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What Governs Attitudes Toward Artifcial Intelligence Adoption and Governance?

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Abstract

Designing effective and inclusive governance and public communication strategies for artificial intelligence (AI) requires understanding how stakeholders reason about its use and governance. We examine underlying factors and mechanisms that drive attitudes toward the use and governance of AI across six policy-relevant applications using structural equation modeling and surveys of both U.S. adults (N=3524) and technology workers enrolled in an online computer science master's degree program (N=425). We find that the cultural values of individualism, egalitarianism, general risk aversion, and techno-skepticism are important drivers of AI attitudes. Perceived benefit drives attitudes toward AI use, but not its governance. Experts hold more nuanced views than the public, and are more supportive of AI use but not its regulation. Drawing on these findings, we discuss challenges and opportunities for participatory AI governance, and we recommend that *trustworthy AI governance* be emphasized as strongly as trustworthy AI.

1 Introduction

Artificial intelligence (AI) may fundamentally reshape our economy and society, but across a wide variety of application areas its prospective benefits are accompanied by potential harms. For example, AI's impact on economic growth may be felt unevenly across the labor market. The use of AI in new medical systems raises questions about trust, fairness, and privacy even as it enables new treatments. And AI-based systems provide new tools for free expression while simultaneously powering authoritarian crackdowns and the spread of disinformation.

Realizing the benefits of emerging technologies like AI while mitigating their accompanying harms requires governance strategies that are respectful of the diverse values and beliefs held by the public [1–4]. Inclusive and participatory governance is a central pillar of AI development frameworks released by academic, industry, government, and international groups [5–8]. In representative suggestions, IEEE's framework suggests that developers and regulators of AI should remain aware of the "diversity of cultural norms among users" [6] while the AI Now Institute stresses the importance of expanding "cultural, disciplinary, and ethnic diversity" in the development and governance of AI [9].

However, the technical complexity of AI makes it difficult to design governance structures that the public can participate in effectively. As a result, discourse about AI governance can become opaque and expert-based, making the policy process ineffective at representing diverse viewpoints, vulnerable to capture by vested interests [3], and liable to "ethics-washing" [4, 10]. Moreover, while recent opinion surveys have found that the U.S. public is generally supportive of AI [11–21], their awareness of it is limited [22]: even as AI is pervasive in applications like resume screening and credit scoring, surveys have found little public support for AI in these "sensitive" settings [17]. These

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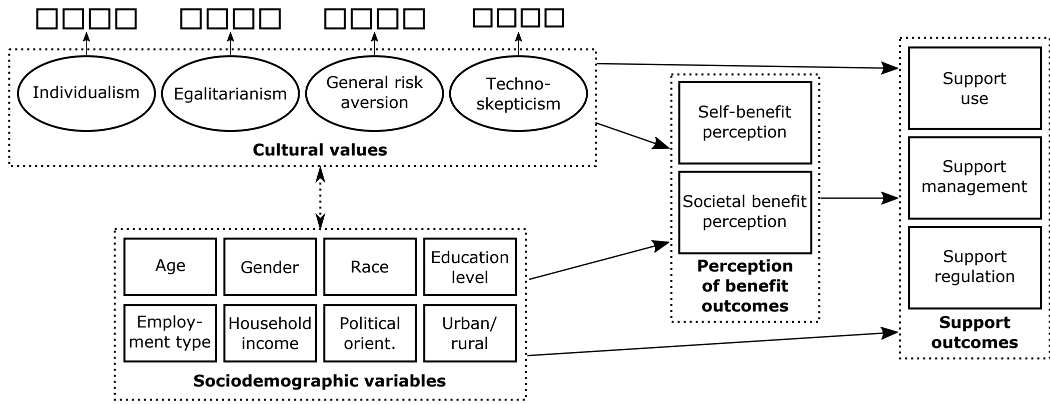

Figure 1: Structural equation model (SEM) used in analysis. The full SEM, $\mathcal{S}$, allows variables within each group (denoted by dashed boxes) as well as cultural values and sociodemographic variables to covary; we treat demographic variables as exogenous. Two nested models are used in our analysis: $\mathcal{S}_{\setminus C}$, which constrains paths from cultural value constructs to outcome variables to zero, and $\mathcal{S}_{\setminus B}$, which constrains paths from perceived benefit outcome variables to support outcome variables to zero.

seemingly contradictory views suggest that public opinion may change rapidly as AI's capabilities, limitations, and societal impacts become more apparent.

Ensuring that diverse public opinion is respected in AI governance processes thus requires that AI developers and policymakers better understand the underlying values and motivations that shape how public attitudes toward AI could evolve. This understanding is also critical for equipping the public to meaningfully engage with AI governance: science communication literature suggests that processes for public outreach and dialogue are most effective when they are tailored to the public's values, beliefs, and motivations [23, 24]. Although previous work has explored how attitudes of AI professionals [25, 26] and the public [11–21] differ across sociodemographic groups, little existing work has explored the *underlying values and mechanisms that drive attitudes toward AI*.

In this paper, we take a step toward better understanding what shapes attitudes toward AI by looking to factors and mechanisms beyond sociodemographic characteristics. We explore the following questions, which are key to designing effective AI governance and science communication strategies:

1. How do sociodemographic factors, cultural values, and perceived benefit influence attitudes toward AI?

2. How do these attitudes — and the factors that inform them — differ between experts and the public?

3. How do these attitudes — and the factors that inform them — differ across common contexts of AI use?

Two explore these questions, we conducted two online surveys in April and May 2021. The first survey sampled $N = 3524$ U.S. adults recruited and compensated through the Lucid Theorem platform, which uses quota sampling to obtain participants representative of adult U.S. residents on age, gender, race, and region. The second survey sampled $N = 425$ students who had recently completed a graduate artificial intelligence course at a top-10 U.S. engineering school in Georgia Tech's online master's in computer science program. Most (93.9%) of these students had undergraduate degrees in technical subjects, and 93.5% previously or concurrently worked in computer science or another STEM field.[1] In addition to standard sociodemographic variables, we consider the impact on attitudes of perceived self- and societal benefit, and of the cultural values of individualism, egalitarianism, general risk aversion, and techno-skepticism — constructs found to inform the perception of many other technological risks [27–29].

The main contribution of this work is to increase understanding of attitudes toward AI use and governance by a) exploring a set of attitudinal drivers that is broader than the typically-considered sociodemographic variables, including both perceptions of benefit and cultural values inspired by the cultural theory literature; b) directly comparing the attitudes of experts and the public; and c) considering attitudes across a range of policy-relevant contexts of AI use. Our preregistered analysis strategy uses the structural equation model (SEM) shown in Figure 1 (described in more detail in the next section), which allows us to naturally address the three key research questions defined above. Our results provide insights that can aid policymakers in crafting governance strategies that are respectful of diverse beliefs and assist AI developers in effectively communicating the broader implications of their work to the public.

[1] Prior work has studied other samples of AI experts: [25] surveys AI researchers publishing in prestigious conferences, while [26] surveys AI professionals in industry. See Section 3.1 and Supplement Section A for more details on the characteristics and limitations of these samples.

Drawing on these results, we offer recommendations for engaging the public in dialogue about AI governance and offer suggestions for future research.

2 Background and theory

2.1 Underlying factors governing attitudes toward technology

Prior work has found that race, gender, and political ideology [30] are highly predictive of attitudes toward issues such as nuclear power [31], climate change [32], genetically engineered food [33], and radiation [34]. Similar sociodemographic divides have been found in attitudes toward AI. Those reporting familiarity and comfort with AI are more likely to be young, male, educated, live in urban areas, and have higher incomes [11, 16, 19–21, 35]. Sociodemographic divides also shape perceptions of AI's impact on society. Those in urban areas, blue collar workers, and political liberals are more likely to believe that AI will deepen inequality and reduce employment [11, 15], while those with more education, white collar jobs, and higher incomes are more likely to believe that AI will be beneficial to society and the economy [11, 13, 15, 16, 19].

The cultural theory of risk perception posits that "cultural" worldviews can be more concise and informative predictors of attitudes toward technological risk than sociodemographic factors alone [27, 36, 37]. These cultural values have been hypothesized to define identity groups, imbue potential risks with affective qualities [34], and encourage biased information processing [38]. Indeed, literature has found that successfully communicating scientific topics to the public benefits from careful attention to how messages may interact with the cultural values held by the public [23, 24, 39]. For policymakers seeking to design inclusive governance and communication strategies, it is critical to understand how cultural values relate to views on AI and whether this relationship differs across specific AI use cases.

We use two cultural values that originate with the grid-group cultural theory of Douglas & Wildavsky [40], were operationalized for survey research by Kahan et al.'s "cultural cognition theory" [41], and have been identified as salient to technological risk perception [27, 42]. The first represents attitudes toward the role of individuals in society: *individualists* favor social orderings in which individuals are responsible for "securing their own well-being without assistance or interference from society," and thus prefer to minimize the role of government when ensuring collective welfare comes into tension with individual preferences [23]. The second cultural value represents attitudes toward well-defined social hierarchies: *egalitarians* favor greater equality between groups defined by race, gender, wealth, and political power; they spurn stratified social orderings based on fixed characteristics. Literature in risk analysis and related disciplines has used cultural theory generally — and the conceptions of individualism and egalitarianism we borrow from cultural cognition theory in particular — to explain differences in opinion between environmentalists and the public [43], disagreements on controversial issues such as gun control and global warming [27], and divides in acceptance of scientific consensus [23].

We also consider two cultural values that describe general attitudes toward risk and technology. First, many individuals tend to avoid small risks even at the cost of foregoing larger benefits; general *risk aversion* has been found to be a powerful predictor of attitudes toward technology [28]. Here we use the risk aversion construct of Sharma [44], which assesses attitudes toward general lifestyle risks. Second, *techno-skeptics* are uncomfortable with the use of new technology, cynical about the intentions of groups developing new technological advancements, and opposed to the use of technology to solve social problems [45, 46]. Techno-skepticism has been found to partially explain divides in opinion on topics such as nuclear waste [47], climate change adaptation [48], and autonomous vehicles [29]. In the context of AI, techno-optimism and techno-skepticism are well-reflected in popular narratives about utopian and dystopian scenarios driven by AI [49].

2.2 Perceived benefit and hypothesized model

In contrast to technologies whose benefits are perceived as broadly shared, popular narratives about AI often feature clear losers [50]: workers who lose their jobs to automation, for example, or minorities who suffer discrimination at the hands of automated decision systems. These narratives may make views about AI governance — perhaps more so than views about other technological risks — subject to perceptions of who stands to benefit and lose from the continually increasing adoption of AI. But while there is some evidence that perceived self-interest informs support for AI-based technologies [16, 51, 52], other literature has suggested that perceived benefit does not always eclipse affective and value-based concerns [53, 54]. To evaluate how perceived benefit influences attitudes toward AI (and understand how it is influenced by sociodemographic variables and cultural values), we use a structural equation model (SEM) [55] analysis framework.

The SEM that forms the core of our analysis describes hypothesized relationships between demographic variables, cultural values, perceived individual and societal benefit from AI, and support for AI use and governance. The

SEM also mathematically defines how each variable is measured. In SEM analysis, model parameters (e.g., path coefficients and (co)variances) are estimated by minimizing the difference between the observed covariance matrix and the model-implied covariance matrix according to a certain statistical criterion [55].

Our model, shown in Figure 1, assumes that demographic variables and cultural values drive both categories of outcome measures (perceived benefit, support for AI adoption and governance), but that the reverse driving relationships do not exist. This reflects the assumption that cultural values are broad concepts likely to integrate beliefs and experiences from a wide variety of sources, and that views about AI are unlikely to be sufficiently present in the public discourse to fundamentally alter cultural values.[2] Each cultural value construct was measured by four survey items. While the cultural value constructs were allowed to covary in our SEM, each survey response item was modeled as independent (i.e., each survey items are independent from each other when conditioned on their parent construct). Our SEM also assumes that perceived self- and societal benefit drive support for AI use and governance, but that the support outcomes do not drive perceived benefit.

The relationship between sociodemographic variables and cultural values is a more subtle question. For example, it seems likely that age and gender drive cultural values, and conversely, literature has suggested that cultural values drive political orientation [30]. Our model includes sociodemographic variables as exogenous variables, allowing unmodeled covariance between them and between sociodemographic variables and cultural values. This represents the possibility that there exist causal relationships between these variables, or that unmodeled confounding is present. These covariances are denoted by the bidirectional dotted line in Figure 1. Similarly, variables within each group may be causally related or be jointly affected by unmodeled variables. For example, techno-skepticism and risk aversion may be driven by individualism and egalitarianism, rather than existing as discrete constructs[3] We model this by allowing variables within each group (sociodemographic variables, cultural values, perception of benefit, and AI support) to covary.

Our SEM bears some similarities to popular models of technology acceptance and adoption used in psychology and marketing research literatures. The Theory of Reasoned Action [56] focuses on the relationship between behavior and behavioral intention, which is modeled as being shaped by attitudes and subjective norms. The Multi-Attribute Attitude Model [57] models an individual's attitude toward a brand or product as a weighted linear combination of attributes. Unlike this model, in which each individual is modeled by a unique set of weights, our SEM models all respondents collectively with a single set of inferred parameters. The influential Technology Acceptance Model [58] posits that attitudes toward technology use are governed by perceived usefulness and ease of use, which are in turn governed by a set of "external factors." While extensions of this model use more extensive sets of external factors (including culturally-relevant variables such as gender [59]), the set of sociodemographic and cultural variables we use in our SEM is broader than typically considered in this literature.

2.3 Differences between experts and the public

It is particularly important to understand the ways in which public and expert attitudes diverge when discourse about policy is dominated by experts. Research on other emerging technologies has suggested that technical experience often negatively associates with risk perception, with experts tending to be particularly tolerant of risks stemming from technology aligned with their discipline [60, 61]. Restricting policy discourse to those who are most knowledgeable therefore threatens to limit the influence of the very people who may perceive the most risk. Previous work has also found that scientists' views on risk vary based on gender, institutional affiliation, and cultural and political values [47, 62, 63]. AI experts differ from the public along each of these dimensions; failure to appreciate how these factors influence attitudes toward AI may hinder the creation of an inclusive policy dialogue.

Indeed, prior surveys comparing the attitudes of AI experts and the public have found major differences in trust placed in government, technology companies, the U.S. military, and international organizations [25, 26], suggesting a potentially wide gulf in attitudes toward who should be responsible for governing AI. AI professionals also differ from the public on many sociodemographic variables that typically predict regulatory preferences: compared to the public, AI practitioners tend to be better educated, more racially diverse but overwhelmingly male, higher income, and live in more urban areas [25]. Understanding expert attitudes is particularly relevant in the context of AI because technology workers have demonstrated substantial leverage in determining where and how AI is used and governed [64].

2.4 Differences across use contexts

Further complicating the design of inclusive governance and science communication strategies is the diversity of contexts in which AI can be used. This diversity makes it difficult to know how findings relevant to AI's impact on

[2]Our survey assessed cultural values before AI was introduced to avoid attitudes toward AI influencing cultural values through priming effects.
[3]We consider this alternate model in Supplement Section E.1.4.

labor automation, for example, generalize to AI used in medical research or automated weapons systems. To better understand these differences, in addition to examining attitudes toward AI in general, we explore attitudes toward AI used in six policy-relevant contexts: predictive policing, labor automation, medical diagnosis, automated vehicles, personalization, and weapons systems. (See Section 3.3 and Supplement Section B for more details on these contexts.)

The use of AI in each of these contexts raises different questions about risks, distribution of impacts, and ethical questions like fairness. Modeling each of these contexts allows us to understand how the factors we study — sociodemographic variables, cultural values, and perceived benefit — impact attitudes differently across application areas.

3 Methods

Our survey and analysis procedure were preregistered at https://osf.io/pcsvf/. Supplement Section E contains results from the complete analysis procedure specified in the preregistration; Supplement Section G describes minor deviations from the preregistration. The research was approved by the (*anonymized for review*) Institutional Review Board under protocol number H21112. Our first sample consisted of $N = 3524$ U.S. adult participants recruited and compensated online through the Lucid Theorem platform, which uses quota sampling to match the U.S. census marginal distributions on age, gender, ethnicity, and region [65].

3.1 Data

Our first sample consisted of $N = 3524$ U.S. adult participants recruited and compensated online through the Lucid Theorem platform, which uses quota sampling to match the U.S. census marginal distributions on age, gender, ethnicity, and region. Previous research has found that samples provided by Lucid provide results generally similar to U.S. probability samples or samples provided by Amazon Mechanical Turk [65]. However, this sample may not generalize to U.S. adults on dimensions such as comfort with technology. Recent studies have found decreased participant attention on Lucid and other online survey platforms coinciding with the Covid-19 pandemic [66, 67]; we expected that this would reduce effect sizes. As a robustness check we replicated our results with inattentive respondents removed (see Section 3.4). The completion rate (defined as the number of participants entering the survey who completed it) for this sample was 86%.

Our second sample consisted of $N = 425$ master's students at the conclusion of a graduate-level AI class in the Online Master of Science in Computer Science (OMSCS) or Analytics (OMSA) programs of Georgia Tech's Online Master of Science in Computer Science (OMSCS) or Analytics (OMSA) programs. OMS students have undergraduate degrees in technical subjects, and in 2020 most work full-time in technical fields in industry while completing the degree. In their current and post-graduation roles, most will be in a position to have an impact on how AI is used and governed. Recruitment materials for this sample are provided in Supplement Section C. Participants were provided course extra credit, and non-participants were offered an alternative method for obtaining the extra credit. The response rate was 61.7%.

Differences between these two samples go beyond academic and professional AI-related experience. In 2020, 81% of OMSCS students were male, and over one-third were not U.S. citizens or permanent residents. While the OMSCS program has enrolled students from 122 countries and 53 U.S. states/territories, most work full-time in computing-related jobs and are therefore likely more geographically concentrated than our nationally representative U.S. sample. They also tend to be younger and have higher incomes than the U.S. public. Table 1 shows summary statistics comparing sociodemographic variables and cultural values in our two samples.

Previous research has revealed differences in opinion between distinct groups of AI and computer science practitioners, such as between AI-skilled professionals at U.S. technology companies [26] and active researchers who publish at machine learning conferences [25]. Our graduate student expert sample adds an additional perspective to this literature; OMS students may differ from previously-surveyed expert samples in their propensity to work in industry versus academia, their level of experience with AI, and on sociodemographic and cultural factors. Respondents in our OMS sample completed undergraduate degrees largely in North America (66.1%) or Asia (25.6%), primarily in computer science (43.1%) or other STEM fields (50.8%). Most concurrently or recently worked in computer science or software engineering, but not specifically in AI (63.8%); 18.1% reported working in another field of science or engineering; and 11.8% reported working directly in AI (see Supplemental Section A.)

3.2 Survey design

Our survey consisted of two parts. The first portion assessed sociodemographic information, cultural values, opinion on risks posed by technologies other than AI, and self-reported familiarity with AI. We included standard sociodemo-

	$\bar{x}_{\text{Lucid}}$	$\bar{x}_{\text{OMS}}$	$\bar{x}_{\text{Lucid}} - \bar{x}_{\text{OMS}}$	p-value
Age group (0-4)	1.75 (1.12)	0.89 (0.56)	(0.79, 0.92)	$<$0.001***
Gender = Male	0.49 (0.50)	0.81 (0.39)	(-0.37, -0.29)	$<$0.001***
Ethn = White	0.75 (0.43)	0.41 (0.49)	(0.29, 0.39)	$<$0.001***
Ethn = Black	0.13 (0.33)	0.03 (0.16)	(0.08, 0.12)	$<$0.001***
Ethn = Asian	0.05 (0.22)	0.48 (0.50)	(-0.48, -0.38)	$<$0.001***
Education (0-3)	1.36 (1.08)	2.24 (0.43)	(-0.94, -0.83)	$<$0.001***
Cognitive employment	0.25 (0.43)	0.97 (0.17)	(-0.75, -0.70)	$<$0.001***
Manual employment	0.14 (0.35)	0.00 (0.05)	(0.12, 0.15)	$<$0.001***
Social employment	0.22 (0.42)	0.01 (0.10)	(0.20, 0.23)	$<$0.001***
Household income (0-3)	1.23 (1.06)	2.19 (0.91)	(-1.05, -0.87)	$<$0.001***
Political orientation (-2-+2)	-0.01 (1.23)	-0.52 (0.93)	(0.42, 0.61)	$<$0.001***
Urban (0-3)	1.59 (1.05)	2.16 (0.79)	(-0.66, -0.49)	$<$0.001***
Individualism (standardized)	0.06 (0.92)	-0.47 (0.73)	(0.46, 0.61)	$<$0.001***
Egalitarianism (standardized)	-0.05 (0.90)	0.21 (0.78)	(-0.34, -0.18)	$<$0.001***
Techno-skepticism (standardized)	0.06 (0.92)	-0.45 (0.81)	(0.43, 0.59)	$<$0.001***
Risk aversion (standardized)	0.03 (0.89)	-0.24 (0.69)	(0.20, 0.34)	$<$0.001***

Table 1: Means, standard deviations, 95% confidence intervals for differences in means, and p-value (Welch's two-tailed t-test) for each variable in U.S. public (Lucid) and expert (OMS) samples. Gender was coded as a binary variable (male, female or other gender), and age was coded using Pew's classification of generational groups (18-25, 26-40, 41-56, 57-75, 76+). Race was coded as White, Black, Asian, or other, as we anticipated that only these groups would be large enough in both samples to detect effects. We used four-level scales for each of education, household income, and urban/rural residence. Political orientation was collected using a five-point Likert scale with endpoints "strong liberal" and "strong conservative."

graphic factors that have been found to associate with opinion on questions related to AI in previous surveys [11–21, 69–72]: gender, age group, race/ethnicity, job type (cognitive/analytical, manual/physical, social/people-oriented, or other), education level, household income, urban/rural residence, and political orientation. (See Table 1 for coding details.) We also included questions assessing attitudes toward other technologies for which expert and public risk perception has been well-studied. Participants were asked, on a five-point Likert scale ("risks significantly outweigh benefits" to "benefits significantly outweigh risks"), about their perception of genetically modified foods, nuclear power, coal burning power plants, vaccines, and synthetic biology.[4]

The cultural values of individualism and egalitarianism, described in Section 2.1, were adapted from Kahan et al.'s operationalization of grid-group cultural theory for survey research [27].[5] Two clarifications are needed to position our use of these constructs within the broader cultural theory literature. First, Kahan et al.'s cultural cognition theory differs from the broader cultural theory literature by constructing survey items directly from the "grid" and "group" axes of Douglasian cultural theory [40]. These survey items for individualism and egalitarianism improve on conceptual issues with other cultural theory measurement strategies [41], have demonstrated high predictive validity in studies of other technological risks, and are perhaps the most popular measurement approach in cultural theory [37]. However, they have been shown to be facially and empirically limited, particularly because they do not incorporate the cultural values of hierarchy and fatalism [75].[6] Second, we depart slightly from the "cultural cognition" hypothesis of [27] by analyzing the effects of individualism and egalitarianism as *individual* constructs rather than analyzing their intersection.[7]

The techno-skepticism construct was created from items previously used in literature and modified after testing in two small pilot surveys (see Supplemental Section D); the final construct consisted of the four items "new technologies are more about making profits rather than making peoples' lives better," "I am worried about where all this technology is leading," "technology has become dangerous and unmanageable," and "I feel uncomfortable about new technologies." The general risk aversion construct was adapted directly from [44].

The second portion of the survey assessed opinion about AI. We first provided respondents with a brief definition of AI adapted from Zhang et al. [19]: "Artificial intelligence (AI) refers to computer systems that perform tasks or make decisions that usually require human intelligence. AI can perform these tasks or make these decisions without explicit human instructions. Today, AI has been used in the following applications: identifying people from their photos, diagnosing diseases like skin cancer and common illnesses, blocking spam email, helping run factories and warehouses, and predicting what one is likely to buy online." We then assessed five outcome measures separated into two groups. The first two outcomes assessed whether respondents believed that a) they personally and b) society more generally would benefit from AI. These outcome measures (self-benefit and societal benefit) were intended to disambiguate respondents who were supportive or apprehensive about AI use because of its perceived effect on their own lives from respondents were excited or concerned about its effects on society at large. The remaining three outcomes assessed, again on five-point Likert scales, support for whether AI should be a) "use[d]," b) "carefully managed," and c) "regulated by the government," language adapted from [19]. The differentiation of management and regulation was intended to better disambiguate opinion on *whether* some form of AI governance should occur from opinion on *who* is best suited to perform this governance. This distinction is particularly salient in light of impending regulatory efforts and ongoing debates on the comparative merits of self-regulation, soft law, and formal government regulation.

These five outcome measures, which assessed outcome measures for AI in general, were repeated for each of the six AI application contexts described below. Before answering items for each application, respondents were provided with two-sentence vignettes describing the potential benefits and harms of AI use in that context (see below). To reduce participant fatigue in the U.S. public (Lucid) sample, each respondent was provided with only three of the six contexts,

[4]Because we anticipated that synthetic biology was likely to be less familiar to respondents, this technology featured a one-sentence description.

[5]In two small pilot surveys using the Lucid Theorem platform ($N = 50$ and $N = 150$; see Supplementary Materials for details), we found that the condensed cultural cognition worldview scale of [27], which used both positively- and negatively-worded items for each construct, had poor reliability. Based on the results of other recent studies that found reliability issues with the negatively-worded cultural cognition theory items [73, 74], we followed the strategy of [73], by restricting our preregistered final survey to four positively-worded items each for individualism and egalitarianism. The resulting scales had satisfactory reliability in both the full samples and attentive subsamples (Supplementary Tables 11 and 39). Our results, however, may not be directly comparable to other work that used the full scale of [27].

[6]Specifically, cultural theory inspired by the work of Douglas and Wildavsky [40] posits that the intersection of two axes, "grid" and "group," define quadrants corresponding to four distinct cultural biases: individualism, egalitarianism, hierarchy, and fatalism. Initial attempts to operationalize cultural theory for survey research using these four scales found that many participants did not uniquely belong to a single cultural bias. The cultural cognition theory scales of [27] that we use directly measure the "grid" and "group" axes as hierarchy-egalitarianism and individualism–communitarianism. This approach sidesteps the issues of participants scoring highly on multiple cultural biases, and is argued to improve on the scale reliability and predictive validity of other approaches [41], but has been criticized for its lack of inclusion of discrete hierarchy and fatalism factors [74, 76, 77]. See [37] for a review of cultural theory's development and its relationship to the cultural cognition theory of [27].

[7]The "cultural cognition" hypothesis of [27] posits that the *intersection* of individualism and egalitarianism define identity groups that imbue attitudes toward risk with affective qualities and lead to directionally motivated reasoning. Other work (e.g., [74]) has also treated these factors as discrete.

so that the sample size for each of the six specific AI contexts in the U.S. public sample was $N \approx 3524/2$. The expert respondents, who we anticipated would suffer less fatigue, each provided data for all six contexts. The full survey instrument is contained in Supplement Section C.

3.3 AI application contexts

We assessed our five outcome variables (perceived self-benefit, perceived societal benefit, and support for use, "careful management," and "regulat[ion] by the government") for AI in general and in the context of six policy-relevant application contexts. Before being asked about AI in general, participants were provided a brief definition of AI adapted from Zhang et al. [19] (see above). Before being asked about each context, participants were provided a two-sentence vignette describing both potential benefits and concerns about the use of AI in that context. The points highlighted in each vignette were chosen in an attempt to reflect arguments present in typical discourse about AI, particularly those that may associate affective qualities to the application:

- Predictive policing: "Some police departments use AI to predict where crime is likely to occur, helping them decide where to deploy their resources. But civil rights groups and some researchers argue that these AI systems simply increase arrests in minority neighborhoods without actually reducing crime."
- Economic/labor impact: "AI systems are likely to automate many tasks. Some think that these AI systems will make work less tedious and produce higher standards of living. Others believe that these AI systems will increase unemployment and inequality."
- Medical systems: "AI-powered medical systems can detect diseases earlier and more accurately than human doctors. But some fear that these AI systems could occasionally produce incorrect results without doctors understanding why."
- Autonomous vehicles: "AI-powered self-driving cars could save lives by reducing traffic accidents caused by human error. But some are concerned that the AI systems in self-driving cars are vulnerable to malfunctioning or being hacked."
- Personalization: "AI systems can provide personalized news, social media content, and product recommendations using data collected from users. But some worry that this can undermine individual privacy and lead to misinformation and political polarization."
- Autonomous weapons: "Lethal autonomous weapons controlled by AI systems could improve our national security while putting fewer service members in danger. But some worry that AI-powered weapons could be dangerous or lead to a reckless arms race."

Supplement Section B contains a more detailed discussion of each application context along with tables summarizing the impact of sociodemographic and cultural factors on support for AI in each context.

3.4 Survey administration and attention model

The U.S. public (Lucid Theorem) survey ran from May 3, 2021 to May 30, 2021, with most responses collected from May 3–5. Based on recent research on the Lucid platform [66, 67], we anticipated that pandemic-induced structural changes in populations completing online surveys might result in reduced effect sizes. The expert (master's student) survey ran from April 28, 2021 to May 8, 2021. Two pilot surveys (N = 50 and 150) were administered on March 22, 2021 and April 1, 2021 (see Supplemental Section D).

Respondent attention is a concern when using online survey data. Following the recommendations of [78], we assessed participant attention using four attention check questions: three simple grid-type attention checks and one stand-alone attention check. We modeled respondent attention using an item response theory (IRT) model similar to that used by [78]. Specifically, we used the standard two-parameter Rasch model

$$p(y_{ij} = 1) = \frac{e^{a_j(\theta_i - b_j)}}{1 + e^{a_j(\theta_i - b_j)}}, \tag{1}$$

where y_{ij} denotes whether the i^{th} participant correctly answered the j^{th} attention check question, a_j denotes the discriminability of the j^{th} attention check question, θ_i denotes the i^{th} particpant's attention, and b_j denotes the difficulty of the j^{th} attention check question. Inattentive respondents were defined as those in the bottom quartile of attentiveness $\{\theta_i\}$ (computed across the combined U.S. public/expert sample). The U.S. public sample was less attentive overall

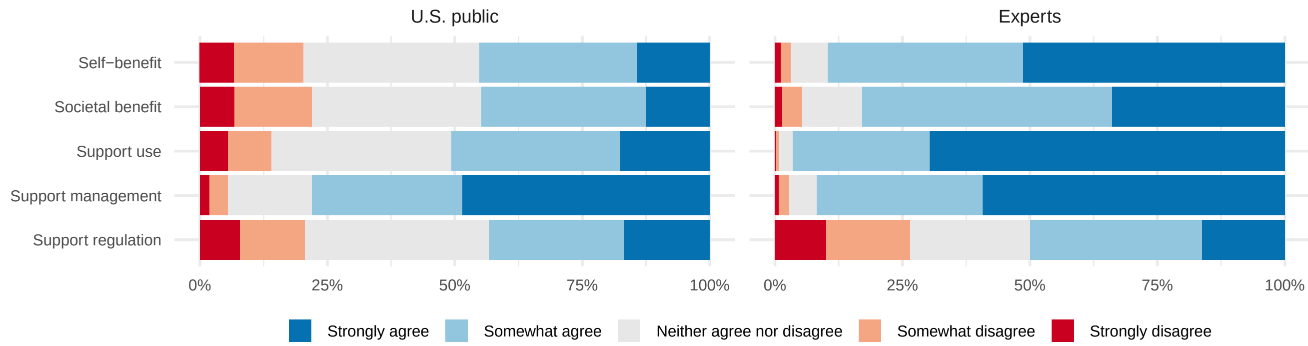

Figure 2: Outcome measures after respondents are presented with a general (context-free) definition of AI.

(two-tailed t-test on mean attention θ_i: $P<0.001$); 86.1% of the expert sample was retained in the attentive subsample, compared to 73.7% of the U.S. public sample. We expected that including inattentive respondents in our analysis would reduce effect sizes, but that excluding them would bias results: respondent attention has been found to associate with characteristics such as age, gender, and education [79] and may thus influence outcomes. All results reported in the paper body are therefore based on analyses that retained the complete sample. As a robustness check, these results are reproduced in Supplement Section F with inattentive respondents removed. Overall, differences between the full-sample and attentive-subsample results were minor.[8]

3.5 Structural equation model and estimation

We used R version 1.3.9 and lavaan version 0.6-9 [80] with the default NLMINB optimizer to fit the SEMs defined in our analysis. Because outcome measures and cultural values were measured with Likert-scale (ordinal) items, we used the mean- and variance-adjusted weighted least-squares estimator with polychoric correlations [81] and robust standard errors. Polychoric correlations were also used to compute construct reliabilities. For identifiability, cultural construct variances were fixed to unity and each factor loading was allowed to vary. The only instances of missing data in our survey involved context-specific outcome measures (as only half of the U.S. public sample was asked about each application). The metrics and thresholds we used to assess quality of fit were preregistered and stemmed from typical recommendations [55].

4 Results

4.1 Public and expert attitudes differ in key areas

Compared to the U.S. public, experts were more confident and positive in their attitudes toward AI (Figure 2). Experts were much more likely to perceive self-benefit (1.04 points on a five-point Likert scale, Welch's unequal variances t-test: $P<0.001$) and societal benefit (0.82 points, $P<0.001$). While a plurality of the U.S. public also believed that AI would benefit both them personally (45.2%) and society at large (44.8%), few professed strong opinions. Similarly, our expert sample was much more likely to support the general use of AI than the more ambivalent U.S. public (1.17 points, $P<0.001$), with almost no experts expressing opposition to AI use. In both samples, support for AI use was strikingly similar to perceived benefit (Supplemental Figure 14), a pattern we explore in more detail below.

Recent surveys have found strong public support for the "careful management" of AI [12, 17, 19, 72], but differing opinions on whether this management should be performed by researchers, technology companies, nonprofit groups, or the government [19, pg. 22]. To disentangle attitudes toward AI governance in general from attitudes toward government regulation, we asked respondents both whether AI should be "carefully managed" and whether AI should be "regulated by the government," phrasing adopted from [19]. We found that both experts and the U.S. public were highly supportive of "careful management" and generally supportive of government regulation (Figure 2). Notably, we found similar support for government regulation between experts and the public (0.02 point difference, P=0.715) despite experts being more likely to support management (0.28 points, $P<0.001$). Past surveys have found that, unlike

[8] One notable exception was the covariance between individualism and egalitarianism constructs. In the full results we found that this negative covariance had much larger magnitude in the expert sample than the U.S. public sample; when restricting the sample to attentive respondents we found the inferred covariance for the U.S. public sample was much closer to the inferred value in the expert sample.

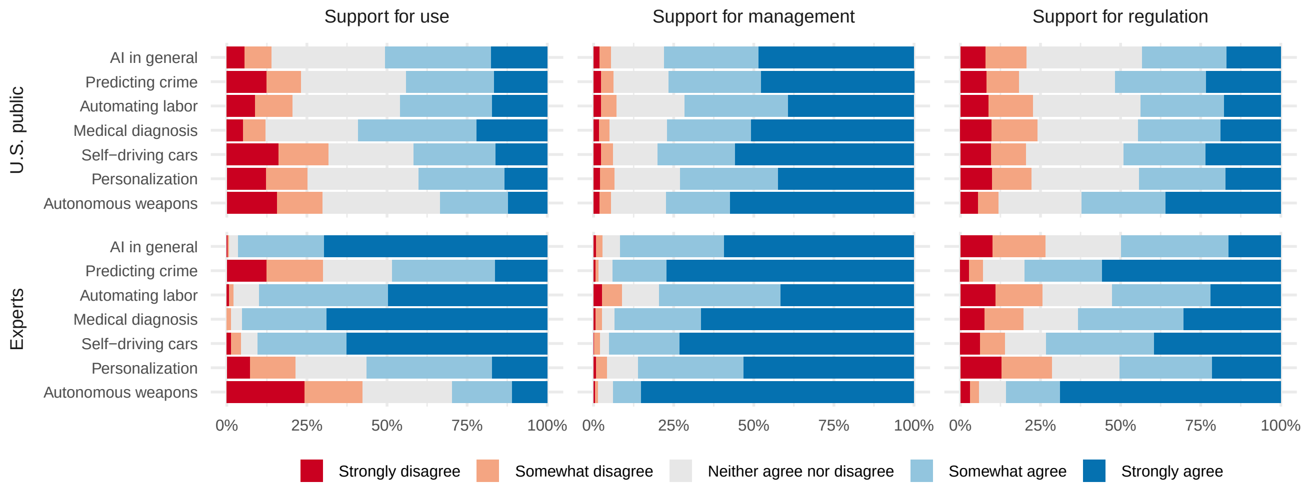

Figure 3: Comparison of support outcome measures between samples and among common AI application areas. Before responding, participants were provided two-sentence vignettes, listed in Section 3.3, describing arguments for and against the use of AI in the context.

the public, AI experts place more trust in scientific and international organizations than their own government to "develop and manage" AI [25], suggesting that compared to the public, experts may be more inclined to support soft law governance approaches to governance (see, e.g., [82]).

The public's support for the use and governance of AI, shown in Figure 3, was largely similar across contexts — a notable finding that persisted when analysis was restricted to only attentive respondents (Supplemental Figure 24; see Section 3.4 for definition of attentive subsample). By contrast, experts' views were more nuanced, varying much more significantly across contexts. While expert and public attitudes trended in the same direction in many contexts, they featured distinct splits in others. For example, both experts and the public were more wary of AI use in autonomous weapons, recommendation systems, and predictive policing, but experts' overwhelming support for AI use in autonomous vehicles, medical diagnosis, and automating labor stood in stark contrast to the much more divided public.

