What Does the Public Think About AI?

An overview of the public's attitudes towards AI and a resource for future research

Noemi Dreksler, Harry Law, Chloe Ahn, Daniel S. Schiff, Kaylyn Jackson Schiff, Zachary Peskowitz

Centre for the Governance of AI

GRAIL
GOVERNANCE & RESPONSIBLE AI LAB

Authors and affiliations

NOEMI DREKSLER
Centre for the Governance of AI

HARRY LAW
University of Cambridge

CHLOE AHN
University of Pennsylvania

DANIEL S. SCHIFF
Purdue University

KAYLYN JACKSON SCHIFF
Purdue University

ZACHARY PESKOWITZ
Emory University

C.A., D.S.S., K.J.S., and Z.P. developed the AI Survey Hub for Attitudes and Research Exchange (AI SHARE) database alongside other collaborators. C.A., D.S.S., K.J.S., and Z.P. are affiliated with the the Governance and Responsible AI Lab (GRAIL) at Purdue University.

Contact
Corresponding author: Noemi Dreksler (noemi.dreksler@governance.ai)
To get in contact about the AI SHARE database, please reach out to Daniel Schiff (dschiff@purdue.edu).
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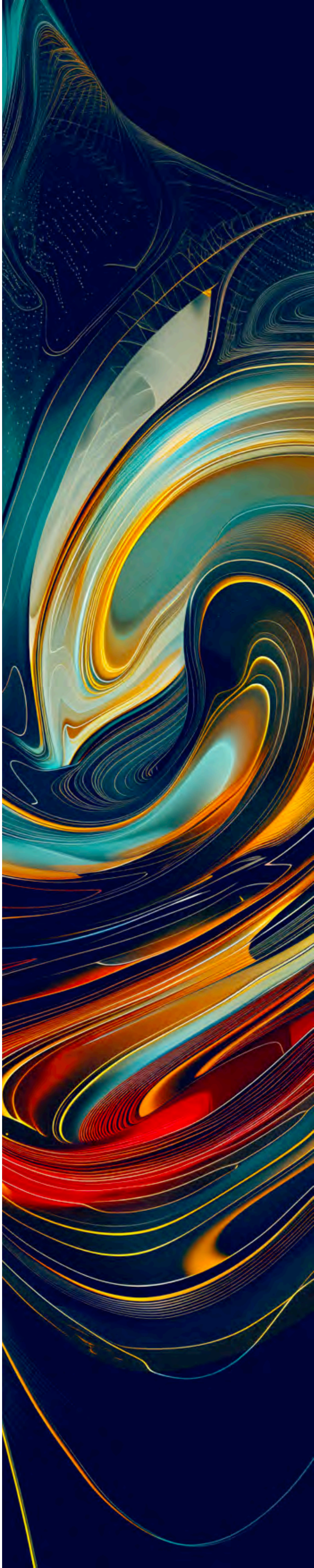

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TABITHA AKOTO

ANJALI BHATI

JOLIN LI

YUNZHE LIU

YU LU

PAOLA SALAS

RYAN WEIDENAAR

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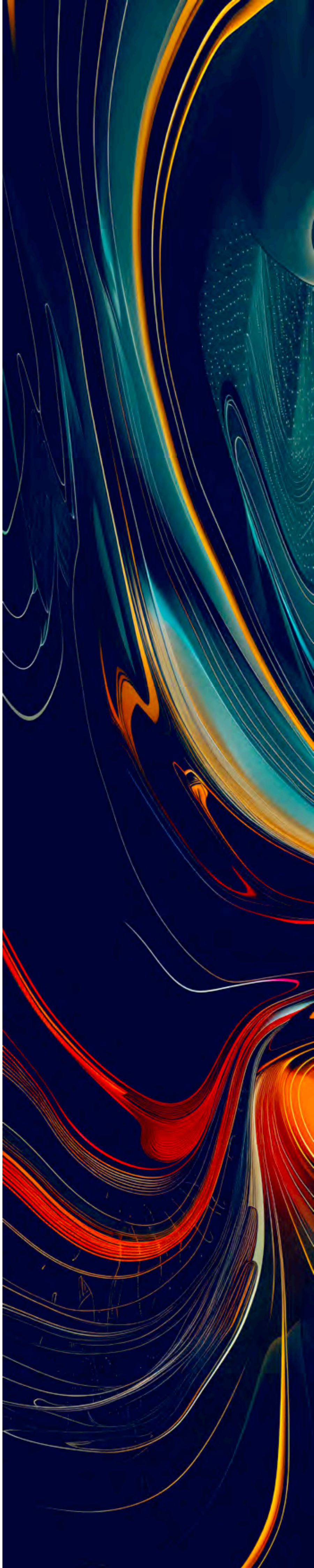


Executive summary

Understanding what the public thinks about AI is important. It will shape both where AI development and policy *should* go and where it *will* go. AI public opinion research can help AI developers make informed development choices, help civil society groups advocate effectively, help policymakers craft responsive regulations, and help media organizations provide coverage that improves public understanding. As the influence of AI grows, public opinion research will become increasingly vital for monitoring impacts and ensuring governance decisions are informed by diverse perspectives.

But there are several fundamental challenges in studying public opinion on AI. For example, attitudes are multifaceted, AI is a varied and shifting concept, and the research landscape is fragmented. Survey research adds additional complexity, with results heavily dependent on question framing, sampling methods, and timing. These challenges mean that, especially where such insights are used for strategy and decision-making, it is important for consumers of survey research to be cautious in how they interpret the findings and to remember that understanding what the public thinks about AI requires careful nuance. In addition to these challenges for understanding public opinion of AI, there are limited syntheses and overviews of research findings to date despite the growing importance of this topic.

This report provides such an overview of research that has been conducted on public attitudes towards AI. It combines findings from academic research, public polling, and a new database of AI public opinion studies. We examine traditional survey findings and also canvass research from participatory methods, media analysis, and studies of sociotechnical imaginaries. The literature spans multiple disciplines and sources, from peer-reviewed academic work to reports from polling institutes, companies, think tanks, and governments. The report also aims to build our collective understanding of the importance of AI attitudes research, the challenges it poses, and the future opportunities it presents.

Our non-systematic review of the survey literature focuses primarily on findings from North America and Europe, particularly the United States and United Kingdom. This geographic scope allows us to provide a more thorough analysis of available research in these regions. But evidence suggests that public attitudes can vary significantly across cultures and regions, emphasising the need for similar reviews of findings from other parts of the world and caution against generalising our findings.

So, what does the public think about AI? Some of the key early insights we draw from our review of six themes we have identified in the literature include:

1. **AI use and awareness have been steadily increasing.** Awareness and familiarity with AI are increasing as the public is, for the first time, knowingly using AI-powered tools at-scale, but they remain uneven across the public. [More on background AI beliefs, awareness, use, and knowledge]
2. **Sentiment about AI is mixed but expectations about its impacts may lean somewhat towards concern.** There is mixed evidence on whether people are more positive or negative about AI and how this may be changing across time. Both the US and UK public may be more concerned than optimistic about the impacts of AI, but this can vary between surveys and many respondents also express a mixture of positive and negative sentiments. [More on general attitudes towards AI]
3. **Concern about labour automation is something to watch.** A non-negligible concerned minority across countries worries about their own jobs being replaced by AI, but the majority of people in North America and Europe do not think AI will replace them in the next years. However, people generally think that AI is more likely to increase than decrease unemployment, and even if it is not yet an overwhelming concern, it is one of the most prominent perceived risks. [More on views on the risks, benefits, and impacts of AI]
4. **The public is supportive of AI governance but there often is only low to middling trust in tech companies or governments to do this well.** The public expresses general support for careful AI management, regulation, and international governance. While there is only low to middling trust in self-governance by tech companies, general trust in governments is also often not found to be high. [More on views on AI development, regulation, and governance]
5. **Individual and geographic differences can be stark.** There are notable differences between countries in terms of their attitudes and preferences with respect to AI. For example, individuals in China and India are often more positive and optimistic about AI than those in Western countries like the United States and Great Britain. Those who understand more about AI are often more optimistic but can also express heightened concern about certain risks or uses. [More on the role of individual and group characteristics]
6. **Context matters.** Support for and perceptions of AI applications can vary widely depending on the domain, task, or application. For example, the task characteristics and perceived agent-task fit can play a role in attitudes towards specific AI applications. [More on attitudes towards different specific AI applications or use domains]

Our report also draws on a new resource for studying public opinion on AI: the AI Survey Hub for Attitudes and Research Exchange (AI SHARE).[1] Currently, conducting reviews of the AI public opinion literature is challenging, and existing efforts, including our review of the survey research findings, are largely non-systematic in approach. To address this gap, AI SHARE aggregates and categorises survey questions about AI attitudes from both academic research and 'grey' literature[2]. Currently, the database contains approximately 1,800 survey questions from 218 studies conducted between 2014 and 2023.

We use this database to analyse broad trends in how researchers have studied public opinion on AI – for example, examining the topics covered, methods used, and populations studied. Once publicly available, AI SHARE will enable more systematic analyses of public attitudes towards AI, help researchers identify gaps in current understanding, and provide policymakers with comprehensive data about public views. The database aims to improve research practices and ensure decision-makers have better access to evidence about public attitudes towards AI, with plans to further expand the database and potentially add raw data and replication code.

[1] AI SHARE was developed by the Governance and Responsible AI Lab (GRAIL) at Purdue University with collaborators at the University of Pennsylvania, the University of Michigan, and Emory University.

[2] **Grey literature** refers to materials like reports, working papers, pre-prints, government publications, white papers, or policy briefs from organisations and institutions that are not peer-reviewed and are not published through traditional publication routes such as books or academic journals.

Policymakers, civil society, funders, and other consumers of survey research		
1	Fund and set up high-quality longitudinal public opinion trackers.	Establish long-term, high-quality public opinion trackers on AI to inform policy and track attitudes over time. Existing large-scale surveys, like the European Social Survey, should consider integrating AI-related questions.
2	Establish infrastructure to monitor and forecast AI impacts.	Governments should create mandates to monitor AI's societal, economic, and personal impacts over time, including labour, information environment, and mental health impacts.
3	Consume survey findings with care, considering their limitations.	Users of AI public opinion data should account for the limitations of surveys, including timing, cross-cultural differences, and nuances in question interpretation.
4	Examine complete survey results instead of relying on editorialising.	Survey readers should always analyse full percentage breakdowns in surveys to avoid misinterpretation of public opinion results and not rely solely on editorialised summaries.
5	Fit survey findings into broader evidence-based models of the world.	Survey findings should be considered within wider evidence-based frameworks to understand their implications for AI regulation, use, and public behaviours.
Researchers in academia, think tanks, government, and industry		
6	Advance hypothesis-driven AI public research agendas.	Researchers should develop hypothesis-driven agendas connecting AI attitudes to relevant behaviours such as political support, AI use, and wellbeing, integrating insights from other fields.
7	Develop and use reliable and validated AI attitude constructs.	Researchers should use validated constructs for AI attitudes, such as scales measuring trust and AI knowledge, to improve data quality and comparability across studies.
8	Conduct systematic reviews and meta-analyses of the field.	The field would benefit from comprehensive reviews and meta-analyses to synthesise existing findings and support better-informed research going forward.
9	Coordinate and collaborate across research teams.	Researchers should coordinate and collaborate in order to conduct comparative analyses and to measure the development of AI attitudes over time. The AI SHARE resource can support such joint efforts.
10	Address open questions in AI governance and public opinion.	Researchers should consider critical issues such as how AI automation will reshape political and economic behaviour, effects of AI incidents on public trust, polarization of AI discourse, the role of public opinion in global AI governance, interplay of AI and climate anxieties, AI social movements, etc.

Figure A: Recommendations for improving our understanding of public opinion on AI.

We find that our understanding of public attitudes towards AI could be improved by several changes to how this research is conducted and used. Our review of the literature reveals several critical gaps in current AI public opinion research: the lack of high-quality tracking studies, limited systematic synthesis of findings, and insufficient use of validated measures. To address these gaps, we offer recommendations for both producers and users of public opinion research – from academic researchers and think tanks to policymakers and civil society organizations. These recommendations, summarised in Figure A, provide concrete steps for developing more reliable and useful insights into public attitudes towards AI.

Selected US and UK focused public opinion survey insights

Awareness	Awareness and familiarity with AI among the general public have been steadily increasing in recent years, likely driven by increasing use and public discourse, but they remain uneven across the public.
Use	The public has long used AI (e.g. social media, spam detection, search) but often have not realised that they are doing so. New generative AI tools are the first AI-powered tools that the public is knowingly using at scale and their use is increasing both at work and for personal use. Use is more prevalent amongst younger generations.
Sentiment	There is mixed evidence on whether people are more positive or negative about AI and how this is shifting across time. Both the US and UK public may be more concerned about the impacts of AI than they are optimistic about AI's effects, but this can vary between surveys and many respondents also express a mixture of positive and negative sentiments.
AI risks	We cannot yet draw firm conclusions about how people weigh AI risks against one another due to a large amount of heterogeneity in the items presented to respondents and the questions asked about them, including the timeframe within which they will occur. Although research on this is limited and not up to date, it appears that AI currently still ranks low in comparison to other global risks when asked about in terms of likelihood, severity of impact, and concern.
Automation	People are generally worried that AI will increase unemployment but it is not yet an overwhelming concern for the public. There is a concerned minority in most countries that worry about their own jobs being replaced by AI, but the majority of people in North America and Europe do not think AI will replace them in the next years. Based on existing studies it is currently difficult to get a clear picture of how the public's concern about automation is changing across time, but it may be increasing slowly in the US and the UK. Automation concern can increase support for some worker-targeted redistributive policies such as extending unemployment benefits or implementing job loss compensation, as well as implementing worker protections. However, it does not appear to significantly boost support for other social investment policies like education and retraining programs.
AI governance	There is general support for AI governance among the public, including across a broad range of regulatory approaches and international governance. Where strong majority support is not found for AI regulation, support usually still outweighs opposition and there is substantial fence-sitting. The majority of people do not trust tech companies to develop AI responsibly without external, independent auditing and oversight mechanisms. However, while the public appears to prefer independent oversight or government regulation, there is also generally low to middling trust in governments and other actors expressed in surveys. Support for specific international governing bodies is also less apparent.
Context	Context can significantly influence perceptions, with variations across domains, tasks, and cultures. Support for specific AI applications, for example, can vary notably depending on the domain, nature of the task, or application.
Group differences	There can be notable differences between countries in terms of their attitudes towards AI and associated beliefs. In some cases, individuals in countries like China and India are more positive and optimistic about AI than individuals in Western countries like the United States and Great Britain.
Individual differences	Young people are more optimistic about and engaged with AI. Associations with political affiliation depend on the country and are not always straightforward. AI knowledge and awareness leads to general optimism about AI but can also make some benefits or risks more salient.

Contents

Introduction

Public opinion plays a crucial role in shaping AI development, deployment, and governance, yet our understanding of these attitudes remains fragmented and incomplete. While the academic literature on applications of AI has seen efforts towards consolidating knowledge in some specific domains, there remain significant gaps in our understanding of general public opinion on AI. This report aims to provide a multi-layered evidence-based overview of research on public attitudes towards AI, focusing primarily on surveys conducted in North America and Europe – particularly the United States and United Kingdom.

Our analysis serves multiple stakeholders: AI developers seeking to develop systems responsibly, civil society organizations working to represent public interests, policymakers crafting regulations, and researchers studying public attitudes. By synthesising existing research and identifying key challenges, we aim to provide an empirical foundation for both public discourse and policy decisions about AI governance and aid future research efforts that aim to assess public opinion of AI.

We begin by discussing why understanding AI public opinion is important. Next, we examine the challenges inherent in studying AI public opinion, including the complexities of studying attitudes, the rapidly evolving nature of AI technology, and survey design issues.

