Community involvement in coastal infrastructure adaptation should balance necessary complexity and perceived effort.

An online experiment compared risk perceptions elicited using multiple risk categories (intervention) to a control group. Risk perceptions did not differ for 2/3 of the coastal infrastructure examples. Perceived effort was elevated for participants in the intervention group.

Highlights

- An online experiment explored the utility of risk perception feedback methods.
- Cognitive load was measured to understand tradeoffs affecting public participation.
- The complex and simple methods did not produce different outcomes in most cases.
- Mental demand, perceived success, and frustration increased for the complex method.
Community involvement in coastal infrastructure adaptation should balance necessary complexity and perceived effort

Bethany Gordon1,3,* and Leidy Klotz2

SUMMARY
Successful adaptation of coastal infrastructure requires public participation, and it is important to elicit accurate feedback from surveys and in-person interactions. But there remains a need for evidence about the efficacy of potential risk communication design metrics. This online experiment (n = 261) sought to understand the necessity of a multifaceted risk perception questionnaire to capture public input. Using six coastal infrastructure examples, risk perceptions were collected using a questionnaire highlighting multiple types of risk (intervention) or not (control). Public evaluations of risk did not differ in most cases. Moreover, the intervention imposed more cognitive strain on participants, which could unintentionally discourage public participation in the climate adaptation process. In this case, the single question provides the same input, with less effort. This finding is a reminder that effective risk communication for managing adaptation processes requires considering both the quality of public input and the effort required to provide it.

INTRODUCTION
Effective climate adaptation requires participatory risk communication

The number of people living below projected annual flood levels globally is projected to triple by mid-century (Kulp and Strauss, 2019a, 2019b). With up to 630 million people being affected, maintaining quality and feasibility of coastal life in the face of global climate change is a reality that municipalities and society, broadly, must plan for (2019a, 2019b). The relationship between daily life and the coastal infrastructure that supports it is complex and cannot be represented solely with probabilistic analyses created by experts of risk and design (engineering, city planners, and policy makers). The public can serve as a “check on the value judgment of experts” and to add context to the risk calculations that experts are making (Serrao-Neumann et al., 2015). To create a holistic plan for the future of built environments, professional designers must work with the public and challenge a technocratic approach to climate adaptation (2015).

The nuances of public participation have been explored in previous work. For example, the local context of a community will strongly influence what specific engagement strategies are appropriate (e.g., roundtable discussions, design charrettes, or surveys). Davies and Hügel note that interventions should be “sensitive to matters of place and difference” (Davies and Hügel, 2021). This necessary flexibility to accommodate local context poses challenges for assessing whether participation actually improved project outcomes and from that, techniques for “participatory (Toth and Hizsnyik, 2008), deliberative (Hindmarsh and Matthews, 2008; Videira et al., 2006), and cooperative (Renn, 2006)” participation have been analyzed (Serrao-Neumann et al., 2015). A theme that runs throughout the literature is a concern about the potential for placation and tokenism as the primary utility of public participation in decision-making processes (e.g., Hindmarsh and Matthews, 2008).

Research about public participation in climate adaptation has been dominated by themes of risk, risk perception, and risk communication (Hügel and Davies, 2020). Risk perception describes the subjective outcome of evaluating the potential for loss or damage using individual emotions and experiences (Slovic, 2016). Risk communication describes a variety of interactions ranging from experts talking “at” the public to experts and the public working together in a participatory design format (e.g., the “consult” level and higher on the IAP2 Spectrum of Public Participation) (IAP2, 2018). This latter approach to risk
communication is underutilized for large-scale infrastructure projects and the appropriate risk communication design strategies for these interactions are still in development. It is important to assess the costs and benefits of these approaches because, if effective, they provide opportunities to make informed decisions that include public risk perceptions and shape the long-term outcomes of a project.