Our results suggest that greater public awareness about the unique impacts of AI in different applications may be necessary to fully empower the public to share its perspectives on AI use and governance. The cross-context divides we find also suggest that limited support for the regulation of AI *in general* (among both experts and the public) may belie support for tailored government intervention in specific application contexts such as autonomous weapons.

4.2 Cultural factors are strongly informative of attitudes

What drives these expert-public divides that persist across outcome measures and application contexts? These gaps may be due to differences in technical knowledge, or due to socialization during AI training. But they may also be driven by differences in sociodemographics and cultural values. Our expert and U.S. public samples differed significantly on all sociodemographic variables (Table 1) as well as across all four cultural values ($Ps<0.001$): experts were less individualistic (0.53 points), less techno-skeptical (0.51 points), less risk averse (0.27 points), and more egalitarian (0.26 points) (see Supplementary Figure 7).

To better understand how these factors inform attitudes, we used the preregistered structural equation model (SEM) shown in Figure 1 to explore the relationship between sociodemographic variables, cultural values, perceived benefit, and support for AI use and governance. (The size of our expert sample limited this SEM analysis to the U.S. public.) We first assessed the reliability and fit of the cultural value components of the model. The fit in each sample (evaluated using thresholds defined in our preregistration) was adequate to good, construct reliabilities were satisfactory, constructs loaded appropriately onto each item (with similar loadings in each sample), and model correlation residuals indicated adequate local fit (Supplementary Tables 11, 12, and 15).[9] To assess the impact of

[9]Although cultural construct loadings were similar between samples, there were some notable between-sample differences in the cultural construct covariances between cultural constructs (Supplementary Tables 13 and 14). In the U.S. public sample, techno-skepticism was more highly correlated with risk aversion and individualism, suggesting that experts separate their views of technology from their overall risk preferences and individualism somewhat more than the general public does. There was also a much larger negative covariance between egalitarianism and individualism in the expert sample. These differences, however, were much smaller when analysis was restricted to the attentive subsample

	Model fit statistics					R^2 (benefit)		R^2 (support)		
	χ^2 (df, P)	CFI	RMSEA (90% CI)	SRMR	$\Delta\chi^2$ (Δdf, P)	Self	Soc.	Use	Mgt.	Reg.
Model $\mathcal{S}$	4650.2 (350, <0.001)	0.903	0.059 (0.058, 0.061)	0.034	–	0.274	0.262	0.470	0.235	0.201
Model $\mathcal{S}_{\setminus C}$	8204.2 (370, <0.001)	0.822	0.078 (0.076, 0.079)	0.094	1764.8 (20, <0.001)	0.134	0.110	0.461	0.090	0.084
Model $\mathcal{S}_{\setminus B}$	5554.4 (356, <0.001)	0.882	0.064 (0.063, 0.066)	0.047	1173.4 (6, <0.001)	0.552	0.544	0.774	0.220	0.190

Table 2: Fit statistics for the complete SEM $\mathcal{S}$ and two nested models used for analysis. χ^2: model chi-square test, along with model degrees of freedom and P-value, CFI: comparative fit index, RMSEA: root mean squared error of approximation, SRMR: standardized root mean square residual, $\Delta\chi^2$: chi-square difference test (compared to full model $\mathcal{S}$). R^2 values show coefficients of determination for the five endogenous variables in the model. The complete model $\mathcal{S}$ achieved adequate-to-good global fit, with CFI and RMSEA indicating adequate fit, and SRMR indicating good fit. Reduced models $\mathcal{S}_{\setminus C}$ (used to assess the evidence for paths from cultural values to support outcomes) and $\mathcal{S}_{\setminus B}$ (used to assess the evidence for paths from perceived benefit to support outcomes) achieved adequate fit on RMSEA and SRMR, but poor global fit on CFI.

cultural values on our outcome variables, we compared the fit of $\mathcal{S}$, the full SEM shown in Figure 1, with $\mathcal{S}_{\setminus C}$, the nested model that constrains to zero the paths from cultural values to outcome measures. We found consistent global (Table 2) and local (Supplementary Tables 21 and 22) evidence that the inclusion of pathways from cultural values to our outcome variables produced better model fit, indicating that the four cultural values we considered were indeed informative factors in explaining attitudes toward AI.

We next fit the full SEM shown in Figure 1 to data from the U.S. public sample. Fit statistics are shown in Table 2 along with statistics for the two modified (nested) models used to evaluate the roles of cultural values and perceptions of benefit. The full model achieved the standard thresholds for adequate fit listed in our preregistration.[10] Correlation residuals, shown in Supplementary Table 22, generally indicated satisfactory local model fit.[11] Finally, we observed relatively small covariances between support outcomes, consistent with a lack of highly influential unmodeled common causes of these variables. It is important to note that our SEM represents *hypothesized* relationships between variables, and that "equivalent" models with different hypothesized relationships can produce the same covariance structure [83]. Thus, while the fit statistics in Table 2 provide circumstantial evidence in support of our SEM, the primary evidence for the model's correctness is based on our theoretical arguments above.

Inferred SEM path coefficients are shown in Figure 4. Overall, the results indicated that the cultural values of individualism, egalitarianism, risk aversion, and techno-skepticism were strongly predictive of attitudes toward AI. The influence of sociodemographic variables also contained interesting patterns. Like past surveys [11, 16, 19], we found that those who were male, younger, better educated, and higher income both perceived more benefit from AI and were more supportive of its use. Yet we found that support for government regulation was — perhaps surprisingly — often divorced from perceived benefit and support for use, and more directly informed by sociodemographic and cultural variables. For example, older and more conservative respondents were more hesitant about AI use. But despite perceiving less benefit from AI and expressing less support for its use, they were also less supportive of the government regulating AI. Similarly, those who held cognitive/analytical jobs, lived in urban areas, and had higher incomes perceived greater self-benefit from AI and were more supportive of its use. However, these groups were also more likely to believe that AI should be carefully managed and regulated.

4.3 Cultural determinants of attitudes differed in some applications

Developing effective "culturally pluralized" [37] strategies for science communication and governance requires an understanding of how cultural values affect attitudes toward specific technologies and their applications. While

(Supplementary Tables 41 and 42; see Section 3.4).

[10] While the model χ^2 statistic indicated a statistically significant difference between the observed and model-implied covariance matrix (a potential indication of inadequate fit), this test is known to be sensitive to large sample sizes such as ours; concluding that a model achieves adequate fit despite a statistically significant result from this test is consistent with standard SEM practice and our preregistration [55].

[11] One notable exception was the residual variance of the support for use variable (-0.16), whose relatively large magnitude suggested some caution when interpreting results such as the coefficient of determination for this variable.

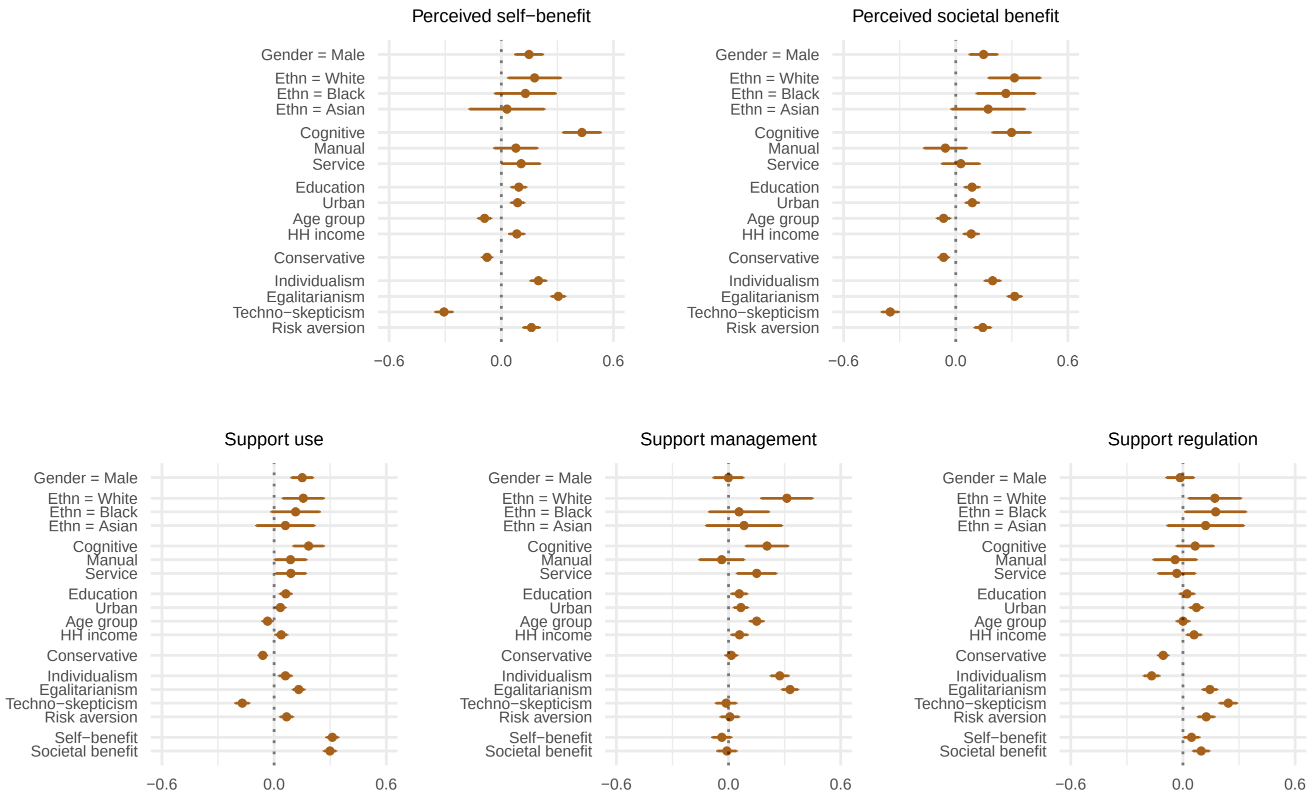

Figure 4: Inferred path coefficients (with 95% confidence intervals) for full SEM $\mathcal{S}$ fit with U.S. public data. Gender, race/ethnicity, and work type were coded as binary; education, household income, and urban residence were coded as four-level variables; age group and political orientation were coded as five-level variables; and cultural constructs and perceived benefit variables were standardized. See Table 2 for fit statistics.

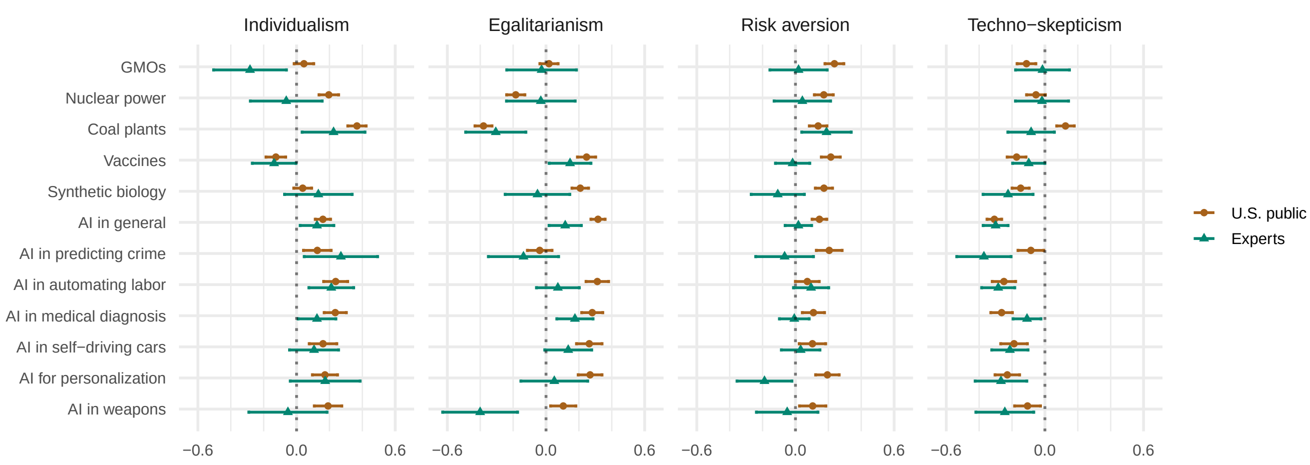

Figure 5: Comparison of cultural values' effects on support for AI contexts and other technologies. Markers show ordinary least-squares regression estimates and 95% confidence intervals when controlling for sociodemographic variables. For support for AI contexts, respondents were asked whether they supported the use of AI in a particular application. For other technologies, respondents were asked whether the technology's benefits outweighed its risks. Each outcome was measured on a five-point Likert scale; cultural value constructs were standardized and inferred from a confirmatory factor analysis model. This analysis was exploratory.

previous research has evaluated how cultural values inform support for other emerging technologies, it is not clear how — or whether — these results generalize to applications of AI.

Notably, our results found that some effects of cultural values (Figure 4) had reversed directions from the patterns observed for other technologies. For example, both individualism and egalitarianism predicted *increased* perceptions of self-benefit from AI — a contrast with many other technologies, where egalitarianism has been found to associate with lower support.[12] This reversed effect of egalitarianism suggests that AI may be perceived differently from many other technological risks, perhaps due to perceptions that automated systems can temper certain hierarchical social structures that egalitarians perceive as harmful. If this perception does indeed hold among the public, however, it stands in sharp contrast to the increasing realization among AI developers that bias and fairness are significant problems in automated decision making systems [85] and evidence that awareness of these problems negatively affects perceptions of their performance [86].

We used a linear regression model to compare the effects of cultural values on support for AI use between experts and the public. Our use of linear regression rather than SEM was due to the limited size of our expert sample; this portion of the analysis was exploratory (i.e., not preregistered). We found that the direction of cultural values' effects on support for AI use was generally consistent across AI application areas (Figure 5), and again found that experts' opinions were more nuanced than the public's. Supplemental Figures 15–16 provide additional evidence for this phenomenon, showing that experts' attitudes toward both AI and other technologies varied more than the public's, a pattern that persisted when analysis was restricted to attentive respondents. This evidence suggests that the public's attitudes toward AI may evolve considerably as they become more informed, underlining the importance of public education on broader impacts of AI use in specific applications. These results also revealed patterns across the six contexts we explored. For example, attitudes toward the predictive policing and autonomous weapons application contexts were similar, particularly among experts (Supplemental Figure 15).

To examine whether the factors driving attitudes toward these applications were also similar, we fit a multigroup version of the SEM shown in Figure 1 to data from the U.S. public sample. This multigroup SEM facilitated between-context comparison by allowing path coefficients to differ for each context while constraining the model aspects that defined cultural values to be constant. Some notable patterns emerged from this model, for which inferred parameters are shown in Supplemental Section E.4.2. We indeed found key sociodemographic and cultural variables whose impact on attitudes toward predictive policing and autonomous weapons differed from their impact on other contexts. For example, older and politically conservative respondents were *less* supportive of AI in general, but were *more* supportive of AI use for predictive policing and autonomous weapons. The impact of egalitarianism on support for AI use in these two contexts similarly differed from its impact on most other contexts. More broadly, there were substantial between-context differences in the impact of age on support for AI. For example, older respondents were much less supportive of the use of AI in autonomous vehicles and recommendation systems than they were of the use of AI for medical diagnosis. See Supplement Section B for tables highlighting where these results matched expectations based on prior literature.

Unsurprisingly, AI's impact on labor and the economy was perceived to be more beneficial by respondents with cognitive/analytical jobs and higher education. However, we found that manual/physical employment also predicted greater perceived benefit from AI's impact on labor and the economy. This result is potentially surprising but consistent with findings that many U.S. workers believe automation is more likely to affect others' jobs than their own [87]. Interestingly, we also found that perceived societal benefit had a stronger impact on support for labor-automating AI than it does on AI in general (Supplemental Table 32).

Prior work has found that individualism generally predicts higher support for technology, and we found that individualism had a similarly positive impact on support for AI. Less consistent with work on other technologies, however, we found that egalitarianism *also* tended to predict greater support for AI. Perhaps unexpectedly, we found overall positive effects of the general risk perception construct of [44] on support for AI across contexts, suggesting that the risk aversion and techno-skepticism constructs used in our survey measured relatively orthogonal aspects of technological risk perception.

That the U.S. public perceived AI as more egalitarian than experts did (Figure 3) suggests that the public viewed AI as shaping society to be more equitable than experts did. Particularly striking is the positive impact of egalitarianism on support for the use of AI-based weapon systems, suggesting that recent discourse and activism in the AI community opposing autonomous weapons [64] may have been effective in driving experts' opinions but not in breaking through to the general public, who may have been more swayed by our vignette's description of potential safety benefits to service members. It is also notable that egalitarianism drove greater support for labor-automating-AI among the public than among experts.

[12] Recall from Section 3.2 that two divides in related literature limit direct comparison of our results to some other work on the impact of cultural values on public attitudes toward technology. First, the constructs of individualism and egalitarianism that we adapt from [84] do not model hierarchy and fatalism, cultural elements argued to be important by the broader cultural theory literature [74, 76]. Second, like some other literature but unlike [84], we model individualism and egalitarianism as discrete constructs rather than examining effects of their intersection.

4.4 Perceived benefit substantially informs support for AI use — but not for management and regulation

Our SEM (Figure 1) hypothesized that perceived self- and societal benefit drove support for AI use and governance. To assess the impact of perceived benefit on these support outcomes, we compared the full SEM $\mathcal{S}$ to a nested model $\mathcal{S}_{\setminus B}$, in which paths from perception of benefit outcomes to support outcomes were fixed to zero. Overall, global and local comparisons of $\mathcal{S}_{\setminus B}$ and $\mathcal{S}$ provided mild support for the existence of an impact of perceived benefit on our support outcomes (Table 2; Supplemental Tables 22 and 28).[13]

As shown in Figure 4, perceived benefit (to both the respondent individually and society at large) predicted substantially greater support for AI use, but had much less impact on attitudes toward its governance. Indeed, the total effect of sociodemographic and cultural variables on support for AI *use* was split roughly evenly between direct and indirect effects (Supplemental Figure 10). By contrast, support for AI *management and regulation* was impacted much less by indirect effects. These findings were generally consistent across AI contexts (Supplemental Tables 30–36).

Experts' attitudes were again more nuanced than the public's: we found much larger gaps between perceived *self*-benefit and perceived *societal* benefit among experts than among the public. Indeed, in the U.S. public sample we did not find statistically significant differences between perceived self- and societal benefit in any application (Ps$>$0.123).

Prior literature has conjectured that AI developers may engage in a form of motivated reasoning that makes them more likely to believe that AI has a positive impact on society [88] when it is professionally advantageous for them. We find mixed evidence for this theory. Consistent with this motivated reasoning conjecture, we found that experts were indeed more likely than the U.S. public to believe that AI was beneficial to society (0.82 points on a five-point Likert scale; $P<0.001$). Our expert sample was also much more likely than the public to believe that AI was beneficial for society in applications with significant commercial opportunity such as automating labor (0.76 points; $P<0.001$) and self-driving cars (1.29 points; $P<0.001$). However, AI experts differed from the public on almost every sociodemographic and cultural trait, typically in ways that our results suggest would predict higher support for AI use (Figure 2(b)). And experts were somewhat *less* likely to report that AI-based recommendation systems — a context in which AI experts as a whole have a large commercial interest — were beneficial to society (0.16 points; P=0.020). This counterexample suggests the AI experts' attitudes might be more substantially driven by underlying sociodemographic and cultural traits rather than by a motivated reasoning mechanism related to their professional orientation, though we would expect that these results may differ in samples of other types of AI experts.

5 Conclusion and discussion

5.1 Summary of key results

The complex and subtle sociotechnical concepts inherent to AI make it challenging to design effective governance and science communication strategies that are informed by and respectful of diverse public views and values. In light of these challenges, this work evaluated underlying factors, values, and mechanisms that influence attitudes toward AI. We explored the role of sociodemographic variables; the impact of the cultural values of egalitarianism, individualism, techno-skepticism, and risk aversion; the potentially moderating effects of perceived self- and societal benefit; differences between experts and the public; and differences across prominent policy-relevant applications of AI.

One consistent finding of our study is that the U.S. public's attitudes toward AI were much less nuanced than experts'. Compared to experts, the public's views on the use, management, and regulation of AI were largely similar across application areas, and the public reported perceiving little distinction between how AI might affect them personally and how it might affect society more generally. We did, however, find greater support for government regulation in applications such as autonomous weapons and predicting crime, indicating that while recent suggestions for soft law approaches to AI governance [82] may be more likely to find public and expert support in the U.S., ambivalence toward broad AI regulation might belie support for "hard" legally-binding regulatory actions narrowly targeted to certain contexts.

Second, we found that the four cultural values we studied were meaningful predictors of public attitudes toward AI. The relationships between cultural values and attitudes are similar both across application contexts and between experts and the U.S. public (Figure 5). For example, individualism tended to predict greater support for AI use while techno-skepticism tended to predict reduced support for AI use. These similarities — particularly between experts and

[13] The evidence in support of accepting $\mathcal{S}$ over $\mathcal{S}_{\setminus B}$ was more equivocal than the evidence in support of accepting $\mathcal{S}$ over $\mathcal{S}_{\setminus C}$. For example, while overall we found evidence in support of retaining model $\mathcal{S}$ over $\mathcal{S}_{\setminus B}$, one piece of evidence supported retaining $\mathcal{S}_{\setminus B}$: the large residual variance on support for AI use in models $\mathcal{S}_{\setminus C}$ and $\mathcal{S}$ vanished in $\mathcal{S}_{\setminus B}$.

the public — advance the hypothesis that cultural values are a useful tool for understanding attitudes toward AI and how these attitudes may evolve. Thus, research on a larger set of cultural values, performed in different regions and with different populations, may be a valuable tool for creating participatory and culturally sensitive AI applications and governance strategies.

A third key finding of our study is that although cultural values had significant impacts on support for AI adoption and governance, these cultural values did not impact attitudes in the same way that they impact attitudes toward many other technologies. For example, egalitarianism and risk aversion are traditionally associated with skepticism toward the use of emerging technologies [27]; by contrast, we find that these values predicted *greater* support for AI. This implies that AI's impact on society may be perceived differently from the impacts of other technologies. Governance and public dialogue strategies may be more successful if they take these novel aspects of AI into account. Indeed, previous work has found that science communication is most effective when it tailors its messages to the specific cultural values held by the public [23, 24]. The relationships we find between specific cultural values and specific AI applications (shown in Figure 5) suggest which potential dimensions and applications could be emphasized in outreach efforts to more effectively build credibility with the public and honor public values.

5.2 Theoretical implications and contrasts with prior literature

The satisfactory fit of our SEM serves as a proof of concept for the benefits of using a combination of sociodemographic and cultural variables in modeling attitudes toward AI, and suggests that a similar approach may be fruitful for studying public attitudes toward other culturally-polarized technologies. In addition, the presence of both strong direct effects and strong indirect effects in our fit model provides tentative (but not conclusive) support for the value of considering self- and societal benefit as mediating variables in understanding attitudes toward technology.

The SEM used in this study shares some features with popular frameworks in the broader technology acceptance literature, such as the Technology Acceptance Model (see Section 2.2). Our work also carries implications for this class of models, providing evidence that factors adopted from cultural theory might also be successfully incorporated as external factors in models of attitudes toward (and use of) other technologies.

Finally, our work provides evidence for cultural theory more broadly, though survey operationalization details (discussed in Section 2.1) suggest that some caution is warranted when interpreting these generalizations. First, the large and statistically significant effects of cultural values on public and expert attitudes toward AI we identified provide evidence in favor of the applicability of cultural theory to attitudes toward AI and toward technology more generally. Enumerating and categorizing values that shape attitudes is particularly valuable for understanding general purpose technologies such as AI that have multiple overlapping impacts on society, and our work suggests that cultural theory may provide a useful framework for such an effort. Second, our results in Figure 5 — which depict associations of cultural values across multiple technologies and AI application contexts — offer a basis for comparing the impacts of the four cultural values we studied here on a variety of technologies and use cases.

Previous work has found that those who are more comfortable with AI are more likely to be young, male, educated, and to live in urban areas [11, 16, 19–21, 35]. Our results reflect these divisions. Moreover, we found that across most contexts these demographic traits had positive and statistically significant effects on support for AI not only directly, but also indirectly through paths mediated by perceived self- and societal benefit. Our findings also largely align with prior evidence that individuals with more education, white collar jobs, and higher incomes are more likely to perceive both self and societal benefit from AI [11, 13, 15, 16, 19].[14]

Our results contrasted most sharply with previous findings that blue collar workers, those in urban areas, and political liberals are most likely to report believing that AI will exacerbate inequality and lower employment [11, 15]. In seeming contrast, we found that those living in urban areas and political liberals tended to report perceiving a *benefit* to themselves and society from AI, both in general and in the economic context of labor automation.

5.3 Lessons for public engagement in AI governance

Our study was motivated by the near-universal calls for diverse, interdisciplinary, and public participation in AI governance from global industry, government, and civil society actors. Despite these calls, there are persistent concerns about opaque policy processes vulnerable to industry capture, culturally insensitive uses of AI techniques, and shallow or ineffectual participatory mechanisms. How can those interested in inclusive governance bridge this gap? Our work both provides insights and suggests challenges that may face even well-intentioned efforts to develop participatory structures.

[14] For example, we found that employment in a "cognitive" role had a particularly strong positive effect on perceived self-benefit, perceived societal benefit, and support for use for both AI in general and for AI used in labor automation, perhaps the most economically-oriented application we considered.

A first challenge is the sizable gap between the significant public support we find for "careful management" of AI and the more limited support for "government regulation" (Figure 3), a finding that echoes prior research, particularly in the U.S. context [19]. However, a growing international expert consensus — including among corporate actors — has articulated a need for AI regulation, and regulatory efforts continue to develop. This reveals a fundamental tension in how public opinion should be respected in AI governance [89]. Should regulators take a technocratic approach and base regulatory strategies on the views of experts, even in the face of skepticism from some quarters of the public? Or should regulators, presented with equivocal public support for U.S. government regulation of AI, limit the scope of their involvement even if they believe that public attitudes may evolve significantly as the impacts of AI become more apparent?

One response to this tension that has been embraced by a number of participatory design and governance strategies is to promote public education and genuine public-expert dialogue as part of outreach efforts. In these methods, trained facilitators, researchers, or policymakers may initiate public engagement experiences by providing information about the stakeholders, benefits and costs, policy implications, and trade-offs that can help the public make more informed judgments. The public-expert gaps identified in our study point to the value of these cooperative strategies.

Importantly, these dialogues are not unidirectional; discussion is structured and restructured by the public's situated experiences and values. Examples of relevant approaches can be found both in long-standing participatory design strategies (e.g., Multi-Criteria Decision Analysis [90] and the Delphi Method [91]), and in strategies formulated or adapted specifically for science and technology (e.g., the Citizen Visions on Science, Technology and Innovation method [92], the Reflect! platform [93], and Deliberative Mapping [94]). These engagement methods can elicit qualitative and quantitative data to inform policy preferences, pointing not only to general values, but also guiding specific choices [95]. Engage2020's Action Catalogue database of participatory strategies (http://actioncatalogue.eu/search) provides one starting point.

Our results also point to specific contexts and value orientations in which further unpacking the complex factors driving attitudes toward AI governance may be particularly useful. We find, for instance, that in AI applications like predictive policing and autonomous weapons experts are much more likely than the public to support government regulation of AI. Moreover, in these contexts there are statistically significant differences between experts and the public in how cultural values affect attitudes. For example, our finding that egalitarianism predicts *greater public support* for AI-based weaponry but *less expert support* may suggest that efforts in the AI community to advocate against lethal autonomous weapons (e.g., [96]) may not have reached the public eye. Similarly, our study's finding that risk aversion predicted greater public support for AI-based recommendation systems but less expert support may suggest that increased public awareness about the potential benefits and harms of these systems could be particularly impactful.

However, our findings also caution that in many application domains increased public awareness of AI's impacts might not produce major changes in attitudes toward AI governance. We find that public support for AI governance is relatively independent from arguably more malleable factors like perceived self- and societal benefit from AI. Instead, our results suggest that public support for AI governance is more strongly related to factors reflective of broader regulatory preferences such as political orientation and individualism (Figure 4).

The contrast our study finds between the U.S. public's desire for AI governance and skepticism for government involvement suggests an opportunity for governance strategies. A major focus of AI policy discourse is "trustworthy AI," an attempt to shape the ways AI is developed and applied in an effort to promote user trust. Our results reveal an additional need for *trustworthy AI governance*. Previous research has indicated that the U.S. public places higher trust in, for instance, military and higher education institutions to manage AI than in the federal government at large [19, 35]. Identifying the aspects that have built trust in these institutions could help government and industry actors demonstrate their own trustworthiness in AI governance. Alternatively, governments could leverage these institutions to develop and implement governance strategies, drawing on trusted local authorities and civil society actors to develop, communicate, and administer aspects of AI governance.

In turn, researchers can help identify participatory strategies, messages, and governance approaches that promote (and deserve) public trust. Little is currently known about which strategies (e.g., third-party conformity assessments, labeling, industry standards, or human rights or well-being impact assessments) are most likely to foster trust. In short, there are many opportunities to promote inclusive AI governance for both AI developers and formal governance bodies. However, the time horizon for doing so is not unlimited. AI systems with major impacts are already commonplace, and a variety of national and international regulatory efforts are currently underway. Understanding effective strategies for trustworthy AI governance — and the role of public views in these efforts — will be a pressing need in the coming years.

5.4 Limitations and future work

Our research has several limitations. The four cultural values used in our model were selected because of their effects in governing public opinion on other technologies, but they may not, of course, be either root or comprehensive causes of differing attitudes toward AI; many other sources of cultural diversity are important to respect when designing AI governance strategies. The broader literature on technology acceptance (for example, the many variants of the Technology Acceptance Model [97]) describes many examples of factors that may also be influential in the formation of attitudes toward AI. Moreover, while previous work has posited that the *interaction* between cultural values may drive some differences in risk perception [23], our SEM analysis strategy does not analyze interactions between variables.

A second limitation concerns our descriptions of the six AI application contexts used in our survey: while we attempted to faithfully reflect the way each application is framed in public discourse, it is likely that this discourse will evolve in ways that change their associations with particular cultural values. Respondents also differed in their familiarity with AI; knowledgeable participants (and the expert sample in particular) likely considered information from previous knowledge about the AI application contexts beyond what was provided in our vignettes, limiting fair comparisons between samples.

Third, while we believe our graduate student sample provides one informative view on the beliefs of AI experts, this group differs from other samples of AI experts, such as those studied by [26] or [25]. Future work should explore how our findings generalize to groups involved in other aspects of AI development and governance. Our U.S. public sample also suffers from the typical limitations of online surveys: although respondents were representative of U.S. adults on age, gender, race, and region, online samples tend to differ from the general population in ways not captured by these variables.

This work represents a first step toward understanding underlying mechanisms governing expert and public attitudes toward AI. Future research should extend these findings by exploring how attitudes differ in non-U.S. (and non-Western) contexts [6, 98]. Despite their limitations, the four cultural values we used here provide a tool for quantitatively exploring cross-cultural differences in values and attitudes relevant to AI governance; results may help explain emerging transnational political differences in AI governance strategies. It would also be valuable to study other groups of AI experts and practitioners, more fine-grained conceptions of governance than management and regulation, and using other narratives and frames for the application areas we considered.

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Supplementary Materials

Table of Contents

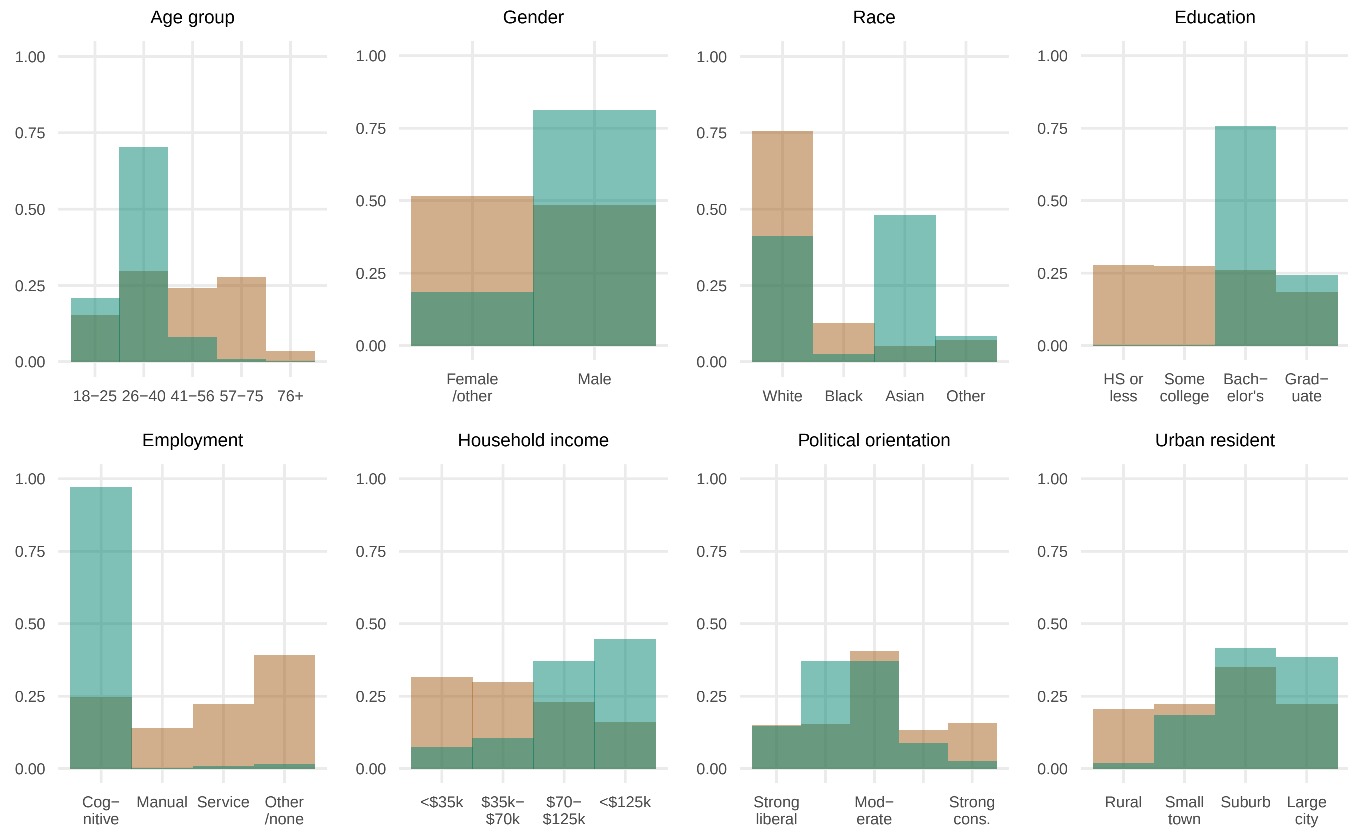

Figure 6: Between-sample comparison of sociodemographic variable distributions.

A Details of samples

Histograms in Figures 6 and 7 show between-sample differences in distributions of sociodemographic variables and cultural values, respectively. Summary statistics are shown in Table 1.

We also collected information about the OMS student sample's region of undergraduate degree, field of undergraduate degree, region of previous or current employment, and field of previous or current employment. For field of degree and field of employment, we used answer choices designed to facilitate a comparison with the AI/ML researcher sample of [25].

	Undergraduate	Work
North America	0.661	0.805
Europe	0.033	0.028
Asia	0.256	0.118
Other	0.045	0.031
Not applicable or prefer not to answer	0.005	0.019

Table 3: Region of undergraduate institution and past/current employment for OMS sample.

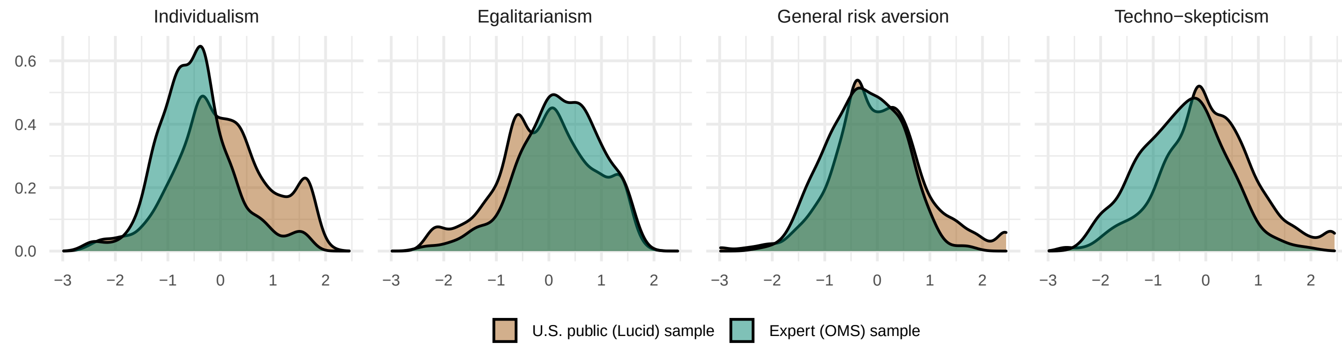

Figure 7: Between-sample comparison of cultural value distributions, inferred using the reduced model containing the confirmatory factor analysis blocks of the SEM in Figure 1.

	Undergraduate field
Computer science or similar	0.431
STEM field outside of CS	0.508
Non-STEM field	0.054
Not applicable or prefer not to answer	0.007

Table 4: Field of undergraduate degree for OMS sample.

	Work field
AI	0.118
CS or software engineering but not AI	0.638
STEM field but not AI or CS	0.181
Other	0.035
Not applicable or prefer not to answer	0.028

Table 5: Field of previous or current work for OMS sample.