We then present findings from our review of the AI public opinion literature, organised around six themes. Throughout, we draw on insights from the AI SHARE database,[3] a new database containing around 1,800 survey questions from 218 studies conducted between 2014 and 2023. In particular, we report meta-level findings from the 189 public opinion surveys in the AI SHARE database (e.g., what kinds of attitudes surveys have investigated, what kinds of sampling methods studies use).

[3] **The AI SHARE database** This database, developed by the Governance and Responsible AI Lab (GRAIL) at Purdue University, aims to aggregate AI attitude questions from both academic and grey literature, creating a centralised resource for researchers and policymakers. Currently, the database houses around 1,800 AI attitude questions drawn from 218 studies, categorised along various dimensions. The database comprises survey questions from 2014 to 2023. The ultimate goal is to expand this collection further, potentially including access to raw data and replication code where feasible.

Grey literature refers to materials like reports, working papers, pre-prints, government publications, white papers, or policy briefs from organisations and institutions that are not peer-reviewed and are not published through traditional publication routes, such as books or academic journals.

Next, we examine other methods for understanding public opinion on AI, including participatory and deliberative methods; qualitative techniques such as interviews and focus groups; media, social media, and content analysis; and the study of sociotechnical imaginaries. We also draw insights from research on attitudes towards other emerging technologies and risks. The report concludes with a framework for understanding public attitudes towards AI and recommendations for improving future research.

It is important to note several caveats. First, the insights presented in this report primarily relate to evidence from North America and Europe, with an emphasis on the United States and the United Kingdom. Given the evidence for significant cross-cultural differences in AI attitudes, we urge caution in transferring these findings to other geographies. We hope others will create more detailed overviews of other regions and countries, including the Global South, which is starkly underrepresented in the AI survey corpus. Second, the field of AI public opinion research is rapidly evolving, and the findings can quickly become outdated as AI technology and public awareness progress. Finally, while we have made efforts to make this report as comprehensive as possible, the breadth of the field and sprawling literature mean that some areas are not covered in full depth and that we will likely have missed studies and topics.

Why is it useful to understand what people think about AI?

What the public thinks about AI will shape both where AI development and policy should go and where it will go. Understanding public opinion of AI fulfils at least three broad functions:

1. **Understanding attitudes and behaviours.** It helps us to make sense of people's attitudes and behaviours towards key topics of interest. It also helps us understand how factors such as beliefs, perceptions of risks and benefits, and emotions are linked to personal and political attitudes and behaviours. This understanding provides an empirical grounding for public and expert discourse, as well as improved governance decision-making.[4]
2. **Monitoring impacts of AI.** Monitoring, evaluating, and forecasting the impacts of AI will be important for various actors to proactively manage the harms from AI and to successfully thread the needle between mitigating the risks and realising the benefits of AI progress. Survey findings are especially valuable for monitoring the societal and human impacts of AI that can be difficult to measure.
3. **Democratisation of input to AI.**[5] Public opinion research facilitates including and making heard the voices of those who will be affected by AI systems, providing public voice in the development, deployment, and governance of AI systems. Understanding what people think of AI across various groups further provides signals to AI system developers and deployers on how to best shape model behaviour.

For stakeholders like AI developers, civil society, policymakers, and the public, understanding AI attitudes can inform strategies, support advocacy, guide policy, and improve discourse and ultimately the impacts of AI. To summarise, we outline the different purposes that high-quality research on AI attitudes could fulfil for different groups in Figure 1.

[4] For example, certain societal adaptations to AI risks will require public awareness, understanding, and support to be implemented effectively (Bernardi et al., 2024; Hutson, 2024).

[5] Though note that there are distinct limitations and challenges in using surveys as means of enabling participation (see e.g., Tahaei et al., 2024)

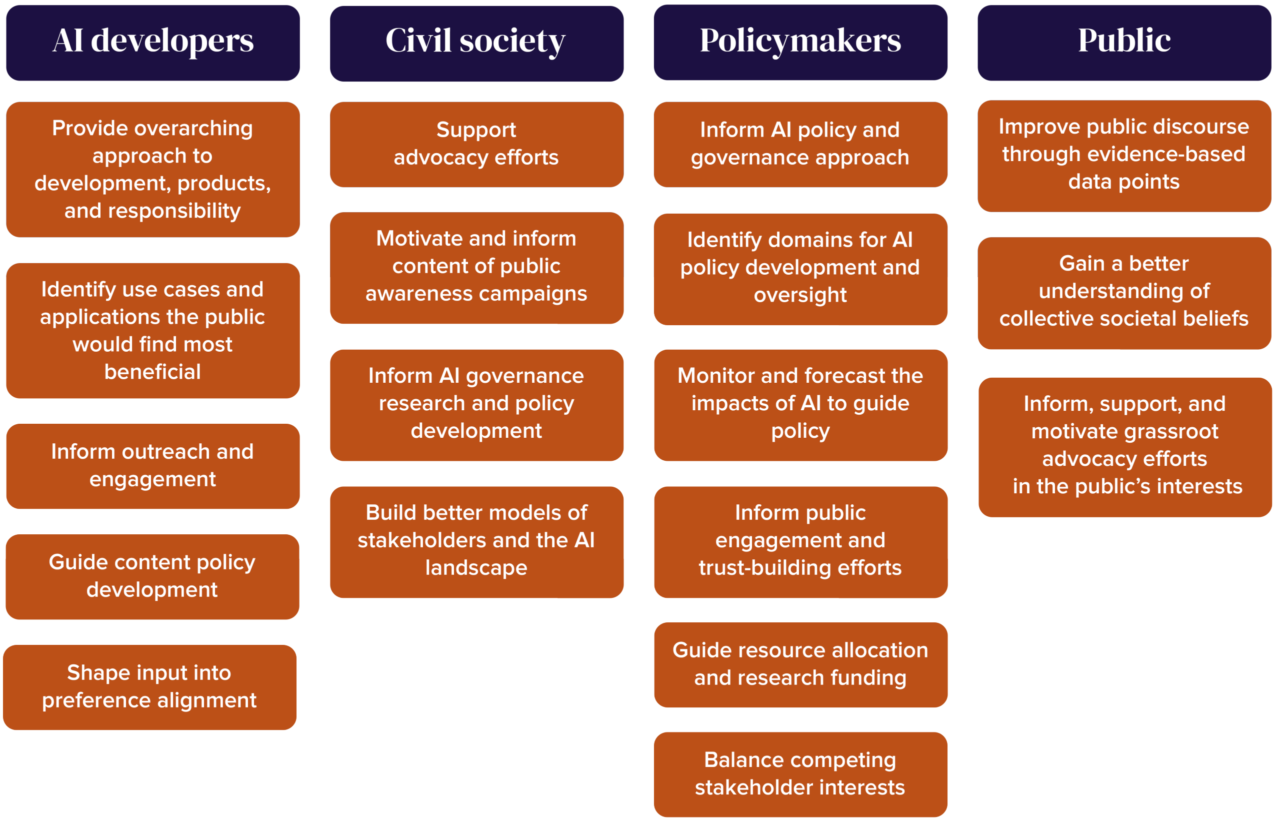


Figure 1: Uses of AI public opinion and attitude research for different actors.

However, researching and understanding public opinion of AI comes with a variety of challenges, some of which we turn to next.

Learning from other research fields. Where collective action is important, such as with respect to climate change, research has tracked the actual and perceived support for climate action globally to better understand hindrances to meaningful action (Andre et al., 2024; Dixon et al., 2024). Similar work could help inform and guide grassroots efforts to address AI's opportunities and challenges.

The challenges of understanding AI public opinion and attitudes

Studying public opinion is not a simple matter. Complicating the aforementioned ambitions, understanding what people think and feel about any particular topic can require navigating an intellectual minefield of splintered and sparring factions, ideas, and methods. The simple bar charts many associate with public opinion research do not reflect well the complexity underlying understanding attitudes and the many decisions that researchers face when conducting such research. Surveys conducted outside of academia often omit deeper and more robust treatment of public opinion practice, and there is wide variation across academic disciplines as well in how – and how rigorously – they approach survey research. This leads to a wide array of ways in which researchers conceptualise and model how we think, feel, and act, as well as the kind of questions and constructs[6] that we see in surveys.

There is no consensus on how to think about what we think about things. Indeed, the lay audience may be surprised by the lack of consensus and contention that remains after almost a century of dedicated study of public opinion and attitudes in psychology, political science, and beyond (e.g., Ajzen, 2011; Berinsky, 2017), as well as the wide array of frameworks and theories that are used to model our attitudes and behaviours.

However, there are some guiding considerations to keep in mind for thinking about attitudes and public opinion. As a starting point, three broad cross-disciplinary and hard-won insights are helpful to keep in mind when thinking about surveys and public opinion (of AI):

1. Surveys of public opinion and the measurement of attitudes come with a wide range of challenges connected to two central issues: 1) the **sample**, in other words, who to invite and how to survey them, 2) the **content** of the survey, that is, what to ask about and how to construct the survey questions (Berinsky, 2017).
2. There are **cognitive**,[7] **affective**,[8] and **behavioural components** to how we evaluate and respond to the world. What someone *thinks* about something, is different to how they *feel* about it, which likewise does not directly translate into how they *act*.
3. What people think, feel, and do in relation to an attitudinal object, such as AI, can be highly **context-dependent**, depend on their **individual characteristics**, and is subject to **cross-cultural differences**.

There are a range of considerations and challenges to keep in mind when interpreting survey findings. These include issues such as question wording and order, response bias, sample representativeness, and

[6] In psychology and social science, a construct refers to a concept or characteristic that is abstract and not directly observable but can be measured through specific indicators or questions. For example, "trust" is a construct that might be assessed through questions about one's confidence in the reliability, integrity, or competence of another party. Constructs are often operationalised in research to test theories and explore relationships between variables.

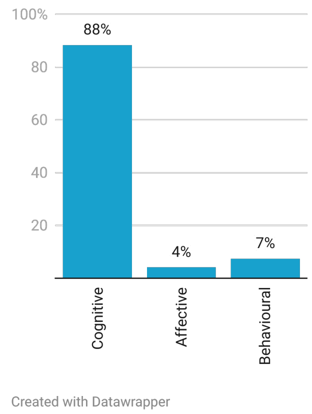


Figure 2: AI SHARE database finding: The vast majority of AI public opinion survey questions evaluate cognitive aspects of attitudes.

[7] The cognitive aspect of attitudes includes both the knowledge and evaluative beliefs and predispositions a person may have about something.

[8] The past decades have seen researchers across disciplines studying attitudes, such as psychology and political science, highlight and investigate the role of affective factors such as emotions, affect, and sentiments (e.g., Smith-Lovin, 1989; Marcus et al., 2013).

construct measurement. In the Appendix, we detail a list of considerations for conducting and understanding surveys. A key lesson from the complexity and nuance of attitude and public opinion research at large is the need for high-quality research that takes seriously who to sample in a survey, what to measure, and how to measure it. As a consumer of surveys, it is equally important to take care when evaluating or interpreting surveys by considering the factors noted in the Appendix, as well as checking the raw, detailed, or disaggregated results, rather than merely depending on the editorialising or top-level statements of those presenting the research findings.[9]

There are additional challenges when trying to understand AI public opinion. Understanding public opinion, attitudes, their relationship to behaviours, and how to measure them is a challenging field of inquiry in its own right. But AI offers additional challenges:

- **AI is not just one thing**, and attitudes towards it have been investigated for specific AI systems, applications, and tasks (e.g., autonomous driving, chatbots, facial recognition technology), for broad domains (e.g., medicine, education, government, art), for functions (e.g., algorithmic decision-making), and for broadly conceived conceptions of AI, algorithms, or robotics. There can even be disagreements amongst experts on what constitutes AI in the first place.
- **AI is a fast-moving and shape-shifting topic.** AI progress provides a continually moving target for researchers seeking to understand the public's attitudes towards it. This increases the value of regular and periodic surveys that establish high-quality longitudinal data of consistent questions, along with the flexibility to rotate in new modules of questions that can react to ongoing issues.
- **AI attitude and opinion research findings are spread across academic disciplines** with few review or systematising efforts and, to our knowledge, no meta-analysis to date that focuses on public opinion of AI broadly. The more academic literature focused on AI attitudes towards specific AI applications has seen more of such synthesising efforts.
- **Research on AI is conducted by a wide range of actors**[10] and is often also published outside of traditional academic venues, meaning reviewing the research requires the scouring of a growing grey literature that can be difficult to evaluate in terms of its quality and provenance, and challenging to slot into existing theoretical frameworks, trends, or the academic literature.
- **Research looking at AI public opinion is still pre-paradigmatic** in its approach, sometimes borrowing from previous frameworks used in other fields of inquiry, but also still often conducted in a way that does not clearly link into existing theories of how to

[9] Illustratively, if a survey reports that only 28% of people think AI has more risks than benefits, you may think this points to low pessimism about AI. If you were then told that 14% of respondents said there were more benefits than risks, you would conclude that people are twice as likely to be pessimistic than optimistic about AI. But missing out that 43% of the respondents said the risks and benefits were equal would mean overlooking a key aspect of this study on public opinion of AI – the largest fraction of people in this survey expressed the belief that AI will have similar levels of risks and benefits. These percentages are taken from a study of British adults conducted by the Office for National Statistics (2023c)

[10] Research on public opinion and attitudes towards AI has been conducted by polling firms, companies, think tanks, governments, and academic institutions. Beyond the research that has been made publicly available which we discuss here, further research resides behind paywalls (e.g., Rappoport-Hankins, 2023) or has been conducted by firms or political polling actors that generally keep their findings private.

> model attitudes and their impacts, or point to reliable, consistent ways to measure constructs. As such, the studies and polls looking at broad AI public opinion that we discuss below largely lack established ways to consistently measure specific constructs across studies. Further, generally, these constructs have not undergone much testing in terms of their validity and reliability.

Using AI public opinion research insights is not straightforward. For example, it is important to remember that even with solid research findings in hand, it is not sufficient to take that result and insert it simply into one's own mental model of how the world works. For instance, knowing someone supports a use case of AI is not necessarily a direct indicator that they intend to use it themselves (Horowitz et al., 2024), nor does lack of support clearly suggest how likely someone is to have this attitude affect their day-to-day or political behaviours. It is important to base broader takeaways on research that investigates the relationship between public opinion and other outputs, indicators, or actions you care about, and be otherwise cautious about making assumptions about such associations.

Answering the question of what the public thinks about AI, then, requires both nuance and breadth. There is currently no clear cut way to summarise across such findings for a review of AI public opinion and attitudes. This makes it more difficult to draw clear conclusions about the findings of AI public opinion research, or even have a good line of sight to what is out there. Aiding with this challenge is one of the motivations for this report and creating the AI SHARE database.

The AI SHARE database

The AI Survey Hub for Attitudes and Research Exchange (AI SHARE) was developed by the Governance and Responsible AI Lab (GRAIL) at Purdue University with collaborators at the University of Pennsylvania, the University of Michigan, and Emory University to gain a broad understanding of how survey researchers measure opinions on AI, the target populations for AI opinion studies, and the substantive findings from these studies. The creators of AI SHARE systematically collected English-language survey questions on attitudes and opinions of AI from the growing number of publicly-released polls, descriptive surveys, and survey experiments produced by academic researchers, think tanks, and survey firms.

The initial launch of the AI SHARE database consists of 218 studies from academic journals, think tanks, and survey firms between 2014 and 2023, and these studies include 1,872 survey items on AI issues. In this report, we present meta-level findings from 189 public opinion surveys on AI. Of these surveys, 92% (174 out of 189) were from academic publications, either peer-reviewed or shared online as working papers.[11] For each study, the database includes information on the study itself – such as its sample size, the countries of residence of respondents, and sampling approach – as well as on the individual survey questions asked – such as the type of AI technology referenced in the question, the sector of interest, and survey topic of interest. **The database includes 189 public opinion studies, from which we derive data for this report**, but also includes some surveys from experts, researchers, or industry-specific workforces.