An example of the potential benefit of these risk communication design metrics is illustrated by Covi and Kain (2016), who evaluated risk communication materials (visual information). They found that a coastal community in North Carolina expressed feelings of “fear, fatalism, skepticism, and loss” when confronted with this messaging about the existing state of infrastructure and projected effects of sea level rise. Their results highlight a primary reason risk communication and risk perceptions are intertwined: once major decisions have been made about infrastructure adaptation, these emotional responses may encourage unproductive behavior, such as failing to take any individual actions to protect oneself against the increased likelihood of flooding (skepticism) or retreating prematurely from a coastal community (fear). Skepticism and distrust in climate-related authorities have been linked to low risk perceptions about flood risk (Zinda et al., 2021) and though fear can be somewhat effective at drawing attention to climate-related issues, it rarely creates genuine engagement (O’Neill and Nicholson-Cole, 2009). However, while major decisions about infrastructure adaptation are still being made, these perceptions could serve as guideposts for engineers, policymakers, and urban planners who are striving to make these coastal futures possible for communities. For example, case studies in Australia demonstrated that public involvement earlier in a climate adaptation project led to support, whereas involvement later in the process led to opposition (Serrao-Neumann et al., 2015). In these cases, it was evident that public involvement and deliberation earlier in the projects (at the design stages) were more effective than initiating involvement at the later stages, such as implementation (Lahiri-Dutt, 2004; Serrao-Neumann et al., 2015).

Though risk perceptions and risk communication are often linked in the literature and in practice, they are rarely framed as interlocking mechanisms for improving infrastructure design. Therefore, the utility of measuring risk perceptions is often presented as a way to understand and correct perceptions that do not align with calculated risk. This perspective assumes that risk perceptions are based on a misunderstanding (Bucchi, 2008; Suldovsky, 2016) and that emotions are unimportant in the decision-making process (Salama and Aboukoura, 2018). However, when approaching risk communication as a participatory endeavor that happens early in the decision-making process, the utility of public risk perceptions shifts. Because this framing is less common, there is not a tool for eliciting risk perceptions that are directly useful to technical design decision-making.

When the purpose of collecting risk perception data is to account for risk perceptions in design rather than influence them afterward, the output of the tool needs to align with a style of input that is useful for designers. In alignment with the understanding that risk perceptions are multifaceted, it is typically important that a tool designed for this purpose contains multiple dimensions of risk (Weber et al., 2002). One model that contains useful categories for design is the Domain-Specific Risk-Taking (DOSPERT) scale (Blais and Weber, 2006). The DOSPERT scale utilizes domains of health/safety, financial, social, recreational, and ethical risk to characterize facets of risk perception and risk-taking behavior. These categories are both commonly known to the public and apply to existing design considerations. Health/safety and financial risk considerations are core to all infrastructure projects, social and recreational utility are accounted for through analyses of social sustainability, and ethical considerations are warranted through the professional codes of ethics of various design fields (ASCE, 2021).

However, one consideration of a multidimensional risk communication tool is the toll it may take on public participants’ enthusiasm for and ability to engage with participatory design. Delving into multiple dimensions of risk is likely to increase the cognitive load (i.e., increased perceptions of how much effort, time, or stress is required to participate) that the public experiences through their participation and may decrease risk-taking tendencies (Deck and Jahedi, 2015). It is important to measure and account for these potential costs.

This experiment seeks to explore the potential of the DOSPERT categories as a tool for communicating public risk perceptions about coastal infrastructure adaptation for climate change. By testing this intervention in a variety of green (e.g., vegetated shoreline) and gray (e.g., seawall) coastal infrastructure contexts, this study acknowledges that environmental management often takes place at the nexus of the built environments and natural environments. In doing so, it seeks to determine for which—if any—of the types of
coastal infrastructure the DOSPERT categories would be useful to include in an elicitation method for designers and whether the effort invested in making that distinction is worthwhile.

**Approaches to risk communication**

Experts think about risk in terms of the probability of an event and its impact (Okrent, 1980; Stephens and Richards, 2020). In contrast, the public tends to include additional dimensions like perceived expert knowledge and perceived dread in their personal evaluations of risk (Slovic, 2010). These differing approaches to risk have often been characterized as a public deficit—an inability to understand the science (Bucchi, 2008; Sul dovsky, 2016). In cases where planning efforts are focused on short-term impacts of climate change, such as natural disasters, it may be appropriate to characterize the communication gap between experts and the public as a public deficit. In these cases, increasing awareness so that stakeholders, as individuals, may make informed decisions about how to protect themselves may need to be a priority (Kuser Olsen et al., 2018). However, long-term planning situations, the communication “gap” can be an opportunity for meaningful collaboration with the public in the planning process.