B Details of AI application contexts and informal hypotheses

To probe how the identified factor may govern AI opinion across several important contexts and issues, we collect opinion about six different specific applications in which AI has been used. Here we provide brief background about each context and survey the rhetorical frames present in public discourse for each.

Table 7 presents informal hypotheses for the associations between these application contexts, on the one hand, and, on the other, key cultural values and sociodemographic variables for which we are able to generate educated hypotheses. Table 8 presents a summary of our results in this format. Two categories of perhaps unexpected results stand out in this format: first, the associations of egalitarianism, risk aversion, and political conservatism; and second, determinants associated with privacy/personalization and autonomous weapons. These surprises suggest that determinants of public attitudes toward these increasingly important AI policy areas are deserving of further study and public dialogue. (We are grateful to an anonymous peer reviewer for suggesting this presentation style; the informal hypotheses shown in Table 7 were not preregistered.)

Predictive policing. Predictive policing describes the use of data-based approaches to allocate limited policing resources to locations where computational models predict crime is more likely to occur in the future. Proponents have claimed that these methods can make policing more effective and efficient, while critics such as civil rights groups and some academics have stated that basing policing decisions on past crime data further entrenches racial biases in policing. Academic research is limited by a lack of publicly available data, but has found limited causal evidence of either crime reduction or increased arrest rates in minority neighborhoods [99, 100].

The description of predictive policing used in our survey (Table 6) reflects contemporaneous public discourse, suggesting that "some" police departments use predictive policing and attributing opposition to "civil rights groups and some researchers." It thus connects AI to public discourse about racial inequality and trust in police, civil rights organizations, and academia.

Economic and labor impact. A large part of the public conversation about AI has focused on its economic and labor impact. AI is often presented as contributing to improved quality of life, better and cheaper consumer products, and accelerated economic growth. Some research has found that, like previous technological advancements, AI is less likely to cause a secular decrease in jobs as it is to change the character of work, focusing human labor on more creative and potentially rewarding tasks [101, 102]. But AI is also often portrayed as a harbinger of mass unemployment that eliminates low-skilled jobs in favor of jobs that many see as beyond their interests or skillset. This may be particularly true when the phrase "artificial intelligence" conjures the specter of superintelligence that can accomplish all tasks humans can [49].

The description of economic and labor impact used in our survey (Table 6) lends equal credence to each of these possibilities (that AI could either "increase inequality and unemployment" or "make work less tedious and produce higher standards of living"), allowing respondents to process the information using prior worldviews about technology, equality, and wealth. In this context, responses about the likelihood of self- or societal benefit allow us to disentangle individuals' views of AI as threatening their own economic status from their views on how AI affects society at large.

Medical diagnosis and interpretability. AI and machine learning techniques have the potential to make major contributions to medicine by enabling better and cheaper medical imaging, aiding drug discovery, and producing earlier diagnosis of disease [103]. However, these potential benefits are accompanied by ethical and technical challenges [104]. The description of AI systems used in our survey (Table 6) specifically contrasts the potential benefit that AI can bring to medical diagnostics with potential risks stemming from uninterpretable "black-box" systems [105]. The real-life implication of this uninterpretability is made clear by the statement that "some fear [the AI systems] might occasionally produce incorrect results." This vignette therefore contrasts improvements in technology with trust in medicine.

Autonomous vehicles and AI safety. The public discourse about autonomous vehicles has been characterized by optimistic promises of preventing a majority of crashes and lives lost in transportation while eliminating the tedious task of driving [106]. At the same time, these optimistic predictions may have been jaundiced by high-profile accidents and repeatedly delayed timelines for development [107], and the public has indicated hesitancy related to potential failures or vulnerability to hacking [108]. The description of autonomous vehicles used in our survey (Table 6) contrasts the safety benefits of autonomous vehicles (described as "AI-powered self-driving cars") with the potential safety risks of the systems as "vulnerable to malfunctioning or being hacked." Related research has found that individualism and perceptions of benefit predict support for autonomous vehicles [52].

Context	Vignette
Policing	Some police departments use AI to predict where crime is likely to occur, helping them decide where to deploy their resources. But civil rights groups and some researchers argue that these AI systems simply increase arrests in minority neighborhoods without actually reducing crime.
Economic/labor	AI systems are likely to automate many tasks. Some think that these AI systems will make work less tedious and produce higher standards of living. Others believe that these AI systems will increase unemployment and inequality.
Medical	AI-powered medical systems can detect diseases earlier and more accurately than human doctors. But some fear that these AI systems could occasionally produce incorrect results without doctors understanding why.
Autonomous vehicles	AI-powered self-driving cars could save lives by reducing traffic accidents caused by human error. But some are concerned that the AI systems in self-driving cars are vulnerable to malfunctioning or being hacked.
Privacy/ personalization	AI systems can provide personalized news, social media content, and product recommendations using data collected from users. But some worry that this can undermine individual privacy and lead to misinformation and political polarization.
Autonomous weapons	Lethal autonomous weapons controlled by AI systems could improve our national security while putting fewer service members in danger. But some worry that AI-powered weapons could be dangerous or lead to a reckless arms race.

Table 6: Contexts and vignettes used in survey.

Context	Ind	Egl	Tsk	Rav	Age	Male	Educ	Cogn.	Conserv
Policing	+	-	-	+	+	+	$\times$	$\times$	+
Economic/ labor	+	-	-	+	-	+	+	+	+
Medical	+	+	-	-	+	+	+	+	+
Autonomous vehicles	+	+	-	-	-	+	+	+	+
Privacy/ personalization	-	-	-	-	-	+	-	-	$\times$
Autonomous weapons	+	-	-	-	-	+	$\times$	$\times$	$\times$
AI in general	+	-	-	-	-	+	+	+	+

Table 7: *Expected* associations between, on the one hand, support for AI in specific application contexts, and on the one hand, key cultural values and sociodemographic variables. Expected positive association denoted by +; expected negative association denoted by -; and no association denoted by $\times$. Cultural values: Ind = individualism; Egl = egalitarianism; Tsk = techno-skepticism; Rav = general risk aversion. Cogn = cognitive employment.

Context	Ind	Egl	Tsk	Rav	Age	Male	Educ	Cogn.	Conserv
Policing	+	×	-	+	×	+	+	+	+
Economic/ labor	+	+	-	+	-	+	+	+	-
Medical	+	+	-	+	×	+	+	+	-
Autonomous vehicles	+	+	-	×	-	+	+	+	-
Privacy/ personalization	+	+	-	+	-	×	×	+	-
Autonomous weapons	+	+	-	+	×	+	+	+	×
AI in general	+	+	-	+	-	+	+	+	-

Table 8: *Actual* associations found between, on the one hand, support for AI in specific application contexts, and on the one hand, key cultural values and sociodemographic variables. Statistically significant ($p < 0.05$) positive association denoted by +; statistically significant negative association denoted by -; and no statistically significant association denoted by ×. Shaded boxes denote results that match the informal hypotheses in Table 7. Cultural values: Ind = individualism; Egl = egalitarianism; Tsk = techno-skepticism; Rav = general risk aversion. Cogn = cognitive employment.

Privacy and personalization. One of the most widespread current uses of AI is in recommendation systems, which use information from users' previous activity and other customers to make inferences about their preferences. These systems are used to individually target online ads and personalize news, social media feeds, and product recommendations. While these personalized systems can make online content more engaging, there is controversy about whether they violate users' privacy, particularly when used for political advertising [14, 109] or in ways that could perpetuate misinformation and political polarization [110]. A national survey in Spain found that privacy concerns predicted opposition to AI [111].

The description of AI-based recommendation used in our survey contrasts the value of "personalized news, social media content, and product recommendations" with the potential of "undermine[d] individual privacy" and "misinformation and political polarization" (Table 6).

Autonomous weapons. AI can be used to create weapon systems that require minimal or no human oversight. These AI systems have been identified as important components of future military competitiveness under the premise that they can make quicker and more accurate decisions than humans and expose service members to less danger [112]. However, advocacy groups and prominent figures in AI research have argued that these systems — particularly with insufficient governance structures in place — are dangerous and unethical [96]. Global competition features prominently in this debate, with proponents arguing that the development of AI-based weapons is necessary to compete with other state actors, and opponents arguing that this competition can create a dangerous race to the bottom.

The description of autonomous weapons in our survey (Table 6) contrasts these two frames, positioning potential benefits to national security and service member safety against the possibility that weapons could be "dangerous or lead to a reckless arms race." A previous survey found low support for "lethal autonomous weapons" internationally, with only 24% of U.S. respondents supporting their use [69].

C Full survey

C.1 Informed consent statement

Consent Document for Enrolling Adult Participants in a Research Study

Project title: Understanding public opinion on new technologies
Investigators: Matthew O'Shaughnessy, Daniel Schiff, Lav Varshney, Ph.D., Christopher Rozell, Ph.D., and Mark Davenport, Ph.D.
Address: Georgia Tech School of Electrical & Computer Engineering, 777 Atlantic Drive NW, Atlanta, GA 30332 USA
Telephone: (404) 894-2881

You are being asked to volunteer in a research study. This page will give you important information to help you decide if you would like to participate. Your participation is voluntary.

The purpose of this study is to better understand public opinion about new technologies. Participants must be 18 years or older [*for Lucid sample:* , reside in the United States, and not currently be located in the European Economic Area (the European Union, Iceland, Liechtenstein, or Norway)] [*for OMSCS sample:* and be enrolled in Georgia Tech's Online Master of Science in Computer Science program]. If you decide to participate in the study, we will provide you with short descriptions of some technologies and ask you to indicate how much you agree with a series of statements about how the technologies should be used. Your participation is expected to last about 10 minutes.

We believe there are minimal risks associated with this research study. A risk of breach of confidentiality always exists; however, your responses will not be associated with your name or any personally identifiable information. There are no costs to you, other than your time, for participating in this study. It is possible that your survey responses will be valuable for other research purposes. By participating, you consent for your responses to be stored by the the researcher and to be shared with other researchers in future studies. No identifiable information [*for OMSCS sample:*, including your IP address or location data,] will be collected with your survey responses. Neither the researchers of this study or future researchers will have any way to identify you. We will comply with any applicable laws and regulations regarding confidentiality. To make sure that this research is being carried out in the proper way, the Georgia Institute of Technology IRB may review study records. The Office of Human Research Protections may also look at study records.

You are not likely to benefit in any way from joining this study. However, your participation in the study may assist researchers in understanding how new technologies should be used. You will be compensated with [*for Lucid sample:* payment through the survey provider] [*for OMSCS sample:* extra credit] for your participation. [*for OMSCS sample:* Participating in this survey is not the only way to earn this extra credit. You may also write a four page paper on a topic related to the role of public opinion in shaping the development and use of new technologies.]

It is fully your decision if you wish to be in this study or not. If you choose not to participate, or choose to participate and later determine you no longer wish to, you will not lose any rights, services, or benefits as a result of your withdrawal. The study is completely voluntary. If you have any questions about this study, you may contact the principle investigators at crozell@gatech.edu and mdav@gatech.edu. If you have any questions about your right as a research participant, you may contact Ms. Melanie Clark, Georgia Institute of Technology Office of Research Integrity Assurance, at (404) 894-6942.

By completing the online survey you are indicating that you are at least 18 years old, have read this consent form, and agree to participate in this research study.

C.2 GDPR compliance

These questions are asked only of OMS respondents for GDPR compliance. The required GDPR compliance form was contained in a separate survey so that names and digital signatures would not associated with survey responses.

- (GDPR1) "Are you currently located in the European Economic Area (the European Union, Iceland, Liechtenstein, or Norway)? This question is asked for GDPR compliance." [Yes, No]
- (GDPR2) [*only shown if respondent answers yes to GDPR1*] "Because you are currently located in the European Economic Area, you must complete a GDPR consent to participate in the survey. Before continuing, please click on the following link to provide your consent. This uses a separate survey to ensure your name will not be associated with your survey responses. [*link here*] Have you completed the GDPR consent form and indicated your consent?" [Yes, No]

The survey was terminated for respondents who answered yes to GDPR1 but no to GDPR2.

C.3 Assess demographics/values and prior opinion

C.3.1 Demographic information

"First we'd like to ask some questions about you. No data or analysis will be tied to you individually, and answering these questions is very helpful for us."[15]

- (AGEG) [*Provided by Lucid.*] Age group ["What is your age?" 18-25, 26-40, 41-56, 57-75, 76+][16]
- (GEND) [*Provided by Lucid.*] Gender ["What is your gender?" Male, Female, Other gender][17]
- (RACE) Race ["What is your race?" White, Black or African American, Asian, Other race or ethnicity][18]
- (EDUC) Education level ["What is the highest level of education you have completed?" High school degree or less, Associate's degree or some college (including two-year college or vocational training), Bachelor's degree, Graduate or professional degree][19]
- (EMPL) Type of employment ["What category best describes the type of work you currently do, previously did, or expect to do in the future?" Cognitive or analytical tasks (such as finance, management, IT, or engineering), Manual or physical tasks (such as manufacturing, sanitation, construction, or maintenance), Social or people-oriented tasks (such as nursing, customer service, or teaching), Other or not applicable]
- (HINC) Household income ["What is your current annual household income before taxes?" Less than $34,999/$35,000-69,999/$70,000-$124,999/More than $125,000][20]
- (PORT) Political orientation ["Generally speaking, where would you place yourself along the political spectrum?" Strong liberal, Lean liberal, Moderate, Lean conservative, Strong conservative][21]
- (URBN) Urban/rural ["What type of community do you live in?" Rural area, Small city or town, Suburb near a large city, Large city][22]

C.3.2 Individualism

"People in our society often disagree about how far to go in making decisions for themselves. How strongly do you agree or disagree with each of these statements?" [Rotate questions; Strongly disagree; Moderately disagree; Neither agree nor disagree; Moderately agree; Strongly agree.][23]

- (IND1) "The government interferes far too much in our everyday lives."
- (IND2) "The government should stop telling people how to live their lives."

[15] Most demographics adapted from [113], with the exception of type of employment and urban/rural.
[16] Corresponds to Pew age groups: Gen Zers (born after 1995; ages 18-25 in 2021), Millennials (born 1981-1995; ages 26-40 in 2021), Gen Xers (born 1965-1980, ages 41-56 in 2021), Baby Boomers (born 1946-1964; ages 57-75 in 2021), Greatest Generation (born 1945 and earlier; ages 76 and older in 2021). Used by [19]. For Lucid respondents, exact age is provided and is converted to an age group for analysis.
[17] Text of question provided by Lucid: "What is your gender? [Male/Female]"
[18] Question and answer choice wording from Lucid.
[19] Question wording based on Lucid.
[20] Question wording from Lucid, response choices selected to approximate quartiles for U.S. household income.
[21] Question based on Prolific.
[22] Question and response choices adapted from 2012 Pew survey.
[23] Taken from [27]; scale changed from original 6-point scale ("Strongly disagree, Moderately disagree, Slightly disagree, Slightly agree, Moderately agree, Strongly agree").

- (IND3) "If the government spent less time trying to fix everyone's problems, we'd all be a lot better off."
- (IND4) "Too many people today expect society to do things for them that they should be doing for themselves."
- (SCR1) [*Attention screener #1*] "Please select the 'somewhat agree' response."[24]

C.3.3 Egalitarianism

"People in our society often disagree about issues of equality and discrimination. How strongly do you agree or disagree with each of these statements?" [Rotate questions; Strongly disagree, Moderately disagree, Neither agree nor disagree, Moderately agree, Strongly agree.][25]

- (EGL1) "Our society would be better off if the distribution of wealth was more equal."
- (EGL2) "We need to dramatically reduce inequalities between the rich and the poor, white people and people of color, and men and women."[26]
- (EGL3) "Discrimination against minorities is still a very serious problem in our society."
- (EGL4) "We live in a sexist society that is fundamentally set up to discriminate against women."

C.3.4 Techno-skepticism

"People in our society often disagree about how new technology benefits us. How strongly do you agree or disagree with each of these statements?" [Rotate questions; Strongly disagree, Moderately disagree, Neither agree nor disagree, Moderately agree, Strongly agree.]

- (TSK1) "New technologies are more about making profits rather than making peoples' lives better."[27]
- (TSK2) "I am worried about where all this technology is leading."[28]
- (TSK3) "Technology has become dangerous and unmanageable."[29]
- (TSK4) "I feel uncomfortable about new technologies."
- (SCR2) [*Attention screener #2.*] "World War I came after World War II."[30]

C.3.5 Risk aversion

"How strongly do you agree or disagree with each of these statements?" [Rotate questions; Strongly disagree, Moderately disagree, Neither agree nor disagree, Moderately agree, Strongly agree.][31]

- (RAV1) "I tend to avoid talking to strangers."
- (RAV2) "I prefer a routine way of life to an unpredictable one full of change."
- (RAV3) "I would not describe myself as a risk-taker."
- (RAV4) "I do not like taking too many chances to avoid making a mistake."

[24] Patterned after the first grid-type attention screener in [78], "Please click the 'neither agree nor disagree" response."

[25] Taken from [27]; scale changed from original 6-point scale ("Strongly disagree, Moderately disagree, Slightly disagree, Slightly agree, Moderately agree, Strongly agree").

[26] Slightly modernized from original question in [27]: "We need to dramatically reduce inequalities between the rich and the poor, whites and people of color, and men and women."

[27] From Gaskell et al. 2005; slightly adapted.

[28] Adapted from [29].

[29] From [47].

[30] Second grid-type attention screener in [78].

[31] Items from the risk aversion scale of [44].

C.3.6 Other technological risks.

"Some people believe that the potential risks of new technology outweigh their benefits, while others believe that the benefits new technologies bring are worth their potential risks." [Rotate questions; Risks significantly outweigh benefits; Risks slightly outweigh benefits; Don't know either way; Benefits slightly outweigh risks; Benefits significantly outweigh risks]

- (OGEN) "Which best represents your view on *genetically modified foods*?"[32]
- (ONUC) "Which best represents your view on *nuclear power*?"[33]
- (OCOL) "Which best represents your view on *coal burning power plants*?"[34]
- (OVAC) "Which best represents your view on *vaccines*?"
- (ONEU) "Which best represents your view on *neurotechnology*, devices that interact directly with the brain that could help treat neuologic disorders?"
- (OBIO) "Which best represents your view on *synthetic biology*, a branch of science that will allow scientists to design and build new biological organisms?"[35]
- (SCR3) [*Attention screener #3.*] "Which best represents your view on *bitcoin*? Please select 'risks significantly outweigh benefits' regardless of your actual beliefs. Yes, ignore the question and just select that option."

C.3.7 AI knowledge

"Artificial intelligence (AI) refers to computer systems that perform tasks or make decisions that usually require human intelligence. AI can perform these tasks or make these decisions without explicit human instructions. Today, AI has been used in the following applications: identifying people from their photos, diagnosing diseases like skin cancer and common illnesses, blocking spam email, helping run factories and warehouses, and predicting what one is likely to buy online."[36]

- (AIKW) "How much have you heard about Artificial Intelligence (AI) before today?" [Nothing at all, A little, A moderate amount, A lot][37]

C.4 AI perception

C.4.1 General AI opinion

"How strongly do you agree or disagree with each of these statements about artificial intelligence (AI)?" [Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree]

- (AISE) "Thinking about *me personally*, the benefits of AI outweigh the risks."[38]
- (AISO) "Thinking about *society more generally*, the benefits of AI outweigh the risks."[39]
- (AIMG) "AI should be carefully managed."[40]
- (AIRG) "AI should be regulated by the government."
- (AIUS) "I support the use of AI."[41]

[32] Risk of "genetically modified foods" surveyed in [32, 114]; scale adapted from [114] (used "The benefits significantly outweigh the risks" etc.).
[33] Risk of "nuclear power" surveyed in [32, 114]; scale adapted from [114].
[34] Risk of "coal/oil burning plants" surveyed in [32]; scale adapted from [114].
[35] Description and scale adapted from [114].
[36] The definition of AI (and applications) is taken from [19].
[37] Answer choices from [11].
[38] Loosely adapted from [84], which used "Thinking about the risks and benefits of AI *to you personally*, which of the following best describes your belief?" [the risks of AI will greatly outweigh its benefits, the risks of AI will slightly outweigh its benefits, the benefits of AI will slightly outweigh its risks, the benefits of AI will greatly outweigh its risks].
[39] Loosely adapted from [84]; see above.
[40] Loosely adapted from [19], which found that variations in question wording produced statistically insignificant differences in responses.
[41] Loosely adapted from [19].

C.4.2 Context-specific AI opinion

"Now we would like to know how you think AI should be used in a few specific applications. We will provide you with a short description of places where AI has been used. After each we will ask a few questions about your opinion."

Sequentially display the six vignettes (or, for Lucid sample, three of the six vignettes) shown in Table 6. After each vignette: "How strongly do you agree or disagree with each of these statements?" [Strongly disagree, Somewhat disagree, Neither agree nor disagree, Somewhat agree, Strongly agree]

- (**SE) "Thinking about *me personally*, the benefits of AI used in [*task description*] outweigh the risks."
- (**SO) "Thinking about *society more generally*, the benefits of AI used in [*task description*] outweigh the risks."
- (**MG) "AI used in [*task description*] should be carefully managed."
- (**RG) "AI used in [*task description*] should be regulated by the government."
- (**US) "I support the use of AI in [*task description*]."

Task descriptions: "predicting crime" (AP**); "automating labor" (AL**); "medical diagnosis" (AM**); "self-driving cars" (AV**); "[for] personalization" (AR**); and "weapons" (AW**).

C.5 Stand-alone screener

"Now, we would like to get a sense of your general preferences.

Most modern theories of decision-making recognize that decisions do not take place in a vacuum. To demonstrate that you read this much, just go ahead and select both red and green among the alternatives below, no matter what your favorite color is. Yes, ignore the question below and select both of those options.

- (SCR4) What is your favorite color?" [Multiple selections allowed: White, Black, Red, Pink, Green, Blue]

C.6 Technical background [OMS sample only]

[*Questions in this section are asked of OMS participants only and are intended to help characterize differences between the OMS population and other surveys of ML practitioners/researchers, e.g., [25].*]

"Finally, we would like to ask a few more questions about your technical background."

- (BRGU) "What region did you obtain your undergraduate degree in?" [North America, Europe, Asia, Other, Not applicable or prefer not to answer][42]
- (BFDU) "What field was your undergraduate degree in?" [Computer science or similar; STEM (science, technology, engineering, and math) field outside of CS; Non-STEM field; Not applicable or prefer not to answer]
- (BRGW) "If you are currently working, or were working prior to starting the OMSCS program, what region do/did you work in?" [North America, Europe, Asia, Other, Not applicable or prefer not to answer][43]
- (BFDW) "If you are currently working, or were working prior to starting the OMSCS program, how would you characterize your work?" [Work in AI; Work in CS or software engineering but not artificial intelligence; Work in a science or engineering field but not AI or CS; Other; Not applicable or prefer not to answer]

C.7 Conclusion

"This concludes the survey. Thank you for your time! Your response is valuable to help understand how our society should use and manage AI." [*for OMS sample:* "To receive your extra credit: press the next button. You will be taken to a new form where you can provide your name to the CS 6601 instructional team without it being linked to your survey responses."]

C.8 Recruitment emails

The following email text was used to recruit OMS participants. Lucid participants were supplied by the Lucid platform, so no recruitment materials were needed.

[42] Based on demographic information reported in [25].

[43] Based on demographic information reported in [25].

C.8.1 Initial email

Dear all,

Our research team is conducting a study to understand how those in computing-related fields believe new technologies should be used and regulated. As a current or future worker in a computing-related field, we would like you to complete a short survey.

The survey will take approximately 10 minutes. **You will receive one-half point of extra credit on your final grade for your participation.** However, the survey is completely voluntary. You may also earn this extra credit by writing a four page paper on a topic related to the role of public opinion in shaping the development and use of new technologies. No personally identifiable information (including your IP address) will be collected during the survey; for extra credit purposes, at the end of the survey you will be redirected to a separate form to provide your GT username to the CS 6601 instructional team.

You can complete the survey here: [*link to survey*].

We are extremely grateful for your participation!

Thank you,
Matt O'Shaughnessy, Daniel Schiff, Lav Varshney, Christopher Rozell, and Mark Davenport

C.8.2 Reminder email

Dear all,

This is a reminder to complete the survey regarding how new technologies should be used and regulated.

If you have already taken the survey, thank you! If you have not yet completed the survey, please details about the study and extra credit below. You can complete the survey here: [*link to survey*].

Thank you,
Matt O'Shaughnessy, Daniel Schiff, Lav Varshney, Christopher Rozell, and Mark Davenport

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Our research team is conducting a study to understand how those in computing-related fields believe new technologies should be used and regulated. As a current or future worker in a computing-related field, we would like you to complete a short survey.

The survey will take approximately 10 minutes. **You will receive one-half point of extra credit on your final grade for your participation.** However, the survey is completely voluntary. You may also earn this extra credit by writing a four page paper on a topic related to the role of public opinion in shaping the development and use of new technologies. No personally identifiable information (including your IP address) will be collected during the survey; for extra credit purposes, at the end of the survey you will be redirected to a separate form to provide your GT username to the CS 6601 instructional team.

You can complete the survey here: [*link to survey*].

We are extremely grateful for your participation!

Concern	Survey modification
Long completion time (9.6 ± 2.4 minutes) in graduate student pilot	Changed Lucid version of survey to collect data about only three randomly selected contexts for each participant
Low reliability of hierarchy-egalitarianism construct	Updated survey to use four egalitarianism and four individualism items from the full scales of [27] (see text for details)
Low reliability of techno-optimism construct	Redesigned construct with new items validated in second pilot (see text for details)
Additional cultural value constructs may be appropriate	Explored additional possibilities in second pilot; added risk aversion construct (see text for details)
Many "other" responses to employment question.	Updated wording of question to include past or future work, if applicable (e.g., for students or retirees)
Many instances of missing data in some lucid-provided demographic information	Added race, education level, and household income as required questions in Qualtrics survey for Lucid sample

Table 9: Summary of survey modifications made based on pilot surveys.

D Pilot surveys and development of final survey instrument

Before finalizing and preregistering the final version of our survey instrument we modified the original draft based on three pilot surveys. The first pilot used a small convenience sample of machine learning graduate students and the OMS version of the survey. The second and third pilots used the Lucid Theorem platform with $N = 50$ and $N = 150$ participants, respectively. Changes made to the original survey draft based on these three pilots are summarized in Table 9.

D.1 OMS pilot

A small convenience sample pilot survey was run to estimate completion time and identify any confusing or misleading aspects of the survey. The pilot survey used the OMS version of the survey with all six AI contexts; the sample consisted of graduate students studying areas related to machine learning. The average completion time for the complete survey was 9.6 ± 2.4 minutes; of this, the six contexts took 4.0 ± 0.8 minutes. Based on this completion time, the Lucid version of the survey was modified so that each participant would only be presented with three randomly selected contexts, reducing the total completion time of this survey version by approximately 2 minutes. Due to the relatively small sample size and less anticipated participant fatigue, all six contexts were kept in the OMS version of the survey. No major concerns with survey structure or wording were identified.

D.2 First Lucid pilot

A first ($N = 50$; March 22, 2021) pilot survey was run on the Lucid platform to estimate completion time and identify any confusing aspects. The pilot survey used the Lucid version of the survey, and contained only three randomly-selected contexts per participant. The mean completion time was 7.5 ± 5.1 minutes (median: 6.2 minutes). At the end of the survey, participants were prompted to enter feedback on the survey.[44] No major concerns were identified from this feedback.

The original survey draft used the "short-form" hierarchy-egalitarianism and individualism-communitarianism constructs from [23], which contains three positively-framed (i.e., 'strongly agree' = high hierarchy) and three negatively-framed (i.e., 'strongly agree' = high egalitarianism) items for each construct, and a new four item construct for techno-optimism/skepticism. In our first Lucid pilot we found that the reliability of the individualism-communitarianism and techno-optimism/skepticism constructs were low (hierarchy-egalitarianism: $\alpha = 0.78$, AVE = 0.32; individualism-communitarianism: $\alpha = 0.45$, AVE = 0.31; techno-optimism/skepticism: $\alpha = 0.58$, AVE = 0.31). Further investigation revealed weak consistency between the positively-framed and negatively-framed items for each of the three cultural value constructs. To further evaluate the reliability of these constructs and evaluate possible remedies we conducted a

[44] Question text: "Do you have any feedback for the researchers developing this survey? For example, were any parts of the survey confusing?"

larger second pilot survey on the Lucid platform that included additional items for each construct and three additional constructs.

D.3 Second Lucid pilot

The second Lucid pilot (N = 150; April 1, 2021) included the full 13-item hierarchy-egalitarianism and 17-item individualism-communitarianism scales from [27]. It also included additional items to aid in the design of a more reliable techno-optimism construct and additional candidate constructs for other cultural values.

We again observed weak consistency between positively-framed and negatively-framed (reverse coded) items (hierarchy-egalitarianism: $\alpha = 0.54$, AVE = 0.34; individualism-communitarianism: $\alpha = 0.67$, AVE = 0.31). In response, we conducted a literature review of other recent work that had used the scales of [27], and replicated the procedure of [73], who retained only positively-framed items from the Kahan et al. cultural cognition constructs in response to weak consistency between positively- and negatively-framed items. We found similar patterns in the other constructs we evaluated, and also used questions framed in only one direction for the final techno-optimism/skepticism construct. Our modifications differed from those of [73], who used most positively-framed hierarchy and individualism items from [27], in two ways. First, we restricted our survey to the four highest-loading items for each context. Based on the results of our pilot survey, we expected that this would allow us to shorten the length of our survey without a meaningful decline in construct reliability. Second, we used positively-framed egalitarianism and individualism (rather than hierarchy and individualism) items to avoid any perception of ideological slant in our survey. The reliability of these modified scales in our pilot survey was high (four-item egalitarianism: $\alpha = 0.87$, AVE = 0.64; four-item individualism: $\alpha = 0.85$, AVE = 0.61).

Our second pilot contained eight techno-optimism/skepticism items with the goal of allowing us to create a reliable four-item construct. We again found that positively- and negatively-framed items coalesced poorly with each other, and identified the four highest-loading negatively-framed items for the final survey. The reliability of this techno-skepticism construct was satisfactory ($\alpha = 0.78$, AVE = 0.50).

We also evaluated constructs for additional relevant cultural values from prior literature, and adopted the risk aversion construct of [44] for the final survey. This construct showed satisfactory reliability in the pilot ($\alpha = 0.75$, AVE = 0.43) and may be a more direct determining factor of AI skepticism than some demographic factors, making it relevant for our first research question described in the Introduction.

Table 9 summarizes the changes made to the survey based on the three pilot surveys.

Metric	Adequate fit	Good fit
χ^2 test	$p \geq 0.05$*	
CFI	≥ 0.90	≥ 0.95
RMSEA	< 0.10	< 0.05
SRMR	< 0.10	< 0.05

Table 10: Metrics and cutoffs used for evaluation of SEM fit. *The chi-square test is known to be sensitive to sample size [55]; because we have a large sample size we expect to obtain a significant P-valueeven with satisfactory model fit.

E Supplemental results

This section contains the complete results from the analysis prescribed by our preregistered analysis plan. Where needed to evaluate SEM fit quality, we used the fit statistic thresholds (based on recommendations of [55]) defined in our pre-analysis plan and shown in Table 10.

E.1 Role of cultural values

E.1.1 Psychometrics for cultural worldview constructs

We first verified the reliability of the cultural value constructs in isolation from the rest of the SEM. Table 11 shows fit statistics for a CFA model that included the four cultural constructs and their indicators. As in our full SEM, the four cultural constructs were allowed to covary with each other, while their indicators were constrained to have zero covariance with each other. Cultural constructs were standardized, and the indicators were treated as ordinal (see Methods). We evaluated the model with three samples: a) the Lucid sample, b) the OMS sample, and c) a multigroup model fit to both samples in which indicator loadings were constrained to be equal between groups (samples). This multigroup model (results from which are shown in the right-most columns of Tables 11 and 13) was used to infer the predicted latent cultural construct values shown in Figure 2. Each of the three models satisfied our preregistered thresholds for adequate-to-good fit, which are shown in Table 10.

The items used to measure each cultural value construct demonstrated good reliability (Table 12) and loaded appropriately onto each construct (Table 13).

While the inferred loadings were fairly similar between the Lucid and OMS samples, the covariances between constructs differed between samples (Table 14). This difference was less pronounced when analysis was restricted to the attentive subsample (See Supplement Section F, Table 42). Table 15 shows correlation residuals in the CFA model fit to Lucid data, which are commonly used to assess local model fit. No correlation residuals had magnitude greater than 0.10, a common heuristic threshold for poor local fit [55].

	Lucid	OMS	Multigroup
χ^2_M (df_M, p)	1207.0 (98, <0.001)	258.6 (98, <0.001)	1370.8 (208, <0.001)
CFI	0.974	0.963	0.977
RMSEA (90% CI)	0.057 (0.054, 0.060)	0.062 (0.053, 0.071)	0.053 (0.051, 0.056)
SRMR	0.038	0.056	0.041

Table 11: Fit statistics for CFA model of cultural values.

	Lucid		OMS		Combined	
	α	AVE	α	AVE	α	AVE
Individualism	0.840	0.644	0.782	0.537	0.874	0.645
Egalitarianism	0.864	0.691	0.821	0.656	0.894	0.691
Techno-skepticism	0.806	0.578	0.775	0.567	0.840	0.578
Risk aversion	0.696	0.430	0.699	0.420	0.740	0.430

Table 12: Construct reliabilities of four cultural values. α: Chronbach's alpha, AVE: average variance extracted. AVE in the combined sample is computed using a multigroup model in which indicator loadings are constrained to be equal between samples.

Item	λ (Lucid)	λ (OMS)	λ (Multigroup)
Individualism			
IND1: The government interferes far too much in our everyday lives.	0.855 (0.006)	0.730 (0.027)	0.852 (0.006)
IND2: The government should stop telling people how to live their lives.	0.784 (0.008)	0.623 (0.031)	0.778 (0.008)
IND3: If the government spent less time trying to fix everyone's problems, we'd all be a lot better off.	0.834 (0.007)	0.831 (0.025)	0.840 (0.007)
IND4: Too many people today expect society to do things for them that they should be doing for themselves.	0.732 (0.009)	0.732 (0.027)	0.738 (0.009)
Egalitarianism			
EGL1: Our society would be better off if the distribution of wealth was more equal.	0.821 (0.007)	0.772 (0.027)	0.818 (0.007)
EGL2: We need to dramatically reduce inequalities between the rich and the poor, white people and people of color, and men and women.	0.888 (0.006)	0.881 (0.019)	0.890 (0.006)
EGL3: Discrimination against minorities is still a very serious problem in our society.	0.851 (0.007)	0.821 (0.024)	0.850 (0.006)
EGL4: We live in a sexist society that is fundamentally set up to discriminate against women.	0.760 (0.008)	0.761 (0.025)	0.762 (0.008)
Techno-skepticism			
TSK1: New technologies are more about making profits rather than making peoples' lives better.	0.677 (0.010)	0.569 (0.038)	0.670 (0.010)
TSK2: I am worried about where all this technology is leading.	0.825 (0.007)	0.863 (0.020)	0.828 (0.007)
TSK3: Technology has become dangerous and unmanageable.	0.820 (0.007)	0.844 (0.022)	0.822 (0.007)
TSK4: I feel uncomfortable about new technologies.	0.708 (0.010)	0.698 (0.032)	0.707 (0.009)
Risk aversion			
RAV1: I tend to avoid talking to strangers.	0.560 (0.014)	0.552 (0.043)	0.560 (0.013)
RAV2: I prefer a routine way of life to an unpredictable one full of change.	0.686 (0.012)	0.628 (0.041)	0.683 (0.012)
RAV3: I would not describe myself as a risk-taker.	0.626 (0.012)	0.753 (0.042)	0.634 (0.012)
RAV4: I do not like taking too many chances to avoid making a mistake.	0.736 (0.011)	0.645 (0.044)	0.732 (0.011)

Table 13: Standardized loadings and standard errors for cultural constructs from CFA models. The multigroup model constrained indicator loadings to be equal between samples.

	Lucid			OMS		
	I	E	TS	I	E	TS
Egalitarianism	-0.245 (0.018)	1.000		-0.574 (0.045)	1.000	
Techno-skept.	0.442 (0.016)	0.140 (0.018)	1.000	0.147 (0.051)	0.144 (0.052)	1.000
Risk aversion	0.265 (0.019)	0.308 (0.019)	0.453 (0.017)	-0.130 (0.054)	0.062 (0.059)	0.203 (0.057)

Table 14: Covariances between cultural value constructs from multigroup CFA.

	I1	I2	I3	I4	E1	E2	E3	E4	T1	T2	T3	T4	R1	R2	R3	R4
I1	0.00															
I2	0.04	0.00														
I3	-0.02	-0.03	0.00													
I4	-0.05	-0.01	0.04	0.00												
E1	0.01	0.06	-0.08	-0.04	0.00											
E2	0.02	0.08	-0.06	0.02	0.02	0.00										
E3	-0.01	0.05	-0.09	-0.00	-0.03	0.00	0.00									
E4	0.07	0.05	-0.04	0.01	-0.02	-0.03	0.03	0.00								
T1	0.05	0.02	0.00	0.01	0.12	0.07	0.04	0.13	0.00							
T2	0.03	-0.01	-0.00	0.02	0.00	-0.05	-0.08	0.03	-0.01	0.00						
T3	0.02	-0.03	-0.01	-0.01	-0.03	-0.06	-0.08	0.04	-0.00	0.01	0.00					
T4	-0.02	-0.04	-0.01	-0.05	-0.04	-0.06	-0.08	0.06	-0.06	0.00	0.02	0.00				
R1	0.00	0.01	-0.02	-0.03	0.05	0.01	0.01	0.08	0.04	-0.01	0.00	0.06	0.00			
R2	0.01	0.04	0.04	0.07	0.01	0.00	-0.01	0.01	0.03	-0.02	-0.04	0.02	-0.04	0.00		
R3	-0.03	-0.02	0.00	-0.00	-0.05	-0.04	-0.03	0.02	-0.03	-0.04	-0.03	0.08	-0.04	0.01	0.00	
R4	-0.03	-0.04	-0.01	0.00	-0.00	-0.03	-0.03	0.01	-0.01	-0.01	-0.04	0.05	0.00	-0.01	0.04	0.00

Table 15: Correlation residuals for CFA model fit with Lucid sample.