The data in AI SHARE can be used to characterise the state of current knowledge on AI attitudes, to understand how researchers conceptualise and measure AI opinion, and to identify areas for improvement in public opinion research on AI, both in terms of the target populations that researchers attempt to study and survey research practices.

The AI SHARE database shows, for example, that the overwhelming majority of studies on AI opinion seek to understand 1) the cognitive aspects of attitudes towards AI, as opposed to people's affective responses or behaviours, and 2) opinions of the aggregate US adult population, as opposed to sub-populations such as policymakers, citizens who are exposed to the risk of job loss due to automation, or non-US populations. Moreover, many surveys tend to assume participant familiarity with AI as opposed to inquiring about and measuring respondents' baseline levels of knowledge and familiarity with AI.

[11] **Important note**
While we present meta-level findings from the AI SHARE database throughout the report, the literature review sections are not based on the AI SHARE database. In the future, the database will be used to create such finding-level insights as well.

What does the public think about AI? Early insights from survey research

The AI public opinion literature is growing. Based on the AI SHARE database, the majority of these studies (91% of 175 studies) are conducted online, and there has been a steady increase in AI-related surveys being published (see Figure 3). Not all studies make use of sampling best practices. According to the AI SHARE database, 43% of 112 studies recruit online samples without any quotas or adjustments made,[12] while 39% make such efforts to improve the representativeness of samples. Only 18% of surveys use probability samples,[13] which can better capture the natural variability in the population.

[12] A **quota** or **adjustment** in survey sampling is a method used to match the characteristics of the sample with the population by setting targets for specific demographics or applying weights, rather than relying on random selection.

[13] **Probability sampling** is a sampling method where every individual in the population has a known, non-zero chance of being selected, ensuring a representative and unbiased sample that supports valid statistical inference.

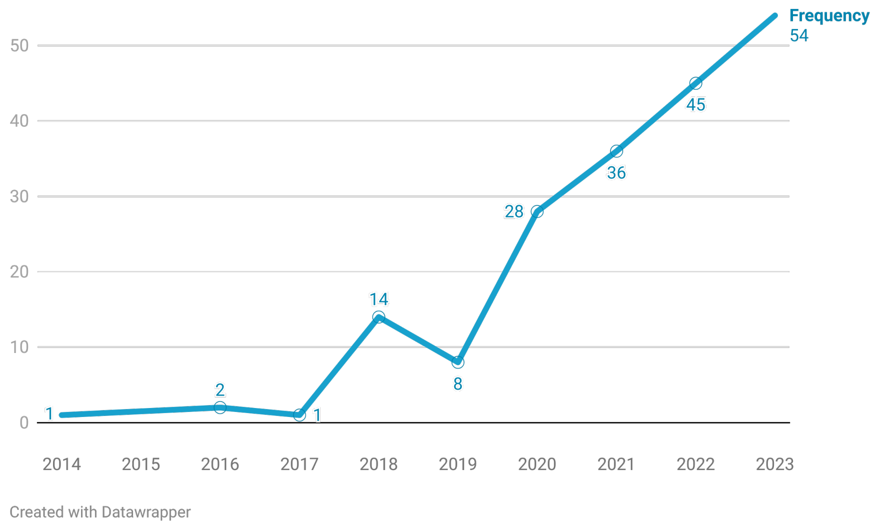


Figure 3: AI SHARE database finding: There are a growing number of AI public opinion survey publications.

A variety of actors conduct such surveys. These include: *academics* (e.g., Scantamburlo et al., 2023; Pham et al., 2023; O'Shaughnessy et al., 2023) as well as *polling organisations* (e.g., YouGov, 2023a; Pew Research Center, 2024), *market research* or *business intelligence organisations and consultancies* (e.g., Ipsos, 2022b, 2023b; Morning Consult, 2017, 2021; Deloitte, 2023), *think tanks* and *civil society organisations* (Public First, 2023a, 2023b; Ada Lovelace Institute and The Alan Turing Institute, 2023), *governments* or *official national institutes* (e.g., Department for Business, Energy and Industrial Strategy, 2019, 2020, 2021, 2022; Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023a; Office for National Statistics, 2023a), and *groups at the intersection of these sectors* or in co-operation between them (e.g., Gillespie et al., 2023).

The surveys can differ in geographical scope. Aside from surveys focusing on *single countries* (e.g., Selwyn et al., 2020; Zhang and Dafoe, 2019; Kieslich et al., 2023), there are some large-scale *regional* surveys that have been conducted on the topic of AI (e.g., European Commission, 2017, 2019, 2020) as well as *global* surveys (Ipsos, 2022b, 2023b, 2024b; Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024; Gillespie et al., 2023; World Risk Poll, 2019; 2021, 2024).

It is a pre-paradigmatic research field. Much of the research, surveys, and polling done on these topics is lighter on theoretical frameworks, descriptive in nature, and is also spread across the academic and grey literature. Within academia, such research is conducted across different disciplines. These factors make the area more pre-paradigmatic and difficult to review. Indeed, only few reviews exist of the broad AI public opinion field (see Past reviews of AI public opinion survey research). This is not the case for the extensive academic literature that has focused on attitudes towards AI in specific applications or domains, for which more theoretical frameworks as well as synthesising and meta-analytic efforts exist (see Attitudes towards specific AI applications or use domains).

Past reviews of AI public opinion surveys

To our knowledge, few attempts exist to review and summarise the AI attitudes and public opinion literature. Existing reviews include:

- Zhang (2022b) looked at some key topics in AI public opinion research, conducting a non-systematic review of findings relating to AI knowledge and trust in AI amongst the public, as well as four applications of AI and setting out four future research directions for AI public opinion research.
- Eom et al. (2024) reviewed and synthesised the findings of eleven surveys conducted in the United States over the past four years.
- Beets et al. (2023) systematically reviewed eleven studies across the academic and grey literature looking at US public opinion of AI use in healthcare.
- Stein-Perlman (last updated 2024) has collected 45 surveys of US public opinion and briefly summarised each of their findings.
- Tahaei et al. (2024) systematically reviewed 44 public opinion of AI papers to better understand the methodological approaches being used in such studies, such as, how participants were recruited, geographic diversity of authors, funding sources, and whether participants were compensated.

There are limited longitudinal data. Additionally, there are little longitudinal data that allow us to identify trends as of yet. A contributing factor is that there are remarkably few public opinion trackers that consistently poll representative samples of the public regarding AI. There is, for example, to our knowledge, no longitudinal tracker of AI attitudes in the United States. In addition, efforts rarely have long term reliable funding that ensure the survey continues to be fielded.

There was a detailed monthly tracker of AI public opinion in Germany between 2020 and 2024. The perhaps most exhaustive and long-running tracker of public opinion on AI was the *MeMo:KI – Opinion Monitor Artificial Intelligence*. The survey covered topics such as whether AI should be used in specific realms, how people judge their own knowledge of AI, how people assess the balance of AI's risks vs. benefits, and which tasks respondents think can be done by AI at all. The survey involved periodic monthly surveys of one thousand German respondents and the results are displayed via dynamic data visualisations online, along with media and social media analysis (e.g., Kieslich et al., 2022a). This project ensured that for the years 2020 and 2024, there are surprisingly fine-grained, high-quality data on German public opinion on AI.

There are some efforts to track public opinion in the United Kingdom. The UK currently has (and previously had) a number of governmental efforts to track public opinion on AI. The *BEIS public attitudes tracker* collected views on AI in the years 2019 to 2022 in Great Britain (Department for Business, Energy and Industrial Strategy, 2019, 2020, 2021, 2022). It covered the following topics: awareness of AI, interest in AI, sentiment about the impact of AI, and attitudes towards and awareness of specific AI applications (e.g., facial recognition applications, "computer apps" used to recognise speech and answer questions). It is unclear whether this public opinion tracker will continue to be fielded.

The *Public Attitudes to Data and AI Tracker Survey (CDEI)* has been fielded for three waves between 2021 and 2023 (Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2021, 2022, 2023b). The *UK's Office for National Statistics* has conducted some surveys with questions on AI previously (Office for National Statistics, 2023a, 2023c, 2024), and is now running fortnightly surveys of AI-related questions as part of its Opinion and Lifestyle Survey (OPN; Office for National Statistics, 2024). It asks the British public about whether they think they can recognise the use of AI, their views on whether AI has more benefits or risks, whether they think AI will benefit them, their personal AI use in a variety of domains, actions taken to learn more about AI, and what AI topics they are interested in learning more about.

The terminology used can be diverse. AI public opinion surveys use terms other than just AI, such as algorithms, robots, digital technologies, automation, and combinations of these with the term AI (e.g., Grzymek et al., 2019; Smith, 2018; European Commission, 2017). This is also the case for academic research that has focused on different AI applications and use domains. For example, some studies have been influenced by other long-standing literatures and concepts related to algorithm aversion (Dietvorst et al., 2014; Jussupow et al., 2020) or automation (Borwein et al., 2023; Kurer and Häusermann, 2022; Pew Research Center, 2017a).

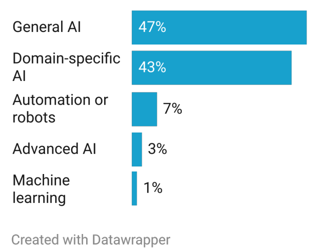


Figure 4: AI SHARE database finding: What kind of concepts do AI-related survey questions ask about?

Of course, it is unclear to what extent the public considers these concepts to be comparable. Studies have found that AI is connected to robotics in some people's minds (Selwyn and Gallo Cordoba, 2022; Kieslich et al., 2023), though we imagine this could shift as the public becomes more aware through increased exposure to AI tools like ChatGPT, or to consumer robotics, for example. In 2018, Zhang and Dafoe (2019) found little difference in responses when using the terms AI, robots, or AI and robots, when asking respondents which applications used such technologies, suggesting such words point to broad overlapping concepts in people's minds. The AI SHARE database finds that the majority of AI public opinion questions in the database ask about AI generally followed by domain-specific applications of AI (see Figure 4).

We identified six themes in the literature. The AI public opinion literature covers many topics including individual and societal beliefs, concerns, and expectations related to the adoption of AI. We have identified at least six broad themes of questions that have been asked about in surveys that explore AI public opinion (see Figure 5).

Figure 5: Themes in the AI public opinion survey literature

You can jump to each theme here:
1. Background AI beliefs, awareness, use, and knowledge
2. General attitudes towards AI
3. Views on the risks, benefits, and impacts of AI
4. Views on AI development, regulation, and governance
5. Attitudes towards different specific AI applications or use domains
6. Individual and group characteristics and differences

Reviewing the literature. Below, for each theme in turn, we first survey the types of questions and topics that studies and polls have covered. Then, where possible, we offer our best-guesses which attempt to summarise the current evidence-base for selected topics within each of the six themes, and note some relevant findings that motivate our belief. These insights are based mainly on research from North America and Europe, with a focus on the United States and the United Kingdom. Since marked cross-cultural differences are likely to exist between countries and regions, care should be taken not to assume that these trends hold in different geographies.

We hope these early insights can motivate and aid the creation of more systematic efforts to create frameworks for understanding public opinion on AI, serve as a useful starting point for identifying gaps in data collection efforts, and provide, where possible, falsifiable hypotheses.

Background AI beliefs, awareness, use, and knowledge

Topics and questions

Academic AI attitude research on specific applications of AI, as well as research examining societal attitudes towards other emerging technologies and risks, has found that knowledge and understanding of the technology itself can be an important antecedent to understanding attitudes and behaviours.[14] Based on the 189 public opinion studies in the AI SHARE database, 88% of survey questions probed cognitive constructs related to AI, while only 4% explored affective/emotional responses and 7% examined behavioural responses. Not e that the cognitive aspect of attitudes includes both the knowledge and evaluative beliefs and predispositions a person may have about something.

[14] Although note that associations are not necessarily found for all kinds of constructs, for example, see this section below.

Within this theme, we have identified at least five clusters of the kind of questions asked about:[15]

[15] **Subthemes:**

1. Knowledge
2. Awareness
3. Belief about AI capabilities
4. Recognition of AI
5. Use of AI

Knowledge Surveys have asked questions about understanding, knowledge, and expertise of AI and related topics. Such questions often ask respondents to self-report their level of knowledge by rating their expertise or familiarity with AI (e.g., Scantamburlo et al., 2023), stating whether they understand what AI or an algorithm is (e.g., Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024) or indicating how much they know about AI or its various applications (Department for Business, Energy and Industrial Strategy, 2019, 2020, 2021, 2022; Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023a). Beyond self-reported knowledge, in some cases knowledge tests or written responses are evaluated to provide a more objective measure of whether individuals' knowledge (e.g., Bewersdorff et al., 2024; Cave et al., 2019).[16] Researchers may also try to understand levels of expertise and knowledge by asking respondents about their relevant educational attainments or work experience. Zhang and Dafoe (2019), for example, ask whether respondents have computer science or engineering degrees or related work experience to evaluate the level of relevant technical knowledge of survey participants.

[16] Academic psychologists have developed scales to measure AI literacy and self-efficacy (Bewersdorff et al., 2024; Hornberger et al., 2023).

Awareness and exposure Another common and related theme of questions focuses on respondents' exposure to, awareness of, and interest in AI. This often involves asking about how much someone has heard, read, or otherwise learned about AI or specific applications or systems (e.g., Gillespie et al., 2023; Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024; The Associated Press-NORC Center for Public Affairs Research, 2023; Cave et al., 2019). The BEIS tracker (Department for Business, Energy and Industrial Strategy, 2019, 2020, 2021, 2022) of British adults asks a question that is more focused on the level of interest in AI.

Belief about AI capabilities Another category of questions relates to what people think AI systems can currently do or will be able to do in the future. This may involve asking people whether they think AI systems have or will have certain capabilities (e.g., Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024) or how intelligent they think AI systems are or will be, especially in comparison to humans (YouGov, n.d.(a), n.d.(b), 2024a; Morning Consult, 2021; Zhang and Dafoe, 2019; West, 2018a). YouGov US and UK, for example, track how intelligent the public thinks robots are. Similar to surveys of AI researchers (Grace et al., 2018, 2022, 2024; Zhang et al., 2022), the public has also been asked to forecast when AI systems will attain certain levels of skill or intelligence, e.g., the ability to complete tasks as well as humans (Zhang and Dafoe, 2019) or when they may have experiences such as sentience (Pauketat et al., 2022, 2023). Another approach has been to ask respondents about the pace at which they expect AI to advance (YouGov and The AI Policy Institute, 2023a).

Recognition of AI Some survey questions focus on whether the public is able to recognise the use of AI, including whether they are aware of or believe AI is used in specific contexts. For example, they may be asked to identify whether a specific application or tool uses AI (e.g., Gillespie et al., 2023; Scantamburlo et al., 2023) or whether AI has been used in specific domains (Scantamburlo et al., 2023). Surveys have asked respondents to self-report whether they think they can recognise AI when it is used or whether they can distinguish AI-generated content from human-generated content (Office for National Statistics, 2023c).

Use of AI Surveys also commonly ask whether respondents have used different AI applications like virtual assistants or specific systems such as ChatGPT (e.g., Gillespie et al., 2023; European Commission, 2017; Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024). They may further ask about how often they are used and whether they are used in specific contexts such as for work or personal life (e.g., Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024; Office for National Statistics, 2023c; Humlum and Vestergaard, 2024).