For example, tidal flooding is the temporary inundation of low-lying areas that coastal communities need to be aware of and prepare for in advance. When this communication gap is viewed as a unidirectional public relations issue, the communication may end with recommendations for alternative driving routes or tools to check inundation online (Yoe, 2017). When this communication gap is viewed as an opportunity, public risk perceptions may be valued as a mechanism for the collaborative development of infrastructure plans. An example of public collaboration effort can be found in the development of a GIS modeling project in Detroit, Michigan, which included the development of Google Maps overlays documenting green, blue, and gray infrastructure in a subset of Detroit neighborhoods with the intent to “convince community, political, and economic leadership to embrace a broader interpretation of value” (Bodurow et al., 2009).

This contrast between public relations and participatory design exemplifies the spectrum of approaches to risk communication. This paper focuses on when the latter has the potential to impact infrastructure adaptation for climate change—in both a tidal flooding context or in the event of more far-off extreme hazards—acknowledging that science and design are connected to the rest of the world and an expert perspective is far from the only input that matters in successful communication and in successful design (Bucchi, 2008; Trench, 2006).

For projects where fewer resources are available for community engagement, there is a need to develop channels of feedback that balance efficiency with accuracy. While interviews and focus groups have been shown to be effective, surveys can be utilized in tandem to collect a wider range of perspectives (DeLorme et al., 2018). Surveys that are designed to elicit probabilistic responses from participants—essentially asking them to think like experts—have been shown to be an ineffective method of communication (Fischhoff, 1995; Salman and Li, 2018). In response, the Intergovernmental Panel on Climate Change (IPCC) has turned probabilities into quantified likelihood to measure uncertainty (i.e. a 10-point Likert scale) (Stocker et al., 2013). The method of quantified likelihood can be applied to a wide array of questions and is utilized in this study.

**Dimensions of risk**

There are two general approaches to characterizing the dimensions of risk perceptions. The first focuses on the characteristics of the risk in question. This approach has been heavily influenced by seminal works like those that introduced the psychometric paradigm (Fischhoff et al., 1978; Slovic, 1987; Slovic et al., 1984). In these studies, participants were asked to assess the risk of dying as a result of the intervention. The results produced nine dimensions of risk: voluntariness of risk, immediacy of effect, knowledge about risk, control over risk, newness of risks, chronic vs. catastrophic risk, level of dread associated with risk, and severity of consequences (Fischhoff et al., 1978). This paradigm has been widely adopted and revised over the last several decades. For example, computational models are being developed using the dimensions of the psychometric paradigm to predict decision-making (Bhatia, 2019).

More recently, Wilson et al. (2019) put forth an analysis of unidimensional, general risk perception vs. multi-dimensional risk perceptions focused in three categories: affect, probability, and consequences. This model is intended to be widely applicable as a measure of risk perception and would likely be most beneficial in the risk communication strategy of dialog, where the public provides input but does not participate in the design process. The difficulty with this approach for participatory design is that it focuses on individual behaviors as outcomes and is not providing feedback that would be accessible to feedback into the
design process. In contrast, the categories of the DOSPERT scale (health/safety, financial risk, social risk, ethical risk, and recreational risk) offer that potential because they align with considerations that are already present in a design process (ASCE, 2021; Blais and Weber, 2006).

Cognitive load
Another factor that should be considered in efforts to increase public participation in the climate adaptation decision-making process is the cognitive load that a participatory task imposes on an individual. Cognitive load refers to the amount of information that an individual can process (Sweller, 1988) and can overwhelm participants and negatively impact the quality of questionnaire responses (Brosnan et al., 2021). It has also been associated with increased risk aversion (Deck et al., 2021; Deck and Jahedi, 2015). Cognitive load can be assessed by a number of factors including mental demand, perceived success, and frustration with a task (Hart, 2006). Attention to cognitive load may provide insight into whether a participation activity is reasonable.

This study explores the necessity of a multifaceted risk perception questionnaire to capture public input and the perceived cognitive demand of the task.

RESULTS
For the majority of infrastructure examples, there were not statistically significant differences between the groups

We hypothesized that the intervention group would report different risk perceptions compared to a control group for all infrastructure types in the study. The hypothesis was supported for the breakwater option and for the option representing natural reclamation of the space, “no further action” (Table 1). However, it was not supported for the remaining scenarios.

