makers; and decision-makers, to inform the work. Social and behavioural science research informs each step of this process by addressing questions such as how to elicit experts' knowledge, describe the preferences and constraints of decision-makers, convey those preferences to experts hoping to create attractive options, and communicate the costs, benefits and uncertainties of those options to decision-makers.

The decision science approach is most effective when it: (1) draws broadly on basic social and behavioural science research, rather than restricting itself to a sub-discipline or theory; (2) uses methods appropriate to the task; and (3) is involved early in the design process, so that it can shape options in their formative stages[15]. To those ends, the studies summarized here applied research from cognitive psychology (for example, confirmation bias), personality psychology (political identity) and social psychology (group norms). They included formal analyses, systematic reviews, mental models interviews, structured surveys, experiments and user testing of websites. They came at the beginning of design processes, during critical reassessments, and after failures.

The formal analyses that structure decision science applications facilitate such inclusiveness by their theoretical neutrality and their ability to accommodate knowledge from social, behavioural, natural and engineering sciences. The decision science approach can improve not only communication among the sciences, but also between them and the public they hope to serve. It can increase the chance of a programme being attractive and being understood as such, thereby increasing the public's faith in its experts. It can also help experts to diagnose the sources of failures, thereby increasing their faith in the public, which will not be seen as rejecting programmes for inexplicable reasons. Thus, by helping experts and decision-makers to understand one another, decision science might improve options and decisions, as well as respect between the parties.

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