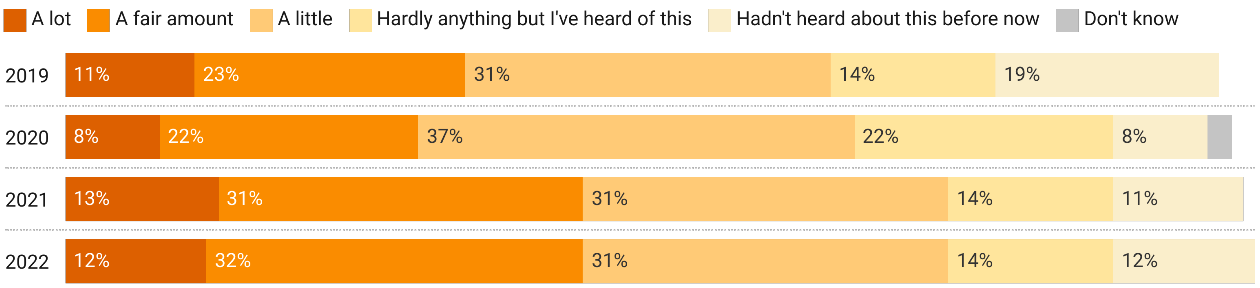
Insights

Awareness Overall awareness of AI among the general public has been steadily increasing in recent years, likely driven by increasing use and public discourse, but remains uneven across the public.

- Both awareness and objective understanding of AI were found to have increased from 2020 to 2022 in a survey fielded in the United States, the United Kingdom, Australia, Canada, and Germany (Gillespie et al., 2023). Awareness that different products or services use AI has increased from 46% to 56%. More people had also read or heard about AI in 2022 (78%) than in 2020 (62%).
- In August 2023, a Pew Research Center poll found that 33% of US adults said they'd heard a lot about AI, 7% more than in December 2022 (Tyson and Kikuchi, 2023). A further 56% said they had heard a little about AI.

Awareness of AI in the United Kingdom between 2019 and 2022

GOV.UK BEIS Public Attitudes Tracker data of U.K. adults answering the question: "Before today, how much, if anything, have you heard or read about artificial intelligence otherwise known as 'AI'?"



Source: GOV.UK • Created with Datawrapper

Figure 6: Data from the UK government's BEIS Public Attitudes Tracker (2019; Department for Business, Energy and Industrial Strategy, 2020; Department for Business, Energy and Industrial Strategy, 2021; Department for Business, Energy and Industrial Strategy, 2022)

- As can be seen in Figure, 6[17] between 2019 and 2022, the UK government regularly tracked awareness of AI, finding a shift towards a somewhat larger fraction of people reporting they had heard a lot or a fair amount about AI in the years 2021-2022 as compared to the period from 2019-2020 (Department for Business, Energy and Industrial Strategy, 2019, 2020, 2021, 2022).
- In a UK survey of over one thousand respondents conducted in or before 2019, 42% of respondents were able to provide what the authors determined to be a plausible definition of AI. A quarter

[17] All survey waves from the UK government's BEIS Public Attitudes Tracker can be found online currently. The figure was created based on Wave 30 (Department for Business, Energy and Industrial Strategy, 2019), Wave 34 (Department for Business, Energy and Industrial Strategy, 2020), Autumn 2021 (Department for Business, Energy and Industrial Strategy, 2021), and Summer 2022 (Department for Business, Energy and Industrial Strategy, 2022) results.

of respondents thought that it referred simply to robots (Cave et al., 2019).

- Academic studies reporting surveys fielded in 2020 still find patchier levels of AI awareness (Nader et al., 2024; Owsley and Greenwood, 2024) than later levels appear to indicate.
- In 2022, 82% of all respondents globally had heard, read, or seen something about AI. In the US, this was 75%, in the UK, 78%. The highest awareness (>90%) was seen in South Korea, China, Finland, Singapore, and India (Gillespie et al., 2023).
- In 2023, 67% of US respondents and 64% of British respondents said they agreed "somewhat" or "very" much that they had a good understanding of AI. This represents 7 and 4 percentage point increases for Great Britain and the United States, respectively, since December 2021 (Ipsos, 2022b; 2023b).
- In May 2023, 9% of British respondents said they never heard of AI, 19% said they had heard of it but could not explain what it is, 53% said they had heard of it and could give a partial explanation, and 19% said they had heard of AI and could explain what it is in detail (Office for National Statistics, 2023a).
- In May 2023, 51% of UK respondents said that they have a great deal or fair amount of understanding about what AI is, while 41% said "not very much." Only 5% of respondents reported no understanding of AI whatsoever. In terms of the issues surrounding AI, 41% said they knew a great deal or a fair amount, 45% said that they did not know very much, and 10% said they had no understanding of these issues (YouGov, 2023a).
- In August 2023, 95% of UK adults had heard of AI and 66% claimed to be able to give at least a partial explanation of what it means, up from 56% in 2022 (Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023c).
- Those who have never heard of AI decreased from 11% to 5% from the 2022 to 2023 survey waves of the UK government's Public Attitudes to Data and AI Tracker Survey (Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2022, 2023b).
- The majority of US and UK respondents agree that they understand what the term AI means, while a tenth or less of respondents disagree. When respondents are asked about whether they know what an algorithm is, agreement decreases (Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024).

Caveats A caveat to consider is that few surveys evaluate objective knowledge and awareness of AI with most asking respondents to self-report. For example, even respondents who self-report expertise may not be accurately be able to identify which AI applications actually exist or what they do: In 2018, only 28% of US adults correctly classified Netflix or Amazon recommendations as using AI and only 36% of survey respondents correctly classified Facebook photo tagging as AI-based (Zhang and Dafoe, 2019).

Use The public has long used AI (e.g., social media, spam detection, search) but generally has not realised that they are doing so. New generative AI tools are the first AI-powered tools that the public is knowingly using at scale and their use is increasing both at work and for personal needs. Use is more prevalent amongst younger generations.

- Although 68% of adults surveyed globally in October 2022 had used common AI-enabled tools, 41% were unaware that the technologies used AI. The lowest awareness was for housing-sharing apps (64% unaware), ridesharing apps (59%), email filters (50%), social media (45%), and product recommendations (43%). Unsurprisingly, there is greater awareness of AI when it is used in more tangible applications, such as via virtual assistants (only 25% unaware), smart home management (32%), text recognition (32%), and facial recognition (30%) (Gillespie et al., 2023).
- In August 2023, 12% of UK adults used chatbots at least weekly for personal use (vs. 10% for work). 34% used them at least once a month for personal use (vs. 24% for work). Usage rates are higher for younger adults, with 23% of 18-34 year olds using chatbots at least weekly for personal use, and 53% at least monthly (vs. 20% weekly and 48% monthly for work) (Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023c).
- In July 2023, a Pew Research Center poll found that 18% of US adults overall reported to have used ChatGPT, while of those who had heard of ChatGPT, 24% had used it. Usage is higher among younger adults, with 41% of adults who had heard of ChatGPT aged 18-29 having used it. 16% of US adults who are employed and have heard of ChatGPT say they've used it for work (Park and Gelles-Watnick, 2023). By February 2024, this increased to 23% of US adults overall saying that they had used ChatGPT and a fifth overall having used it for work (McClain, 2024; Pew Research Center, 2024).
- In June 2023, 52% of UK 16-75 year olds had heard of generative AI, 26% had used generative AI tools, 10% used them every week, and 8% had used them in work (Deloitte, 2023). Younger generations were more likely to have heard of generative AI than older genera-

tions: 73% of those under 35 had heard of it, in comparison to 27% of 65-75 year olds.

- In the UK in June 2023, Ofcom found that 39% of men and 24% of women aged 16+ said they've used generative AI. Usage is much higher among younger age groups (74% for 16-24 year olds, 50% for those aged 25-34, 35% for 35-44 year olds, and 14% for those aged 45+) (Ofcom, 2023).
- The same survey found that 23% had used ChatGPT (30% male, 17% female); 15% Snapchat MyAI (18%, 12%); 11% Bing Chat (15%, 6%), and 9% Google Bard (14%, 5%) (Ofcom, 2023). Teenagers showed particularly high use: 79% of online 13-17 year olds and 40% of online 7-12 year olds had used at least one of ChatGPT, Snapchat My AI, Midjourney, or DALL-E.
- In 2023, the UK's Office for National Statistics's fortnightly Opinions and Lifestyle Survey found that a third of respondents (33%) reported that they can hardly ever or never recognise when they are using AI, 50% said they could do so some of the time, and 17% said they could do so often or always. Men, younger adults, mixed ethnicity, non-disabled adults, those with a degree, and those working in professional occupations reported they were more confident in their ability to be aware that AI systems were being used (Office for National Statistics, 2023b).
- In May 2024, a survey by Impact Research found that roughly half of teachers, students, and parents are using AI chatbots at least once a week. A quarter or less had never used them (Impact Research, 2024).
- In March 2024, over one in five (22%) US respondents said they used AI tools weekly or more regularly (YouGov, 2024b).

General attitudes towards AI

Topics and questions

There are various ways that surveys attempt to understand people's attitude or sentiment towards AI generally. Currently, many surveys use one-item approaches to capturing this general stance towards AI, though these items have not been systematically assessed in terms of their validity and reliability. Questions used to ascertain this general attitude or sentiment towards AI include:[18]

- to what extent someone supports or opposes AI development and specific forms of the technology (e.g., Zhang and Dafoe, 2019; Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024; Calice et al., 2020),

[18] Some studies also look at support for advanced AI technology, such as high- or human-level machine intelligence and artificial general intelligence (Zhang and Dafoe, 2019, 2023a; Public First, 2023b; YouGov and The AI Policy Institute, 2023c)

- whether they approve or disapprove of AI (e.g., Scantamburlo et al., 2023),
- whether someone is concerned or excited about AI and its development (e.g., Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024; YouGov and The AI Policy Institute, 2023a),
- whether someone feels more positive or negative about the increased use of AI or its impacts (e.g., Department for Business, Energy and Industrial Strategy, 2019, 2020, 2021, 2022; YouGov, 2024b),
- whether respondents think that AI will be harmful or beneficial over different time spans or specifically will either harm or benefit them personally (e.g., Office for National Statistics, 2023c),
- whether respondents think AI will be or is good or bad for society (e.g., Kelley et al., 2021; Funk et al., 2020),
- whether the benefits of AI outweigh its risks (e.g., Gillespie et al., 2023; Office for National Statistics, 2023c; Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023a),
- whether someone believes AI will make the future better or worse (e.g., Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024).

Researchers have also looked at general attitudes towards AI through the lens of trust (e.g., Gillespie et al., 2023). However, to our knowledge, no study has systematically compared responses across such questions to see if they diverge significantly.

Some studies also look at the emotions evoked by AI in people – whether it makes them, for example, concerned, hopeful, excited, afraid, or cautious (e.g., YouGov, 2024b; Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023a; Kelley et al., 2021; Tyson and Kikuchi, 2023; Gillespie et al., 2023; YouGov and The AI Policy Institute, 2023a). However, based on the findings from the AI SHARE database and our canvassing of the literature, such direct ways of measuring affective aspects are much rarer than more cognitive measures of people's attitudes towards AI. A useful approach for gauging levels of AI anxiety day-to-day was applied by Elsey and Moss (2023b), who asked respondents to what extent they worry about the personal and societal negative effects of AI in their daily lives.

Importantly, surveys have made less use of composite index variables or scales to measure general attitudes, as compared to single-item questions, likely in part because these can add considerable length to a survey. Academic psychologists have developed some scales to measure general attitudes or fears towards AI (e.g., AI attitude scale, AIAS-4, Grassini, 2023;

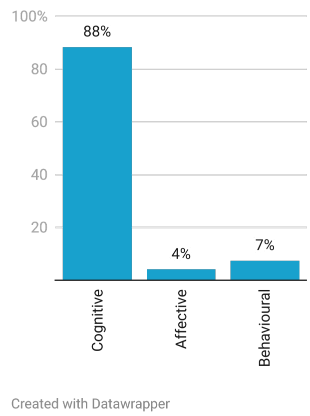


Figure 7: AI SHARE database finding: Limited measurement of affective and behavioural responses to AI.

Negative Attitude toward Robots Scale, NARS, Nomura et al., 2006; General Attitudes towards Artificial Intelligence Scale, Schepman and Rodway, 2020; Schepman and Rodway, 2023; Threats of Artificial Intelligence Scale, TAI, Kieslich et al., 2021) though these have generally not been used much yet in the context of AI public opinion surveys and should be individually evaluated for their merit and utility.

Insights

Sentiment about AI There is mixed evidence on whether people are more positive or negative about AI and how this is shifting over time. Both the US and UK public may be more concerned about the impacts of AI than they are optimistic about AI's effects, but this can vary between surveys and a sizeable number of people also have a mixture of positive and negative sentiments towards AI.

- In August 2023, a Pew Research Center survey found that 52% of US adults said they felt more concerned than excited about the increased use of AI, a large jump from 38% in December 2022. Only 10% were more excited than concerned in 2023, compared to 15% in 2022 (Tyson and Kikuchi, 2023).
- In August 2023, 25% of UK adults thought the impact of AI on society will be net negative, and 58% neutral. Only 14% thought it would be net positive. This is a 5 point increase in pessimism and 3 point decrease in optimism since the previous survey wave in June/July 2022 (Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023c).
- In October 2023, 48% of UK adults thought AI had more risks than benefits and 38% thought it had more benefits than risks. In the United States, the results were similar: 49% and 34% respectively (Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023a).
- In May 2023, 19% of UK adults were optimistic about the impact of AI overall (2% very, 17% fairly), 35% were pessimistic (26% fairly, 9% very), and 34% were neither optimistic or pessimistic (YouGov, 2023a).
- In May 2023, when asked what they thought the impact of AI on society would be on a scale of 0 (very negative) to 10 (very positive), slightly more people in the UK gave positive scores (41%, 6-10) than gave negative scores (27%, 0-4), indicating moderately more optimism. A third of respondents (32%) expected the impacts of AI on society to be neutral (Office for National Statistics, 2023d).
- In a survey of British adults, 28% thought AI has more risks than benefits, double the amount that thought AI has more benefits

than risks (14%). The largest fraction of respondents believed AI has equal benefits and risks (43%) (Office for National Statistics, 2023b).

- In a poll in January 2023, the vast majority of US respondents either thought AI would do equal amounts of harm and good (46%) or that it would do more harm to society overall (41%) (Monmouth University Poll, 2023). Only 9% of respondents believed computer scientists' ability to develop AI would do more good than harm to society. These results appear to not have shifted since 2015.
- As can be seen in Figure 8, between 2019 and 2022, there was a small shift towards more positive views about the increasing use of AI in Great Britain, although there has been no updated data since that period from this public opinion tracker (Department for Business, Energy and Industrial Strategy, 2019, 2020, 2021, 2022). This also highlights that the type of question can lead to a very different impression of sentiment towards AI.

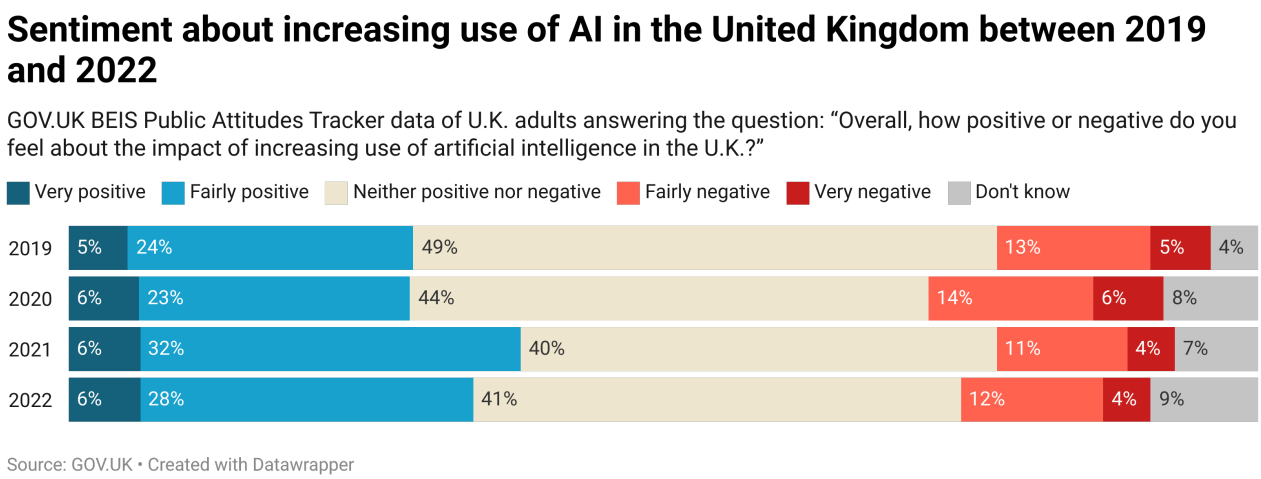


Figure 8: Data from the UK government's BEIS Public Attitudes Tracker. All survey waves from the UK government's BEIS Public Attitudes Tracker can be found online currently. The figure was created based on Wave 30 (Department for Business, Energy and Industrial Strategy, 2019), Wave 34 (Department for Business, Energy and Industrial Strategy, 2020), Autumn 2021 (Department for Business, Energy and Industrial Strategy, 2021), and Summer 2022 (Department for Business, Energy and Industrial Strategy, 2022) results.