**Statistically significant results**

**Breakwater.** The intervention group (M = 3.30, SD = 0.99) reported higher risk perceptions than the control group (M = 2.99, SD = 1.07) according to Welch’s test, t (257.81) = −2.41, p = 0.017. The resulting confidence interval for this t-test was (−0.30, −0.06). The effect size was d = 0.30. This result supports our hypothesis.

**Natural reclamation: “No further action”**. The intervention group (M = 4.03, SD = 0.93) reported lower risk perceptions than the control group (M = 4.39, SD = 0.85) according to Welch’s test, t (256.5) = 3.22, p = 0.001. The resulting confidence interval was (0.14, 0.57). The effect size was d = 0.40. This result supports our hypothesis.

**Non-significant results**

**Vegetated shoreline.** The intervention group (M = 2.68, SD = 1.08) did not report significantly different risk perceptions than the control group (M = 2.72, SD = 1.21) according to Welch’s test, t (256.4) = 0.29,
p = 0.775. The resulting confidence interval was (−0.24, 0.32). The effect size was d = 0.04. This result does not support our hypothesis.

**Vegetated shoreline with rock sill.** The intervention group (M = 2.76, SD = 1.00) did not report significantly different risk perceptions than the control group (M = 2.85, SD = 1.14) according to Welch’s test, t(254.87) = 0.74, p = 0.463. The resulting confidence interval was (−0.016, 0.36). The effect size was d = 0.09. This result does not support our hypothesis.

**Oyster reef.** The intervention group (M = 3.07, SD = 0.99) did not report significantly different risk perceptions than the control group (M = 2.90, SD = 1.03) according to Welch’s test, t(258.72) = −1.48, p = 0.140. The effect size was d = 0.14. The resulting confidence interval was (−0.43, 0.06). This result does not support our hypothesis.

**Seawall.** The intervention group (M = 3.72, SD = 0.87) did not report significantly different risk perceptions than the control group (M = 3.50, SD = 1.24) according to Welch’s test, t(233.5) = −1.72, p = 0.088. The resulting confidence interval for this t-test was (−0.49, 0.09). The effect size was d = 0.21. This result does not support our hypothesis.

**Task load index.** In addition to the hypothesized relationships tested above, Welch’s tests were conducted to compare the differences in self-reported cognitive load experienced by the intervention and control groups (Table 2). Mental demand, perceived effort, and frustration levels were all higher for the intervention group than for the control group. Perceived success, physical demand, and temporal demand were not statistically different. The effect sizes for the statistically significant items ranged from small (perceived effort and frustration) to moderate (mental demand).

### Socio-demographic summary of the sample

The sample consisted of 261 online participants in the United States. Among the 261 respondents in this sample, 53.6% were female, the mean age was 41.8 years old (+/− 13.2 years), 53.6% had a 4-year college degree or more, 74.7% identified as White/Caucasian, and 5.0% identified as Hispanic or Latinx (Table 3).

### DISCUSSION

The results indicate that, for the majority of infrastructure scenarios presented in this study, the multifaceted question structure did not produce differing outcomes from the single question. Additionally, factors associated with cognitive load were elevated for participants who participated in the multifaceted version of the questionnaire (intervention group).

**A more complex questionnaire does not guarantee richer data and may dissuade public participation**

Many of the measures developed for quantifying risk perceptions of hazards and risk-taking behaviors of individuals contain multiple dimensions (Siegrist and Árvai, 2020). Therefore, one may presume that
when collecting public input about risks for integration into design decision-making that these factors are a necessary component for risk communication between the public and infrastructure professionals. However, the results of this study suggest that in the majority of scenarios, the introduction of different facets of risk did not impact risk perceptions any more than a single question about risk. Additionally, mental demand, perceived effort, and frustration were higher for the group that was asked to consider