E.1.2 Impact of demographics

To evaluate the impact of demographics, we fit the reduced model $\mathcal{S}_{\setminus C}$ shown in Figure 8 using the Lucid sample. The path coefficients estimated in this reduced model are shown in Table 16 and visualized in Figure 9. We report both direct and total effects. Direct effects show the estimated path coefficient from the independent variable to the outcome variable, while total effects show the total impact (including both direct and indirect effects) of each independent variable on support outcome variables. For instance, the total impact of age group ("age") on support for use ("SU") was computed as

$$\begin{aligned}\text{TE}\,(\text{Age} \to \text{SU}) = {} & \underbrace{\text{Age} \to \text{SU}}_{\text{Direct effect}} + \\ & \underbrace{(\text{Age} \to \text{Self-ben}) \times (\text{Self-ben} \to \text{SU}) + (\text{Age} \to \text{Soc-ben}) \times (\text{Soc-ben} \to \text{SU})}_{\text{Indirect effect}}.\end{aligned}$$

The estimated covariances for the reduced model $\mathcal{S}_{\setminus C}$ are shown in Table 18. Fit statistics for $\mathcal{S}_{\setminus C}$, shown in Table 17, indicated poor-to-adequate fit.

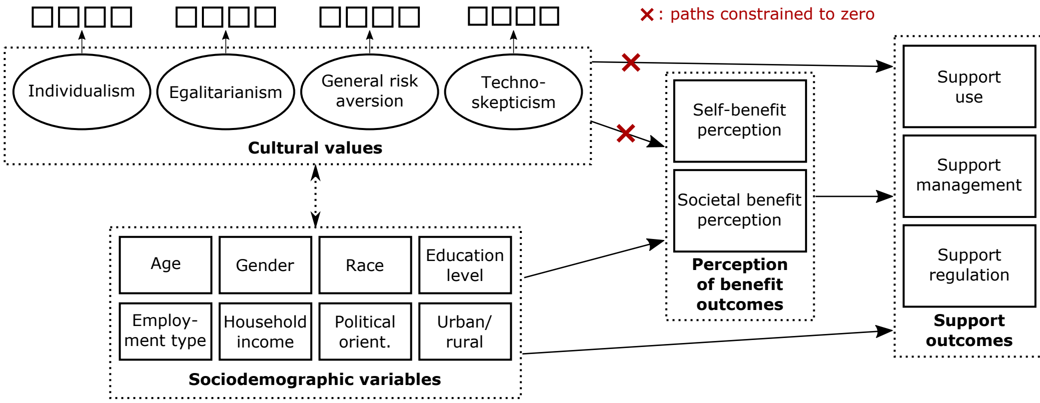

Figure 8: Reduced SEM $\mathcal{S}_{\setminus C}$, derived from the full SEM $\mathcal{S}$ shown in Figure 1 by constraining path coefficients from cultural value constructs to outcome variables to zero. Variables within each group (denoted by dashed lines), as well as cultural values and sociodemographic variables, are allowed to covary; we treat demographic variables as exogenous.

			Supp. Use		Supp. Management		Supp. Regulation	
	Self-ben	Soc. ben	DE	TE	DE	TE	DE	TE
Gender=male	0.148***	0.149***	0.129***	0.241***	-0.021	-0.007	-0.021	0.007
	(0.037)	(0.038)	(0.029)	(0.038)	(0.040)	(0.040)	(0.037)	(0.038)
Ethn=white	0.178*	0.314***	0.119*	0.305***	0.280***	0.303***	0.161*	0.210**
	(0.071)	(0.070)	(0.055)	(0.071)	(0.070)	(0.069)	(0.071)	(0.072)
Ethn=black	0.129	0.268***	0.085	0.235**	0.030	0.049	0.168*	0.207*
	(0.082)	(0.079)	(0.066)	(0.082)	(0.080)	(0.081)	(0.082)	(0.084)
Ethn=asian	0.030	0.173	0.045	0.121	0.070	0.080	0.118	0.139
	(0.102)	(0.100)	(0.079)	(0.101)	(0.102)	(0.103)	(0.104)	(0.106)
Job=cognitive	0.431***	0.299***	0.133***	0.408***	0.156**	0.188***	0.050	0.114*
	(0.051)	(0.052)	(0.040)	(0.052)	(0.056)	(0.056)	(0.050)	(0.050)
Job=manual	0.078	-0.056	0.087*	0.095	-0.039	-0.039	-0.043	-0.044
	(0.058)	(0.057)	(0.043)	(0.056)	(0.061)	(0.061)	(0.059)	(0.060)
Job=service	0.106*	0.027	0.081*	0.131*	0.141**	0.146**	-0.036	-0.025
	(0.051)	(0.051)	(0.040)	(0.052)	(0.053)	(0.053)	(0.050)	(0.050)
Education	0.093***	0.087***	0.050**	0.118***	0.045*	0.053*	0.018	0.035
	(0.020)	(0.020)	(0.016)	(0.020)	(0.021)	(0.021)	(0.020)	(0.020)
Urban	0.087***	0.089***	0.021	0.087***	0.054**	0.062***	0.068***	0.085***
	(0.018)	(0.017)	(0.014)	(0.018)	(0.019)	(0.019)	(0.018)	(0.018)
Age group	-0.090***	-0.065***	-0.024	-0.082***	0.161***	0.154***	0.004	-0.010
	(0.017)	(0.018)	(0.014)	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)
HH income	0.083***	0.083***	0.026	0.089***	0.048*	0.055*	0.056**	0.071***
	(0.020)	(0.020)	(0.016)	(0.020)	(0.022)	(0.022)	(0.019)	(0.020)
Pol.=conservative	-0.076***	-0.065***	-0.051***	-0.104***	0.025	0.019	-0.103***	-0.116***
	(0.014)	(0.014)	(0.011)	(0.014)	(0.016)	(0.016)	(0.014)	(0.014)
Self-benefit	–	–	0.375***	–	0.038	–	0.072***	–
			(0.013)		(0.027)		(0.021)	
Societal benefit	–	–	0.379***	–	0.052	–	0.113***	–
			(0.013)		(0.027)		(0.022)	
R^2	0.134	0.110	0.461		0.090		0.084	

Table 16: Path coefficient estimates and standard errors for reduced model $\mathcal{S}_{\setminus C}$ fit with Lucid sample. DE = direct effect, TE = total effect.

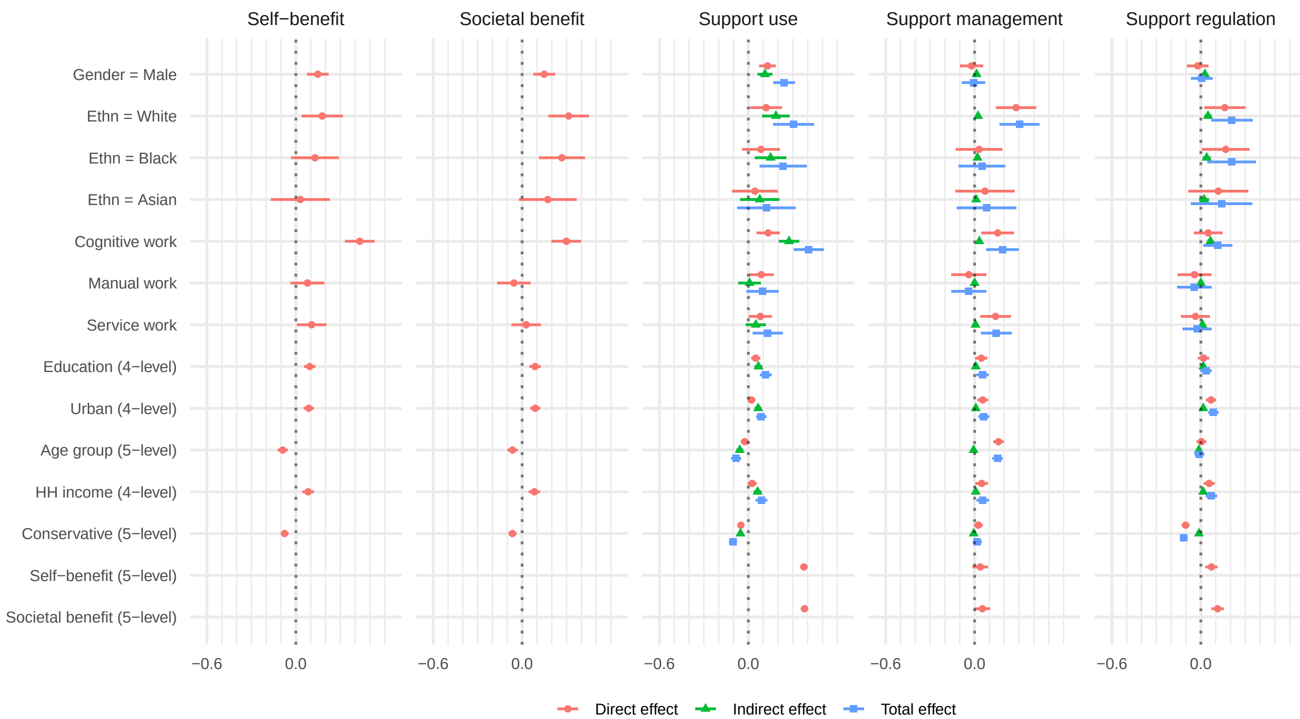

Figure 9: Direct, indirect, and total effects in the reduced model $\mathcal{S}_{\backslash C}$ fit with the Lucid sample. Variables are unstandardized; error bars show 95% confidence intervals.

	$\mathcal{S}_{\backslash C}$	$\mathcal{S}$
χ^2_M (df_M, p)	8204.2 (370, <0.001)	4650.2 (350, <0.001)
CFI	0.822	0.903
RMSEA (90% CI)	0.078 (0.076, 0.079)	0.059 (0.058, 0.061)
SRMR	0.099	0.036
χ^2_D (df_D, p)	1764.8 (20, <0.001)	

Table 17: Fit statistics for $\mathcal{S}_{\backslash C}$ and $\mathcal{S}$ fit with Lucid sample.

Cultural values	I	E	TS
Egalitarianism	-0.038* (0.019)	1.000	
Techno-skept.	0.453*** (0.016)	0.206*** (0.018)	1.000
Risk aversion	0.289*** (0.019)	0.343*** (0.018)	0.451*** (0.017)
Perception of benefit	Self	Society	
Self	0.713*** (0.007)	1.000	
Support	Use	Mgt.	Reg.
Management	0.135*** (0.014)	1.000	
Regulation	0.028* (0.011)	0.270*** (0.017)	1.000

Table 18: Fit covariances for reduced model $\mathcal{S}_{\setminus C}$ fit with Lucid sample.

E.1.3 Comparison of $\mathcal{S}$ and $\mathcal{S}_{\setminus C}$

To evaluate the importance of the paths from cultural values to outcome variables, we estimate the full model $\mathcal{S}$ (Figure 1) and compare its fit to the reduced model $\mathcal{S}_{\setminus C}$ (Figure 8). Estimated path coefficients for $\mathcal{S}$ are shown in Table 19 and visualized in Figure 10. Estimated covariances are shown in Table 20. We observe that the estimated coefficients for paths from sociodemographic variables to outcome variables display minimal differences between $\mathcal{S}_{\setminus C}$ and $\mathcal{S}$. This is a consequence of the fact that sociodemographic variables were modeled as exogeneous and have relatively small magnitude effects.

Table 17 shows fit statistics for both $\mathcal{S}_{\setminus C}$ and $\mathcal{S}$. The full model $\mathcal{S}$ achieves adequate to good fit; the fact that $\mathcal{S}$ produces a better fit than $\mathcal{S}_{\setminus C}$ across all fit statistics we consider provides global evidence that cultural values are valuable in modeling our outcome variables.

To examine local evidence for the importance of the paths from cultural values to outcome variables, we compare variance explained and correlation residuals in $\mathcal{S}_{\setminus C}$ and $\mathcal{S}$. Outcome variable R^2 values are shown in Table 16 (for $\mathcal{S}_{\setminus C}$) and Table 19 (for $\mathcal{S}$). We generally see that R^2 values are larger in $\mathcal{S}$ than in $\mathcal{S}_{\setminus C}$, providing local evidence for the importance of the paths from cultural values to outcome variables. Correlation residuals for $\mathcal{S}_{\setminus C}$ and $\mathcal{S}$ are shown in Tables 21 and 22, respectively. We see smaller magnitude correlation residuals in $\mathcal{S}$, providing further local evidence for the importance of the paths from cultural values to outcome variables.

	Self-ben	Soc. ben	Supp. Use		Supp. Management		Supp. Regulation	
			DE	TE	DE	TE	DE	TE
Gender=male	0.148***	0.149***	0.150***	0.241***	-0.001	-0.007	-0.015	0.007
	(0.037)	(0.038)	(0.029)	(0.038)	(0.040)	(0.040)	(0.037)	(0.038)
Ethn=white	0.178*	0.314***	0.156**	0.305***	0.312***	0.303***	0.171*	0.210**
	(0.071)	(0.070)	(0.056)	(0.071)	(0.070)	(0.069)	(0.071)	(0.072)
Ethn=black	0.129	0.268***	0.115	0.235**	0.056	0.049	0.175*	0.207*
	(0.082)	(0.079)	(0.066)	(0.082)	(0.081)	(0.081)	(0.082)	(0.084)
Ethn=asian	0.030	0.173	0.060	0.121	0.083	0.080	0.121	0.139
	(0.102)	(0.100)	(0.079)	(0.101)	(0.103)	(0.103)	(0.104)	(0.106)
Job=cognitive	0.431***	0.299***	0.184***	0.408***	0.206***	0.188***	0.065	0.114*
	(0.051)	(0.052)	(0.041)	(0.052)	(0.057)	(0.056)	(0.050)	(0.050)
Job=manual	0.078	-0.056	0.088*	0.095	-0.036	-0.039	-0.042	-0.044
	(0.058)	(0.057)	(0.043)	(0.056)	(0.061)	(0.061)	(0.059)	(0.060)
Job=service	0.106*	0.027	0.090*	0.131*	0.151**	0.146**	-0.033	-0.025
	(0.051)	(0.051)	(0.041)	(0.052)	(0.053)	(0.053)	(0.050)	(0.050)
Education	0.093***	0.087***	0.062***	0.118***	0.057**	0.053*	0.022	0.035
	(0.020)	(0.020)	(0.016)	(0.020)	(0.021)	(0.021)	(0.020)	(0.020)
Urban	0.087***	0.089***	0.034*	0.087***	0.066***	0.062***	0.072***	0.085***
	(0.018)	(0.017)	(0.014)	(0.018)	(0.019)	(0.019)	(0.018)	(0.018)
Age group	-0.090***	-0.065***	-0.035**	-0.082***	0.151***	0.154***	0.001	-0.010
	(0.017)	(0.018)	(0.014)	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)
HH income	0.083***	0.083***	0.038*	0.089***	0.059**	0.055*	0.059**	0.071***
	(0.020)	(0.020)	(0.016)	(0.020)	(0.022)	(0.022)	(0.019)	(0.020)
Pol.=conservative	-0.076***	-0.065***	-0.061***	-0.104***	0.015	0.019	-0.106***	-0.116***
	(0.014)	(0.014)	(0.011)	(0.014)	(0.016)	(0.016)	(0.014)	(0.014)
Individualism	0.198***	0.197***	0.060***	0.181***	0.274***	0.265***	-0.168***	-0.139***
	(0.021)	(0.021)	(0.017)	(0.021)	(0.024)	(0.023)	(0.021)	(0.020)
Egalitarianism	0.305***	0.315***	0.131***	0.320***	0.329***	0.315***	0.144***	0.189***
	(0.019)	(0.019)	(0.016)	(0.018)	(0.022)	(0.020)	(0.020)	(0.018)
Techno-skepticism	-0.307***	-0.350***	-0.170***	-0.370***	-0.013	0.001	0.243***	0.194***
	(0.023)	(0.022)	(0.018)	(0.022)	(0.028)	(0.025)	(0.023)	(0.022)
Risk aversion	0.161***	0.145***	0.067***	0.160***	0.007	0.000	0.125***	0.146***
	(0.022)	(0.022)	(0.017)	(0.022)	(0.025)	(0.024)	(0.022)	(0.022)
Self-benefit	–	–	0.311***	–	-0.036	–	0.046*	–
			(0.016)		(0.026)		(0.021)	
Societal benefit	–	–	0.299***	–	-0.009	–	0.098***	–
			(0.016)		(0.026)		(0.022)	
R^2	0.274	0.262	0.470		0.235		0.201	

Table 19: Effect estimates for $\mathcal{S}$ fit with Lucid sample. DE = direct effect, TE = total effect.

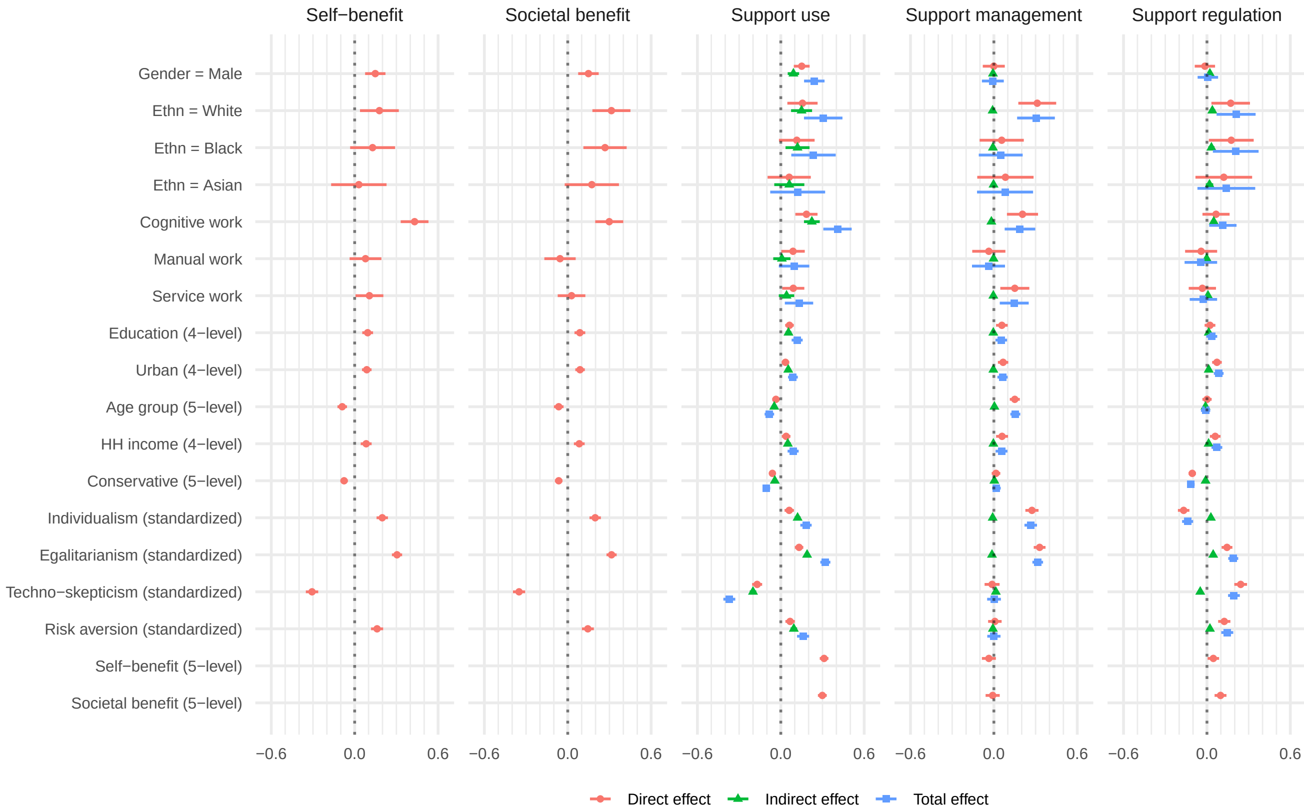

Figure 10: Direct, indirect, and total effects in the full model $\mathcal{S}$ fit with the Lucid sample. Variables other than cultural values are unstandardized except where noted; error bars show 95% confidence intervals.

Cultural values	I	E	TS
Egalitarianism	-0.038* (0.019)	1.000	
Techno-skept.	0.453*** (0.016)	0.206*** (0.018)	1.000
Risk aversion	0.289*** (0.018)	0.343*** (0.018)	0.451*** (0.017)
Perception of benefit	**Self**	**Society**	
Self	0.548*** (0.013)	1.000	
Support	**Use**	**Mgt.**	**Reg.**
Management	0.110*** (0.013)	1.000	
Regulation	0.037*** (0.010)	0.203*** (0.016)	1.000

Table 20: Covariance estimates for $\mathcal{S}$ fit with Lucid sample.

	I1	I2	I3	I4	E1	E2	E3	E4	T1	T2	T3	T4	R1	R2	R3	R4	SE	SO	US	MG	RG
I1	0.00																				
I2	0.04	0.00																			
I3	-0.02	-0.02	0.00																		
I4	-0.05	-0.01	0.05	0.00																	
E1	0.00	0.05	-0.08	-0.03	0.00																
E2	-0.00	0.07	-0.08	0.02	0.03	0.00															
E3	-0.02	0.05	-0.09	0.01	-0.03	0.01	0.00														
E4	0.08	0.06	-0.03	0.02	-0.03	-0.05	0.03	0.00													
T1	0.05	0.02	0.02	0.03	0.10	0.05	0.03	0.12	0.00												
T2	0.01	-0.03	-0.00	0.02	0.02	-0.04	-0.07	0.04	-0.01	0.00											
T3	0.01	-0.03	0.00	-0.00	-0.02	-0.06	-0.09	0.04	-0.01	0.01	0.00										
T4	-0.02	-0.05	0.00	-0.05	-0.03	-0.07	-0.08	0.07	-0.07	0.01	0.02	0.00									
R1	0.02	0.02	0.01	0.01	0.02	-0.02	-0.01	0.06	0.03	-0.01	-0.00	0.07	0.00								
R2	-0.01	0.01	0.02	0.04	0.04	0.02	0.02	0.03	0.02	-0.03	-0.04	0.02	-0.03	0.00							
R3	-0.03	-0.03	0.00	-0.01	-0.04	-0.04	-0.02	0.02	-0.03	-0.05	-0.02	0.08	-0.02	0.00	0.00						
R4	-0.02	-0.03	0.01	0.02	-0.00	-0.03	-0.03	-0.00	-0.02	-0.01	-0.03	0.05	-0.01	-0.01	0.04	0.00					
SE	0.03	0.07	0.10	0.10	0.21	0.25	0.24	0.23	-0.05	-0.07	-0.09	-0.04	0.12	0.14	0.12	0.12	0.00				
SO	0.01	0.05	0.09	0.06	0.23	0.23	0.26	0.19	-0.09	-0.12	-0.13	-0.05	0.08	0.11	0.10	0.11	-0.00	0.00			
US	0.00	0.03	0.04	0.09	0.22	0.26	0.26	0.19	-0.09	-0.10	-0.14	-0.11	0.08	0.12	0.10	0.10	0.00	-0.00	-0.28		
MG	0.19	0.21	0.12	0.25	0.23	0.27	0.30	0.16	0.21	0.20	0.12	0.03	0.07	0.20	0.10	0.10	0.00	-0.00	-0.00	-0.00	
RG	-0.03	-0.04	-0.01	0.03	0.27	0.23	0.21	0.19	0.19	0.19	0.18	0.15	0.14	0.19	0.17	0.18	-0.00	0.00	0.00	-0.00	-0.02

Table 21: Correlation residuals for $\mathcal{S}_{\setminus C}$ fit with Lucid sample. SE: perception of self-benefit; SO: perception of societal benefit; US: support for use; MG: support for management; RG: support for regulation.

	I1	I2	I3	I4	E1	E2	E3	E4	T1	T2	T3	T4	R1	R2	R3	R4	SE	SO	US	MG	RG
I1	0.00																				
I2	0.04	0.00																			
I3	-0.01	-0.02	0.00																		
I4	-0.06	-0.01	0.04	0.00																	
E1	0.00	0.05	-0.08	-0.03	0.00																
E2	-0.00	0.07	-0.08	0.02	0.03	0.00															
E3	-0.02	0.05	-0.09	0.01	-0.04	0.01	0.00														
E4	0.08	0.06	-0.03	0.02	-0.03	-0.04	0.04	0.00													
T1	0.05	0.02	0.02	0.02	0.10	0.05	0.03	0.12	0.00												
T2	0.01	-0.03	-0.00	0.02	0.02	-0.04	-0.07	0.04	-0.02	0.00											
T3	0.01	-0.03	0.00	-0.01	-0.02	-0.06	-0.09	0.04	-0.01	0.01	0.00										
T4	-0.02	-0.05	0.01	-0.05	-0.03	-0.07	-0.08	0.07	-0.06	0.01	0.02	0.00									
R1	0.02	0.03	0.01	0.01	0.02	-0.02	-0.02	0.06	0.03	-0.01	-0.00	0.07	0.00								
R2	-0.02	0.01	0.02	0.03	0.03	0.02	0.01	0.03	0.02	-0.03	-0.04	0.01	-0.03	0.00							
R3	-0.03	-0.03	0.00	-0.01	-0.04	-0.04	-0.02	0.02	-0.03	-0.05	-0.02	0.08	-0.02	-0.00	0.00						
R4	-0.02	-0.03	0.01	0.02	-0.00	-0.03	-0.03	0.00	-0.02	-0.01	-0.03	0.06	-0.01	-0.01	0.04	0.00					
SE	-0.05	-0.00	0.03	0.03	-0.02	-0.00	-0.00	0.02	0.00	-0.00	-0.02	0.02	0.01	0.01	0.00	-0.02	0.00				
SO	-0.04	-0.01	0.04	0.02	0.00	-0.02	0.02	-0.01	0.00	-0.02	-0.02	0.04	-0.01	0.00	0.01	-0.00	-0.00	0.00			
US	-0.04	-0.00	-0.00	0.05	-0.01	0.01	0.02	-0.02	0.02	0.02	-0.02	-0.01	-0.01	0.01	0.00	-0.01	0.05	0.05	-0.16		
MG	-0.02	0.02	-0.07	0.08	-0.01	0.01	0.05	-0.06	0.08	0.04	-0.03	-0.10	-0.03	0.08	-0.02	-0.03	-0.01	-0.00	-0.00	-0.00	
RG	-0.02	-0.02	0.01	0.04	0.04	-0.01	-0.02	-0.01	0.03	0.00	-0.02	-0.01	-0.01	0.01	0.01	-0.01	0.01	0.02	0.01	-0.00	-0.01

Table 22: Correlation residuals for $\mathcal{S}$ fit with Lucid sample. SE: perception of self-benefit; SO: perception of societal benefit; US: support for use; MG: support for management; RG: support for regulation.

E.1.4 Results with mediated cultural values model

In this section we consider the alternative SEM $\mathcal{S}_{\mathrm{mc}}$ shown in Figure 11, which modifies the cultural values portion of the model to posit that the cultural values of individualism and egalitarianism influence the cultural values of techno-skepticism and risk aversion. In this model, paths exist from individualism and egalitarianism to techno-skepticism and risk aversion. Individualism and egalitarianism are free to covary, as are techno-skepticism and risk aversion. As in $\mathcal{S}$, paths exist from each of the four cultural constructs to each outcome variable.

As discussed in Sections 2.2 and 4.2, the four cultural constructs in $\mathcal{S}$ are allowed to covary in order to accommodate potential directed relationships or unmeasured confounding between them. This structure — in which the cultural constructs are allowed to covary — produces equivalent models that fit the collected data equally well. The modified model $\mathcal{S}_{\mathrm{mc}}$ is one such equivalent model, so the fit statistics of $\mathcal{S}$ match those of $\mathcal{S}_{\mathrm{mc}}$.

Table 23 shows model covariances for $\mathcal{S}_{\mathrm{mc}}$ and the estimated path coefficients from individualism and egalitarianism to techno-skepticism and risk aversion. Table 24 shows estimated direct effects for $\mathcal{S}_{\mathrm{mc}}$.

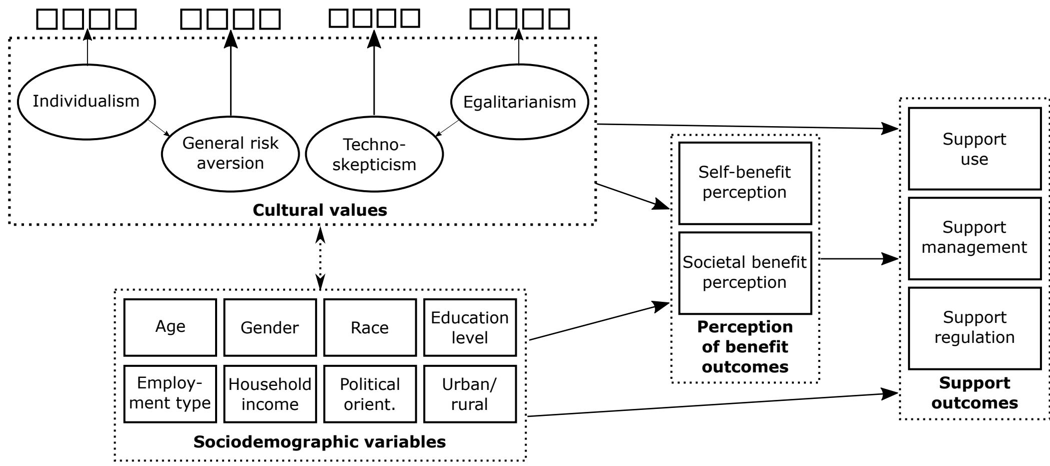

Figure 11: Alternate SEM $\mathcal{S}_{\text{mc}}$ (for "mediated cultural values"), in which paths exist from individualism and egalitarianism to techno-skepticism and risk aversion. Individualism and egalitarianism are free to covary, as are techno-skepticism and risk aversion. As in $\mathcal{S}$, paths exist from each of the four cultural constructs to each outcome variable.

Cultural values	I	E	TS
Egalitarianism	-0.038* (0.019)	1.000	
Techno-skept.	–	–	1.000
Risk aversion	–	–	0.314*** (0.020)
Path coefficients			
Ind $\to$ Tsk	0.535*** (0.023)		
Ind $\to$ Rav	0.340*** (0.022)		
Egl $\to$ Tsk	0.259*** (0.020)		
Egl $\to$ Rav	0.399*** (0.023)		

Table 23: Covariance estimates for $\mathcal{S}_{\text{mc}}$ fit with Lucid sample.

	Self-ben	Soc. ben	Supp. Use	Supp. Management	Supp. Regulation
Individualism	0.198*** (0.021)	0.197*** (0.021)	0.060*** (0.017)	0.274*** (0.024)	-0.168*** (0.021)
Egalitarianism	0.305*** (0.019)	0.315*** (0.019)	0.131*** (0.016)	0.329*** (0.022)	0.144*** (0.020)
Techno-skepticism	-0.307*** (0.023)	-0.350*** (0.022)	-0.170*** (0.018)	-0.013 (0.028)	0.243*** (0.023)
Risk aversion	0.161*** (0.022)	0.145*** (0.022)	0.067*** (0.017)	0.007 (0.025)	0.125*** (0.022)
R^2	0.274	0.262	0.470	0.235	0.201

Table 24: Direct effect estimates for $\mathcal{S}_{\text{mc}}$ fit with Lucid sample.

E.2 Role of perception of benefit

E.2.1 Comparison of $\mathcal{S}$ and $\mathcal{S}_{\setminus B}$

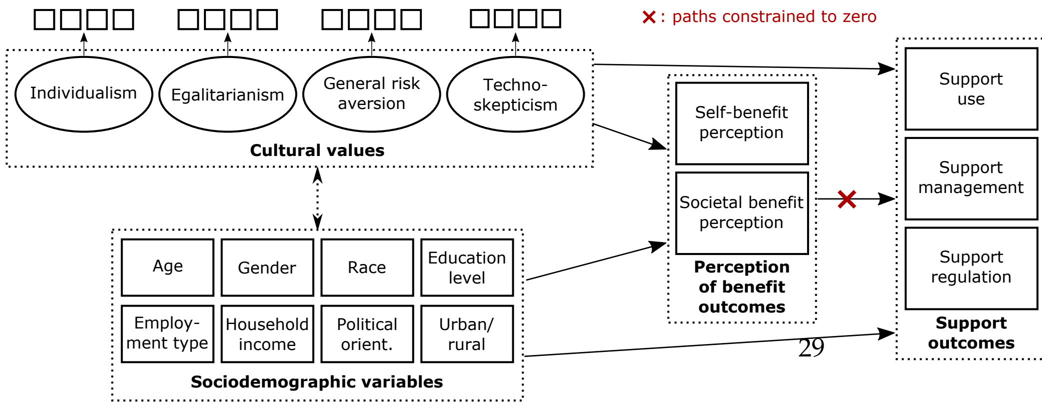

Figure 12: Reduced SEM $\mathcal{S}_{\setminus B}$, derived from the full SEM $\mathcal{S}$ shown in Figure 1 by constraining path coefficients from perception of benefit outcome variables to support outcome variables to zero. Variables within each group (denoted by dashed lines), as well as cultural values and sociodemographic variables, are allowed to covary; we treat demographic variables as exogenous.

To evaluate whether demographic variables and cultural values directly affected support for AI use and governance — or whether these are indirect effects actually driven by different perceptions of self- and societal benefit — we fit the reduced model $\mathcal{S}_{\setminus B}$ shown in Figure 12 using the Lucid sample. The path coefficients estimated in this reduced model are shown in Table 25 and visualized in Figure 13. Estimated covariances are shown in Table 26.

Table 27 show fit statistics for both $\mathcal{S}_{\setminus B}$ and $\mathcal{S}$. Both $\mathcal{S}_{\setminus B}$ and $\mathcal{S}$ achieved adequate-to-good fit according to our preregistered thresholds (Table 10), but the full model $\mathcal{S}$ achieved slightly better fit than $\mathcal{S}_{\setminus B}$ on each metric we consider. This provides global evidence that our perception of benefit outcomes are related to the support outcome variables. Note, however, that this does not provide conclusive evidence that the causal structure hypothesized in our full SEM (i.e., that perceived benefit drive support outcomes) because of the existence of "equivalent" models that fit the data equally as well as $\mathcal{S}$, but with different causal relationships [83].

To examine *local* evidence for the importance of the paths from perceived benefit to support outcomes, we compared variance explained and correlation residuals in $\mathcal{S}_{\setminus B}$ and $\mathcal{S}$. Outcome variable R^2 values are shown in Table 25 (for $\mathcal{S}_{\setminus B}$) and Table 19 (for $\mathcal{S}$). Comparing R^2 values in $\mathcal{S}_{\setminus B}$ and $\mathcal{S}$ painted a mixed picture: a substantially better fit was achieved for perceived benefit and support for use in $\mathcal{S}_{\setminus B}$ than in $\mathcal{S}$, while a slightly better local fit was achieved for support for management and regulation in $\mathcal{S}_{\setminus B}$. Overall, this provides cautionary local evidence against the hypothesized role of perceptions of benefit.

	Self-ben	Soc. ben	Supp. Use	Supp. Mgt.	Supp. Reg.
Gender=male	0.148***	0.149***	0.241***	-0.007	0.007
	(0.037)	(0.038)	(0.038)	(0.040)	(0.038)
Ethn=white	0.178*	0.314***	0.305***	0.303***	0.210**
	(0.071)	(0.070)	(0.071)	(0.069)	(0.072)
Ethn=black	0.129	0.268***	0.235**	0.049	0.207*
	(0.082)	(0.079)	(0.082)	(0.081)	(0.084)
Ethn=asian	0.030	0.173	0.121	0.080	0.139
	(0.102)	(0.100)	(0.101)	(0.103)	(0.106)
Job=cognitive	0.431***	0.299***	0.408***	0.188***	0.114*
	(0.051)	(0.052)	(0.052)	(0.056)	(0.050)
Job=manual	0.078	-0.056	0.095	-0.039	-0.044
	(0.058)	(0.057)	(0.056)	(0.061)	(0.060)
Job=service	0.106*	0.027	0.131*	0.147**	-0.025
	(0.051)	(0.051)	(0.052)	(0.053)	(0.050)
Education	0.093***	0.087***	0.118***	0.053*	0.035
	(0.020)	(0.020)	(0.020)	(0.021)	(0.020)
Urban	0.087***	0.089***	0.087***	0.062***	0.085***
	(0.018)	(0.017)	(0.018)	(0.019)	(0.018)
Age group	-0.090***	-0.065***	-0.082***	0.154***	-0.010
	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)
HH income	0.083***	0.083***	0.089***	0.055*	0.071***
	(0.020)	(0.020)	(0.020)	(0.022)	(0.020)
Pol.=conservative	-0.076***	-0.065***	-0.104***	0.019	-0.116***
	(0.014)	(0.014)	(0.014)	(0.016)	(0.014)
Individualism	0.515***	0.505***	0.625***	0.244***	-0.047*
	(0.024)	(0.024)	(0.027)	(0.023)	(0.021)
Egalitarianism	0.459***	0.467***	0.539***	0.303***	0.225***
	(0.022)	(0.021)	(0.024)	(0.019)	(0.018)
Techno-skepticism	-0.838***	-0.867***	-1.089***	0.023	0.043
	(0.026)	(0.026)	(0.030)	(0.028)	(0.025)
Risk aversion	0.463***	0.445***	0.558***	-0.006	0.214***
	(0.025)	(0.025)	(0.029)	(0.025)	(0.023)
R^2	0.552	0.544	0.774	0.220	0.190

Table 25: Effect estimates for $\mathcal{S}_{\setminus B}$ fit with Lucid sample. DE = direct effect, TE = total effect.