- In the United States, a survey of 1,501 respondents in 2019 conducted as part of a larger eight country study found that 21% of US Americans expected AI to be mostly good for society in the long term, 17% thought it would be mostly bad for society, 40% thought that it depends and could be either good or bad, and 13% believed it would be good and bad in equal amount (Kelley et al., 2021).

- The World Risk Poll surveys 150,000 respondents around the world every two years with at least one thousand respondents in each country. It found that North Americans have been divided on whether AI will mostly help or mostly harm people in their country in the next 20 years – both in 2019 (41% help, 47% harm) and in 2021 (33% help, 34% harm), with a larger fraction of respondents saying that they do not have an opinion in 2021. Respondents in North/West Europe shifted towards more positive views from 2019 (41% help, 42% harm) to 2022 (48% help, 27% harm). The risk perception results from 2023 were released in November 2024 but do not appear to report AI-related findings (World Risk Poll, 2019, 2021, 2024).
- In a UK survey of over one thousand respondents, the majority of common narratives about AI (with half being optimistic narratives and half pessimistic) elicited more concern than excitement (Cave et al., 2019).
- From a more product-focused perspective, a 2023 survey found that a majority in Great Britain (65%) and the US (63%) agree that AI products and services make them nervous. This is a 16 and 11 percentage point increase for Great Britain and the US, respectively, since December 2021 (Ipsos, 2022b; 2023b).
- A 2022 survey found that respondents in the US and UK held ambivalent emotions towards AI with optimistic, fearful, and worried responses being reported the most, followed by excitement (more closely so in the US). Only very few respondents across countries reported feeling outrage towards AI (Gillespie et al., 2023).
- In a survey of 1,126 US and 1,090 UK adults conducted in October 2023, nervous (23% US/29% US), hopeful (17%/17%), and excited (16%/17%) were the three most commonly chosen emotions to describe how respondents felt about AI (Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023a).
- YouGov found in March 2024, that 1,073 US Americans were more likely to feel cautious (54%) or concerned (49%) about AI advances, than curious (29%), excited (19%), or hopeful (19%) (YouGov, 2024b).

Caveats Varying questions used, belief in mixed impacts, mixed emotions about AI, notable cross-cultural differences, and only a lack of longitudinal datasets make it difficult to reliably determine current public sentiments and their changes over time. In addition, too few studies examine to what extent such sentiments and concern affect people day-to-day. Finally, note that more differentiated analysis of results by the type of question asked (e.g., views on risks and benefits, trust, optimism or concern, evoked emotions, etc.)

would be helpful to better understand sentiments towards AI generally.

Views on the risks, benefits, and impacts of AI

Topics and questions

Surveys have looked at perceptions and evaluations of different risks, benefits, and impacts of AI.[19] Several studies ask respondents for their general assessment of whether AI has more benefits or risks (Gillespie et al., 2023; Office for National Statistics, 2023c; Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023a). Questions about the risks of AI often ask respondents about the extent to which they are concerned or worried about a range of different risks (Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024 Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023a; European Commission, 2019; YouGov and The AI Policy Institute, 2023a).

[19] Note that, in practice, many of the questions used to understand people's general attitudes (how concerned vs. excited, whether there will be more harms or benefits) towards AI could also be seen as an abstracted way of assessing people's risk and benefit perceptions and attitudes.

Researchers have also asked respondents which applications, domains, and uses of AI they are most excited about or anticipate will benefit from AI (e.g., Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023a; Office for National Statistics, 2023b; Google and Ipsos, 2024), or more generally whether AI will benefit them personally (Office for National Statistics, 2023b). Some surveys have asked respondents to estimate the likelihood and impact of a range of risks (Zhang and Dafoe, 2019; Gruetzemacher et al., 2024), including in comparison to other global risks (Zhang and Dafoe, 2019; Public First, 2023a, 2023b; World Economic Forum, 2024).

Some research and questions focus on extreme risks, such as catastrophic and extinction risks (Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024; Saeri et al., 2024; Elsey and Moss, 2023b; Moss and Sleegers, 2023; YouGov, 2023b; Samoylov, 2023;[20] Gruetzemacher et al., 2024) or societal-level risks (Gruetzemacher et al., 2024). Such studies have also often made use of quantitative forecasts for such risks from AI, as do some studies of subjective automation-driven job loss concern (e.g., Kurer and Häusermann, 2022). Some surveys ask about views on specific features of AI systems and associated risks when these features are lacking in areas like explainability or accuracy (e.g., YouGov and The AI Policy Institute, 2023c; Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023c; Ada Lovelace Institute and The Alan Turing Institute, 2023).

[20] Note this survey is conducted by an advocacy group, the Campaign for AI Safety, and does not provide much information on their methodology or quality of the sample.

To understand what the public thinks will happen because of AI, surveys also ask about the impacts of AI on a range of societal outcomes such as those related to the economy, unemployment, democracy, misinformation, healthcare, or inequality (e.g., Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024; Tyson and Kikuchi, 2023; Calice et al., 2020). At least one study asks about the impacts of advanced AI in the long-term (Zhang and Dafoe, 2019), a question that has also been asked in a slightly adapted form in several iterations of surveys of AI researchers (Grace et al., 2018, 2022, 2024; Zhang et al., 2022). A more personal flavour of question about the risks and impacts of AI asks respondents to what extent they think AI has affected their lives or will in the future: this can be a general question about their daily lives (e.g., Scantamburlo et al., 2023; Arntz et al., 2022), or about specific concerns, for example, about their jobs or the jobs of their immediate family and friends (Gillespie et al., 2023).

Both personal and societal-level automation concern, in particular, has been studied in more depth in the political science and economics literature (e.g., Kurer and Häusermann, 2022; Arntz et al., 2022) and is also a common topic in public opinion polls (e.g., Northeastern-Gallup, 2018; Ipsos, 2023a; American Psychological Association, 2023). Such surveys ask a wide array of versions of questions that can vary along the societal-individual spectrum in terms of the effect of AI focused on. These surveys also differ in terms of the time spans asked about or whether the term AI is used specifically vs. other terms like automation (e.g., Gillespie et al., 2023; European Commission, 2017; Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024).

Insights

Comparing risks

Weighing AI risks against each other We cannot yet draw firm conclusions about how people weigh AI risks against one another due to a large amount of heterogeneity in the items presented to respondents and the questions asked about them, including the time frame within which they will occur.

- In 2018, US respondents believed that surveillance, digital manipulation, data privacy, and cyber-attacks were the AI governance challenges most likely to impact a large number of people in the US in the next ten years. Data privacy, autonomous weapons, and cyber-attacks were seen as the most important issues to be managed carefully by tech companies and governments. However, all AI governance challenges were seen as at least somewhat important and more than 50% likely to impact a large number of people in the US over the next decade (see Figure 9).

- In 2023, in a sample of approximately one thousand US registered voters, a strong majority were either very or extremely concerned about AI being used to hack their personal data (81%), hack government systems (77%), create a bioweapon (75%), and act against human values or intentions (70%). Fewer, but still half or more than half of people, showed such concern in regard to AI having racial or gender biases (56%), AI being used to fly an unmanned military drone (51%), and AI causing humans to go extinct (50%) (YouGov and The AI Policy Institute, 2023a).
- Out of three extreme risks: loss of control of power-seeking AI systems (US: 63%, UK: 61%), AI-enabled cyber-attacks on critical infrastructure (69% / 70%), and AI-enabled bioweapons (68% / 67%), the majority of respondents in 2023 were fairly or very worried about all three risks, but a little more concerned about the latter two than loss of control over AI (Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023a).

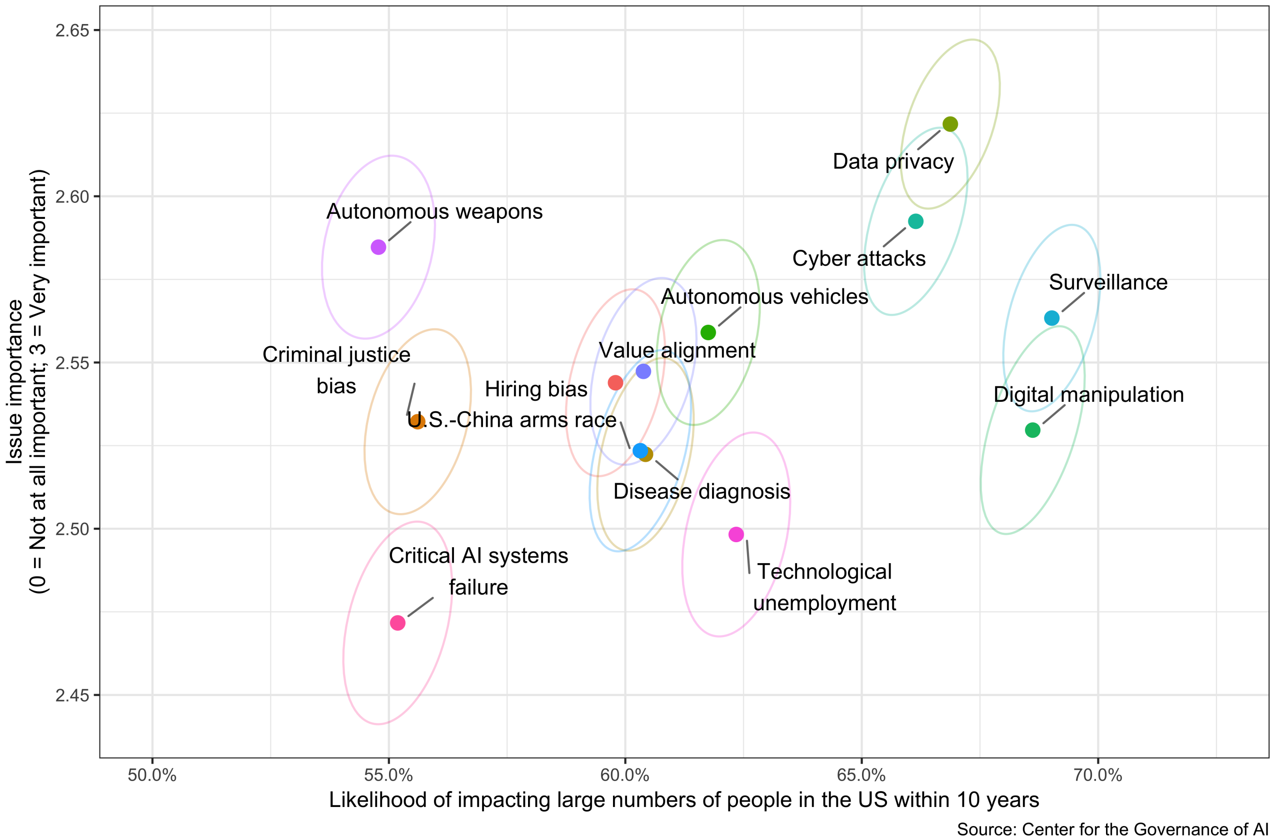


Figure 9: Data visualisation of the public's perceived likelihood and importance of carefully managing a range of AI governance challenges. The survey was completed by 2,000 US respondents in 2018. The data visualisation is taken from Zhang and Dafoe (2019).

- In a sample of almost 15,000 German adults, ethical issues, especially those related to discrimination and fairness, were found to have relatively low salience for members of the German public (Kieslich et al., 2023). The study used an agenda-setting approach (Smith, 1980), allowing respondents to answer the question: "If you think about recent times, which issues related to artificial intelligence have been of most concern to you personally?" however they wanted, including expressing no concern. The most prevalent ethical concerns mentioned were about AI needing to be controlled or if it can be controlled, followed by surveillance through AI, and user privacy.
- In a study of 400 US registered voters and 120 AI researchers fielded in October 2023, the societal-scale risks of AI seen as most likely (more than 50% likelihood) over the next decade or two by the US public sample were: information warfare, privacy, economic instability, knowledge deterioration, monopolies, terrorist AI weapons, cyber attacks, bias/discrimination. The US public generally rated all societal-scale risks as more likely and more impactful than did AI researchers (Gruetzemacher et al., 2024). Terrorist use of weapons of mass destruction, civilisation collapse, terrorist use of AI weapons, and extinction were seen as the most impactful. In Figure 10, we visualize perceived AI risks when the public's mean likelihood estimates and impact ratings are multiplied. Information warfare, cyber attacks, terrorist use of AI weapons, knowledge deterioration, privacy, and economic instability emerge as particularly important perceived risks by the US public.

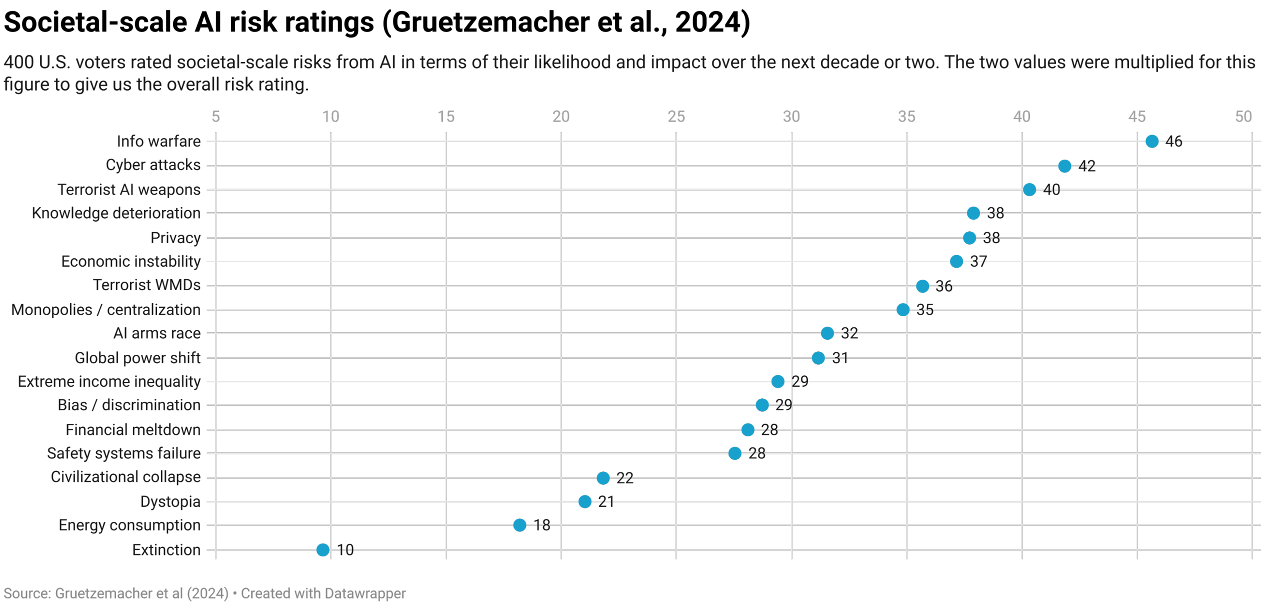


Figure 10: Data visualisation created from data taken from figures in Gruetzemacher et al. (2024). The US public's mean likelihood (as a probability) was multiplied with the mean impact rating.