| Table 3. Socio-demographic summary of the sample | Control | Intervention | Overall |
|------------------------------------------------|---------|-------------|---------|
| N = 131 | N = 130 | N = 261     |
| **Sex** |         |             |         |
| Female | 62 (47.3%) | 78 (60.0%) | 140 (53.6%) |
| Male | 66 (50.4%) | 52 (40.0%) | 118 (45.2%) |
| Non-binary | 3 (2.3%) | 0 (0%) | 3 (1.1%) |
| **Age** |         |             |         |
| Mean (SD) | 41.0 (13.0) | 41.3 (13.4) | 41.2 (13.2) |
| Median [Min, Max] | 37.0 [22.0, 78.0] | 38.0 [20.0, 79.0] | 37.0 [20.0, 79.0] |
| **Education** |         |             |         |
| No high school diploma | 2 (1.5%) | 2 (1.5%) | 4 (1.5%) |
| High school diploma | 18 (13.7%) | 10 (7.7%) | 28 (10.7%) |
| Some college, but no degree | 27 (20.6%) | 33 (25.4%) | 60 (23.0%) |
| Associate degree | 14 (10.7%) | 15 (11.5%) | 29 (11.1%) |
| Bachelor’s degree | 49 (37.4%) | 52 (40.0%) | 101 (38.7%) |
| Master’s degree | 16 (12.2%) | 18 (13.8%) | 34 (13.0%) |
| Doctoral degree | 3 (2.3%) | 0 (0%) | 3 (1.1%) |
| Professional degree | 2 (1.5%) | 0 (0%) | 2 (0.8%) |
| **Race** |         |             |         |
| Asian | 6 (4.6%) | 10 (7.7%) | 16 (6.1%) |
| Black | 12 (9.2%) | 25 (19.2%) | 37 (14.2%) |
| Multiracial | 4 (3.1%) | 5 (3.8%) | 9 (3.4%) |
| White | 106 (80.9%) | 89 (68.5%) | 195 (74.7%) |
| Prefer not to say | 3 (2.3%) | 1 (0.8%) | 4 (1.5%) |
| **Ethnicity** |         |             |         |
| Hispanic | 9 (6.9%) | 3 (2.3%) | 12 (4.6%) |
| Spanish | 2 (1.5%) | 1 (0.8%) | 2 (0.8%) |
| Latine | 0 (0%) | 0 (0%) | 1 (0.4%) |
| None of the above | 120 (91.6%) | 126 (96.9%) | 246 (94.3%) |
| **Income** |         |             |         |
| Less than $10,000 | 7 (5.3%) | 6 (4.6%) | 13 (5.0%) |
| $10,000 to $19,999 | 12 (9.2%) | 12 (9.2%) | 24 (9.2%) |
| $20,000 to $29,999 | 6 (4.6%) | 15 (11.5%) | 21 (8.0%) |
| $30,000 to $39,999 | 20 (15.3%) | 10 (7.7%) | 30 (11.5%) |
| $40,000 to $49,999 | 14 (10.7%) | 17 (13.1%) | 31 (11.9%) |
| $50,000 to $59,999 | 11 (8.4%) | 15 (11.5%) | 26 (10.0%) |
| $60,000 to $69,999 | 16 (12.2%) | 11 (8.5%) | 27 (10.3%) |
| $70,000 to $79,999 | 13 (9.9%) | 10 (7.7%) | 23 (8.8%) |
| $80,000 to $89,999 | 9 (6.9%) | 11 (8.5%) | 20 (7.7%) |
| $90,000 to $99,999 | 8 (6.1%) | 5 (3.8%) | 13 (5.0%) |
| $100,000 to $149,999 | 11 (8.4%) | 10 (7.7%) | 21 (8.0%) |
| $150,000 or more | 4 (3.1%) | 8 (6.2%) | 12 (4.6%) |
multiple facets of risk. From the results of the cognitive load measure, one may infer that a project asking participants to engage in a task that is taking more effort and evoking negative emotions (“How insecure, discouraged, irritated, stressed, and annoyed were you?”) may be negatively affecting public participation and limiting the extent to which the public is able to critically engage with and challenge the values imbued by professional decision-makers in charge of the project. These findings do not suggest that the more complex approach is universally incorrect; the literature has thoroughly established the importance of locally tailored approaches and interventions (Davies and Hügel, 2021; Few et al., 2007). The findings suggest that it is necessary to question the application of a more complex survey as the default or as a best practice.