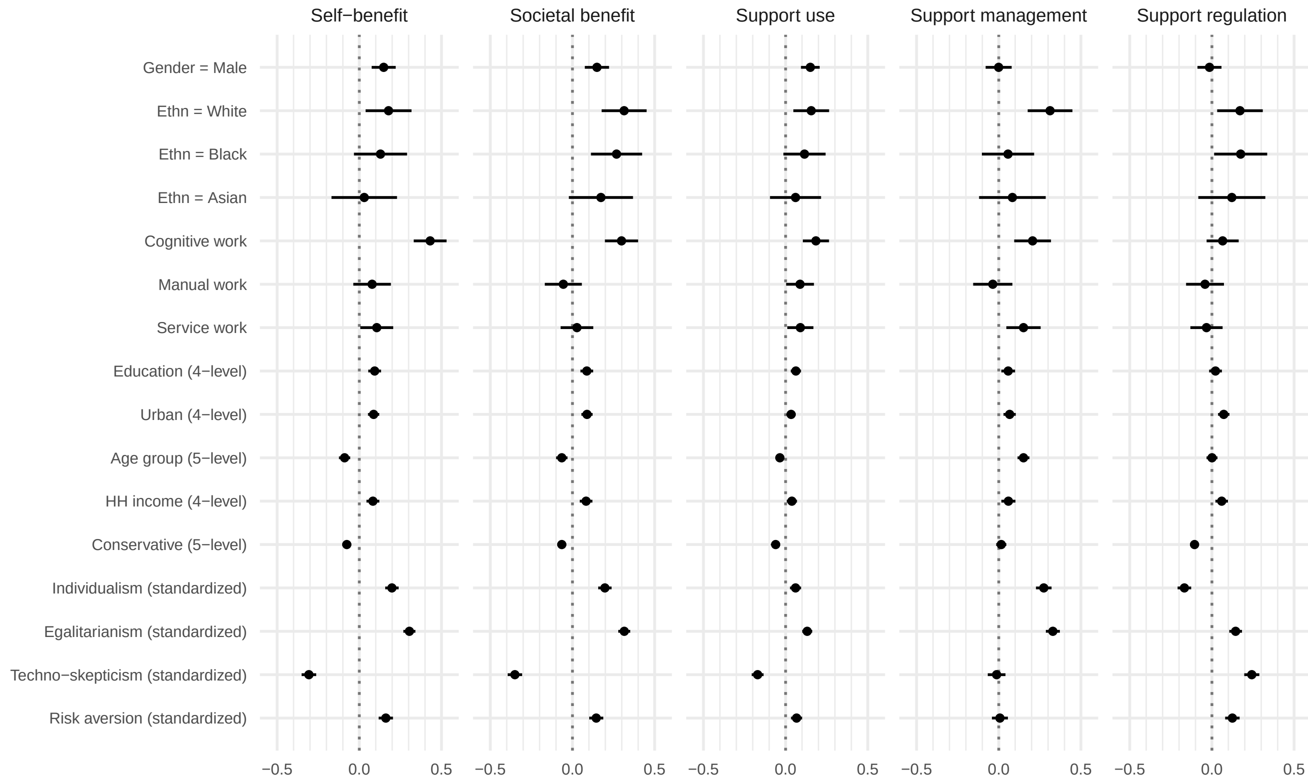

Figure 13: Direct effects in the reduced model $\mathcal{S}_{\setminus B}$ fit with the Lucid sample. Variables other than cultural values are unstandardized except where noted; error bars show 95% confidence intervals.

Cultural values	I	E	TS
Egalitarianism	-0.076*** (0.019)	1.000	
Techno-skept.	0.540*** (0.015)	0.280*** (0.018)	1.000
Risk aversion	0.247*** (0.020)	0.309*** (0.019)	0.569*** (0.016)
Perception of benefit	**Self**	**Society**	
Self	0.229*** (0.014)	1.000	
Support	**Use**	**Mgt.**	**Reg.**
Management	0.060*** (0.015)	1.000	
Regulation	0.029* (0.012)	0.185*** (0.016)	1.000

Table 26: Covariance estimates for $\mathcal{S}_{\setminus B}$ fit with Lucid sample.

	$\mathcal{S}_{\setminus B}$	$\mathcal{S}$
χ^2_M (df_M, p)	5554.4 (356, $<$0.001)	4650.2 (350, $<$0.001)
CFI	0.882	0.903
RMSEA (90% CI)	0.064 (0.063, 0.066)	0.059 (0.058, 0.061)
SRMR	0.049	0.036
χ^2_D (df_D, p)	1173.4 (6, $<$0.001)	

Table 27: Fit statistics for $\mathcal{S}_{\setminus B}$ and $\mathcal{S}$ fit with Lucid sample.

	I1	I2	I3	I4	E1	E2	E3	E4	T1	T2	T3	T4	R1	R2	R3	R4	SE	SO	US	MG	RG
I1	0.00																				
I2	0.05	0.00																			
I3	-0.00	-0.01	0.00																		
I4	-0.04	-0.00	0.05	0.00																	
E1	0.02	0.07	-0.06	-0.01	0.00																
E2	0.02	0.09	-0.06	0.04	0.04	0.00															
E3	0.01	0.08	-0.07	0.03	-0.03	0.02	0.00														
E4	0.10	0.08	-0.01	0.04	-0.02	-0.03	0.04	0.00													
T1	0.02	-0.01	-0.01	-0.00	0.07	0.01	-0.01	0.09	0.00												
T2	-0.03	-0.07	-0.04	-0.02	-0.02	-0.09	-0.11	-0.00	0.02	0.00											
T3	-0.03	-0.07	-0.04	-0.04	-0.06	-0.11	-0.13	0.01	0.03	0.06	0.00										
T4	-0.05	-0.08	-0.03	-0.08	-0.07	-0.10	-0.11	0.04	-0.03	0.05	0.06	0.00									
R1	0.05	0.05	0.03	0.03	0.04	0.00	0.01	0.08	-0.00	-0.05	-0.04	0.04	0.00								
R2	0.02	0.03	0.05	0.06	0.06	0.05	0.04	0.05	-0.02	-0.08	-0.09	-0.02	-0.00	0.00							
R3	-0.01	-0.01	0.03	0.01	-0.02	-0.01	0.00	0.04	-0.07	-0.09	-0.07	0.04	-0.00	0.02	0.00						
R4	0.01	-0.00	0.04	0.04	0.02	-0.00	-0.00	0.03	-0.06	-0.06	-0.08	0.02	0.02	0.02	0.07	0.00					
SE	-0.09	-0.04	-0.01	0.00	-0.05	-0.04	-0.03	-0.00	0.06	0.07	0.05	0.08	-0.03	-0.03	-0.04	-0.06	0.00				
SO	-0.08	-0.04	0.00	-0.01	-0.02	-0.05	-0.01	-0.04	0.05	0.04	0.04	0.09	-0.05	-0.04	-0.03	-0.05	-0.00	0.00			
US	-0.11	-0.07	-0.07	-0.00	-0.07	-0.05	-0.03	-0.07	0.10	0.12	0.08	0.08	-0.06	-0.06	-0.06	-0.08	0.05	0.05	0.00		
MG	0.00	0.04	-0.05	0.10	0.01	0.03	0.07	-0.05	0.05	0.01	-0.07	-0.13	-0.02	0.10	0.00	-0.01	-0.05	-0.04	-0.00	0.00	
RG	-0.04	-0.04	-0.01	0.03	0.03	-0.03	-0.04	-0.03	0.06	0.03	0.02	0.02	-0.03	-0.01	-0.01	-0.03	0.04	0.06	0.00	0.00	0.00

Table 28: Correlation residuals for $\mathcal{S}_{\setminus B}$ fit with Lucid sample. SE: perception of self-benefit; SO: perception of societal benefit; US: support for use; MG: support for management; RG: support for regulation.

Correlation residuals for $\mathcal{S}_{\setminus B}$ are shown in Table 28. Comparing these correlation residuals to those of $\mathcal{S}$ (Table 19), we generally observe satisfactory local fit in each model, but note that the relatively large magnitude correlation residual for support for use in $\mathcal{S}$ vanishes in $\mathcal{S}_{\setminus B}$. This provides further mild local evidence suggesting caution for accepting the causal structure hypothesized in $\mathcal{S}$, though this note of caution should be weighed against the generally slightly smaller-magnitude correlation residuals that $\mathcal{S}$ provides (as reflected by $\mathcal{S}$'s more satisfactory SRMR).

E.3 Differences between samples

See Supplement Section A.

E.4 Differences between contexts

Each of our five outcome variables are compared between samples and across contexts (see Supplement Section B) in Figure 14.

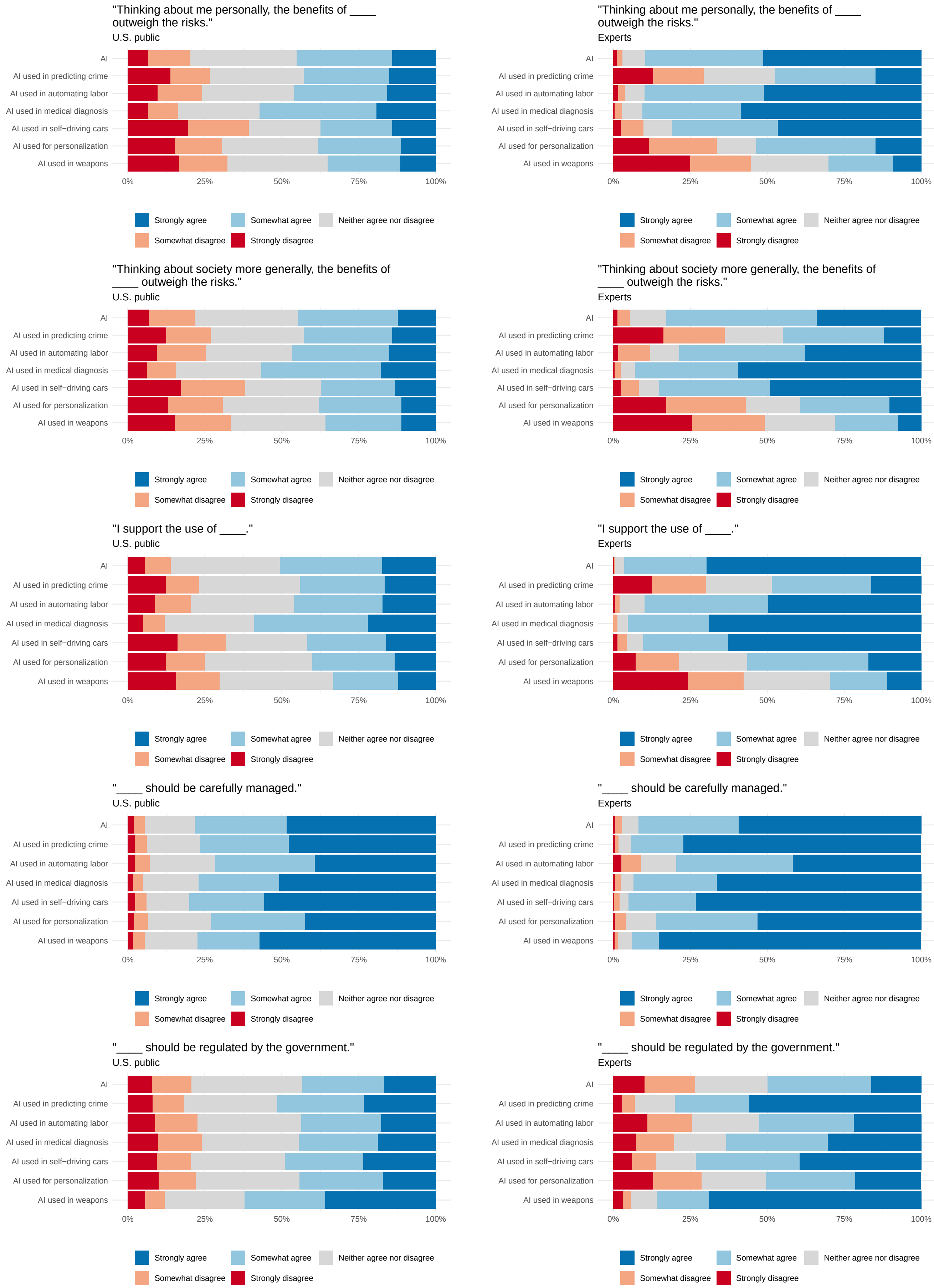

Figure 14: Comparison of outcome variables across contexts.

E.4.1 Correlations between contexts

Correlations across AI use contexts for each outcome variable are shown in Figure 15.

Correlations across AI use contexts and support for other technologies commonly considered in the technological risk perception literature are shown in Figure 16. Note that the question wording differed between AI use contexts ("I support the use of AI in [*context*]," strongly disagree to strongly agree) and other technologies "Which best represents your view on [*technology*]," risks significantly outweigh benefits to benefits significantly outweigh risks). See Supplement Section C for details.

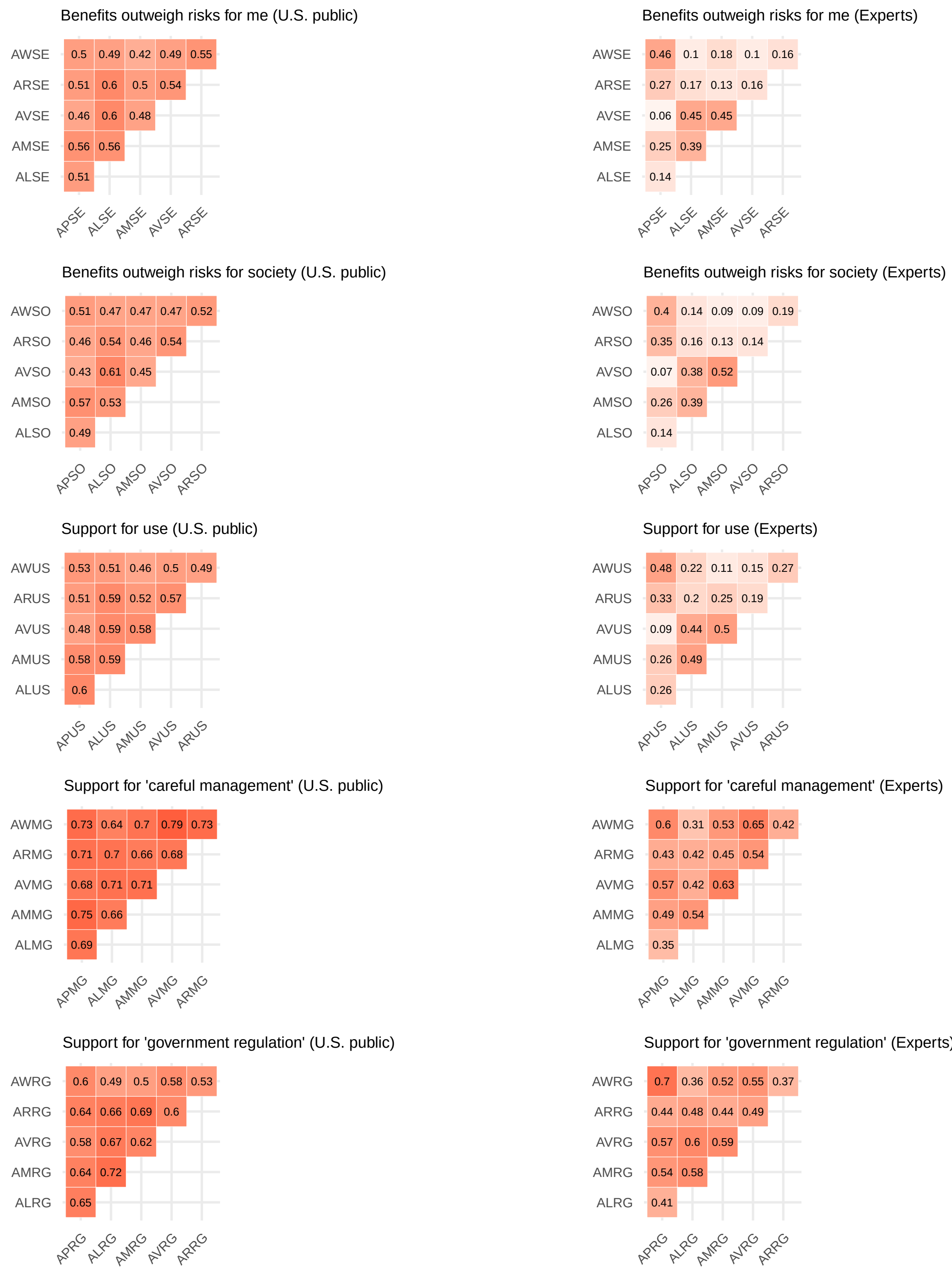

Figure 15: Correlations between contexts for each outcome variable. Task descriptions: AI used in... AW: weapons, AR: [for] personalization, AV: self-driving cars, AM: medical diagnosis, AL: automating labor, AP: predicting crime.

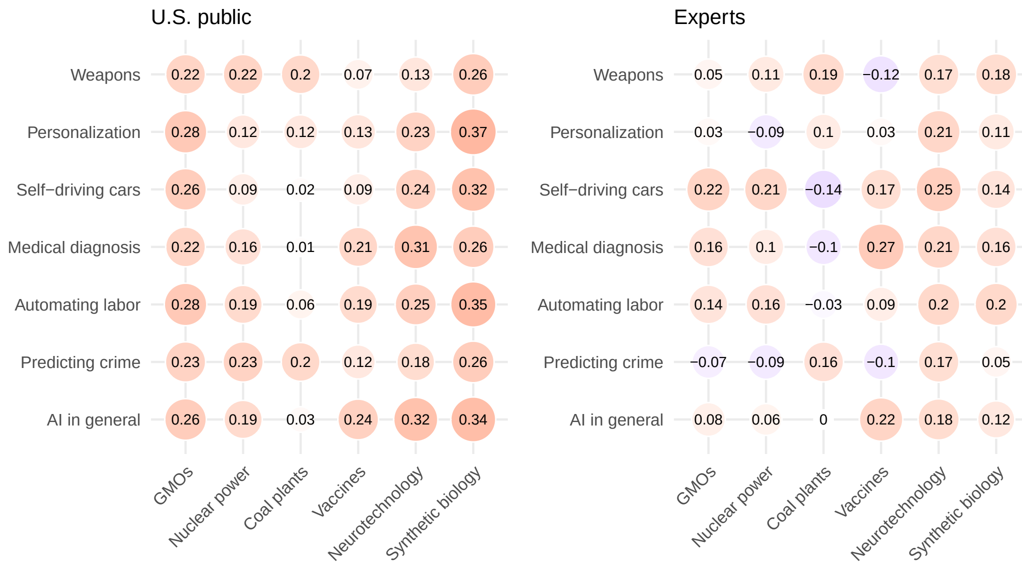

Figure 16: Correlations between support for AI use and belief that benefits outweigh risks for other technologies.

E.4.2 Multigroup SEM analysis across contexts

We next used multigroup SEM analysis to estimate the full SEM $\mathcal{S}$ (Figure 1), assuming that measurement invariance held across contexts. That is, we constrain the factor loadings of the four cultural value constructs to be equal between contexts. The seven groups used to fit this model are AI in general and the six contexts described in Section B. Table 29 shows fit statistics for this multi-group model. Because our survey asked each Lucid (U.S. public) respondent about only three randomly selected contexts, the sample size for each context was approximately half that of the sample size for AI in general. This is reflected in the chi-square test statistic for each group shown in Table 29.

The following tables show effects, covariances, and coefficients of determination estimated in this multigroup SEM for each context: AI in general (Table 30), predictive policing (Table 31), labor automation (Table 32), medical diagnosis (Table 33), autonomous vehicles (Table 34), personalization (Table 35), and autonomous weapons (Table 36).

	Multi-group	AI	Policing	Labor	Medical	Vehicles	Personalization	Weapons
χ^2_M (df_M, p)	25741.9 (2558, 0.000)	3986.2	2149.2	2046.7	1975.9	2214.1	2253.6	2189.4
CFI	0.929	–	–	–	–	–	–	–
RMSEA (90% CI)	0.053 (0.052, 0.053)	–	–	–	–	–	–	–
SRMR	0.040	–	–	–	–	–	–	–

Table 29: SEM fit statistics for multigroup analysis across contexts. Note that because our survey asked each Lucid (U.S. public) respondent about only three randomly selected contexts, the sample size for each context is approximately half that of the sample size for AI in general.

	Self-ben	Soc. ben	Supp. Use DE	Supp. Use TE	Supp. Management DE	Supp. Management TE	Supp. Regulation DE	Supp. Regulation TE
Gender=male	0.148***	0.149***	0.150***	0.241***	-0.001	-0.007	-0.015	0.007
	(0.037)	(0.038)	(0.029)	(0.038)	(0.040)	(0.040)	(0.037)	(0.038)
Ethn=white	0.178*	0.314***	0.156**	0.305***	0.312***	0.303***	0.171*	0.210**
	(0.071)	(0.070)	(0.056)	(0.071)	(0.070)	(0.069)	(0.071)	(0.072)
Ethn=black	0.129	0.268***	0.115	0.235**	0.056	0.049	0.175*	0.207*
	(0.082)	(0.079)	(0.066)	(0.082)	(0.081)	(0.081)	(0.082)	(0.084)
Ethn=asian	0.030	0.173	0.060	0.121	0.083	0.080	0.121	0.139
	(0.102)	(0.100)	(0.079)	(0.101)	(0.103)	(0.103)	(0.104)	(0.106)
Job=cognitive	0.431***	0.299***	0.184***	0.408***	0.206***	0.188***	0.065	0.114*
	(0.051)	(0.052)	(0.041)	(0.052)	(0.057)	(0.056)	(0.050)	(0.050)
Job=manual	0.078	-0.056	0.088*	0.095	-0.036	-0.039	-0.042	-0.044
	(0.058)	(0.057)	(0.043)	(0.056)	(0.061)	(0.061)	(0.059)	(0.060)
Job=service	0.106*	0.027	0.090*	0.131*	0.151**	0.147**	-0.033	-0.025
	(0.051)	(0.051)	(0.041)	(0.052)	(0.053)	(0.053)	(0.050)	(0.050)
Education	0.093***	0.087***	0.062***	0.118***	0.057**	0.053*	0.022	0.035
	(0.020)	(0.020)	(0.016)	(0.020)	(0.021)	(0.021)	(0.020)	(0.020)
Urban	0.087***	0.089***	0.034*	0.087***	0.066***	0.062***	0.072***	0.085***
	(0.018)	(0.017)	(0.014)	(0.018)	(0.019)	(0.019)	(0.018)	(0.018)
Age group	-0.090***	-0.065***	-0.035**	-0.082***	0.151***	0.154***	0.001	-0.010
	(0.017)	(0.018)	(0.014)	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)
HH income	0.083***	0.083***	0.038*	0.089***	0.059**	0.055*	0.059**	0.071***
	(0.020)	(0.020)	(0.016)	(0.020)	(0.022)	(0.022)	(0.019)	(0.020)
Pol.=conservative	-0.076***	-0.065***	-0.061***	-0.104***	0.015	0.019	-0.106***	-0.116***
	(0.014)	(0.014)	(0.011)	(0.014)	(0.016)	(0.016)	(0.014)	(0.014)
Individualism	0.199***	0.197***	0.061***	0.181***	0.274***	0.265***	-0.168***	-0.139***
	(0.021)	(0.021)	(0.017)	(0.021)	(0.025)	(0.023)	(0.022)	(0.022)
Egalitarianism	0.305***	0.315***	0.131***	0.320***	0.329***	0.315***	0.144***	0.189***
	(0.019)	(0.019)	(0.016)	(0.019)	(0.022)	(0.020)	(0.020)	(0.019)
Techno-skepticism	-0.307***	-0.351***	-0.171***	-0.371***	-0.013	0.001	0.243***	0.194***
	(0.022)	(0.022)	(0.019)	(0.022)	(0.028)	(0.026)	(0.024)	(0.022)
Risk aversion	0.162***	0.145***	0.067***	0.161***	0.007	0.000	0.124***	0.146***
	(0.022)	(0.022)	(0.017)	(0.023)	(0.026)	(0.025)	(0.023)	(0.023)
Self-benefit	–	–	0.311***	–	-0.036	–	0.046*	–
			(0.016)		(0.026)		(0.021)	
Societal benefit	–	–	0.299***	–	-0.009	–	0.098***	–
			(0.016)		(0.026)		(0.022)	
Covariances								
Soc. ben	0.548***	1.000						
	(0.013)							
Supp. use	0.000	0.000	1.000					
Supp. management	0.000	0.000	0.110***		1.000			
			(0.013)					
Supp. regulation	0.000	0.000	0.037***		0.203***		1.000	
			(0.010)		(0.016)			
R^2	0.274	0.262	0.470		0.235		0.201	

Table 30: Effects for *AI in general* in model $\mathcal{S}$ fit with multigroup analysis and Lucid sample.

	Self-ben	Soc. ben	Supp. Use		Supp. Management		Supp. Regulation	
			DE	TE	DE	TE	DE	TE
Gender=male	0.138** (0.052)	0.152** (0.052)	0.094* (0.037)	0.206*** (0.052)	-0.043 (0.056)	-0.053 (0.056)	0.220*** (0.052)	0.247*** (0.053)
Ethn=white	0.251* (0.103)	0.201* (0.100)	0.073 (0.085)	0.242* (0.109)	0.166 (0.105)	0.156 (0.106)	0.277** (0.103)	0.317** (0.104)
Ethn=black	0.218 (0.116)	0.133 (0.115)	-0.047 (0.098)	0.081 (0.121)	-0.079 (0.120)	-0.083 (0.121)	0.340** (0.122)	0.370** (0.124)
Ethn=asian	0.113 (0.147)	0.091 (0.149)	-0.006 (0.125)	0.070 (0.158)	0.002 (0.148)	-0.002 (0.148)	0.178 (0.148)	0.196 (0.149)
Job=cognitive	0.429*** (0.073)	0.262*** (0.073)	0.126* (0.051)	0.379*** (0.072)	0.289*** (0.082)	0.282*** (0.081)	0.125 (0.072)	0.185* (0.073)
Job=manual	0.178* (0.084)	0.148 (0.085)	-0.003 (0.064)	0.119 (0.083)	-0.061 (0.088)	-0.068 (0.088)	-0.270** (0.090)	-0.241** (0.090)
Job=service	0.072 (0.069)	0.039 (0.070)	0.015 (0.054)	0.055 (0.072)	0.250*** (0.072)	0.249*** (0.073)	0.169* (0.069)	0.178* (0.070)
Education	0.103*** (0.029)	0.109*** (0.029)	0.027 (0.021)	0.109*** (0.029)	-0.005 (0.030)	-0.012 (0.030)	0.009 (0.029)	0.028 (0.029)
Urban	0.067** (0.024)	0.049* (0.025)	0.003 (0.017)	0.046 (0.024)	0.025 (0.026)	0.023 (0.026)	0.069** (0.025)	0.080** (0.025)
Age group	0.028 (0.026)	0.045 (0.026)	-0.025 (0.019)	0.005 (0.025)	0.175*** (0.026)	0.171*** (0.026)	-0.056* (0.025)	-0.050* (0.025)
HH income	0.091** (0.028)	0.118*** (0.028)	-0.003 (0.020)	0.078** (0.028)	0.065* (0.030)	0.057 (0.030)	0.021 (0.029)	0.040 (0.029)
Pol.=conservative	0.077*** (0.020)	0.067*** (0.020)	0.005 (0.013)	0.059** (0.020)	-0.059** (0.022)	-0.063** (0.022)	-0.156*** (0.020)	-0.143*** (0.020)
Individualism	0.170*** (0.031)	0.184*** (0.031)	0.016 (0.024)	0.153*** (0.032)	0.241*** (0.035)	0.229*** (0.035)	-0.185*** (0.033)	-0.153*** (0.033)
Egalitarianism	-0.013 (0.028)	-0.068* (0.028)	0.016 (0.021)	-0.019 (0.029)	0.350*** (0.027)	0.357*** (0.027)	0.294*** (0.027)	0.286*** (0.027)
Techno-skepticism	-0.130*** (0.034)	-0.127*** (0.035)	-0.022 (0.024)	-0.120*** (0.034)	-0.135*** (0.037)	-0.128*** (0.036)	0.051 (0.036)	0.028 (0.035)
Risk aversion	0.237*** (0.035)	0.220*** (0.036)	0.025 (0.026)	0.198*** (0.035)	0.050 (0.038)	0.038 (0.037)	0.040 (0.037)	0.081* (0.035)
Self-benefit	–	–	0.313*** (0.020)	–	0.049 (0.047)	–	0.077* (0.035)	–
Societal benefit	–	–	0.450*** (0.022)	–	-0.110* (0.046)	–	0.103** (0.034)	–
Covariances								
Soc. ben	0.717*** (0.014)	1.000						
Supp. use	0.000	0.000	1.000					
Supp. management	0.000	0.000	0.029 (0.016)		1.000			
Supp. regulation	0.000	0.000	0.053*** (0.013)		0.274*** (0.020)		1.000	
R^2	0.182	0.166	0.470		0.223		0.232	

Table 31: Effects for *policing* in model $\mathcal{S}$ fit with multigroup analysis and Lucid sample.

	Self-ben	Soc. ben	Supp. Use DE	Supp. Use TE	Supp. Management DE	Supp. Management TE	Supp. Regulation DE	Supp. Regulation TE
Gender=male	0.221*** (0.053)	0.232*** (0.053)	0.076 (0.040)	0.237*** (0.054)	-0.126* (0.056)	-0.122* (0.056)	0.063 (0.053)	0.091 (0.053)
Ethn=white	0.263* (0.106)	0.127 (0.104)	0.086 (0.078)	0.220* (0.102)	0.231* (0.100)	0.238* (0.100)	0.238* (0.105)	0.260* (0.107)
Ethn=black	0.230 (0.122)	0.209 (0.120)	0.014 (0.092)	0.169 (0.116)	-0.105 (0.115)	-0.101 (0.116)	0.153 (0.122)	0.179 (0.125)
Ethn=asian	0.157 (0.144)	0.222 (0.146)	-0.004 (0.111)	0.133 (0.150)	-0.016 (0.144)	-0.014 (0.145)	0.219 (0.151)	0.242 (0.156)
Job=cognitive	0.356*** (0.074)	0.421*** (0.073)	0.131* (0.056)	0.409*** (0.077)	0.176* (0.079)	0.181* (0.079)	0.068 (0.072)	0.116 (0.073)
Job=manual	0.175* (0.081)	0.133 (0.080)	0.091 (0.063)	0.199* (0.080)	0.036 (0.083)	0.040 (0.083)	0.023 (0.081)	0.041 (0.082)
Job=service	0.038 (0.070)	0.027 (0.071)	0.070 (0.051)	0.093 (0.071)	0.150* (0.073)	0.151* (0.073)	0.082 (0.072)	0.086 (0.073)
Education	0.147*** (0.028)	0.125*** (0.028)	0.068** (0.022)	0.164*** (0.028)	0.039 (0.029)	0.042 (0.029)	0.051 (0.028)	0.068* (0.028)
Urban	0.106*** (0.025)	0.086*** (0.025)	0.021 (0.018)	0.088*** (0.025)	0.079** (0.026)	0.082** (0.026)	0.084*** (0.025)	0.096*** (0.026)
Age group	-0.073** (0.025)	-0.073** (0.024)	-0.023 (0.018)	-0.075** (0.025)	0.142*** (0.025)	0.141*** (0.025)	-0.096*** (0.024)	-0.105*** (0.024)
HH income	0.104*** (0.028)	0.084** (0.028)	0.011 (0.020)	0.077** (0.028)	0.073* (0.029)	0.076** (0.029)	0.040 (0.027)	0.051 (0.028)
Pol.=conservative	-0.041* (0.020)	-0.071*** (0.020)	-0.001 (0.015)	-0.042* (0.020)	-0.009 (0.021)	-0.010 (0.021)	-0.096*** (0.019)	-0.103*** (0.019)
Individualism	0.195*** (0.029)	0.171*** (0.029)	0.095*** (0.022)	0.224*** (0.028)	0.199*** (0.032)	0.203*** (0.030)	-0.148*** (0.031)	-0.127*** (0.030)
Egalitarianism	0.295*** (0.026)	0.235*** (0.026)	0.104*** (0.020)	0.290*** (0.026)	0.253*** (0.029)	0.260*** (0.026)	0.186*** (0.027)	0.218*** (0.026)
Techno-skepticism	-0.220*** (0.029)	-0.207*** (0.030)	-0.105*** (0.021)	-0.256*** (0.029)	0.042 (0.032)	0.038 (0.031)	0.181*** (0.029)	0.155*** (0.029)
Risk aversion	0.139*** (0.029)	0.097** (0.030)	-0.013 (0.021)	0.069* (0.029)	0.075* (0.031)	0.079** (0.030)	0.174*** (0.029)	0.188*** (0.029)
Self-benefit	–	–	0.320*** (0.021)	–	0.033 (0.039)	–	0.049 (0.032)	–
Societal benefit	–	–	0.390*** (0.021)	–	-0.015 (0.036)	–	0.072* (0.030)	–
Covariances								
Soc. ben	0.622*** (0.016)	1.000						
Supp. use	0.000	0.000	1.000					
Supp. management	0.000	0.000	0.017 (0.016)		1.000			
Supp. regulation	0.000	0.000	0.026 (0.014)		0.221*** (0.020)		1.000	
R^2	0.279	0.230	0.493		0.224		0.238	

Table 32: Effects for *automating labor* in model $\mathcal{S}$ fit with multigroup analysis and Lucid sample.

			Supp. Use		Supp. Management		Supp. Regulation	
	Self-ben	Soc. ben	DE	TE	DE	TE	DE	TE
Gender=male	0.169**	0.146**	0.041	0.151**	-0.084	-0.054	0.155**	0.177***
	(0.054)	(0.054)	(0.039)	(0.055)	(0.056)	(0.057)	(0.053)	(0.053)
Ethn=white	0.412***	0.472***	0.178*	0.493***	0.150	0.245*	0.038	0.104
	(0.100)	(0.096)	(0.070)	(0.099)	(0.101)	(0.100)	(0.109)	(0.110)
Ethn=black	0.269*	0.294**	0.058	0.258*	-0.135	-0.076	0.105	0.147
	(0.116)	(0.112)	(0.082)	(0.115)	(0.114)	(0.116)	(0.123)	(0.126)
Ethn=asian	0.386**	0.430**	0.052	0.342*	-0.021	0.066	0.095	0.156
	(0.145)	(0.149)	(0.119)	(0.155)	(0.143)	(0.149)	(0.155)	(0.157)
Job=cognitive	0.186*	0.211**	0.011	0.153*	0.077	0.120	0.253***	0.283***
	(0.076)	(0.074)	(0.056)	(0.077)	(0.076)	(0.079)	(0.072)	(0.074)
Job=manual	-0.112	-0.048	0.039	-0.015	-0.091	-0.103	-0.012	-0.022
	(0.079)	(0.079)	(0.060)	(0.080)	(0.080)	(0.083)	(0.080)	(0.081)
Job=service	0.170*	0.159*	0.141**	0.258***	0.180*	0.213**	0.066	0.090
	(0.072)	(0.071)	(0.053)	(0.074)	(0.078)	(0.079)	(0.071)	(0.071)
Education	0.087**	0.121***	0.003	0.077**	-0.013	0.011	-0.003	0.013
	(0.029)	(0.028)	(0.022)	(0.030)	(0.030)	(0.030)	(0.028)	(0.029)
Urban	0.078**	0.039	0.031	0.070**	0.030	0.039	0.060*	0.068**
	(0.025)	(0.025)	(0.019)	(0.026)	(0.027)	(0.027)	(0.025)	(0.026)
Age group	-0.013	0.011	-0.002	-0.001	0.142***	0.143***	-0.072**	-0.072**
	(0.025)	(0.025)	(0.019)	(0.025)	(0.025)	(0.026)	(0.024)	(0.024)
HH income	0.119***	0.106***	0.057**	0.136***	0.005	0.027	0.014	0.030
	(0.029)	(0.029)	(0.021)	(0.029)	(0.031)	(0.032)	(0.028)	(0.029)
Pol.=conservative	-0.036	-0.057**	-0.032*	-0.066**	-0.010	-0.021	-0.083***	-0.090***
	(0.020)	(0.020)	(0.015)	(0.020)	(0.022)	(0.022)	(0.019)	(0.020)
Individualism	0.180***	0.163***	0.133***	0.253***	0.226***	0.260***	-0.184***	-0.160***
	(0.031)	(0.032)	(0.023)	(0.030)	(0.036)	(0.035)	(0.031)	(0.031)
Egalitarianism	0.299***	0.224***	0.086***	0.268***	0.288***	0.336***	0.140***	0.177***
	(0.027)	(0.027)	(0.021)	(0.027)	(0.030)	(0.029)	(0.028)	(0.027)
Techno-skepticism	-0.231***	-0.224***	-0.160***	-0.320***	-0.034	-0.080*	0.102**	0.069*
	(0.035)	(0.036)	(0.026)	(0.033)	(0.038)	(0.038)	(0.035)	(0.033)
Risk aversion	0.119***	0.134***	0.034	0.124***	-0.034	-0.007	0.197***	0.216***
	(0.035)	(0.036)	(0.025)	(0.034)	(0.037)	(0.037)	(0.034)	(0.034)
Self-benefit	–	–	0.311***	–	0.035	–	0.051	–
			(0.025)		(0.052)		(0.038)	
Societal benefit	–	–	0.396***	–	0.171***	–	0.095**	–
			(0.025)		(0.050)		(0.036)	
Covariances								
Soc. ben	0.685***	1.000						
	(0.017)							
Supp. use	0.000	0.000	1.000					
Supp. management	0.000	0.000	0.098***		1.000			
			(0.016)					
Supp. regulation	0.000	0.000	0.113***		0.156***		1.000	
			(0.014)		(0.023)			
R^2	0.222	0.193	0.491		0.228		0.196	

Table 33: Effects for *medical diagnosis* in model $\mathcal{S}$ fit with multigroup analysis and Lucid sample.