- The two potential risks from advanced AI chosen as the most important by both the US and UK public from a list of seven were increasing unemployment (US: 44%, UK: 49%) and the creation of more dangerous military robots (US: 34%, UK: 39%). Significantly increasing electricity consumption (US: 15%, UK: 16%) and increasing economic inequality (US: 22%, UK: 25%) were chosen the least often (Public First, 2023a, 2023b).
- In a global survey of over one thousand respondents in 21 countries, fielded between October and November 2023, the US public and UK public were most concerned about the misuse of AI for nefarious purposes, the impact of AI on jobs, violations of citizens' privacy, and the dehumanisation of services over the next few years (Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024).
- A survey of UK adults conducted in August-September 2023 asking respondents what they believed represented the greatest risks from AI[21] highlighted job displacement due to AI (45%) and potential loss of human creativity and problem-solving skills (35%) as the top concerns. Concerns about humans losing control over AI (34%) were chosen the third most often. AI being used for cybercrime and terrorism, lack of accountability for organisations when mistakes occur, AI making unexplainable decisions, as well as misinformation were chosen by 23% of the respondents. The mental health and wellbeing effects of AI (14%) and AI bias leading to unfair outcomes (14%) were chosen the least often (Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023c).

[21] People could choose up to three items out of a total of nine.

Caveats Results are likely to be highly dependent on the question and item phrasing and the items presented alongside each risk. In addition, questions probing someone's concern often do not make clear whether respondents are expressing their concern given their implicit beliefs about how likely the risk is to occur or only the extent to which they would be concerned if that risk *were* to be truly instantiated. They usually also leave open whether they are concerned from a personal or societal perspective. In turn, it is difficult to make comparative statements when different surveys ask about a varying range of issues across a wide-range of different time ranges and populations.

It is also as of yet generally unclear how these risk and benefit beliefs relate to political behaviours, react to informational treatments, as well as how in practice they trade off against other concerns on the public's agenda. It is thus less clear what role and salience such worries and AI risk perceptions have day-to-day for people. Systematic evaluation of responses to different questions (e.g., which risks the public is most aware of, concerned about, or thinks are most important to address now and in the future, along with likelihood and impact ratings) across more consistent sets of items will be needed.

AI risks vs. other risks Although research on this topic is limited and not up to date, it appears that AI currently still ranks low in comparison to other global risks when individuals are asked about them directly in terms of likelihood, severity of impact, and concern surrounding different risks.

- As can be seen in Figure 11, in 2018 US adults rated all of the risks they were asked about as above moderate (2) impact, but the harmful consequences of AI were seen as the least likely and second least impactful within a 10 year timeframe.
- Though not a survey of the general public, the World Economic Forum similarly found in 2017-2018 that the adverse consequences of technological advances were rated lower in terms of impact than most other risks by around one thousand members of their multi-stakeholder network of businesses, governments, civil society, and thought leaders (World Economic Forum, 2018). In more recent years the World Economic Forum has asked about the adverse outcomes of AI technologies directly. In the 2023-2024 survey, they found that for a 2-year timeframe these still rank low in terms of expected severity, but move up to 6th place, after misinformation and disinformation, when asked about a 10-year timeframe (World Economic Forum, 2024).
- In early 2023, respondents in both the UK and the US were more concerned about a series of other risks in comparison to AI, including a major international war, nuclear war, terrorism, climate change, and a global pandemic in the next fifty years (Public First, 2023a, 2023b). A larger fraction of US Americans (22%) were "very worried" about AI in comparison to UK adults (14%). 28% of the US public and 20% of the UK public believed that there was a real risk that AI could cause a breakdown in human civilisation in the next fifty years. However, this was the lowest proportion of respondents among all the surveyed risks.

Caveats These findings suggest that we may draw overly strong conclusions based on findings where concern for AI risks is measured separately from other concerns. However, the evidence on this issue is very limited, is lacking for the past year, and we do not have an understanding of what AI harms and other risks concern people day-to-day nor which they would prioritise politically. We predict that concern about AI will increase in the coming years as awareness, media attention, politicisation, and experience of the personal and labour impacts of AI increase.

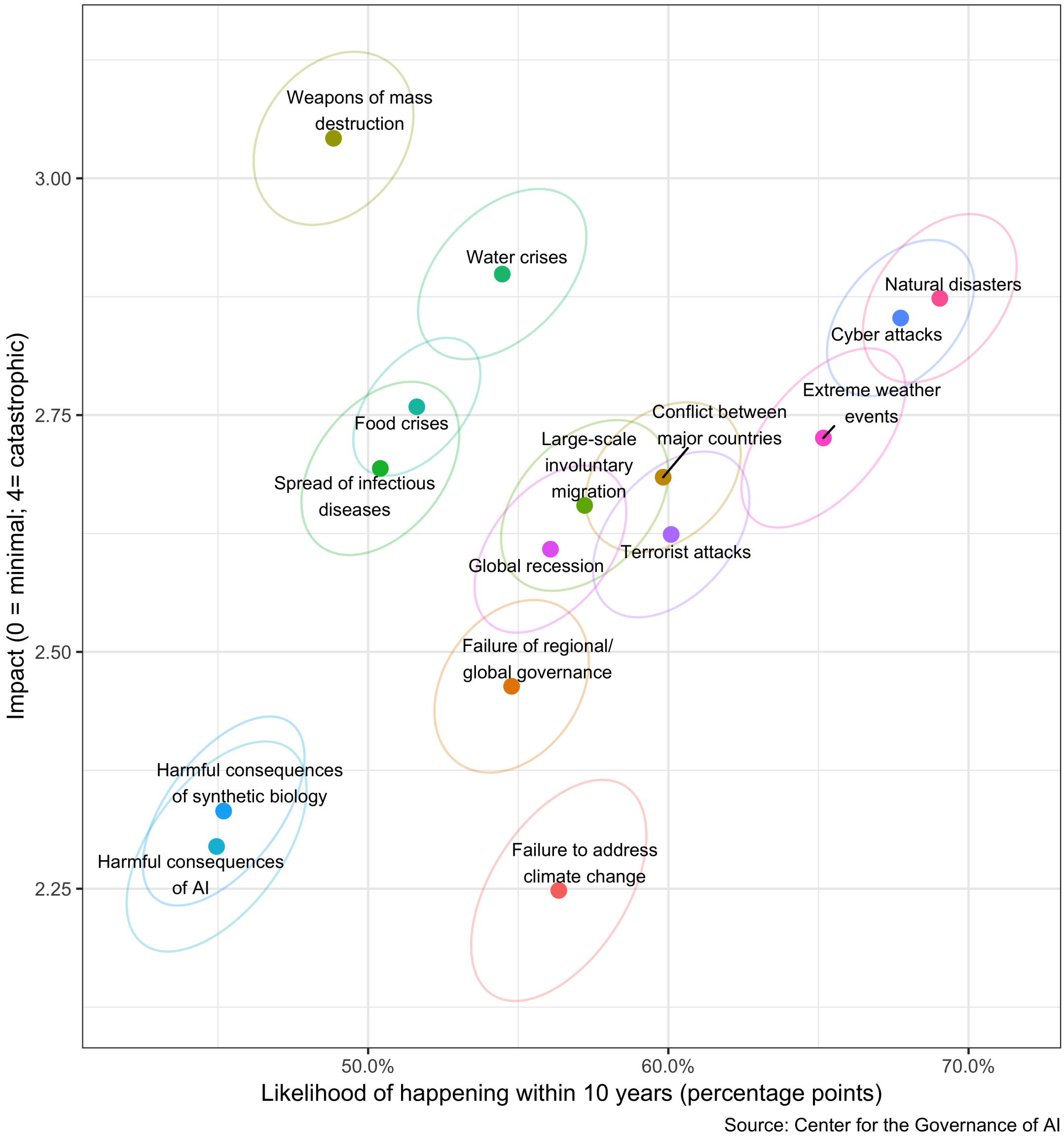


Figure 11: Data visualisation of the likelihood and severity of impact that 2,000 US respondents ascribed to a variety of global risks in 2018. The survey was completed by 2,000 US respondents in 2018. The data visualisation is taken from Zhang and Dafoe (2019).

Automation concern

The risk that has arguably seen the most extensive and detailed academic research due to its attention from the political science and economics academic literature, is automation concern. Such researchers have posited that past and ongoing technological change and automation, are associated with changes in political attitudes and behaviour (e.g., Caprettini and Voth, 2020; Gallego and Kurer, 2022). Of course, public opinion polls and surveys also ask about people's perceptions of the impacts of AI on jobs. We canvass the conjectures that we have derived from this literature and such polls below, including evidence of attitudes and how they have been found to relate to policy preferences.

Unemployment across society People are generally worried that AI will increase unemployment but this does not yet appear to be an overwhelming concern for the public.

- In January 2023, 73% of US adults surveyed felt that machines with the ability to think for themselves would hurt jobs and the economy, largely unchanged since April 2015 (72%) (Monmouth University Poll, 2023).
- In May 2023, 64% of UK adults thought that more jobs will be lost to automation by robotics/AI than will be created (YouGov, 2023a).
- In October 2022, 45% of people surveyed globally disagreed that AI will create more jobs than it will eliminate, and a further 26% were unsure; only 29% agreed. There is significant variation across countries and demographics. About two-thirds (63–67%) of people in China and India, and 37–48% of people in Singapore and Brazil, agreed that AI will create more jobs than it will eliminate, compared to less than 30% in other countries. Those aged 18-39 are a little more optimistic than those aged 56+ (34% vs. 22% agree); and the same for those who are university educated vs. those who are not (36% vs. 22% agree) (Gillespie et al., 2023).
- When surveyed in 2023, 53% of US adults and 64% of UK adults surveyed expected AI to somewhat or significantly increase unemployment (Public First, 2023a, 2023b).
- In the same poll, the increase in unemployment was the top risk chosen by 49% of UK adults when asked to choose the greatest risk from advanced AI from a selection of seven (ahead of worries about more dangerous military robots, chosen by 39%). A similar pattern was observed in the US, with 44% of adults choosing the risk of increasing unemployment, again the top concern ahead of military robots (34%) (Public First, 2023a, 2023b).
- In 2023, only 23% of US respondents thought the increased use of AI would make the economy in the US somewhat or much better in the next 3-5 years. In Great Britain this number was 31%. Similarly, only 21% of Great British and US respondents thought AI would make the job market better in both countries (Ipsos, 2023b).
- In April-May 2024, 21% of US and British respondents thought AI will make the job market better in the next 3-5 years, with roughly double the number of respondents thinking it will make it worse.

In the United States, 24% thought AI will make the economy better in the next 3-5 years and 33% thought it would make it worse. The numbers were 28% and 21% in Great Britain (Ipsos, 2024b).

- In August 2023, 45% of UK adults were worried that AI will take people's jobs. It was the most commonly chosen item when asked what represents the greatest risk from AI along items such as the effect of AI on mental health, creativity and problem-solving skills, loss of control, and misinformation (Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023c).

Personal automation concern There is a non-negligible concerned minority in most countries that worry about their own jobs being replaced by AI, but the majority of people in North America and Europe do not think AI will replace them in the next years.

- As of 2024, 25% of British adults and 33% of US adults are fairly or very worried about their own kind of work being automated in their lifetime (YouGov US, n.d. YouGov UK, n.d.).
- Kurer and Häusermann (2022) found that roughly 10-15% of their 2018 sample, across eight European countries, were somewhat concerned about being automated and ascribed a reasonably high probability to their type of job being automated over the next ten years.
- In 2019, Arntz et al. (2022) found that around a quarter of US (N = 3,066) and German respondents (N = 2,081) were "somewhat" or "absolutely concerned" about being unemployed within the next five years because of digital technologies.
- Across 31 countries globally in 2023, 36% thought that it was somewhat or very likely that AI will replace their current job in the next five years and 57% thought it would change how they do their current job (Ipsos, 2023b). But there were large differences across countries: in the United Kingdom and the United States, for example, 28% said it was somewhat or very likely that AI will replace their current job in the next five years. In Thailand, Malaysia, Indonesia, Brazil, and India, over half of respondents believed it was somewhat or very likely that AI will replace their current job in the next five years.
- In May 2017, 30% of US respondents thought it was somewhat or very likely that their jobs would be replaced by robot computers in their lifetime, while 70% thought it was not at all or not very likely (Pew Research Center, 2017b).

- In March 2023, 45% of US adults and 40% of UK adults surveyed said they believe AI could do their current job better than them in the next decade – although only 29% and 30% respectively expected their job would disappear completely if this were to happen (Public First, 2023a, 2023b).
- In the UK in 2023, 14% were very or fairly worried that AI will have an impact on their current job, while 25% thought that in the next 30 years jobs like theirs will be done primarily by AI systems or robots, rather than humans (YouGov, 2023a).
- In June 2023, only 5% of UK respondents believed that five years from now their job will cease to exist. Respondents were most likely to think that AI would help them in their job or change their main work activities (Ipsos, 2023a).

Automation concern across time Based on existing studies, it is currently difficult to get a clear picture of how the public's concern about automation is changing over time, but it may be increasing slowly in the US and the UK.

- Based on the biannual YouGov trackers of adults in the United States (YouGov US, n.d.) and Great Britain (YouGov UK, n.d.), while not drastic, there does seem to have been an increase in the number of people who are fairly or very worried about their own type of work being automated in their lifetime (see Figure 12).

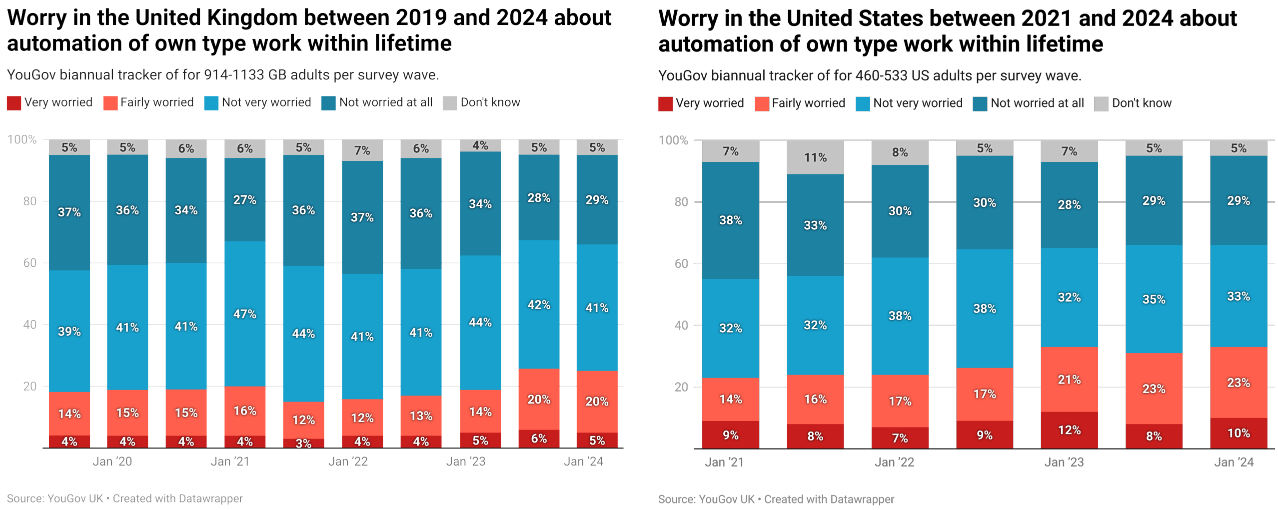


Figure 12: YouGov biannual tracker data from Great Britain (YouGov UK, n.d.) and the United States (YouGov US, n.d.) on to what extent respondents were worried about automation of their own type of work within their own lifetime.