**Easily observable infrastructure may present clearer scenarios for public engagement**

The exceptions included the breakwater and the non-intervention option (no further action). A closer examination of the differences across infrastructure types reveal larger differences in means for the hard infrastructure types (e.g., breakwater $\Delta = 0.31$ and seawall $\Delta = 0.22$) as opposed to softer infrastructure types (e.g., vegetated shoreline $\Delta = 0.04$ and vegetated shoreline with rock sill $\Delta = 0.09$). One explanation for this discrepancy may be that certain types of infrastructure are easier to observe and form opinions about than other types. For example, the breakwater was positioned apart from the shoreline and was presented in repetitive segments. It was also one of the two infrastructure scenarios where the intervention and control groups responses were significantly different. In opposition, the vegetated shoreline is more subtle and may be perceived by fewer participants as a discernable type of infrastructure. This illuminates an important additional consideration regarding public engagement in climate adaptation decision-making: the experience that the public bring to the adaptation process will differ from the expertise that professional designers bring to the project. It will likely vary more widely for the public than for a group of infrastructure professionals but may be less variable for individuals who are dealing with these challenges in their own communities. Future work on the subject may benefit from a case study approach to further understand this impact.

**Implications**

These findings contribute to conversations about best practices for engaging the public in coastal infrastructure adaptation for climate change and can be further explored and applied in several ways:

**Practical applications**

- Risk perception questionnaires or surveys that introduce multiple types of risk may be able to reduce survey length and cognitive load by simplifying the questionnaire.
- Collecting preliminary information including cognitive load data can inform whether public participation activities align with the needs of local communities.
- Non-survey approaches are effective at capturing necessary complexity. Community relationship building and dialog have been a long-standing mechanism for design approaches that value community input. These interaction-based approaches are important and, while they present challenges related to resource availability, remain an important facet of community-inclusive decision-making (Ross et al., 2015).

**Future work**

- These findings need to be studied in a wider variety of climate adaptation circumstances. For example, by increasing understanding of how these issues differ for short-term impacts of climate changes (e.g., fires, hurricanes, and flooding). There are multifaceted models used in evaluating preparedness for short-term climate impacts, such as the Protective Action Decision Model and expectancy-valence models (Becker et al., 2014) that may present different cognitive load tradeoffs than the metric used in this study.
- Further work would be beneficial to understand whether the results would conceptually replicate using different categories.
- Finally, further work should be done to understand the relationship between frustration with complex or difficult participation activities and future intentions to participate in the climate adaptation decision-making process.
Limitations of the study

When interpreting results of this study, readers should keep in mind several potential limitations. While CloudResearch has been a reliable source of risk data in previous studies that compared the performance of online pools of participants to traditional samples, there are limitations to using this online population: the sample is not as diverse as the general United States population and workers on this site complete hundreds of studies each month (Goodman et al., 2013). Additionally, prior experience living along a coastline can be closely related to perceived risk of climate change and flooding (Combest-Friedman et al., 2012; Iglesias et al., 2021). Therefore, the risk perceptions in this study will likely not align with the intuitions of a specific coastal population. Future case studies may ask similar questions to inform this work.

STAR METHODS

Detailed methods are provided in the online version of this paper and include the following:

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SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2022.104852.

ACKNOWLEDGMENTS

This material is based upon work supported by 1) the United States National Science Foundation Graduate Research Fellowship Program under grant number 1842490 and 2) the United States National Science Foundation grant number 153104. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

AUTHOR CONTRIBUTIONS

Conceptualization, B.G. and L.K.; Methodology, B.G. and L.K.; Software, B.G.; Validation, B.G. and L.K.; Formal Analysis, B.G.; Investigation, B.G. and L.K.; Writing – Original Draft, B.G.; Writing Review & Editing, B.G. and L.K.; Funding Acquisition, B.G. and L.K.; Resources, M.E.V. and C.K.B.; Supervision, L.K.

DECLARATION OF INTERESTS

The authors declare no competing interests.

INCLUSION AND DIVERSITY STATEMENT

We worked to ensure that the study questionnaires were prepared in an inclusive way. One or more of the authors of this paper self-identifies as an underrepresented ethnic minority in science. One or more of the authors of this paper received support from a program designed to increase minority representation in science.
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KEY RESOURCES TABLE

| REAGENT or RESOURCE | SOURCE | IDENTIFIER |
|---------------------|--------|------------|
| Deposited data      |        |            |
| Responses           | CloudResearch (formerly TurkPrime) | https://doi.org/10.17632/kbcbprimv394.1 |
| Software and algorithms | https://www.rstudio.com | RRID:SCR_001905 |

RESOURCE AVAILABILITY

Lead contact
Further information and requests for resources should be directed to the lead contact, Bethany Gordon (bmg1@uw.edu).

Materials availability
This study generated data on the variables reported in this study.