	Self-ben	Soc. ben	Supp. Use DE	Supp. Use TE	Supp. Management DE	Supp. Management TE	Supp. Regulation DE	Supp. Regulation TE
Gender=male	0.289***	0.291***	0.019	0.247***	-0.066	-0.111	0.148**	0.166**
	(0.054)	(0.053)	(0.035)	(0.053)	(0.060)	(0.059)	(0.054)	(0.054)
Ethn=white	0.119	0.036	0.017	0.074	0.043	0.031	0.050	0.050
	(0.100)	(0.099)	(0.070)	(0.102)	(0.104)	(0.103)	(0.108)	(0.107)
Ethn=black	0.109	0.045	0.085	0.142	-0.242*	-0.254*	-0.030	-0.029
	(0.116)	(0.117)	(0.088)	(0.118)	(0.122)	(0.120)	(0.123)	(0.124)
Ethn=asian	0.084	0.089	0.171	0.239	-0.059	-0.072	0.194	0.200
	(0.146)	(0.149)	(0.103)	(0.149)	(0.163)	(0.158)	(0.163)	(0.165)
Job=cognitive	0.261***	0.239***	0.127**	0.322***	0.279**	0.241**	0.131	0.145*
	(0.072)	(0.073)	(0.047)	(0.073)	(0.087)	(0.086)	(0.074)	(0.074)
Job=manual	0.066	0.049	0.010	0.054	-0.136	-0.145	-0.065	-0.063
	(0.082)	(0.083)	(0.057)	(0.081)	(0.086)	(0.085)	(0.084)	(0.084)
Job=service	-0.039	-0.011	0.004	-0.014	0.123	0.127	-0.045	-0.045
	(0.071)	(0.069)	(0.050)	(0.071)	(0.077)	(0.077)	(0.071)	(0.071)
Education	0.085**	0.103***	0.030	0.105***	0.014	-0.001	-0.007	0.000
	(0.028)	(0.028)	(0.019)	(0.028)	(0.031)	(0.030)	(0.028)	(0.028)
Urban	0.090***	0.073**	0.039*	0.102***	0.044	0.031	0.081**	0.085***
	(0.025)	(0.025)	(0.017)	(0.025)	(0.029)	(0.028)	(0.025)	(0.025)
Age group	-0.219***	-0.220***	-0.006	-0.178***	0.155***	0.188***	0.092***	0.079**
	(0.024)	(0.025)	(0.018)	(0.025)	(0.026)	(0.026)	(0.025)	(0.025)
HH income	0.056*	0.069*	0.035	0.085**	0.036	0.027	0.059*	0.064*
	(0.028)	(0.028)	(0.019)	(0.029)	(0.030)	(0.030)	(0.028)	(0.028)
Pol.=conservative	-0.121***	-0.118***	-0.045***	-0.138***	-0.040	-0.022	-0.153***	-0.160***
	(0.020)	(0.020)	(0.013)	(0.020)	(0.023)	(0.023)	(0.020)	(0.020)
Individualism	0.099**	0.087**	0.056**	0.128***	0.198***	0.183***	-0.147***	-0.142***
	(0.030)	(0.030)	(0.021)	(0.030)	(0.034)	(0.033)	(0.030)	(0.030)
Egalitarianism	0.226***	0.174***	0.066**	0.220***	0.360***	0.329***	0.224***	0.233***
	(0.027)	(0.028)	(0.020)	(0.027)	(0.029)	(0.028)	(0.027)	(0.027)
Techno-skepticism	-0.073*	-0.097**	-0.105***	-0.173***	-0.105**	-0.092*	0.085**	0.078*
	(0.031)	(0.030)	(0.020)	(0.031)	(0.037)	(0.036)	(0.031)	(0.031)
Risk aversion	0.066*	0.109***	0.021	0.092**	0.092*	0.078*	0.147***	0.155***
	(0.033)	(0.032)	(0.022)	(0.032)	(0.037)	(0.036)	(0.033)	(0.033)
Self-benefit	–	–	0.342***	–	-0.077	–	-0.026	–
			(0.023)		(0.055)		(0.044)	
Societal benefit	–	–	0.442***	–	-0.077	–	0.087*	–
			(0.023)		(0.053)		(0.042)	
Covariances								
Soc. ben	0.763***	1.000						
	(0.013)							
Supp. use	0.000	0.000	1.000					
Supp. management	0.000	0.000	0.065***		1.000			
			(0.018)					
Supp. regulation	0.000	0.000	-0.001		0.275***		1.000	
			(0.015)		(0.023)			
R^2	0.232	0.221	0.546		0.229		0.199	

Table 34: Effects for *autonomous vehicles* in model $\mathcal{S}$ fit with multigroup analysis and Lucid sample.

	Self-ben	Soc. ben	Supp. Use		Supp. Management		Supp. Regulation	
			DE	TE	DE	TE	DE	TE
Gender=male	0.121* (0.053)	0.072 (0.053)	0.006 (0.036)	0.074 (0.053)	-0.088 (0.057)	-0.098 (0.056)	0.027 (0.052)	0.040 (0.054)
Ethn=white	0.238* (0.102)	0.260* (0.103)	-0.019 (0.081)	0.161 (0.100)	0.092 (0.100)	0.067 (0.100)	0.077 (0.099)	0.123 (0.100)
Ethn=black	0.147 (0.118)	0.213 (0.119)	0.048 (0.095)	0.179 (0.119)	0.044 (0.120)	0.026 (0.119)	0.139 (0.120)	0.177 (0.122)
Ethn=asian	-0.027 (0.142)	0.206 (0.143)	-0.027 (0.112)	0.042 (0.145)	-0.012 (0.149)	-0.018 (0.149)	0.107 (0.140)	0.143 (0.142)
Job=cognitive	0.244*** (0.074)	0.225** (0.074)	0.052 (0.050)	0.221** (0.075)	0.209* (0.081)	0.185* (0.081)	0.007 (0.074)	0.047 (0.075)
Job=manual	-0.001 (0.084)	0.084 (0.086)	0.057 (0.061)	0.088 (0.082)	0.041 (0.087)	0.038 (0.087)	0.177* (0.082)	0.192* (0.085)
Job=service	-0.045 (0.072)	0.008 (0.070)	0.009 (0.050)	-0.003 (0.072)	0.106 (0.074)	0.108 (0.074)	-0.022 (0.069)	-0.020 (0.070)
Education	0.037 (0.029)	0.032 (0.029)	0.029 (0.021)	0.054 (0.029)	0.039 (0.029)	0.035 (0.029)	0.081** (0.029)	0.087** (0.029)
Urban	0.079** (0.025)	0.082** (0.025)	0.041* (0.017)	0.099*** (0.025)	0.063* (0.027)	0.055* (0.027)	0.054* (0.025)	0.068** (0.025)
Age group	-0.159*** (0.025)	-0.172*** (0.025)	-0.048** (0.018)	-0.168*** (0.025)	0.187*** (0.026)	0.204*** (0.026)	0.045 (0.024)	0.015 (0.024)
HH income	0.111*** (0.028)	0.120*** (0.029)	0.036 (0.021)	0.119*** (0.029)	0.112*** (0.029)	0.101*** (0.029)	0.059* (0.028)	0.080** (0.028)
Pol.=conservative	-0.107*** (0.020)	-0.090*** (0.020)	-0.031* (0.013)	-0.102*** (0.020)	-0.031 (0.022)	-0.021 (0.021)	-0.109*** (0.020)	-0.125*** (0.020)
Individualism	0.177*** (0.028)	0.176*** (0.028)	0.037 (0.021)	0.164*** (0.029)	0.183*** (0.031)	0.165*** (0.030)	-0.166*** (0.029)	-0.135*** (0.029)
Egalitarianism	0.278*** (0.025)	0.244*** (0.026)	0.061** (0.019)	0.249*** (0.025)	0.273*** (0.029)	0.246*** (0.027)	0.141*** (0.027)	0.185*** (0.026)
Techno-skepticism	-0.204*** (0.030)	-0.251*** (0.030)	-0.076*** (0.021)	-0.241*** (0.030)	0.036 (0.034)	0.059 (0.033)	0.175*** (0.032)	0.131*** (0.031)
Risk aversion	0.173*** (0.029)	0.188*** (0.029)	0.056** (0.020)	0.186*** (0.029)	0.048 (0.032)	0.030 (0.031)	0.105*** (0.031)	0.138*** (0.030)
Self-benefit	–	–	0.339*** (0.023)	–	-0.064 (0.041)	–	0.002 (0.036)	–
Societal benefit	–	–	0.383*** (0.023)	–	-0.040 (0.041)	–	0.175*** (0.036)	–
Covariances								
Soc. ben	0.650*** (0.016)	1.000						
Supp. use	0.000	0.000	1.000					
Supp. management	0.000	0.000	0.010 (0.015)		1.000			
Supp. regulation	0.000	0.000	0.002 (0.013)		0.259*** (0.021)		1.000	
R^2	0.251	0.237	0.492		0.194		0.192	

Table 35: Effects for *personalization* in model $\mathcal{S}$ fit with multigroup analysis and Lucid sample.

	Self-ben	Soc. ben	Supp. Use		Supp. Management		Supp. Regulation	
			DE	TE	DE	TE	DE	TE
Gender=male	0.179*** (0.054)	0.113* (0.054)	0.080* (0.039)	0.184*** (0.054)	-0.030 (0.059)	-0.041 (0.059)	0.091 (0.055)	0.101 (0.055)
Ethn=white	0.087 (0.107)	0.079 (0.107)	-0.058 (0.075)	0.003 (0.109)	0.409*** (0.106)	0.401*** (0.104)	0.232* (0.107)	0.239* (0.109)
Ethn=black	0.130 (0.120)	0.232 (0.119)	-0.090 (0.090)	0.046 (0.122)	-0.043 (0.123)	-0.070 (0.121)	0.132 (0.124)	0.148 (0.125)
Ethn=asian	-0.148 (0.157)	-0.122 (0.165)	-0.068 (0.128)	-0.166 (0.166)	0.015 (0.155)	0.028 (0.155)	0.154 (0.160)	0.144 (0.162)
Job=cognitive	0.131 (0.070)	0.147* (0.071)	0.172*** (0.051)	0.274*** (0.073)	0.150 (0.081)	0.134 (0.080)	0.153* (0.072)	0.164* (0.073)
Job=manual	0.025 (0.085)	0.052 (0.082)	0.211** (0.071)	0.239** (0.087)	-0.025 (0.090)	-0.031 (0.090)	-0.058 (0.087)	-0.055 (0.087)
Job=service	-0.127 (0.072)	-0.044 (0.073)	0.055 (0.054)	-0.005 (0.073)	0.234** (0.077)	0.237** (0.077)	0.088 (0.070)	0.084 (0.070)
Education	0.067* (0.029)	0.068* (0.029)	0.060** (0.021)	0.109*** (0.029)	0.049 (0.032)	0.041 (0.032)	0.116*** (0.029)	0.121*** (0.029)
Urban	0.049 (0.026)	0.031 (0.026)	-0.010 (0.019)	0.018 (0.025)	0.101*** (0.029)	0.098*** (0.029)	0.070** (0.026)	0.072** (0.026)
Age group	-0.013 (0.025)	-0.044 (0.026)	-0.008 (0.019)	-0.030 (0.026)	0.179*** (0.027)	0.185*** (0.027)	0.090*** (0.025)	0.087*** (0.025)
HH income	0.097*** (0.029)	0.125*** (0.029)	0.015 (0.020)	0.097*** (0.029)	0.030 (0.032)	0.016 (0.031)	0.008 (0.029)	0.017 (0.029)
Pol.=conservative	0.002 (0.020)	0.012 (0.020)	0.023 (0.014)	0.028 (0.020)	-0.032 (0.024)	-0.033 (0.024)	-0.114*** (0.021)	-0.113*** (0.021)
Individualism	0.164*** (0.030)	0.143*** (0.031)	0.077** (0.024)	0.189*** (0.031)	0.257*** (0.042)	0.243*** (0.041)	-0.176*** (0.035)	-0.165*** (0.034)
Egalitarianism	0.098*** (0.029)	0.071* (0.029)	0.036 (0.021)	0.096** (0.029)	0.340*** (0.033)	0.333*** (0.032)	0.214*** (0.030)	0.219*** (0.029)
Techno-skepticism	-0.071* (0.033)	-0.080* (0.034)	-0.077** (0.024)	-0.133*** (0.034)	-0.137** (0.044)	-0.128** (0.043)	0.024 (0.037)	0.018 (0.037)
Risk aversion	0.118*** (0.033)	0.142*** (0.034)	0.001 (0.025)	0.097** (0.034)	-0.004 (0.041)	-0.020 (0.040)	0.124*** (0.037)	0.135*** (0.036)
Self-benefit	–	–	0.334*** (0.022)	–	0.022 (0.053)	–	0.015 (0.044)	–
Societal benefit	–	–	0.395*** (0.023)	–	-0.129* (0.053)	–	0.062 (0.044)	–
Covariances								
Soc. ben	0.762*** (0.012)	1.000						
Supp. use	0.000	0.000	1.000					
Supp. management	0.000	0.000	-0.002 (0.023)		1.000			
Supp. regulation	0.000	0.000	0.021 (0.017)		0.469*** (0.020)		1.000	
R^2	0.110	0.105	0.443		0.233		0.183	

Table 36: Effects for *weapons* in model $\mathcal{S}$ fit with multigroup analysis and Lucid sample.

F Results replicated with attentive subsample

This section contains the results restricted to the attentive subsamples.

F.1 Results from main paper

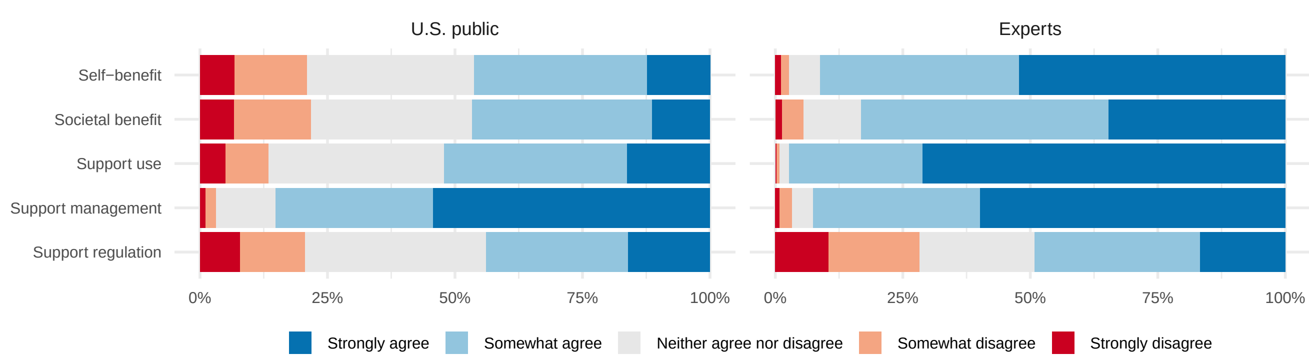

Figure 17: (Replication of Figure 2 with attentive subsample.) Outcome measures for both samples when respondents are presented a general (context-free) definition of AI.

	$\bar{x}_{\text{Lucid}}$	$\bar{x}_{\text{OMS}}$	$\bar{x}_{\text{Lucid}} - \bar{x}_{\text{OMS}}$	p-value
Age group (0-4)	1.75 (1.12)	0.89 (0.56)	(0.79, 0.92)	<0.001***
Gender = Male	0.49 (0.50)	0.81 (0.39)	(-0.37, -0.29)	<0.001***
Ethn = White	0.75 (0.43)	0.41 (0.49)	(0.29, 0.39)	<0.001***
Ethn = Black	0.13 (0.33)	0.03 (0.16)	(0.08, 0.12)	<0.001***
Ethn = Asian	0.05 (0.22)	0.48 (0.50)	(-0.48, -0.38)	<0.001***
Education (0-3)	1.36 (1.08)	2.24 (0.43)	(-0.94, -0.83)	<0.001***
Cognitive employment	0.25 (0.43)	0.97 (0.17)	(-0.75, -0.70)	<0.001***
Manual employment	0.14 (0.35)	0.00 (0.05)	(0.12, 0.15)	<0.001***
Social employment	0.22 (0.42)	0.01 (0.10)	(0.20, 0.23)	<0.001***
Household income (0-3)	1.23 (1.06)	2.19 (0.91)	(-1.05, -0.87)	<0.001***
Political orientation (-2-+2)	-0.01 (1.23)	-0.52 (0.93)	(0.42, 0.61)	<0.001***
Urban (0-3)	1.59 (1.05)	2.16 (0.79)	(-0.66, -0.49)	<0.001***
Individualism (standardized)	0.06 (0.92)	-0.47 (0.73)	(0.46, 0.61)	<0.001***
Egalitarianism (standardized)	-0.05 (0.90)	0.21 (0.78)	(-0.34, -0.18)	<0.001***
Techno-skepticism (standardized)	0.06 (0.92)	-0.45 (0.81)	(0.43, 0.59)	<0.001***
Risk aversion (standardized)	0.03 (0.89)	-0.24 (0.69)	(0.20, 0.34)	<0.001***
Self-benefit (AI; -2-+2)	0.32 (1.08)	1.37 (0.80)	(-1.13, -0.96)	<0.001***
Societal benefit (AI; -2-+2)	0.28 (1.08)	1.10 (0.86)	(-0.90, -0.73)	<0.001***
Suppert use (AI; -2-+2)	0.49 (1.05)	1.65 (0.58)	(-1.23, -1.10)	<0.001***
Support management (AI; -2-+2)	1.19 (0.96)	1.48 (0.76)	(-0.36, -0.21)	<0.001***
Support regulation (AI; -2-+2)	0.32 (1.13)	0.29 (1.21)	(-0.10, 0.14)	0.715

Table 37: (Replication of Table 1 with attentive sample.) Means, standard deviations, 95% confidence intervals for differences in means, and p-value (Welch's two-tailed t-test) for each variable in U.S. public (Lucid) and expert (OMS) samples. Gender was coded as a binary variable (male, female or other gender), and age was coded using Pew's classification of generational groups (18-25, 26-40, 41-56, 57-75, 76+). Race was coded as White, Black, Asian, or other, as we anticipated that only these groups would be large enough in both samples to detect effects. We used four-level scales for each of education, household income, and urban/rural residence. Political orientation was collected using a five-point Likert scale with endpoints "strong liberal" and "strong conservative."

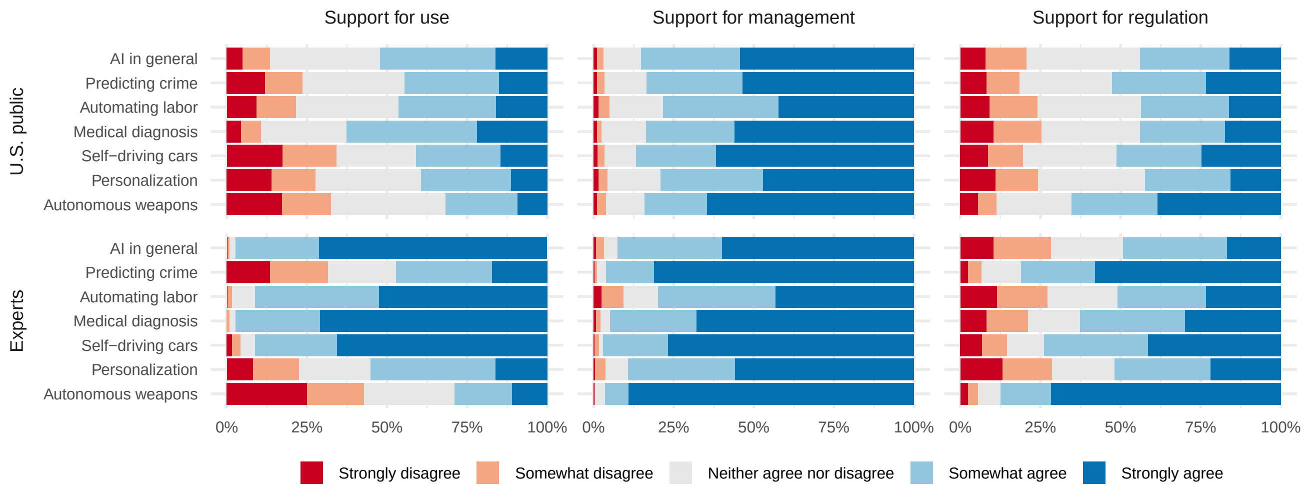

Figure 18: (Replication of Figure 3 with attentive subsample.) Support outcome variables between samples and among common AI application areas. Reported support for use, "careful management," and government regulation in AI contexts. Before responding, participants were provided two-sentence vignettes, listed in Supplemental Section B, describing arguments for and against the use of AI in the context.

	Model fit statistics					R^2 (benefit)		R^2 (support)		
	χ^2 (df, P)	CFI	RMSEA (90% CI)	SRMR	$\Delta\chi^2$ (Δdf, P)	Self	Soc.	Use	Mgt.	Reg.
Model $\mathcal{S}$	4581.5 (350, <0.001)	0.884	0.068 (0.066, 0.070)	0.035	–	0.264	0.257	0.491	0.115	0.145
Model $\mathcal{S}_{\setminus C}$	6549.2 (370, <0.001)	0.830	0.080 (0.078, 0.082)	0.083	1177.5 (20, <0.001)	0.133	0.112	0.482	0.037	0.055
Model $\mathcal{S}_{\setminus B}$	5365.2 (356, <0.001)	0.862	0.074 (0.072, 0.075)	0.050	967.6 (6, <0.001)	0.571	0.566	0.814	0.095	0.125

Table 38: (Replication of Table 2 with attentive subsample.) Fit statistics for the complete SEM $\mathcal{S}$ and two nested models used for analysis. χ^2: model chi-square test, along with model degrees of freedom and P-value, CFI: comparative fit index, RMSEA: root mean squared error of approximation, SRMR: standardized root mean square residual, $\Delta\chi^2$: chi-square difference test (compared to full model $\mathcal{S}$). R^2 values show coefficients of determination for the five endogenous variables in the model. The complete model $\mathcal{S}$ achieved adequate-to-good global fit, with CFI and RMSEA indicating adequate fit, and SRMR indicating good fit. Reduced models $\mathcal{S}_{\setminus C}$ (used to assess the importance of the paths from cultural values to support outcomes) and $\mathcal{S}_{\setminus B}$ (used to assess the importance of the paths from perceived benefit to support outcomes) achieved adequate fit on RMSEA and SRMR, but poor global fit on CFI.

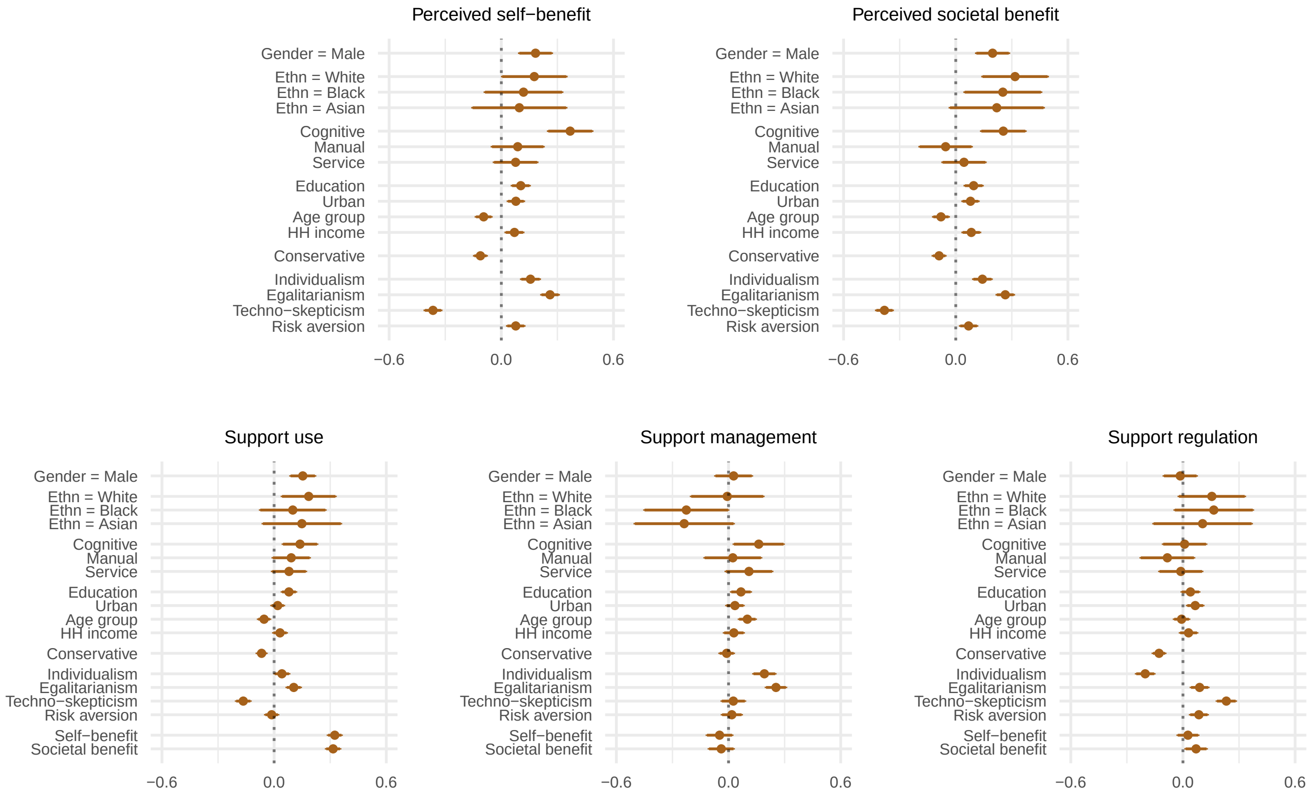

Figure 19: (Replication of Figure 4 with attentive subsample.) Inferred path coefficients (with 95% confidence intervals) for full SEM $\mathcal{S}$ fit with U.S. public data. Gender, race/ethnicity, and work type were coded as binary; education, household income, and urban residence were coded as four-level variables; age group and political orientation were coded as five-level variables; and cultural constructs and perceived benefit variables were standardized. See Table 2 for fit statistics.

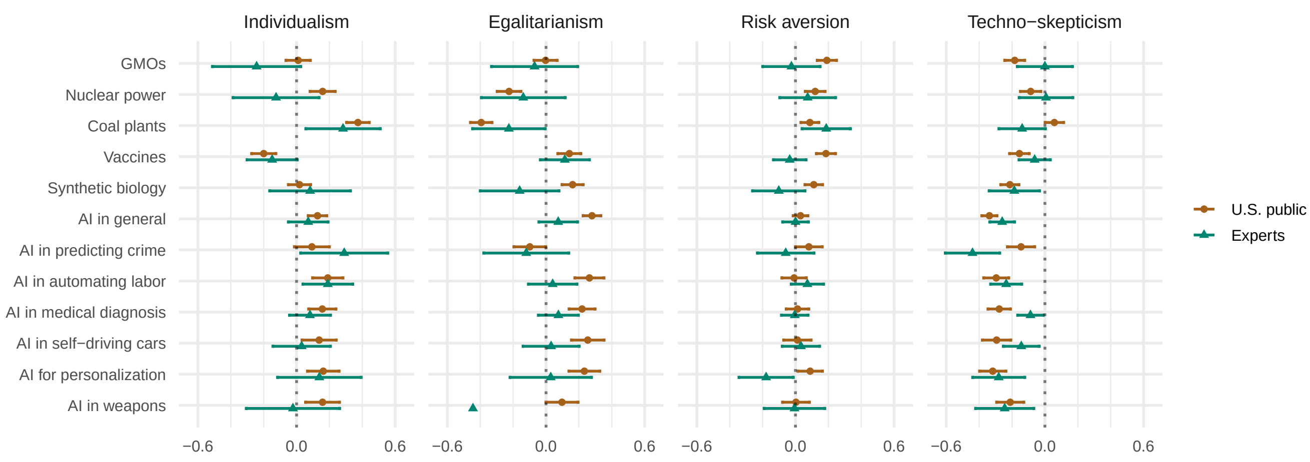

Figure 20: (Replication of Figure 5 with attentive subsample.) Comparison of cultural values' effects on support for AI contexts and other technologies. Markers show ordinary least-squares regression estimates and 95% confidence intervals when controlling for sociodemographic variables. For support for AI contexts, respondents were asked rather they supported the use of AI in a particular application. For other technologies, respondents were asked whether the technology's benefits outweighed its risks. Each outcome was measured on a five-point Likert scale; cultural value constructs were standardized and inferred from a confirmatory factor analysis model. This analysis was exploratory.

F.2 Role of cultural values

F.2.1 Psychometrics for cultural worldview constructs

	Lucid	OMS	Multigroup
χ^2_M (df_M, p)	846.5 (98, <0.001)	220.6 (98, <0.001)	1050.3 (208, <0.001)
CFI	0.979	0.967	0.980
RMSEA (90% CI)	0.054 (0.051, 0.058)	0.059 (0.048, 0.069)	0.052 (0.049, 0.055)
SRMR	0.039	0.057	0.042

Table 39: (Replication of Table 11 with attentive subsample.) Fit statistics for CFA model of cultural values.

	Lucid		OMS		Combined	
	α	AVE	α	AVE	α	AVE
Individualism	0.839	0.648	0.772	0.523	0.873	0.649
Egalitarianism	0.870	0.705	0.812	0.649	0.898	0.705
Techno-skepticism	0.797	0.561	0.770	0.564	0.830	0.561
Risk aversion	0.670	0.400	0.702	0.428	0.715	0.400

Table 40: (Replication of Table 12 with attentive subsample.) Construct reliabilities of four cultural values. α: Chronbach's alpha, AVE: average variance extracted. AVE in the combined sample is computed using a multigroup model in which indicator loadings are constrained to be equal between samples.

Item	λ (Lucid)	λ (OMS)	λ (Multigroup)
Individualism			
IND1: The government interferes far too much in our everyday lives.	0.862 (0.007)	0.723 (0.029)	0.858 (0.007)
IND2: The government should stop telling people how to live their lives.	0.778 (0.009)	0.591 (0.037)	0.771 (0.009)
IND3: If the government spent less time trying to fix everyone's problems, we'd all be a lot better off.	0.849 (0.008)	0.814 (0.028)	0.853 (0.008)
IND4: Too many people today expect society to do things for them that they should be doing for themselves.	0.724 (0.011)	0.748 (0.029)	0.734 (0.010)
Egalitarianism			
EGL1: Our society would be better off if the distribution of wealth was more equal.	0.826 (0.008)	0.779 (0.029)	0.824 (0.008)
EGL2: We need to dramatically reduce inequalities between the rich and the poor, white people and people of color, and men and women.	0.899 (0.006)	0.876 (0.022)	0.900 (0.006)
EGL3: Discrimination against minorities is still a very serious problem in our society.	0.866 (0.007)	0.803 (0.028)	0.864 (0.007)
EGL4: We live in a sexist society that is fundamentally set up to discriminate against women.	0.762 (0.010)	0.761 (0.027)	0.765 (0.009)
Techno-skepticism			
TSK1: New technologies are more about making profits rather than making peoples' lives better.	0.637 (0.013)	0.570 (0.042)	0.631 (0.012)
TSK2: I am worried about where all this technology is leading.	0.844 (0.009)	0.857 (0.023)	0.845 (0.008)
TSK3: Technology has become dangerous and unmanageable.	0.828 (0.009)	0.857 (0.022)	0.830 (0.009)
TSK4: I feel uncomfortable about new technologies.	0.663 (0.013)	0.678 (0.036)	0.664 (0.012)
Risk aversion			
RAV1: I tend to avoid talking to strangers.	0.495 (0.018)	0.524 (0.046)	0.496 (0.017)
RAV2: I prefer a routine way of life to an unpredictable one full of change.	0.671 (0.016)	0.615 (0.046)	0.663 (0.015)
RAV3: I would not describe myself as a risk-taker.	0.598 (0.016)	0.795 (0.042)	0.616 (0.015)
RAV4: I do not like taking too many chances to avoid making a mistake.	0.741 (0.014)	0.654 (0.047)	0.731 (0.014)

Table 41: (Replication of Table 13 with attentive subsample.) Standardized loadings and standard errors for cultural constructs from CFA models. The multigroup model constrained indicator loadings to be equal between samples.

	Lucid			OMS		
	I	E	TS	I	E	TS
Egalitarianism	-0.515 (0.017)	1.000		-0.635 (0.043)	1.000	
Techno-skept.	0.375 (0.019)	-0.023 (0.022)	1.000	0.075 (0.055)	0.162 (0.054)	1.000
Risk aversion	0.110 (0.023)	0.154 (0.024)	0.292 (0.022)	-0.159 (0.062)	0.045 (0.065)	0.212 (0.065)

Table 42: (Replication of Table 14 with attentive subsample.) Covariances between cultural value constructs from multigroup CFA.

	I1	I2	I3	I4	E1	E2	E3	E4	T1	T2	T3	T4	R1	R2	R3	R4
I1	0.00															
I2	0.06	0.00														
I3	-0.03	-0.03	0.00													
I4	-0.05	-0.03	0.04	0.00												
E1	0.04	0.05	-0.06	-0.06	0.00											
E2	0.05	0.08	-0.04	-0.01	0.03	0.00										
E3	0.01	0.04	-0.07	-0.04	-0.05	-0.01	0.00									
E4	0.07	0.04	-0.03	-0.03	-0.03	-0.02	0.04	0.00								
T1	0.05	0.01	-0.01	-0.01	0.13	0.06	0.03	0.12	0.00							
T2	0.04	-0.01	-0.01	0.01	0.02	-0.03	-0.07	0.02	0.00	0.00						
T3	0.03	-0.02	-0.01	-0.01	-0.02	-0.05	-0.09	0.04	0.02	-0.00	0.00					
T4	-0.01	-0.04	-0.02	-0.05	-0.03	-0.05	-0.07	0.04	-0.05	0.00	0.00	0.00				
R1	0.01	0.01	-0.03	-0.05	0.07	0.03	0.03	0.10	0.03	-0.01	-0.03	0.05	0.00			
R2	0.02	0.03	0.04	0.06	0.00	-0.02	-0.03	0.00	0.03	-0.01	-0.03	0.04	-0.01	0.00		
R3	-0.03	-0.02	-0.00	-0.00	-0.06	-0.03	-0.02	0.00	-0.04	-0.05	-0.04	0.09	-0.05	0.03	0.00	
R4	-0.02	-0.03	-0.01	0.01	0.00	-0.02	-0.01	0.00	0.00	0.00	-0.04	0.07	0.02	-0.03	0.02	0.00

Table 43: (Replication of Table 15 with attentive subsample.) Correlation residuals for CFA model fit with Lucid sample.