- Currently, the latest figures in 2024 indicate that one in four (25%) British adults are fairly or very worried about their own type of work being automated in their lifetime, in comparison to less than one in five (18%) in 2019. In the US in 2024, a third of US adults (33%) say that they are fairly or very worried about this in their own lifetime, while this number was ten percentage points lower (23%) three years ago in 2021. Nevertheless, in 2024, the majority of respondents in both countries remain not very worried or not worried at all about their work being automated, although the US public is somewhat less optimistic (62%), down from 70% in 2021, than the British public (70%), down from 76% in 2019.

Caveats Questions asked across surveys often differ, some asking about predictions about whether people think their job will be replaced in the next five years, or over their entire lifetime from technology, and others how worried people are about this occurring across different time spans. We only found the above two trackers that have given consistent data of the same question for at least a few years.

Types of automation concern How concerned someone is about their own job can differ from their assessment of the effect of automation on unemployment generally, as well as measures that try to ascertain the person's objective risk of being automated.

- Individuals are often less concerned about automation affecting their job than they are about its broader impact on unemployment, the economy, society at large and jobs other than their own (e.g., Arntz et al., 2022).[22]
- For example, in May 2023, 64% of UK adults thought that more jobs will be lost to automation by robotics/AI than will be created. Only 7% thought more jobs would be created, and 12% thought it would be about the same. Despite this, only 14% were very/fairly worried about the impact that robotics/AI would have on their current job, and only 22% about its impact on their future career, perhaps because a majority (59%) also thought that their job would primarily still be done by humans in the next 30 years (YouGov, 2023a).
- According to one study, personal job concerns may be more resistant to informational treatments than concerns about automation's wider societal effects (Ladreit, 2022).

[22] There is some evidence that people underestimate their objective risk of being replaced by technologies in their job, and though technological concern does vary with objective automation risk, subjective concern does not necessarily correlate strongly with objective risk (Häusermann and Kurer, 2022; Gallego et al., 2022; Guarascio and Sacchi, 2021; Weisstanner, 2023)

Automation concern and policy preferences Automation concern can increase support for some worker-targeted redistributive policies such as extending unemployment benefits or implementing job loss compensation, as well as implementing worker protections. However, it does not appear to significantly boost support for other social investment policies like education and retraining programs. Some studies find that objective risk from automation can have the same effect, but the evidence is more mixed.

- In a survey in June 2023, 64% of UK adults above the age of 16 agreed that the government should create new regulations or laws to prevent the potential loss of jobs due to AI (Ipsos, 2023a).
- Busemeyer and Tober (2023) looked at the effect of subjective automation concern on support for passive and active policy solutions in 24 OECD countries in 2020 and found that individual concern increased support for compensatory policies but not social investment policies.
- Higher subjective automation risk perception, but not objective risk, predicted support for candidates who said they would protect workers from automation and other economic threats in a survey experiment (Borwein et al., 2024).
- As the more tech-savvy, educated, and higher earning became more concerned about employment risks from technology in this study, an association with an increasing preference for compensatory and protective policies was found (Busemeyer et al., 2023).
- Self-reported concern about technological automation predicts support for fining firms and joining unions, but not increasing unemployment benefits and re-training in a Spanish survey (Bicchi et al., 2023).
- Based on survey evidence from eight European countries, Kurer and Häusermann (2022) find that those who are more concerned about being automated in the near future are more likely to support extending unemployment benefits, but not social investment policies.
- Especially in the UK compared to Sweden, Lee (2024) found that concern about automation, occupational risk, and weaker labour market protections were associated with increased support for automation restriction and job loss compensation. Predominantly amongst those safer from automation risks, the researchers find that where benefits are broadly shared, respondents support accelerating technology-driven change.
- A 2018 survey study of 3,100 adults in Spain, found little evidence that risk of being replaced by automation explains support for redistribution policies or preference for slowing down technological progress. However, higher subjective concern about automation

risk *was* associated with higher support for slowing down technological change and was the better predictor for understanding preferences for protectionist policies (Gallego et al., 2022).

- Objective automation risk has been found by several studies to predict increased support for redistributive policies and compensatory unemployment policies but not to increase support for social investment or basic income support (Thewissen and Rueda, 2019; Busemeyer and Sahm, 2022; Weisstanner, 2023; Dermont and Weisstanner, 2020).
- There is mixed evidence on whether informational treatments can influence personal automation concern and policy preferences (e.g., Zhang, 2022a; Ladreit, 2022; Golin and Rauh, 2022; Magistro et al., 2024).
- There is some evidence that the effects of automation and automation anxiety can spill over to other policy issues such as immigration and globalisation (Buzzelli, 2023; Chaudoin and Mangini, 2022; Wu, 2022; Wu, 2023) but more research is needed to elucidate this effect (Gallego and Kurer, 2022).

Views on AI development, regulation and governance

Topics and questions

Past research has looked at the general support for governance and regulation broadly, as well as for more specific approaches. For example, surveys have looked at public support for whether AI should be "carefully managed" (e.g., Zhang and Dafoe, 2019; Dreksler et al., 2023; European Commission, 2017; O'Shaughnessy et al., 2023) or how carefully specific challenges or applications should be managed (e.g., Selwyn et al., 2020; Gillespie et al., 2023).

Others look at support for regulation broadly (e.g., AI Literacy Lab, 2023; European Commission, 2019), specific regulations, risk mitigation methods, and governance and regulator set-ups (e.g., Gillespie et al., 2023; The AI Policy Institute, 2023c; The AI Policy Institute, 2023d; Elsey and Moss, 2023a; Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024; Saeri et al., 2024; West, 2018a; Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023a), or regulation of specific AI applications (O'Shaughnessy et al., 2023).

Some studies also investigate the importance of addressing specific governance challenges or risks (YouGov and The AI Policy Institute, 2023c; Zhang and Dafoe, 2019). Some studies have looked at governance preferences – ranging from ethical to regulatory – for specific issues, such as misinformation (The Associated Press-NORC Center for Public Affairs Research, 2023 Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024), sustainability (König et al., 2023), automation (e.g., Northeastern-Gallup, 2018), sentient AI systems (Pauketat et al., 2022, 2023), and robot rights (e.g., Lima et al., 2020; Mays et al., 2024; De Graaf et al., 2021, 2022). Researchers have also investigated the perceptions of existing governance and regulation (e.g., Gillespie et al., 2023; Morning Consult, 2021).

Views on AI development, such as what the public's preferences are in regard to the pace of AI development (e.g., Gruetzemacher et al., 2024; YouGov and The AI Policy Institute, 2023a) or their preferences for leadership in AI development and governance are also explored (e.g, Saeri et al., 2024). Some research has investigated questions relating to US-China technological competition (e.g., Center for the Governance of Change, 2023; Zhang and Dafoe, 2019).

Finally, researchers have investigated the perceptions and trust of different actors responsible for AI development, deployment, and governance (e.g., David et al., 2024; Zhang and Dafoe, 2019; Carrasco et al., 2019; Gillespie et al., 2023; Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024; Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023a, 2023c; YouGov and The AI Policy Institute, 2023a; Morning Consult, 2021; Ipsos, 2024a; YouGov and Control AI, 2023).

Insights

AI governance There is general support for AI governance among the public, across a broad range of regulatory approaches. Where majority support is not found for AI regulation, support usually still outweighs opposition and there is substantial fence-sitting.

- In October 2022, 71% of people surveyed globally disagreed with the statement that AI regulation is not needed, with 17% agreeing, when asked across a range of specific AI applications. There is support for a variety of actors that should regulate AI, with 70% agreeing with coregulation by industry, government and existing regulators, 67% with government and existing regulators, 67% with a dedicated independent AI regulator, and 64% with industry that uses/develops AI. There are differences across countries, with, for example, much greater support in the UK, China and India for a dedicated independent AI regulator than in the US, Japan or France (Gillespie et al., 2023).

- More people in the United Kingdom reported that AI regulation was needed in 2022 (80%) than in 2022 (66%). The same was the case in the United States where support for regulation increased from 57% to 66% between 2020 and 2022 (Gillespie et al., 2023).
- In November 2022, 82% of US respondents supported the regulation of AI to "ensure adequate consumer protection" and 70% believed that "industry should invest more in AI assurance measures to protect the public" (MITRE and The Harris Poll, 2023).
- In a survey of the US public and experts conducted in April and May 2021, both groups were more likely to support governmental regulation than oppose it, but support was far lower than when asked whether they support the careful management of AI. When asked about specific applications, support hovered under 50% but far outweighed opposition, with a sizeable fraction of the public sitting on the fence. The exception to this is autonomous weapons, where the majority of the US public supported regulation, and a very strong majority of experts did (O'Shaughnessy et al., 2023; see Figure 13).
- In August 2023, 64% of US adults surveyed thought the government should regulate AI (AI Literacy Lab, 2023).
- In January 2023, 55% US respondents supported and 41% opposed a federal agency akin to the Food and Drug Administration (FDA) regulating AI (Monmouth University Poll, 2023).
- In April 2023, 70% of US respondents said that they leaned yes or supported an FDA-like federal agency regulating AI (Elsey and Moss, 2023a).
- In July 2023, 58% of US voters wanted the federal government to thoroughly regulate AI, with just 15% believing the government should not be involved. 65% supported requiring AI models to demonstrate safety before release. 64% supported requiring licences, evaluations, and audits for AI producers (YouGov and The AI Policy Institute, 2023b). In September 2023, 67% of US voters supported regulating current state-of-the-art models. 69% said AI should be regulated like other dangerous technologies. 63% supported restricting model power until safety was assessed (YouGov and The AI Policy Institute, 2023c). Take note though that both surveys presented an argument for and against each policy which could have affected support in different ways depending on the strength and appeal of the arguments. We recommend reading the questions carefully before basing conclusions on these findings.

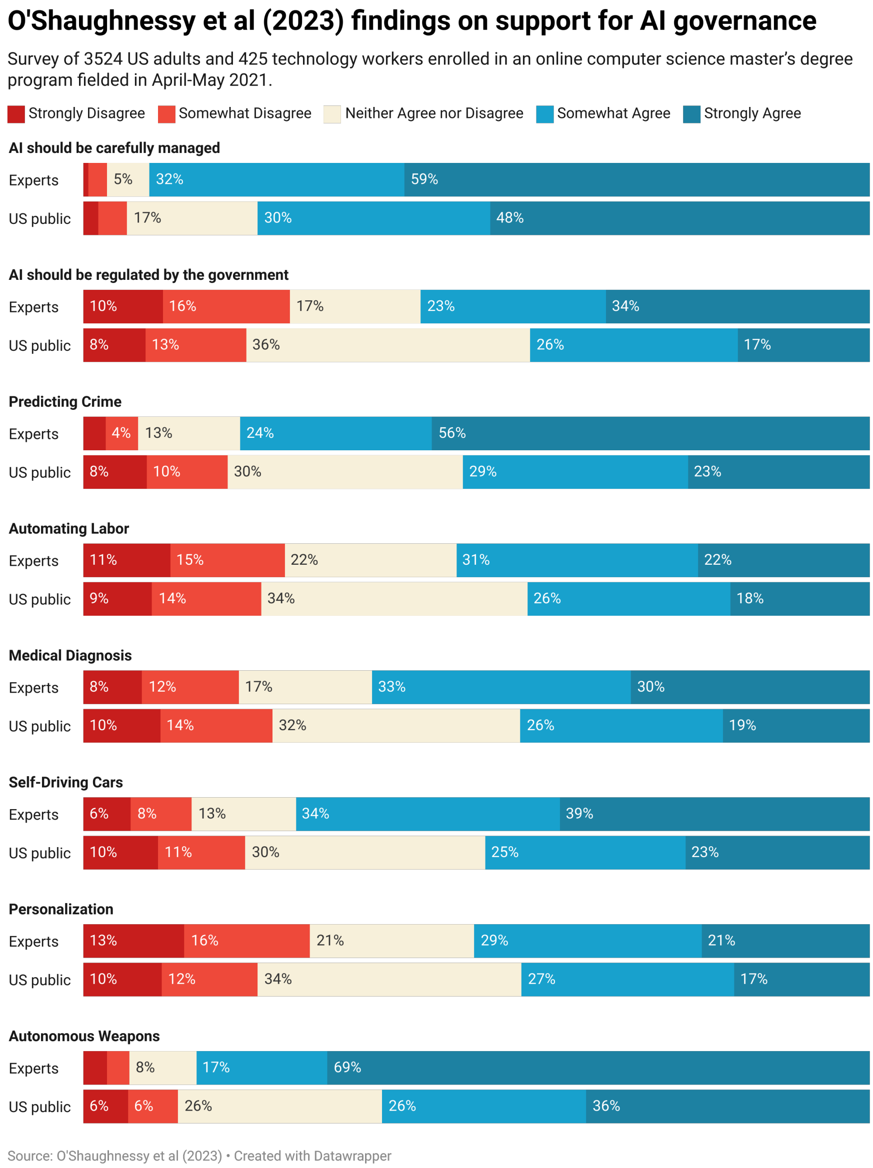


Figure 13: Findings from a study by O'Shaughnessy et al. (2023) showing the percentage of respondents who chose each answer option by group for general items about support for the careful management and government regulation of AI and the regulation of a number of specific AI use cases.

- In July 2023, 56% of US voters supported having a federal agency regulate the use of AI, with only 14% opposed (YouGov and The AI Policy Institute, 2023a).
- In October 2023, 69% of US voters supported the Executive Order on AI (36% strongly and 34% somewhat), with majority support across all demographics (The AI Policy Institute, 2023b).
- In a poll of the US public in July 2023, there was majority support (71%) that congress should pass a law requiring technology companies to make the voluntary commitments on the development and

release of Artificial Intelligence a legal requirement: 37% of respondents strongly agreed and 34% somewhat agreed (Ipsos, 2023c).

- The same survey found that amongst the US public there was majority support for AI companies committing to pre-deployment internal and external security testing (77%), AI developers sharing information across actors to help manage risk (69%), investment in cybersecurity to safeguard model weights (72%), and a variety of other safety commitments (Ipsos, 2023c).
- In October 2022, only 39% surveyed globally agreed somewhat or strongly that current safeguards are sufficient to make AI use safe, albeit with large variations between countries (e.g., 80% India, 74% China vs. 30% in US and UK, and only 13% in Japan) (Gillespie et al., 2023).
- 60% of UK respondents believed the UK government was doing too little to regulate AI when surveyed in September 2023. Only 3% thought the UK government was doing too much, a quarter of respondents (24%) were unsure (Ipsos, 2023d).

Caveats We may see more politicisation of AI issues in the future, which could affect regulatory support and increase polarisation on AI governance issues. Also note that surveys do not tend to provide the public the trade-offs associated with, and feasibility of, implementing multiple options. Neither have we seen sufficient research looking at how AI policy attitudes are weighed against other items on the political agenda (outside of AI) for members of the public, as well as how such attitudes translate into political behaviour.

Self-governance The majority of people do not trust tech companies to develop AI responsibly without there being external, independent auditing and oversight mechanisms. Generally, the public appears to tend towards independent oversight or government regulation in favour of tech company self-governance, however, generally low to middling trust in governments and many other actors expressed in surveys can complicate interpretation of results and reveal added complexity in people's attitudes towards regulation.

- In May 2023, only 18% of UK adults had any confidence that tech companies developing AI would do so responsibly. 66% had little to no confidence in them doing so. But confidence was similarly low about the UK government being able to effectively regulate AI's development and use: 69% had not very much or no confidence (YouGov, 2023a).
- In July 2023, when asked to choose between government regulation and self regulation for AI, 57% of US voters preferred the government, and only 18% self regulation. 26% were unsure. The

question was posed as follows: “Some policymakers say that the government should regulate AI because industry will move too quickly. Others say that industry has more expertise and should self-regulate. What do you think?” (YouGov and The AI Policy Institute, 2023b).