Data and code availability
- Study data have been deposited at Mendeley Data and are publicly available as of the date of publication. Accession numbers are listed in the key resources table.
- This paper does not report original code.
- Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

EXPERIMENTAL MODEL AND SUBJECT DETAILS

Human
A convenience sample was recruited from the Cloud Research (formerly TurkPrime) online population. The Cloud Research population is 57.7% female, the age of Cloud Research users skews younger than the US population and is closely aligned for racial demographics except for African Americans (underrepresented) (Moss, 2020).

Written informed consent was collected from all participants in accordance with the University of Virginia Institutional Review Board (IRB-SBS #2953). Data from participants that did not complete the entire experiment was excluded from the analysis. Participants received $2 for their participation in this study.

METHOD DETAILS

A 2-cell experimental design was used for this study. After completing informed consent, participants were randomly divided into two groups: an intervention group and a control group. The distinguishing factor between these groups was whether they were asked about multiple facets of risk (intervention) or not (control) for the purpose of distinguishing if exposure to these multiple facets of risk made a difference in overall reported risk perceptions.

The facets of risk were operationalized using the categories from the DOSPERT scale, which is widely used in psychology to discern individual differences in risk perception (Blais and Weber, 2006). This manipulation sought to understand how participant groups would respond to questions about perceived risk based on this unidimensional or multidimensional presentation. The authors hypothesized that reports on a single-item risk measure would differ if participants were first asked to consider multiple facets of risk. This hypothesis was tested for a variety of infrastructure types (see Table S1). Images of the survey materials are included in the supplementary materials (see Figures S1–S24).
Background information
All participants received the same introduction: “Imagine you live in a coastal community. Tidal flooding, also known as sunny day flooding, regularly affects your community. The design has been proposed to incorporate several coastal interventions on the shoreline that will help with tidal flooding and erosion. However, all interventions include risk. The designers (engineers, city planners, and policymakers) are seeking your feedback. In the event these technologies break or fail, how high are the risks?”. The term ‘interventions’ and ‘technologies’ are used interchangeably in this study to refer to the range of coastal infrastructure examples.

Experimental manipulation
If participants were randomly selected to be in the intervention group, they received the following additional instructions: “they have asked you to provide input on the following types of risk: health/safety, financial, social, ethical, and recreational.” Common, non-coastal examples of each risk type were listed underneath: not wearing a seatbelt or smoking (health/safety risk), investments or gambling (financial risk); causing conflict in a group of friends or family members (social risk); cheating on an exam or littering (ethical risk); snowboarding or skydiving (recreational risk).

Using a continuous sliding scale (1 = Not at all risky, 5 = Extremely risky) participants in the intervention group were asked to report risk perceptions in the categories of financial risk, health/safety risk, social risk, ethical risk, and recreational risk. The important aspect of this variable is that participants were asked to think about risk from multiple angles that already have common familiarity.

Single-item risk perception
To compare the responses of the intervention group to the control group, all participants responded to a single-item question about risk perceptions for each infrastructure type (Table S1). Using a continuous sliding scale (1 = Not at all risky, 5 = Extremely risky) participants were asked to report overall risk perception. The dependent variable was one question: in the event that these technologies break or fail, how high are the risks?

Task load index
Given the theoretical and practical links between cognitive load, risk perceptions, and public participation in infrastructure decision making, cognitive load was measured using the Task Load Index (Hart, 2006). This measure asked them to rate their experience with providing feedback on a continuous scale from 1 to 5 for three aspects: mental demand, perceived success, and perceived effort. The items are listed in Table S2.

Demographics
Demographic information was collected.

QUANTIFICATION AND STATISTICAL ANALYSIS
The dependent variable means were compared using Welch’s test. We selected the Welch’s test over Student’s t-test because equal variances are not assumed for the Welch’s test, which can help to reduce type 1 error in the event that there are not equal variances (Delacre et al., 2017; Rasch et al., 2011). The assumption of normality is still present for the Welch’s test. While the data did not conform to a normal distribution, Welch’s test is robust to this assumption for large sample sizes (Rochon et al., 2012). The data was analyzed in RStudio using dplyr, ggplot2, tidyr, ggpubr, and rstatix (Kassambara, 2020; Wickham, 2016, 2021). Additionally, the data was checked and cleared for IP fraud using the rIP package (Waggoner et al., 2019).