F.2.2 Impact of demographics

	Self-ben	Soc. ben	Supp. Use		Supp. Management		Supp. Regulation	
			DE	TE	DE	TE	DE	TE
Gender=male	0.183***	0.197***	0.128***	0.275***	0.020	0.011	-0.009	0.004
	(0.044)	(0.044)	(0.033)	(0.044)	(0.049)	(0.049)	(0.044)	(0.044)
Ethn=white	0.176*	0.317***	0.150*	0.342***	-0.015	-0.028	0.160	0.181*
	(0.087)	(0.089)	(0.073)	(0.090)	(0.098)	(0.098)	(0.090)	(0.090)
Ethn=black	0.119	0.252*	0.073	0.218*	-0.232*	-0.241*	0.169	0.186
	(0.105)	(0.104)	(0.090)	(0.107)	(0.114)	(0.114)	(0.106)	(0.107)
Ethn=asian	0.096	0.219	0.126	0.249	-0.242	-0.250	0.108	0.123
	(0.127)	(0.128)	(0.107)	(0.129)	(0.135)	(0.135)	(0.134)	(0.134)
Job=cognitive	0.368***	0.254***	0.098*	0.338***	0.150*	0.134*	0.019	0.036
	(0.060)	(0.060)	(0.046)	(0.060)	(0.067)	(0.067)	(0.058)	(0.058)
Job=manual	0.088	-0.054	0.091	0.103	0.022	0.021	-0.081	-0.085
	(0.070)	(0.071)	(0.049)	(0.069)	(0.077)	(0.077)	(0.073)	(0.073)
Job=service	0.076	0.044	0.072	0.118*	0.107	0.104	-0.009	-0.006
	(0.059)	(0.058)	(0.045)	(0.060)	(0.063)	(0.063)	(0.058)	(0.058)
Education	0.104***	0.096***	0.066***	0.143***	0.063*	0.058*	0.043	0.050*
	(0.024)	(0.024)	(0.019)	(0.024)	(0.026)	(0.026)	(0.023)	(0.024)
Urban	0.078***	0.079***	0.009	0.069**	0.031	0.027	0.068**	0.073***
	(0.021)	(0.021)	(0.016)	(0.022)	(0.023)	(0.023)	(0.022)	(0.022)
Age group	-0.095***	-0.079***	-0.042**	-0.110***	0.104***	0.108***	-0.010	-0.015
	(0.021)	(0.021)	(0.016)	(0.021)	(0.022)	(0.022)	(0.020)	(0.020)
HH income	0.070**	0.083***	0.021	0.081***	0.026	0.022	0.032	0.038
	(0.024)	(0.023)	(0.018)	(0.024)	(0.026)	(0.026)	(0.023)	(0.023)
Pol.=conservative	-0.112***	-0.089***	-0.054***	-0.131***	-0.006	-0.001	-0.131***	-0.137***
	(0.017)	(0.017)	(0.013)	(0.017)	(0.019)	(0.019)	(0.017)	(0.017)
Self-benefit	–	–	0.380***	–	-0.025	–	0.001	–
			(0.015)		(0.035)		(0.028)	
Societal benefit	–	–	0.394***	–	-0.026	–	0.067*	–
			(0.015)		(0.035)		(0.028)	
R^2	0.133	0.112	0.482		0.037		0.055	

Table 44: (Replication of Table 16 with attentive subsample.) Path coefficient estimates and standard errors for reduced model $\mathcal{S}_{\setminus C}$ fit with Lucid sample. DE = direct effect, TE = total effect.

	$\mathcal{S}_{\setminus C}$	$\mathcal{S}$
χ^2_M (df_M, p)	6549.2 (370, <0.001)	4581.5 (350, <0.001)
CFI	0.830	0.884
RMSEA (90% CI)	0.080 (0.078, 0.082)	0.068 (0.066, 0.070)
SRMR	0.087	0.036
χ^2_D (df_D, p)	1177.5 (20, <0.001)	

Table 45: (Replication of Table 17 with attentive subsample.) Fit statistics for $\mathcal{S}_{\setminus C}$ and $\mathcal{S}$ fit with Lucid sample.

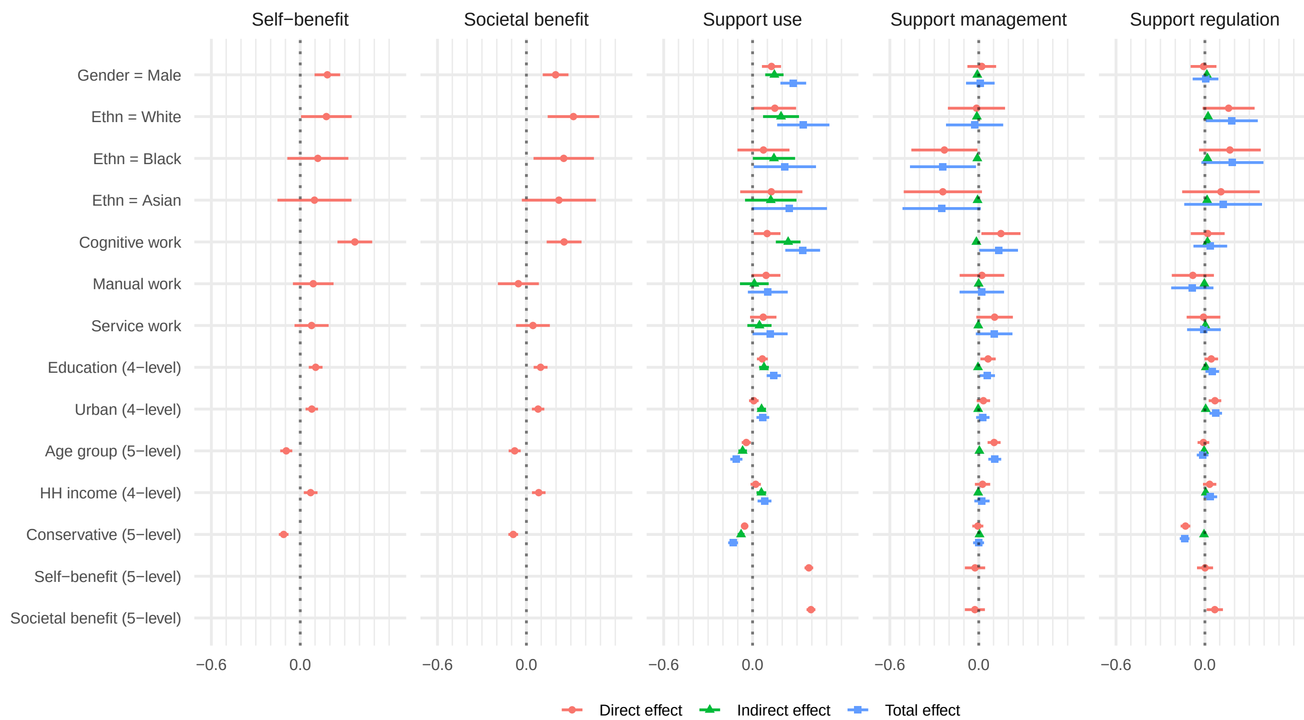

Figure 21: (Replication of Figure 9 with attentive subsample.) Direct, indirect, and total effects in the reduced model $\mathcal{S}_{\setminus C}$ fit with the Lucid sample. Variables are unstandardized; error bars show 95% confidence intervals.

Cultural values	I	E	TS
Egalitarianism	-0.271*** (0.021)	1.000	
Techno-skept.	0.366*** (0.019)	0.064** (0.022)	1.000
Risk aversion	0.123*** (0.023)	0.197*** (0.023)	0.274*** (0.022)
Perception of benefit	**Self**	**Society**	
Self	0.742*** (0.008)	1.000	
Support	**Use**	**Mgt.**	**Reg.**
Management	0.124*** (0.017)	1.000	
Regulation	-0.025 (0.014)	0.242*** (0.021)	1.000

Table 46: (Replication of Table 18 with attentive subsample.) Fit covariances for reduced model $\mathcal{S}_{\setminus C}$ fit with Lucid sample.

F.2.3 Comparison of $\mathcal{S}$ and $\mathcal{S}_{\setminus C}$

	Self-ben	Soc. ben	Supp. Use		Supp. Management		Supp. Regulation	
			DE	TE	DE	TE	DE	TE
Gender=male	0.183***	0.197***	0.153***	0.275***	0.027	0.011	-0.015	0.004
	(0.044)	(0.044)	(0.033)	(0.044)	(0.050)	(0.049)	(0.044)	(0.044)
Ethn=white	0.176*	0.317***	0.185*	0.342***	-0.007	-0.028	0.154	0.181*
	(0.087)	(0.089)	(0.073)	(0.090)	(0.098)	(0.098)	(0.090)	(0.090)
Ethn=black	0.119	0.252*	0.100	0.218*	-0.226*	-0.241*	0.165	0.186
	(0.105)	(0.104)	(0.089)	(0.107)	(0.114)	(0.114)	(0.106)	(0.107)
Ethn=asian	0.096	0.219	0.148	0.249	-0.237	-0.250	0.105	0.123
	(0.127)	(0.128)	(0.106)	(0.129)	(0.135)	(0.135)	(0.134)	(0.134)
Job=cognitive	0.368***	0.254***	0.138**	0.338***	0.162*	0.134*	0.009	0.036
	(0.060)	(0.060)	(0.046)	(0.060)	(0.068)	(0.067)	(0.058)	(0.058)
Job=manual	0.088	-0.054	0.092	0.103	0.023	0.021	-0.083	-0.085
	(0.070)	(0.071)	(0.050)	(0.069)	(0.077)	(0.077)	(0.072)	(0.073)
Job=service	0.076	0.044	0.080	0.118*	0.109	0.104	-0.012	-0.006
	(0.059)	(0.058)	(0.046)	(0.060)	(0.063)	(0.063)	(0.058)	(0.058)
Education	0.104***	0.096***	0.079***	0.143***	0.066*	0.058*	0.040	0.050*
	(0.024)	(0.024)	(0.019)	(0.024)	(0.026)	(0.026)	(0.024)	(0.024)
Urban	0.078***	0.079***	0.019	0.069**	0.034	0.027	0.066**	0.073***
	(0.021)	(0.021)	(0.017)	(0.022)	(0.023)	(0.023)	(0.022)	(0.022)
Age group	-0.095***	-0.079***	-0.054***	-0.110***	0.101***	0.108***	-0.007	-0.015
	(0.021)	(0.021)	(0.016)	(0.021)	(0.022)	(0.022)	(0.020)	(0.020)
HH income	0.070**	0.083***	0.032	0.081***	0.028	0.022	0.030	0.038
	(0.024)	(0.023)	(0.018)	(0.024)	(0.026)	(0.026)	(0.023)	(0.023)
Pol.=conservative	-0.112***	-0.089***	-0.067***	-0.131***	-0.010	-0.001	-0.128***	-0.137***
	(0.017)	(0.017)	(0.013)	(0.017)	(0.019)	(0.019)	(0.017)	(0.017)
Individualism	0.156***	0.143***	0.042*	0.137***	0.192***	0.179***	-0.202***	-0.188***
	(0.025)	(0.025)	(0.019)	(0.025)	(0.030)	(0.028)	(0.025)	(0.024)
Egalitarianism	0.261***	0.265***	0.105***	0.273***	0.254***	0.231***	0.089***	0.115***
	(0.023)	(0.023)	(0.019)	(0.023)	(0.027)	(0.025)	(0.023)	(0.022)
Techno-skepticism	-0.366***	-0.382***	-0.165***	-0.404***	0.026	0.058*	0.232***	0.196***
	(0.022)	(0.022)	(0.019)	(0.022)	(0.031)	(0.028)	(0.025)	(0.023)
Risk aversion	0.077***	0.069**	-0.013	0.033	0.018	0.011	0.085***	0.092***
	(0.023)	(0.023)	(0.017)	(0.023)	(0.027)	(0.026)	(0.024)	(0.023)
Self-benefit	–	–	0.324***	–	-0.048	–	0.027	–
			(0.018)		(0.034)		(0.028)	
Societal benefit	–	–	0.316***	–	-0.039	–	0.070*	–
			(0.019)		(0.033)		(0.028)	
R^2	0.264	0.257	0.491		0.115		0.145	

Table 47: (Replication of Table 19 with attentive subsample.) Effect estimates for $\mathcal{S}$ fit with Lucid sample. DE = direct effect, TE = total effect.

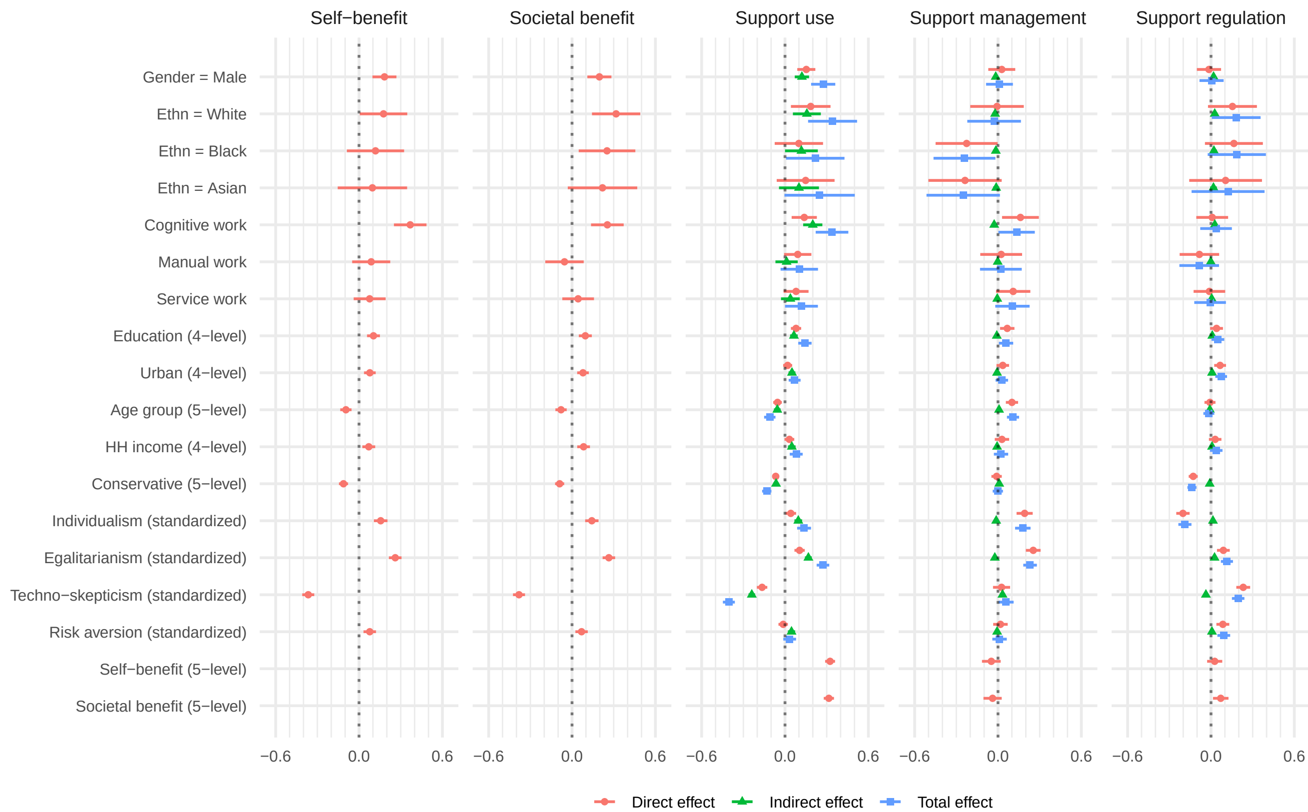

Figure 22: (Replication of Figure 10 with attentive subsample.) Direct, indirect, and total effects in the full model $\mathcal{S}$ fit with the Lucid sample. Variables other than cultural values are unstandardized except where noted; error bars show 95% confidence intervals.

Cultural values	I	E	TS
Egalitarianism	-0.271*** (0.021)	1.000	
Techno-skept.	0.366*** (0.019)	0.064** (0.022)	1.000
Risk aversion	0.123*** (0.023)	0.197*** (0.023)	0.274*** (0.022)
Perception of benefit	**Self**	**Society**	
Self	0.585*** (0.014)	1.000	
Support	**Use**	**Mgt.**	**Reg.**
Management	0.117*** (0.016)	1.000	
Regulation	-0.004 (0.013)	0.213*** (0.021)	1.000

Table 48: (Replication of Table 20 with attentive subsample.) Covariance estimates for $\mathcal{S}$ fit with Lucid sample.

	I1	I2	I3	I4	E1	E2	E3	E4	T1	T2	T3	T4	R1	R2	R3	R4	SE	SO	US	MG	RG
I1	0.00																				
I2	0.05	0.00																			
I3	-0.03	-0.03	0.00																		
I4	-0.06	-0.02	0.06	0.00																	
E1	0.02	0.04	-0.08	-0.05	0.00																
E2	0.04	0.08	-0.07	0.01	0.03	0.00															
E3	0.00	0.04	-0.08	-0.02	-0.06	-0.00	0.00														
E4	0.08	0.04	-0.03	-0.02	-0.03	-0.04	0.06	0.00													
T1	0.06	0.01	0.01	0.01	0.12	0.04	0.01	0.12	0.00												
T2	0.03	-0.03	-0.00	0.02	0.04	-0.04	-0.07	0.02	-0.01	0.00											
T3	0.03	-0.03	-0.00	-0.00	-0.00	-0.06	-0.09	0.04	0.01	0.00	0.00										
T4	-0.02	-0.06	-0.01	-0.06	-0.01	-0.04	-0.07	0.05	-0.05	0.01	0.01	0.00									
R1	0.03	0.03	0.00	-0.01	0.03	-0.02	-0.00	0.08	0.03	-0.00	-0.02	0.08	0.00								
R2	-0.01	0.00	0.02	0.04	0.04	0.01	0.01	0.02	0.03	-0.02	-0.04	0.03	-0.01	0.00							
R3	-0.04	-0.03	-0.01	-0.01	-0.05	-0.02	-0.01	-0.00	-0.04	-0.07	-0.05	0.07	-0.02	0.02	0.00						
R4	-0.01	-0.03	0.01	0.03	-0.00	-0.04	-0.01	-0.02	0.00	0.01	-0.03	0.08	-0.00	-0.02	0.02	0.00					
SE	-0.07	-0.03	-0.01	0.00	0.14	0.19	0.18	0.15	-0.17	-0.22	-0.24	-0.17	0.04	0.05	0.02	0.01	0.00				
SO	-0.08	-0.06	-0.01	-0.02	0.17	0.18	0.19	0.14	-0.19	-0.24	-0.27	-0.16	0.01	0.04	0.04	0.01	-0.00	0.00			
US	-0.09	-0.07	-0.08	0.01	0.15	0.19	0.20	0.13	-0.21	-0.25	-0.28	-0.23	-0.01	0.02	0.01	-0.03	-0.00	0.00	-0.30		
MG	0.10	0.12	0.03	0.18	0.14	0.18	0.19	0.07	0.16	0.17	0.09	-0.01	0.00	0.14	0.05	0.04	-0.00	0.00	-0.00	-0.00	
RG	-0.12	-0.14	-0.10	-0.04	0.21	0.15	0.13	0.12	0.14	0.14	0.10	0.10	0.07	0.11	0.11	0.09	-0.00	0.00	-0.00	-0.00	-0.00

Table 49: (Replication of Table 21 with attentive subsample.) Correlation residuals for $\mathcal{S}_{\setminus C}$ fit with Lucid sample. SE: perception of self-benefit; SO: perception of societal benefit; US: support for use; MG: support for management; RG: support for regulation.

	I1	I2	I3	I4	E1	E2	E3	E4	T1	T2	T3	T4	R1	R2	R3	R4	SE	SO	US	MG	RG
I1	0.00																				
I2	0.04	0.00																			
I3	-0.03	-0.03	0.00																		
I4	-0.06	-0.02	0.06	0.00																	
E1	0.02	0.04	-0.08	-0.05	0.00																
E2	0.04	0.08	-0.07	0.01	0.03	0.00															
E3	0.00	0.04	-0.08	-0.02	-0.06	-0.01	0.00														
E4	0.08	0.04	-0.03	-0.02	-0.03	-0.04	0.06	0.00													
T1	0.06	0.01	0.01	0.01	0.12	0.04	0.01	0.12	0.00												
T2	0.03	-0.03	-0.00	0.02	0.04	-0.03	-0.07	0.02	-0.01	0.00											
T3	0.02	-0.03	-0.00	-0.00	-0.00	-0.06	-0.09	0.04	0.00	0.00	0.00										
T4	-0.02	-0.06	-0.01	-0.06	-0.01	-0.04	-0.07	0.05	-0.05	0.02	0.01	0.00									
R1	0.03	0.03	0.00	-0.01	0.03	-0.02	-0.00	0.08	0.03	-0.00	-0.02	0.08	0.00								
R2	-0.01	-0.00	0.02	0.03	0.04	0.01	0.01	0.02	0.03	-0.02	-0.04	0.03	-0.01	0.00							
R3	-0.04	-0.03	-0.01	-0.01	-0.05	-0.02	-0.01	-0.00	-0.04	-0.07	-0.05	0.07	-0.02	0.02	0.00						
R4	-0.01	-0.03	0.01	0.03	-0.00	-0.04	-0.01	-0.02	0.00	0.01	-0.03	0.08	0.00	-0.02	0.03	0.00					
SE	-0.04	-0.00	0.02	0.03	-0.02	0.00	0.01	0.01	0.01	0.01	-0.01	-0.00	0.02	0.01	-0.01	-0.02	0.00				
SO	-0.03	-0.02	0.03	0.01	0.00	-0.01	0.01	-0.01	0.00	0.00	-0.02	0.03	-0.01	0.01	0.02	-0.01	-0.00	0.00			
US	-0.02	-0.01	-0.01	0.06	-0.01	0.01	0.02	-0.02	0.01	0.03	-0.01	-0.02	-0.01	0.02	0.01	-0.02	0.05	0.05	-0.17		
MG	-0.01	0.02	-0.07	0.09	-0.01	0.02	0.04	-0.06	0.06	0.05	-0.03	-0.10	-0.05	0.08	-0.01	-0.03	-0.01	-0.01	-0.00	-0.00	
RG	-0.00	-0.04	0.01	0.04	0.06	-0.02	-0.02	-0.01	0.04	0.01	-0.03	-0.01	-0.01	0.01	0.02	-0.02	0.00	0.01	0.00	-0.00	-0.00

Table 50: (Replication of Table 22 with attentive subsample.) Correlation residuals for $\mathcal{S}$ fit with Lucid sample. SE: perception of self-benefit; SO: perception of societal benefit; US: support for use; MG: support for management; RG: support for regulation.

F.2.4 Results with mediated cultural values model

Cultural values	I	E	TS
Egalitarianism	-0.245*** (0.022)	1.000	
Techno-skept.	–	–	1.000
Risk aversion	–	–	0.204*** (0.023)
Path coefficients			
Ind → Tsk	0.432*** (0.026)		
Ind → Rav	0.176*** (0.026)		
Egl → Tsk	0.171*** (0.024)		
Egl → Rav	0.256*** (0.027)		

Table 51: (Replication of Table 23 with attentive subsample.) Covariance estimates for $\mathcal{S}_{\text{mc}}$ fit with Lucid sample.

	Self-ben	Soc. ben	Supp. Use	Supp. Management	Supp. Regulation
Individualism	0.145*** (0.025)	0.135*** (0.024)	0.043* (0.019)	0.194*** (0.029)	-0.202*** (0.024)
Egalitarianism	0.250*** (0.023)	0.265*** (0.023)	0.105*** (0.018)	0.250*** (0.026)	0.089*** (0.023)
Techno-skepticism	-0.352*** (0.022)	-0.372*** (0.022)	-0.162*** (0.019)	0.021 (0.031)	0.220*** (0.025)
Risk aversion	0.067** (0.023)	0.054* (0.023)	-0.007 (0.017)	0.013 (0.027)	0.084*** (0.023)
R^2	0.262	0.257	0.492	0.114	0.143

Table 52: (Replication of Table 24 with attentive subsample.) Direct effect estimates for $\mathcal{S}_{\text{mc}}$ fit with Lucid sample.

F.3 Role of perception of benefit

F.3.1 Comparison of $\mathcal{S}$ and $\mathcal{S}_{\setminus B}$

	Self-ben	Soc. ben	Supp. Use	Supp. Mgt.	Supp. Reg.
Gender=male	0.183***	0.197***	0.275***	0.011	0.004
	(0.044)	(0.044)	(0.044)	(0.049)	(0.044)
Ethn=white	0.176*	0.317***	0.342***	-0.028	0.181*
	(0.087)	(0.089)	(0.090)	(0.098)	(0.090)
Ethn=black	0.119	0.252*	0.218*	-0.241*	0.186
	(0.105)	(0.104)	(0.107)	(0.114)	(0.107)
Ethn=asian	0.096	0.219	0.249	-0.250	0.123
	(0.127)	(0.128)	(0.129)	(0.135)	(0.134)
Job=cognitive	0.368***	0.254***	0.338***	0.134*	0.036
	(0.060)	(0.060)	(0.060)	(0.067)	(0.058)
Job=manual	0.088	-0.054	0.103	0.021	-0.085
	(0.070)	(0.071)	(0.069)	(0.077)	(0.073)
Job=service	0.076	0.044	0.118*	0.104	-0.006
	(0.059)	(0.058)	(0.060)	(0.063)	(0.058)
Education	0.104***	0.096***	0.143***	0.058*	0.050*
	(0.024)	(0.024)	(0.024)	(0.026)	(0.024)
Urban	0.078***	0.079***	0.069**	0.027	0.073***
	(0.021)	(0.021)	(0.022)	(0.023)	(0.022)
Age group	-0.095***	-0.079***	-0.110***	0.108***	-0.015
	(0.021)	(0.021)	(0.021)	(0.022)	(0.020)
HH income	0.070**	0.083***	0.081***	0.022	0.038
	(0.024)	(0.023)	(0.024)	(0.026)	(0.023)
Pol.=conservative	-0.112***	-0.089***	-0.131***	-0.001	-0.137***
	(0.017)	(0.017)	(0.017)	(0.019)	(0.017)
Individualism	0.648***	0.629***	0.813***	0.111***	-0.112***
	(0.029)	(0.029)	(0.036)	(0.032)	(0.027)
Egalitarianism	0.628***	0.628***	0.773***	0.178***	0.155***
	(0.027)	(0.026)	(0.031)	(0.027)	(0.024)
Techno-skepticism	-0.836***	-0.846***	-1.045***	0.112***	0.113***
	(0.026)	(0.026)	(0.032)	(0.030)	(0.026)
Risk aversion	0.157***	0.150***	0.144***	0.004	0.105***
	(0.029)	(0.029)	(0.033)	(0.026)	(0.023)
R^2	0.571	0.566	0.814	0.095	0.125

Table 53: (Replication of Table 25 with attentive subsample.) Effect estimates for $\mathcal{S}_{\setminus B}$ fit with Lucid sample. DE = direct effect, TE = total effect.

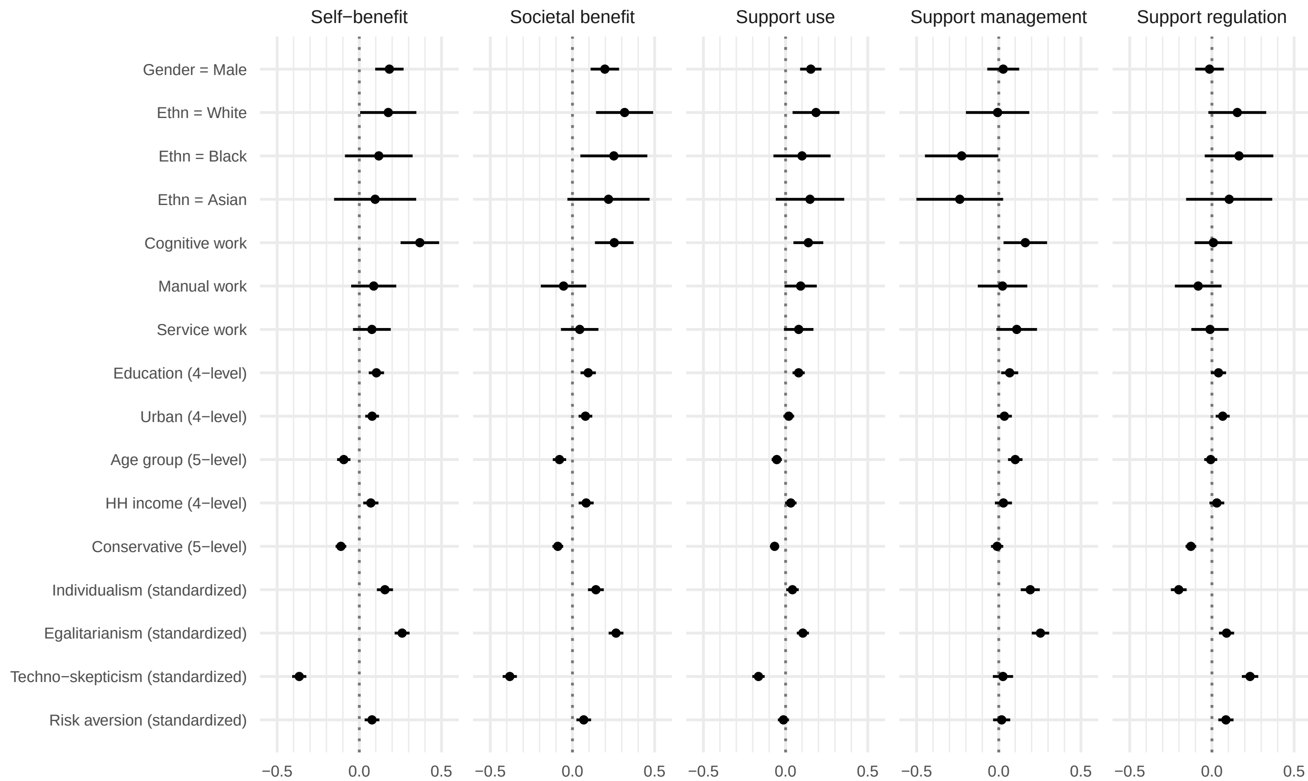

Figure 23: (Replication of Figure 13 with attentive subsample.) Direct effects in the reduced model $\mathcal{S}_{\setminus B}$ fit with the Lucid sample. Variables other than cultural values are unstandardized except where noted; error bars show 95% confidence intervals.

Cultural values	I	E	TS
Egalitarianism	-0.356*** (0.022)	1.000	
Techno-skept.	0.490*** (0.019)	0.175*** (0.022)	1.000
Risk aversion	0.101*** (0.024)	0.177*** (0.024)	0.318*** (0.022)
Perception of benefit	Self	Society	
Self	0.234*** (0.016)	1.000	
Support	Use	Mgt.	Reg.
Management	0.079*** (0.018)	1.000	
Regulation	0.024 (0.016)	0.194*** (0.021)	1.000

Table 54: (Replication of Table 26 with attentive subsample.) Covariance estimates for $\mathcal{S}_{\setminus B}$ fit with Lucid sample.

	$\mathcal{S}_{\setminus B}$	$\mathcal{S}$
χ^2_M (df_M, p)	5365.2 (356, <0.001)	4581.5 (350, <0.001)
CFI	0.862	0.884
RMSEA (90% CI)	0.074 (0.072, 0.075)	0.068 (0.066, 0.070)
SRMR	0.052	0.036
χ^2_D (df_D, p)	967.6 (6, <0.001)	

Table 55: (Replication of Table 27 with attentive subsample.) Fit statistics for $\mathcal{S}_{\setminus B}$ and $\mathcal{S}$ fit with Lucid sample.

	I1	I2	I3	I4	E1	E2	E3	E4	T1	T2	T3	T4	R1	R2	R3	R4	SE	SO	US	MG	RG
I1	0.00																				
I2	0.07	0.00																			
I3	-0.00	-0.01	0.00																		
I4	-0.03	-0.00	0.08	0.00																	
E1	0.07	0.08	-0.03	-0.02	0.00																
E2	0.09	0.12	-0.02	0.04	0.05	0.00															
E3	0.05	0.09	-0.04	0.01	-0.04	0.02	0.00														
E4	0.12	0.07	0.01	0.01	-0.01	-0.01	0.08	0.00													
T1	0.00	-0.03	-0.04	-0.03	0.07	-0.02	-0.05	0.07	0.00												
T2	-0.04	-0.09	-0.07	-0.03	-0.03	-0.11	-0.14	-0.04	0.03	0.00											
T3	-0.04	-0.09	-0.06	-0.05	-0.07	-0.13	-0.16	-0.02	0.04	0.05	0.00										
T4	-0.07	-0.10	-0.06	-0.09	-0.06	-0.10	-0.12	0.01	-0.01	0.06	0.05	0.00									
R1	0.04	0.04	0.01	-0.00	0.04	-0.01	0.01	0.09	0.02	-0.01	-0.04	0.07	0.00								
R2	0.01	0.01	0.03	0.05	0.06	0.02	0.02	0.03	0.02	-0.04	-0.06	0.02	-0.01	0.00							
R3	-0.03	-0.02	0.01	-0.00	-0.04	-0.00	0.00	0.01	-0.05	-0.08	-0.07	0.06	-0.02	0.02	0.00						
R4	0.00	-0.01	0.02	0.04	0.01	-0.02	0.00	-0.00	-0.01	-0.01	-0.05	0.07	0.01	-0.02	0.03	0.00					
SE	-0.09	-0.05	-0.03	-0.02	-0.07	-0.05	-0.04	-0.04	0.06	0.07	0.05	0.04	0.01	0.00	-0.02	-0.03	0.00				
SO	-0.08	-0.07	-0.02	-0.03	-0.04	-0.06	-0.03	-0.05	0.05	0.06	0.04	0.07	-0.02	-0.00	0.00	-0.03	-0.00	0.00			
US	-0.12	-0.09	-0.11	-0.01	-0.09	-0.08	-0.06	-0.09	0.09	0.13	0.09	0.05	-0.03	-0.00	-0.01	-0.05	0.05	0.05	0.00		
MG	0.02	0.05	-0.04	0.11	0.02	0.05	0.06	-0.03	0.03	0.01	-0.07	-0.13	-0.04	0.08	0.00	-0.02	-0.06	-0.05	0.00	0.00	
RG	-0.03	-0.06	-0.02	0.02	0.03	-0.05	-0.05	-0.04	0.06	0.04	0.01	0.02	-0.02	0.00	0.01	-0.02	0.04	0.06	-0.00	-0.00	0.00

Table 56: (Replication of Table 28 with attentive subsample.) Correlation residuals for $\mathcal{S}_{\setminus B}$ fit with Lucid sample. SE: perception of self-benefit; SO: perception of societal benefit; US: support for use; MG: support for management; RG: support for regulation.

F.4 Differences between contexts

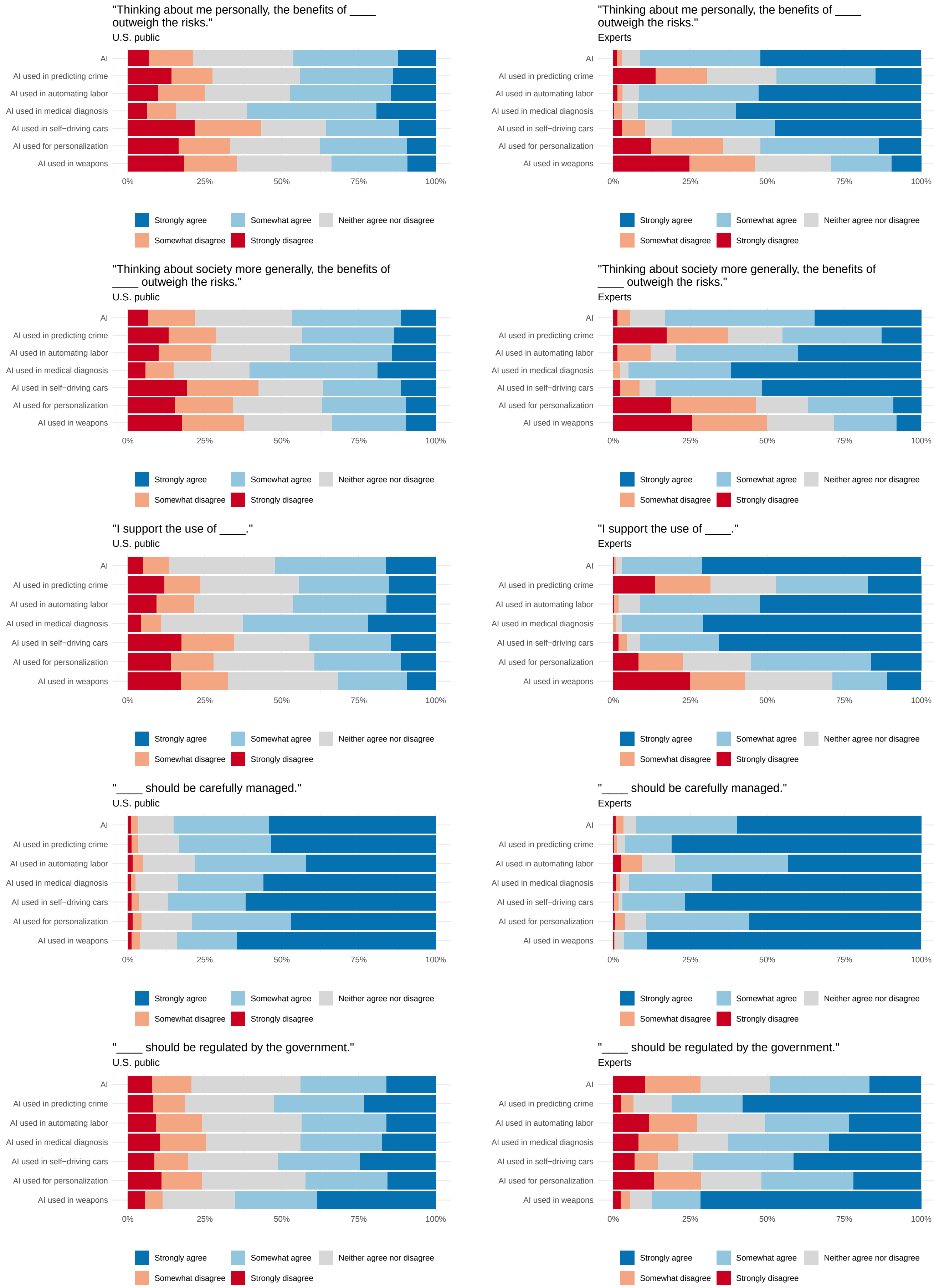

Figure 24: (Replication of Figure 14 with attentive subsample.) Comparison of outcome variables across contexts.

F.4.1 Correlations between contexts

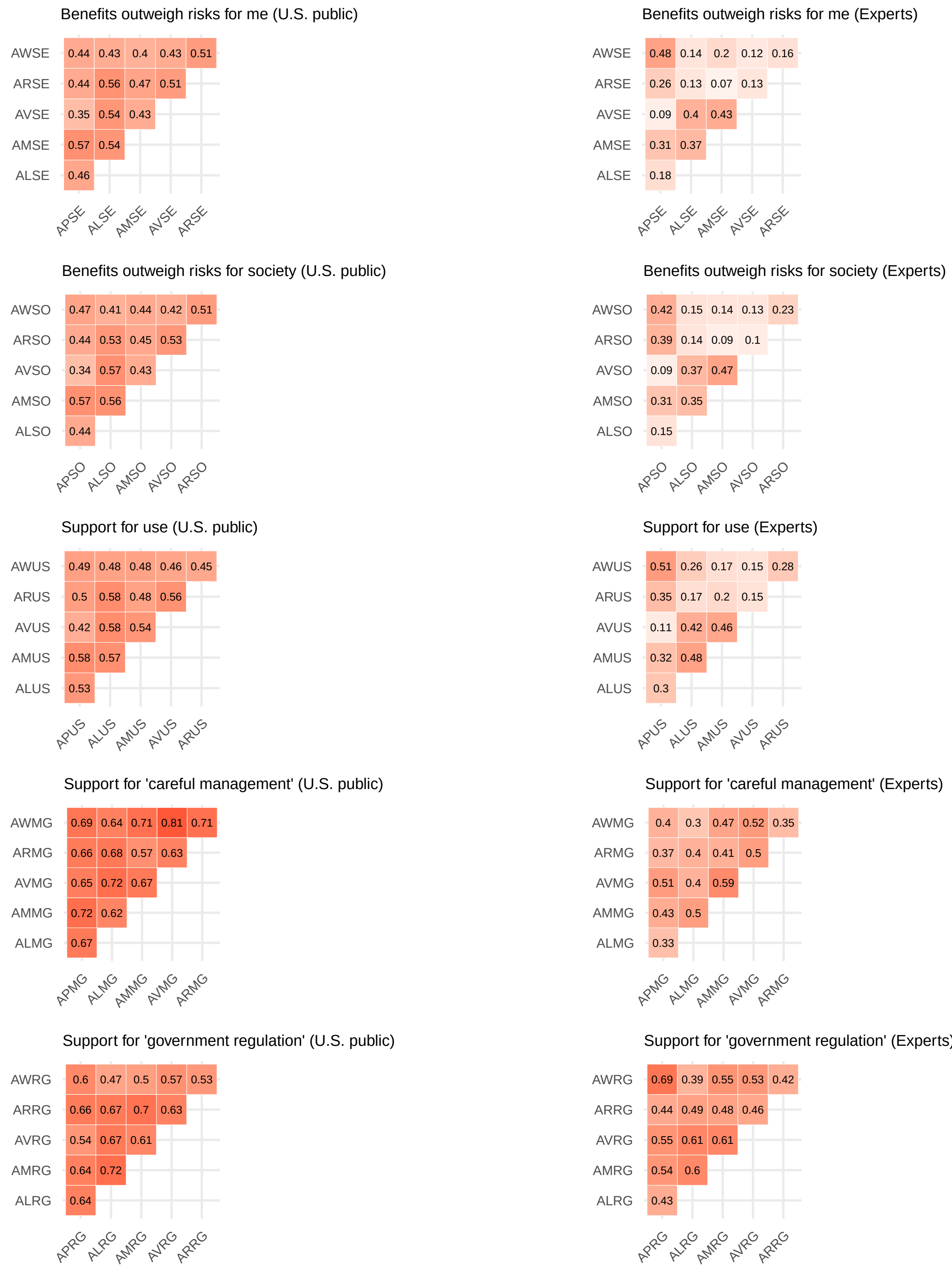

Figure 25: (Replication of Figure 15 with attentive subsample.) Correlations between contexts for each outcome variable. Task descriptions: AI used in... AW: weapons, AR: [for] personalization, AV: self-driving cars, AM: medical diagnosis, AL: automating labor, AP: predicting crime.

Figure 26: (Replication of Figure 16 with attentive subsample.) Correlations between support for AI use and belief that benefits outweigh risks for other technologies.

F.4.2 Multigroup SEM analysis across contexts

	Multi-group	AI	Policing	Labor	Medical	Vehicles	Personalization	Weapons
χ^2_M (df_M, p)	24948.1 (2558, 0.000)	4073.7	2182.6	2089.5	1968.7	2221.9	2265.4	2274.9
CFI	0.917	–	–	–	–	–	–	–
RMSEA (90% CI)	0.062 (0.061, 0.063)	–	–	–	–	–	–	–
SRMR	0.042	–	–	–	–	–	–	–

Table 57: (Replication of Table 29 with attentive subsample.) SEM fit statistics for multigroup analysis across contexts. Note that because our survey asked each Lucid (U.S. public) respondent about only three randomly selected contexts, the sample size for each context is approximately half that of the sample size for AI in general.

	Self-ben	Soc. ben	Supp. Use		Supp. Management		Supp. Regulation	
			DE	TE	DE	TE	DE	TE
Gender=male	0.183*** (0.044)	0.197*** (0.044)	0.153*** (0.033)	0.275*** (0.044)	0.027 (0.050)	0.011 (0.049)	-0.015 (0.044)	0.004 (0.044)
Ethn=white	0.176* (0.087)	0.317*** (0.089)	0.185* (0.073)	0.342*** (0.090)	-0.007 (0.098)	-0.028 (0.098)	0.154 (0.090)	0.181* (0.090)
Ethn=black	0.119 (0.105)	0.252* (0.104)	0.100 (0.089)	0.218* (0.107)	-0.226* (0.114)	-0.241* (0.114)	0.165 (0.106)	0.186 (0.107)
Ethn=asian	0.096 (0.128)	0.219 (0.128)	0.149 (0.106)	0.249 (0.129)	-0.237 (0.135)	-0.250 (0.135)	0.105 (0.134)	0.123 (0.134)
Job=cognitive	0.368*** (0.060)	0.254*** (0.060)	0.138** (0.046)	0.338*** (0.060)	0.162* (0.068)	0.134* (0.067)	0.009 (0.058)	0.036 (0.058)
Job=manual	0.088 (0.070)	-0.054 (0.071)	0.092 (0.050)	0.103 (0.069)	0.023 (0.077)	0.021 (0.077)	-0.083 (0.072)	-0.085 (0.073)
Job=service	0.076 (0.059)	0.044 (0.058)	0.080 (0.046)	0.118* (0.060)	0.109 (0.063)	0.104 (0.063)	-0.012 (0.058)	-0.006 (0.058)
Education	0.104*** (0.024)	0.096*** (0.024)	0.079*** (0.019)	0.143*** (0.025)	0.066* (0.026)	0.058* (0.026)	0.040 (0.024)	0.050* (0.024)
Urban	0.078*** (0.021)	0.079*** (0.021)	0.019 (0.017)	0.069** (0.022)	0.034 (0.023)	0.027 (0.023)	0.066** (0.022)	0.073*** (0.022)
Age group	-0.095*** (0.021)	-0.079*** (0.021)	-0.054*** (0.016)	-0.110*** (0.021)	0.101*** (0.022)	0.108*** (0.022)	-0.007 (0.020)	-0.015 (0.020)
HH income	0.070** (0.024)	0.083*** (0.023)	0.032 (0.018)	0.081*** (0.024)	0.028 (0.026)	0.022 (0.026)	0.030 (0.023)	0.038 (0.023)
Pol.=conservative	-0.112*** (0.017)	-0.089*** (0.017)	-0.067*** (0.013)	-0.131*** (0.017)	-0.010 (0.019)	-0.001 (0.019)	-0.128*** (0.017)	-0.137*** (0.017)
Individualism	0.156*** (0.025)	0.143*** (0.025)	0.042* (0.020)	0.137*** (0.026)	0.192*** (0.030)	0.178*** (0.029)	-0.202*** (0.026)	-0.188*** (0.025)
Egalitarianism	0.260*** (0.023)	0.265*** (0.023)	0.105*** (0.019)	0.273*** (0.023)	0.254*** (0.028)	0.231*** (0.026)	0.089*** (0.024)	0.115*** (0.023)
Techno-skepticism	-0.366*** (0.022)	-0.382*** (0.022)	-0.165*** (0.019)	-0.404*** (0.022)	0.026 (0.031)	0.058* (0.028)	0.232*** (0.026)	0.196*** (0.023)
Risk aversion	0.078*** (0.023)	0.069** (0.024)	-0.013 (0.017)	0.034 (0.024)	0.018 (0.027)	0.011 (0.027)	0.085*** (0.024)	0.092*** (0.024)
Self-benefit	–	–	0.324*** (0.018)	–	-0.048 (0.034)	–	0.027 (0.028)	–
Societal benefit	–	–	0.316*** (0.019)	–	-0.039 (0.033)	–	0.070* (0.028)	–
Covariances								
Soc. ben	0.585*** (0.014)	1.000						
Supp. use	0.000	0.000	1.000					
Supp. management	0.000	0.000	0.117*** (0.016)		1.000			
Supp. regulation	0.000	0.000	-0.004 (0.013)		0.213*** (0.021)		1.000	
R^2	0.264	0.257	0.491		0.115		0.145	

Table 58: (Replication of Table 30 with attentive subsample.) Effects for *AI in general* in model $\mathcal{S}$ fit with multigroup analysis and Lucid sample.

	Self-ben	Soc. ben	Supp. Use DE	Supp. Use TE	Supp. Management DE	Supp. Management TE	Supp. Regulation DE	Supp. Regulation TE
Gender=male	0.156* (0.062)	0.195** (0.063)	0.028 (0.041)	0.175** (0.062)	-0.032 (0.069)	-0.057 (0.069)	0.281*** (0.062)	0.296*** (0.062)
Ethn=white	0.229 (0.124)	0.237 (0.125)	0.096 (0.107)	0.284* (0.135)	-0.200 (0.144)	-0.229 (0.149)	0.269* (0.134)	0.289* (0.134)
Ethn=black	0.071 (0.143)	0.055 (0.149)	-0.046 (0.125)	0.002 (0.154)	-0.316 (0.167)	-0.323 (0.171)	0.348* (0.161)	0.354* (0.162)
Ethn=asian	0.044 (0.185)	0.138 (0.192)	0.114 (0.161)	0.200 (0.204)	-0.375 (0.194)	-0.393* (0.198)	0.136 (0.197)	0.141 (0.195)
Job=cognitive	0.294*** (0.085)	0.184* (0.085)	0.103 (0.054)	0.280*** (0.083)	0.242* (0.096)	0.221* (0.096)	0.026 (0.084)	0.050 (0.084)
Job=manual	0.186 (0.100)	0.203* (0.103)	0.020 (0.067)	0.179 (0.100)	-0.033 (0.112)	-0.058 (0.113)	-0.291** (0.109)	-0.274* (0.109)
Job=service	0.113 (0.081)	0.063 (0.082)	0.001 (0.060)	0.064 (0.086)	0.169* (0.086)	0.162 (0.087)	0.166* (0.083)	0.176* (0.083)
Education	0.131*** (0.035)	0.133*** (0.035)	0.025 (0.023)	0.131*** (0.035)	0.004 (0.038)	-0.013 (0.038)	0.023 (0.035)	0.034 (0.035)
Urban	0.071* (0.030)	0.048 (0.030)	-0.007 (0.020)	0.037 (0.030)	-0.025 (0.032)	-0.031 (0.032)	0.067* (0.032)	0.073* (0.031)
Age group	0.034 (0.030)	0.077* (0.030)	-0.029 (0.020)	0.022 (0.030)	0.149*** (0.031)	0.139*** (0.031)	-0.070* (0.030)	-0.067* (0.030)
HH income	0.087* (0.034)	0.125*** (0.034)	0.011 (0.023)	0.102** (0.034)	0.040 (0.038)	0.024 (0.038)	0.012 (0.035)	0.020 (0.035)
Pol.=conservative	0.110*** (0.024)	0.097*** (0.024)	0.012 (0.015)	0.093*** (0.024)	-0.118*** (0.027)	-0.130*** (0.027)	-0.199*** (0.025)	-0.189*** (0.025)
Individualism	0.105** (0.038)	0.117** (0.038)	0.035 (0.026)	0.126*** (0.038)	0.180*** (0.043)	0.165*** (0.043)	-0.248*** (0.039)	-0.238*** (0.039)
Egalitarianism	-0.069* (0.033)	-0.114*** (0.032)	0.025 (0.024)	-0.055 (0.033)	0.263*** (0.037)	0.278*** (0.037)	0.191*** (0.033)	0.184*** (0.033)
Techno-skepticism	-0.150*** (0.036)	-0.140*** (0.036)	-0.056* (0.023)	-0.172*** (0.036)	-0.111** (0.041)	-0.094* (0.040)	0.040 (0.038)	0.027 (0.037)
Risk aversion	0.129*** (0.036)	0.125*** (0.037)	-0.009 (0.024)	0.093* (0.036)	0.027 (0.040)	0.012 (0.039)	0.000 (0.037)	0.011 (0.036)
Self-benefit	–	–	0.259*** (0.026)	–	0.015 (0.065)	–	0.077 (0.046)	–
Societal benefit	–	–	0.546*** (0.029)	–	-0.140* (0.064)	–	0.011 (0.046)	–
Covariances								
Soc. ben	0.786*** (0.014)	1.000						
Supp. use	0.000	0.000	1.000					
Supp. management	0.000	0.000	0.042* (0.019)		1.000			
Supp. regulation	0.000	0.000	0.045** (0.015)		0.285*** (0.026)		1.000	
R^2	0.142	0.156	0.498		0.139		0.211	

Table 59: (Replication of Table 31 with attentive subsample.) Effects for *policing* in model $\mathcal{S}$ fit with multigroup analysis and Lucid sample.

	Self-ben	Soc. ben	Supp. Use DE	Supp. Use TE	Supp. Management DE	Supp. Management TE	Supp. Regulation DE	Supp. Regulation TE
Gender=male	0.326*** (0.064)	0.353*** (0.064)	0.065 (0.046)	0.319*** (0.065)	-0.075 (0.070)	-0.079 (0.069)	0.080 (0.065)	0.084 (0.064)
Ethn=white	0.103 (0.132)	0.093 (0.130)	0.128 (0.107)	0.200 (0.134)	-0.062 (0.130)	-0.062 (0.131)	0.186 (0.134)	0.187 (0.134)
Ethn=black	0.158 (0.156)	0.195 (0.154)	0.024 (0.126)	0.157 (0.156)	-0.416** (0.149)	-0.420** (0.150)	0.074 (0.160)	0.075 (0.161)
Ethn=asian	0.207 (0.188)	0.218 (0.190)	0.036 (0.148)	0.195 (0.196)	-0.216 (0.191)	-0.218 (0.190)	0.180 (0.201)	0.182 (0.200)
Job=cognitive	0.325*** (0.088)	0.384*** (0.086)	0.135* (0.066)	0.403*** (0.090)	0.144 (0.094)	0.138 (0.094)	0.032 (0.084)	0.035 (0.084)
Job=manual	0.173 (0.100)	0.129 (0.098)	0.129 (0.070)	0.238* (0.096)	0.072 (0.101)	0.074 (0.101)	0.004 (0.098)	0.007 (0.098)
Job=service	0.098 (0.081)	0.105 (0.082)	0.114 (0.059)	0.190* (0.084)	0.137 (0.087)	0.136 (0.087)	0.135 (0.085)	0.137 (0.085)
Education	0.134*** (0.034)	0.119*** (0.033)	0.058* (0.026)	0.151*** (0.034)	0.033 (0.035)	0.034 (0.035)	0.052 (0.034)	0.054 (0.033)
Urban	0.083** (0.030)	0.096** (0.030)	0.038 (0.022)	0.105*** (0.031)	0.042 (0.032)	0.041 (0.032)	0.097** (0.031)	0.097** (0.031)
Age group	-0.049 (0.030)	-0.065* (0.029)	0.005 (0.021)	-0.038 (0.029)	0.128*** (0.031)	0.129*** (0.031)	-0.106*** (0.029)	-0.107*** (0.029)
HH income	0.127*** (0.034)	0.091** (0.034)	0.008 (0.024)	0.086* (0.034)	0.052 (0.036)	0.054 (0.035)	0.025 (0.033)	0.027 (0.033)
Pol.=conservative	-0.071** (0.025)	-0.079*** (0.024)	-0.006 (0.018)	-0.062** (0.024)	-0.036 (0.026)	-0.035 (0.026)	-0.120*** (0.023)	-0.120*** (0.023)
Individualism	0.110** (0.036)	0.124*** (0.036)	0.067** (0.026)	0.155*** (0.034)	0.106** (0.038)	0.104** (0.037)	-0.184*** (0.034)	-0.182*** (0.034)
Egalitarianism	0.227*** (0.032)	0.219*** (0.033)	0.061** (0.023)	0.226*** (0.032)	0.170*** (0.036)	0.170*** (0.034)	0.171*** (0.033)	0.174*** (0.032)
Techno-skepticism	-0.249*** (0.031)	-0.253*** (0.032)	-0.114*** (0.022)	-0.301*** (0.030)	0.083* (0.036)	0.085* (0.034)	0.143*** (0.032)	0.140*** (0.031)
Risk aversion	0.061 (0.031)	0.040 (0.032)	-0.051* (0.021)	-0.015 (0.031)	0.059 (0.034)	0.061 (0.034)	0.146*** (0.031)	0.148*** (0.031)
Self-benefit	–	–	0.305*** (0.025)	–	0.069 (0.049)	–	0.029 (0.040)	–
Societal benefit	–	–	0.439*** (0.029)	–	-0.075 (0.048)	–	-0.015 (0.040)	–
Covariances								
Soc. ben	0.692*** (0.017)	1.000						
Supp. use	0.000	0.000	1.000					
Supp. management	0.000	0.000	0.005 (0.018)		1.000			
Supp. regulation	0.000	0.000	0.005 (0.016)		0.254*** (0.025)		1.000	
R^2	0.234	0.233	0.514		0.108		0.185	

Table 60: (Replication of Table 32 with attentive subsample.) Effects for *automating labor* in model $\mathcal{S}$ fit with multigroup analysis and Lucid sample.

	Self-ben	Soc. ben	Supp. Use DE	Supp. Use TE	Supp. Management DE	Supp. Management TE	Supp. Regulation DE	Supp. Regulation TE
Gender=male	0.227*** (0.064)	0.173** (0.064)	0.042 (0.045)	0.189** (0.065)	-0.028 (0.069)	0.003 (0.070)	0.190** (0.063)	0.210*** (0.062)
Ethn=white	0.420*** (0.116)	0.493*** (0.113)	0.115 (0.078)	0.464*** (0.122)	-0.057 (0.131)	0.027 (0.130)	0.107 (0.136)	0.156 (0.137)
Ethn=black	0.247 (0.141)	0.352* (0.137)	0.036 (0.104)	0.268 (0.148)	-0.167 (0.153)	-0.109 (0.154)	0.288 (0.159)	0.321* (0.161)
Ethn=asian	0.509** (0.168)	0.594** (0.184)	-0.013 (0.135)	0.408* (0.189)	-0.146 (0.182)	-0.045 (0.185)	0.278 (0.189)	0.337 (0.191)
Job=cognitive	0.109 (0.090)	0.137 (0.087)	-0.021 (0.065)	0.074 (0.092)	0.090 (0.095)	0.113 (0.097)	0.242** (0.085)	0.255** (0.086)
Job=manual	-0.099 (0.096)	-0.054 (0.095)	0.110 (0.071)	0.056 (0.096)	-0.094 (0.102)	-0.105 (0.102)	-0.036 (0.097)	-0.043 (0.097)
Job=service	0.178* (0.085)	0.160 (0.085)	0.150* (0.063)	0.276** (0.089)	0.088 (0.091)	0.116 (0.092)	0.065 (0.084)	0.082 (0.084)
Education	0.109** (0.034)	0.143*** (0.034)	0.004 (0.026)	0.102** (0.036)	-0.025 (0.039)	-0.001 (0.039)	0.003 (0.035)	0.017 (0.034)
Urban	0.064* (0.031)	0.027 (0.031)	0.035 (0.021)	0.067* (0.031)	0.004 (0.032)	0.009 (0.033)	0.064* (0.030)	0.068* (0.031)
Age group	-0.025 (0.030)	0.004 (0.029)	-0.021 (0.022)	-0.027 (0.030)	0.123*** (0.031)	0.123*** (0.031)	-0.075** (0.029)	-0.075** (0.029)
HH income	0.104** (0.034)	0.113*** (0.034)	0.072** (0.024)	0.154*** (0.034)	-0.035 (0.037)	-0.016 (0.038)	-0.014 (0.034)	-0.003 (0.034)
Pol.=conservative	-0.054* (0.024)	-0.059* (0.024)	-0.021 (0.017)	-0.063** (0.024)	-0.038 (0.027)	-0.048 (0.027)	-0.098*** (0.023)	-0.104*** (0.024)
Individualism	0.117** (0.036)	0.127*** (0.036)	0.065** (0.025)	0.158*** (0.037)	0.166*** (0.041)	0.188*** (0.041)	-0.236*** (0.034)	-0.223*** (0.034)
Egalitarianism	0.236*** (0.032)	0.205*** (0.032)	0.043 (0.024)	0.207*** (0.033)	0.236*** (0.036)	0.272*** (0.036)	0.094** (0.033)	0.117*** (0.032)
Techno-skepticism	-0.290*** (0.035)	-0.259*** (0.033)	-0.121*** (0.023)	-0.325*** (0.033)	-0.003 (0.041)	-0.048 (0.039)	0.087* (0.036)	0.058 (0.034)
Risk aversion	0.043 (0.036)	0.045 (0.035)	-0.022 (0.024)	0.011 (0.036)	-0.027 (0.038)	-0.020 (0.039)	0.149*** (0.034)	0.154*** (0.035)
Self-benefit	–	–	0.307*** (0.033)	–	0.021 (0.070)	–	0.037 (0.049)	–
Societal benefit	–	–	0.446*** (0.033)	–	0.152* (0.067)	–	0.069 (0.048)	–
Covariances								
Soc. ben	0.733*** (0.018)	1.000						
Supp. use	0.000	0.000	1.000					
Supp. management	0.000	0.000	0.101*** (0.020)		1.000			
Supp. regulation	0.000	0.000	0.055*** (0.016)		0.157*** (0.029)		1.000	
R^2	0.194	0.180	0.505		0.122		0.174	

Table 61: (Replication of Table 33 with attentive subsample.) Effects for *medical diagnosis* in model $\mathcal{S}$ fit with multigroup analysis and Lucid sample.

	Self-ben	Soc. ben	Supp. Use		Supp. Management		Supp. Regulation	
			DE	TE	DE	TE	DE	TE
Gender=male	0.365***	0.383***	0.021	0.322***	0.028	-0.054	0.233***	0.234***
	(0.063)	(0.062)	(0.038)	(0.062)	(0.072)	(0.072)	(0.064)	(0.063)
Ethn=white	-0.024	0.065	-0.040	-0.019	-0.359*	-0.364*	0.054	0.058
	(0.119)	(0.122)	(0.089)	(0.125)	(0.155)	(0.153)	(0.130)	(0.130)
Ethn=black	0.014	0.073	0.003	0.041	-0.674***	-0.684***	0.099	0.101
	(0.142)	(0.147)	(0.113)	(0.149)	(0.174)	(0.171)	(0.157)	(0.157)
Ethn=asian	0.031	0.157	0.067	0.149	-0.286	-0.309	0.259	0.265
	(0.190)	(0.192)	(0.128)	(0.186)	(0.213)	(0.207)	(0.206)	(0.207)
Job=cognitive	0.195*	0.111	0.154**	0.272**	0.249*	0.216*	0.100	0.097
	(0.084)	(0.084)	(0.051)	(0.083)	(0.098)	(0.097)	(0.084)	(0.084)
Job=manual	0.137	0.047	0.020	0.088	0.065	0.046	0.015	0.011
	(0.097)	(0.102)	(0.065)	(0.097)	(0.114)	(0.116)	(0.104)	(0.104)
Job=service	-0.018	0.042	0.047	0.060	0.163	0.159	-0.046	-0.044
	(0.080)	(0.079)	(0.056)	(0.082)	(0.090)	(0.090)	(0.080)	(0.080)
Education	0.096**	0.132***	0.043*	0.137***	0.011	-0.014	0.017	0.019
	(0.033)	(0.033)	(0.021)	(0.033)	(0.037)	(0.037)	(0.033)	(0.033)
Urban	0.054	0.051	0.044*	0.086**	-0.014	-0.026	0.025	0.025
	(0.030)	(0.031)	(0.020)	(0.030)	(0.035)	(0.035)	(0.031)	(0.031)
Age group	-0.222***	-0.242***	-0.022	-0.209***	0.129***	0.180***	0.072*	0.071*
	(0.028)	(0.029)	(0.020)	(0.029)	(0.032)	(0.031)	(0.030)	(0.029)
HH income	0.050	0.044	0.026	0.063	0.008	-0.002	0.036	0.036
	(0.034)	(0.033)	(0.021)	(0.033)	(0.036)	(0.036)	(0.033)	(0.033)
Pol.=conservative	-0.117***	-0.110***	-0.036*	-0.127***	-0.085**	-0.061*	-0.189***	-0.189***
	(0.024)	(0.024)	(0.015)	(0.024)	(0.028)	(0.028)	(0.024)	(0.024)
Individualism	0.055	0.031	0.059*	0.092*	0.098*	0.089*	-0.243***	-0.244***
	(0.037)	(0.037)	(0.023)	(0.037)	(0.042)	(0.042)	(0.036)	(0.035)
Egalitarianism	0.201***	0.139***	0.059**	0.191***	0.276***	0.240***	0.125***	0.122***
	(0.033)	(0.034)	(0.022)	(0.033)	(0.037)	(0.036)	(0.034)	(0.033)
Techno-skepticism	-0.148***	-0.165***	-0.136***	-0.263***	-0.127**	-0.092*	0.102**	0.101**
	(0.032)	(0.032)	(0.021)	(0.032)	(0.040)	(0.040)	(0.035)	(0.034)
Risk aversion	-0.010	0.040	-0.005	0.009	0.087*	0.083*	0.127***	0.129***
	(0.035)	(0.034)	(0.022)	(0.034)	(0.040)	(0.040)	(0.036)	(0.035)
Self-benefit	–	–	0.347***	–	-0.096	–	-0.039	–
			(0.029)		(0.070)		(0.060)	
Societal benefit	–	–	0.455***	–	-0.122	–	0.041	–
			(0.029)		(0.068)		(0.058)	
Covariances								
Soc. ben	0.803***	1.000						
	(0.013)							
Supp. use	0.000	0.000	1.000					
Supp. management	0.000	0.000	0.049*		1.000			
			(0.020)					
Supp. regulation	0.000	0.000	-0.009		0.267***		1.000	
			(0.017)		(0.029)			
R^2	0.214	0.209	0.574		0.158		0.175	

Table 62: (Replication of Table 34 with attentive subsample.) Effects for *autonomous vehicles* in model $\mathcal{S}$ fit with multigroup analysis and Lucid sample.

	Self-ben	Soc. ben	Supp. Use		Supp. Management		Supp. Regulation	
			DE	TE	DE	TE	DE	TE
Gender=male	0.186**	0.164**	-0.015	0.120	-0.014	-0.041	0.033	0.053
	(0.063)	(0.062)	(0.039)	(0.062)	(0.069)	(0.069)	(0.063)	(0.063)
Ethn=white	0.158	0.362**	-0.022	0.183	-0.258	-0.297*	0.123	0.172
	(0.127)	(0.123)	(0.074)	(0.119)	(0.138)	(0.142)	(0.128)	(0.126)
Ethn=black	0.069	0.256	0.087	0.216	-0.261	-0.285	0.090	0.125
	(0.147)	(0.147)	(0.096)	(0.147)	(0.163)	(0.165)	(0.160)	(0.159)
Ethn=asian	-0.076	0.290	0.036	0.127	-0.199	-0.216	0.067	0.110
	(0.185)	(0.178)	(0.119)	(0.180)	(0.200)	(0.203)	(0.182)	(0.180)
Job=cognitive	0.161	0.126	0.061	0.172*	0.123	0.102	-0.046	-0.031
	(0.084)	(0.083)	(0.055)	(0.086)	(0.093)	(0.094)	(0.084)	(0.084)
Job=manual	0.114	0.020	0.005	0.055	0.054	0.044	0.133	0.133
	(0.103)	(0.103)	(0.070)	(0.099)	(0.108)	(0.108)	(0.105)	(0.107)
Job=service	-0.032	-0.036	-0.002	-0.029	0.057	0.063	-0.100	-0.104
	(0.083)	(0.083)	(0.055)	(0.082)	(0.085)	(0.086)	(0.082)	(0.082)
Education	0.052	0.041	0.028	0.063	0.073*	0.066	0.108**	0.113**
	(0.035)	(0.035)	(0.022)	(0.035)	(0.035)	(0.036)	(0.035)	(0.035)
Urban	0.063*	0.071*	0.027	0.079**	0.000	-0.010	0.025	0.034
	(0.030)	(0.030)	(0.020)	(0.030)	(0.032)	(0.032)	(0.031)	(0.031)
Age group	-0.180***	-0.181***	-0.053*	-0.193***	0.137***	0.165***	0.021	-0.002
	(0.030)	(0.030)	(0.021)	(0.030)	(0.031)	(0.031)	(0.029)	(0.029)
HH income	0.121***	0.137***	0.023	0.123***	0.102**	0.083*	0.061	0.078*
	(0.033)	(0.034)	(0.022)	(0.033)	(0.036)	(0.036)	(0.033)	(0.033)
Pol.=conservative	-0.137***	-0.119***	-0.038*	-0.136***	-0.068**	-0.049	-0.153***	-0.168***
	(0.024)	(0.023)	(0.015)	(0.024)	(0.026)	(0.026)	(0.024)	(0.024)
Individualism	0.139***	0.170***	0.025	0.145***	0.135***	0.112**	-0.175***	-0.153***
	(0.033)	(0.033)	(0.023)	(0.035)	(0.038)	(0.037)	(0.034)	(0.034)
Egalitarianism	0.235***	0.222***	0.027	0.204***	0.207***	0.173***	0.132***	0.159***
	(0.032)	(0.032)	(0.021)	(0.032)	(0.037)	(0.035)	(0.032)	(0.031)
Techno-skepticism	-0.266***	-0.316***	-0.094***	-0.320***	0.021	0.065	0.149***	0.109**
	(0.032)	(0.031)	(0.024)	(0.032)	(0.040)	(0.037)	(0.035)	(0.034)
Risk aversion	0.076*	0.102**	0.022	0.091**	0.006	-0.008	0.058	0.071*
	(0.032)	(0.033)	(0.021)	(0.032)	(0.035)	(0.034)	(0.033)	(0.032)
Self-benefit	–	–	0.365***	–	-0.073	–	-0.020	–
			(0.026)		(0.054)		(0.049)	
Societal benefit	–	–	0.409***	–	-0.077	–	0.142**	–
			(0.028)		(0.055)		(0.050)	
Covariances								
Soc. ben	0.723***	1.000						
	(0.018)							
Supp. use	0.000	0.000	1.000					
Supp. management	0.000	0.000	-0.033*		1.000			
			(0.016)					
Supp. regulation	0.000	0.000	-0.037*		0.291***		1.000	
			(0.015)		(0.026)			
R^2	0.227	0.238	0.534		0.106		0.160	

Table 63: (Replication of Table 35 with attentive subsample.) Effects for *personalization* in model $\mathcal{S}$ fit with multigroup analysis and Lucid sample.

	Self-ben	Soc. ben	Supp. Use DE	Supp. Use TE	Supp. Management DE	Supp. Management TE	Supp. Regulation DE	Supp. Regulation TE
Gender=male	0.219*** (0.063)	0.159* (0.063)	0.072 (0.044)	0.211*** (0.063)	-0.003 (0.072)	-0.030 (0.072)	0.131* (0.066)	0.131* (0.066)
Ethn=white	0.162 (0.144)	0.135 (0.145)	-0.082 (0.092)	0.029 (0.152)	0.116 (0.151)	0.094 (0.150)	0.363* (0.149)	0.365* (0.149)
Ethn=black	0.174 (0.164)	0.230 (0.162)	-0.211 (0.114)	-0.053 (0.169)	-0.410* (0.171)	-0.442** (0.169)	0.267 (0.173)	0.278 (0.173)
Ethn=asian	0.032 (0.196)	0.018 (0.212)	-0.073 (0.165)	-0.055 (0.221)	-0.430* (0.197)	-0.434* (0.196)	0.071 (0.203)	0.071 (0.205)
Job=cognitive	-0.064 (0.083)	-0.030 (0.083)	0.124* (0.059)	0.090 (0.085)	0.065 (0.098)	0.072 (0.098)	0.097 (0.084)	0.099 (0.084)
Job=manual	-0.070 (0.102)	-0.097 (0.097)	0.223** (0.079)	0.157 (0.104)	0.006 (0.115)	0.020 (0.116)	-0.015 (0.110)	-0.020 (0.110)
Job=service	-0.118 (0.083)	-0.053 (0.085)	0.053 (0.059)	-0.007 (0.082)	0.220* (0.095)	0.231* (0.095)	0.036 (0.082)	0.038 (0.082)
Education	0.054 (0.034)	0.071* (0.033)	0.079*** (0.023)	0.128*** (0.033)	0.018 (0.039)	0.008 (0.039)	0.138*** (0.035)	0.141*** (0.034)
Urban	0.083** (0.031)	0.054 (0.031)	0.000 (0.021)	0.050 (0.030)	0.081* (0.036)	0.071* (0.036)	0.063* (0.032)	0.062* (0.032)
Age group	0.005 (0.030)	-0.038 (0.030)	0.003 (0.022)	-0.013 (0.030)	0.166*** (0.032)	0.170*** (0.033)	0.068* (0.030)	0.064* (0.030)
HH income	0.105** (0.033)	0.136*** (0.033)	0.011 (0.023)	0.105** (0.034)	0.026 (0.038)	0.006 (0.038)	0.025 (0.034)	0.031 (0.034)
Pol.=conservative	0.034 (0.023)	0.033 (0.024)	0.033* (0.016)	0.058* (0.023)	-0.065* (0.029)	-0.070* (0.029)	-0.147*** (0.025)	-0.146*** (0.025)
Individualism	0.123*** (0.036)	0.136*** (0.036)	0.067* (0.027)	0.166*** (0.036)	0.199*** (0.050)	0.179*** (0.049)	-0.232*** (0.039)	-0.227*** (0.039)
Egalitarianism	0.086* (0.034)	0.068* (0.034)	0.044 (0.026)	0.101** (0.035)	0.293*** (0.041)	0.281*** (0.040)	0.154*** (0.036)	0.155*** (0.036)
Techno-skepticism	-0.121*** (0.035)	-0.147*** (0.035)	-0.119*** (0.025)	-0.222*** (0.034)	-0.104* (0.046)	-0.083 (0.044)	0.036 (0.038)	0.029 (0.038)
Risk aversion	0.040 (0.035)	0.074* (0.034)	-0.044 (0.024)	0.002 (0.034)	-0.017 (0.042)	-0.027 (0.041)	0.098** (0.037)	0.103** (0.037)
Self-benefit	–	–	0.309*** (0.028)	–	-0.048 (0.069)	–	-0.068 (0.054)	–
Societal benefit	–	–	0.451*** (0.029)	–	-0.106 (0.071)	–	0.099 (0.055)	–
Covariances								
Soc. ben	0.813*** (0.012)	1.000						
Supp. use	0.000	0.000	1.000					
Supp. management	0.000	0.000	-0.005 (0.027)		1.000			
Supp. regulation	0.000	0.000	0.015 (0.019)		0.489*** (0.024)		1.000	
R^2	0.073	0.082	0.474		0.173		0.185	

Table 64: (Replication of Table 36 with attentive subsample.) Effects for *weapons* in model $\mathcal{S}$ fit with multigroup analysis and Lucid sample.

G Deviations from preregistration

Survey fielding.

- Due to an editing error, item ONEU (opinion regarding neurotechnology) in the fielded surveys featured a discrepancy between samples that rendered responses incomparable. In the U.S. public survey, the item read "Which best represents your view on neurotechnology, devices that interact directly with the brain that could help treat neurologic disorders?" In the expert survey, the item read "Which best represents your view on neural implants, devices implanted in the brain that could help cure some mental illnesses?" We removed this item from results shown in the main paper, but retained it in results shown in the supplement.
- Due to an editing error, the autonomous weapons vignette used the text "autonomous weapons" rather than "lethal autonomous weapons" as listed in the PAP.
- The PAP referred to Georgia Tech OMS students as OMSCS (Online Master's of Science in Computer Science) students. However, in addition to OMSCS students, the expert sample also contained a small number of students in the Georgia Tech OMSA (Online Master's of Science in Analytics) program who were also enrolled in the artificial intelligence graduate class.

Analysis.

- When computing attention scores from the four attention screening items, we use the two-parameter Rasch IRT model. This model is slightly different from, but more standard than, the model proposed in [78]. We do not expect that this difference produce meaningfully different results.
- When comparing model fits, we do not report likelihood ratio tests or information criteria (AIC and BIC). This is because the diagonally weighted least squares objective recommended in literature for fitting models with ordinal variables does not provide a likelihood.
- The PAP for RQ2 (role of indirect pathways through self- and societal benefit) erroneously did not describe local comparison of models. We include local comparisons in our analysis as well.
- The PAP for RQ3 (differences between U.S. public and OMS samples) calls for comparing effects of sociodemographic and cultural variables between the two samples using multigroup SEM analysis "if the size of the [OMS] sample is sufficient." Our sample size was large enough to meaningfully estimate effect sizes using linear regression, but not large enough to allow for multigroup analysis. The results shown in Figure 5 therefore estimated effects using ordinary least-squares regression. The main text notes that this analysis was exploratory (i.e., non-preregistered).