- In July 2023, 82% of US voters agreed (48% strongly, 34% somewhat) that tech company executives can’t be trusted to self-regulate the AI industry. Only 13% disagreed (YouGov and The AI Policy Institute, 2023a).
- In August 2023, 56% of US adults did not think private companies should be left to themselves to determine standards for AI. Around a third of respondents chose a variety of actors to play a major role in setting ethical standards including government agencies, companies, ethicists and technologists, end users, and academia, with no clear consensus existing (AI Literacy Lab, 2023).
- In October 2023, 42% of UK adults and 48% of US adults surveyed said they trusted tech companies to ensure the AI they develop is safe and will not create harm to society, while disagreement was at 50% and 44%, respectively. While support was low or even lower for many other actors including governments, there was strong support in both the UK (76%) and the US (73%) that powerful AI should be tested by independent experts to ensure it is safe. Only 6% and 7% disagreed, respectively (Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023a).
- In October 2022, globally, national universities (47% high or complete confidence, 32% moderate), international research organisations (45%, 31%), and security and defence forces (47%, 29%) were trusted the most to regulate and govern AI in the best interests of the public. The global public was more divided on technology companies with 31% having no or low confidence in them to govern in the best interests of the public, 32% had moderate confidence, and 34% having high confidence. There was substantial cross-cultural variation in trust in institutions. In both the United States and the United Kingdom confidence in governments fared slightly worse than in tech companies, with about half of UK (45%) and US respondents (49%) lacking confidence in their governments (Gillespie et al., 2023).
- 57% of UK respondents believed tech and social media companies were doing too little to regulate AI when surveyed in September 2023. Only 6% thought they were doing too much, one in five respondents (21%) were unsure (Ipsos, 2023d).
- In 2018, the US public trusted tech companies more (41% a great deal or fair amount of confidence) than the federal government

(27%) to manage the development and use of AI in the best interests of the public, but trust levels were not high for either actor (Zhang and Dafoe, 2019).

- According to the Edelman Trust Barometer, 66% of UK and 63% of US adults believed in 2023 that government regulators lack adequate understanding of emerging technologies to regulate them effectively (Edelman, 2024).
- Overall, there are indications that trust in governments is low in comparison to previous decades in both the the UK and the US (Center, 2024; Seyd, 2024).

International governance The public is generally supportive of international AI governance, especially in relation to safety considerations and military applications. Support for specific international governing bodies is less equivocal.

- In July 2023, 41% of US voters preferred international AI regulation over national regulation (24%). Only 12% preferred neither with 23% unsure. Support for international regulation was clearer in regard to military AI: 60% of US voters supported internationally regulating AI systems used in military applications, similar to nuclear weapons (YouGov and The AI Policy Institute, 2023b). Again, note that the questions presented arguments for and against the policy issue so these should be considered before basing conclusions on these findings.
- 64% of UK respondents believed international governments working together were doing too little to regulate AI when surveyed in September 2023. Only 3% thought they were doing too much, a quarter of respondents (24%) were unsure (Ipsos, 2023d).
- In October 2023, 62% of UK adults and 52% of US adults surveyed supported the creation of an international government-backed AI safety institute that would evaluate the capabilities of powerful AI to test if they are safe (Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023a).
- In August 2023, 57% of US adults felt that AI development should stop until a global ethical framework is in place (AI Literacy Lab, 2023).
- In December 2022, 41% of UK adults felt that 'an independent regulator' should be the most responsible for ensuring that AI is used safely, vs. 23% who felt most responsibility should lie with international standards bodies (Ada Lovelace Institute and The Alan Turing Institute, 2023).
- In June 2018, 28% of US adults were confident (a great deal/fairly) in the UN to manage and develop the use of AI in the best inter-

ests of the public. 28% felt similarly about international organisations, and 38% for intergovernmental research organisations (like CERN). There was similar support for non-profits (39% for Partnership on AI, 38% for non-governmental scientific organisations like AAAI) (Zhang and Dafoe, 2019).

- 64% of UK adults believed in March 2024 that international governments are not doing enough to regulate the development and use of AI, even if there are doubts that countries can effectively work together on AI safety (Ipsos, 2024a).

Attitudes towards specific applications of AI

For the purposes reviewing views on specific applications and use cases of AI, we will divide AI attitude research into two broad strands: societal AI public opinion research and mostly academic applied AI attitudes research:[23]

- **Societal AI public opinion research** has looked at AI attitudes through the lens of the societal adoption of AI and related perceptions, concerns, and expectations and has been conducted by academics in various disciplines but also by polling institutes, companies, think tanks, governments, and other actors. It can be viewed as a pre-paradigmatic field formed of research and polling efforts across different sectors, which heavily depends on straightforward representative surveys of the public. Most studies we have looked at so far fall in this category.
- **Applied AI attitudes research** is focused on studying attitudes and behaviours in relation to specific AI systems and AI applied in specific contexts, and has been conducted across a broad range of academic disciplines. Such studies can involve large representative surveys but often make use of experimental study designs conducted on smaller sample sizes.

This is by no means a neat or categorical divide: for example, findings from the former are relevant to what the public thinks about the societal adoption of AI, not just specific use cases, such as when studies examine how people feel about the use of algorithms in public service decisions. Societal public opinion research sometimes asks questions about specific AI applications or use of AI in specific contexts when canvassing public opinion as well (e.g., Carrasco et al., 2019). And some studies straddle methodologies and frameworks quite evenly in terms of understanding public attitudes towards AI in applied contexts and in terms of their broad societal adoption (e.g., Araujo et al., 2022).

[23] Koenig (2024) presents an overarching account of three theoretical perspectives on the acceptance of AI: user-centred technology acceptance (attitudes of consumers or users of AI systems), delegation and automation acceptance (attitudes towards delegating to AI systems, automation and AI decision-making, and human-AI co-operation in different domains), societal adoption acceptance (societal perspective on the adoption of AI and related attitudes). These three traditions are a useful starting point but they do not neatly delineate research across the AI attitudes and public opinion space either, much like our two categories.

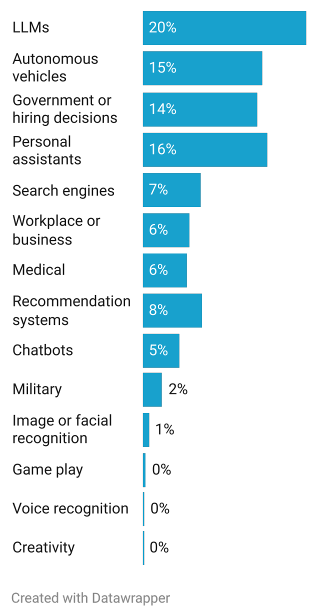


Figure 14: AI SHARE database finding: What kind of specific AI applications do AI-related survey questions ask about?

Societal AI public opinion research

Topics and questions

Studies more aligned with societal AI public opinion research, often ask about to what extent people support the use of AI in a range of different contexts, applications, or domains (e.g., healthcare, education, insurance, law enforcement, military, finance, agriculture, transportation, improving predictions, hiring). Usually this involves respondents being asked about a range of functions or tasks within one domain, such as healthcare, or across a wide-range of them to cover various use cases. Where domain-specific AI applications are asked about, the current AI SHARE database finding is that around one in five are about Large Language Models (LLMs), with autonomous vehicles, algorithmic decision-making in government or hiring, and personal assistants also being common question topics.

For each domain respondents are asked things, such as, whether they support, approve, or agree with the use of AI in this application domain (e.g., Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024; Department for Business, Energy and Industrial Strategy, 2019, 2020, 2021, 2022; O'Shaughnessy et al., 2023; Scantamburlo et al., 2023; Pew Research Center, 2019; Calice et al., 2020; YouGov and Cavendish Advocacy, 2023), where AI should best be used (Ada Lovelace Institute, 2019; Public First, 2023a, 2023b; Monmouth University Poll, 2023), or about their willingness to trust and their comfort with AI being used for different tasks or relying on information from AI systems in a domain (Gillespie et al., 2023; Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024; European Commission, 2017).

Insights

Divergences within and across stakeholder groups' views on some AI uses Some AI applications that have received extensive criticism from AI ethicists have sizeable public support, such as use of facial recognition in policing. Conversely, there is less public support for some applications that most AI practitioners endorse, such as autonomous vehicles. There can be substantial disagreement on some specific use cases of AI amongst members of the public as well. This means that democratisation of input to AI is not necessarily a straightforward process and will have to balance opposing views across and within stakeholder groups.

The study that has tested alignment and divergences between the public and experts most directly found that AI experts[24] were highly supportive of the use of AI for autonomous vehicles, medical diagnosis, and automating labour, while the public was more divided on these matters

[24] The study surveyed 425 masters students of a graduate-level AI class, the majority of which were working full-time in industry in technical roles. These are labelled as "experts" in Figure 15.

(O'Shaughnessy et al., 2023) (see Figure 15). Both groups were more divided on the use of AI for autonomous weapons, recommender systems, and predictive policing. To understand divergences properly, further studies are needed that compare public and different expert groups' opinions to determine consensus and divergences between the two.

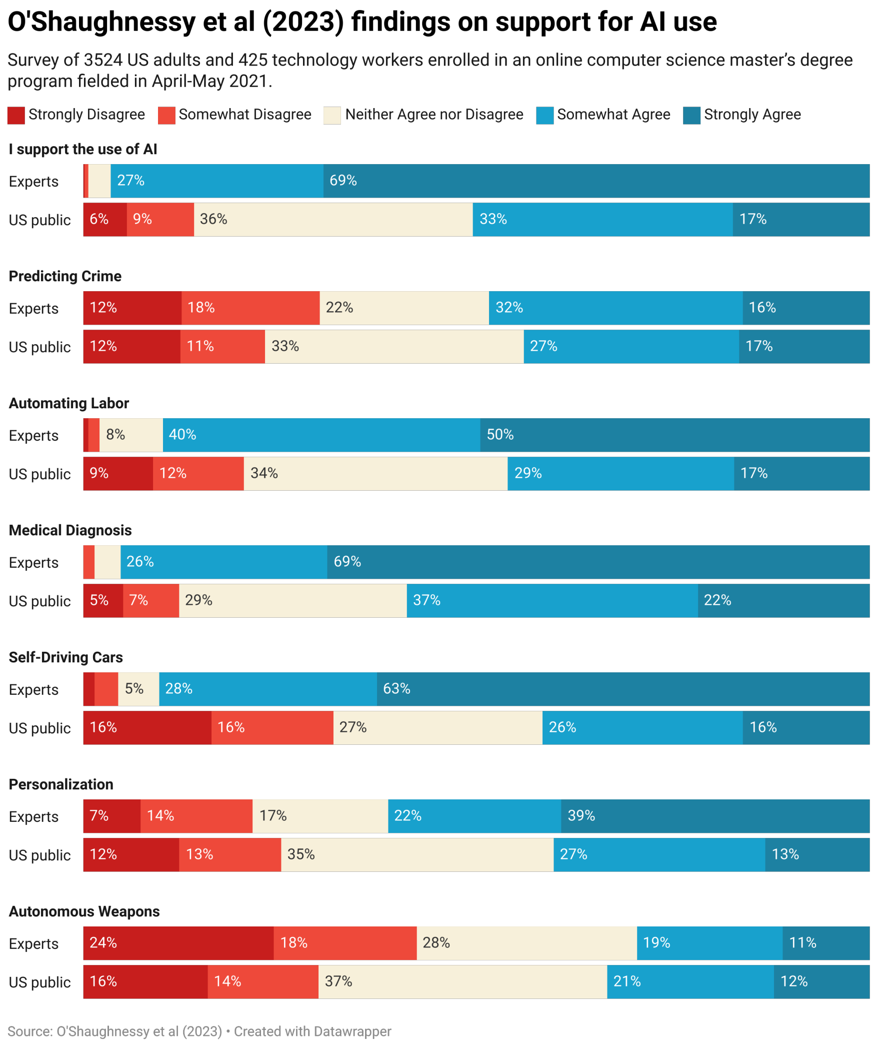


Figure 15: Findings from a study by O'Shaughnessy et al. (2023) showing the percentage of respondents who chose each answer option by group for a general item about support for AI use and a number of specific AI use cases.

Other examples of findings that highlight potentially important disagreements within the public or between the public and some expert groups include:

Facial recognition for policing The public appears reasonably supportive of the use of facial recognition for policing while this has received extensive criticism due to concerns about bias and violating civil liberties (e.g., Hill et al., 2022; Leslie, 2020; Fussey et al., 2021):

- In December 2022, 86% of UK adults either strongly (45%) or somewhat (41%) considered police use of facial recognition to be beneficial; and 87% felt the same about using it in border control. In fact, there is higher support for these sensitive use cases than for the use of facial recognition in unlocking phones (79%) (Ada Lovelace Institute and The Alan Turing Institute, 2023).
- In July 2019, 70% of UK adults supported the use of facial recognition technology by police in criminal investigations. Certain minority segments were slightly less comfortable with the use of facial recognition technology in a policing scenario, but still showed majority support (Ada Lovelace Institute, 2019).
- In August 2023, 60% of Americans thought it would be good for society to use AI to identify police suspects using facial recognition (AI Literacy Lab, 2023).
- In November 2021, 46% of US adults thought that widespread use of facial recognition by police would be good for society, with 27% thinking it would be bad (although with some caveats – e.g., 70% felt that facial recognition technology alone should not be good enough evidence to make an arrest) (Rainie et al., 2022; Pew Research Center, 2022).
- 59% of US adults say that the use of facial recognition technology by law enforcement to assess security threats in public spaces is acceptable (Smith, 2019; Pew Research Center, 2019).
- There appear to be only slight differences in views by race with 47% of white, 40% of black and 48% of hispanic respondents surveyed in November 2021 saying the use of facial recognition technology by police would be good (vs. 26%, 30% and 26% respectively who say it would be bad). This is despite more black/hispanic respondents than white respondents believing that the use of facial recognition would cause disproportionate surveillance of black-/hispanic neighbourhoods (18% white, 48% black, 37% hispanic) (Rainie et al., 2022; Pew Research Center, 2022).
- 65% of the public is comfortable with the law enforcement using facial recognition for identifying and monitoring criminals (Morning Consult, 2021).
- The majority of UK adults said in March 2024 that they are comfortable with CCTV footage being used to identify known criminals or missing people (60% comfortable, 21% uncomfortable), although support was more muted for monitoring surveillance footage for threats (44% comfortable, 31% uncomfortable) (Ipsos, 2024a).

AI surveillance A sizeable fraction of people report being comfortable with AI use in some situations that AI ethics experts would likely deem too sensitive. At the same, even amongst the public concerns remain prominent for some of these uses, highlighting substantial disagreement amongst the public:

- In March 2023, 56% of US adults and 67% of UK adults were in favour of using AI to automatically recognise and alert staff/police when a train passenger was posing a threat. Only 12% and 9% were opposed (Public First, 2023a, 2023b).
- In March 2023, 35% of US adults and 44% of UK adults were in favour of using AI for automatic age verification at a supermarket, although there was also significant opposition (34% in US, 27% in UK) (Public First, 2023a, 2023b).
- 48% of US respondents reported being very (20%) or somewhat comfortable (28%) with the use of facial recognition technology to monitor people at rallies and marches, higher than the proportion that reported being uncomfortable with this use (37%) (Morning Consult, 2021). Democrats (56%) were more comfortable with this use than Republicans (42%).

AI in government Use of AI in government is another area that is poised for public discourse and disagreement, both in regards to the use of AI in the delivery of public sector services and in terms of AI being integrated into higher level decision-making usually done by elected officials.

- A survey fielded at the end of 2023 found that both UK and US respondents are almost evenly split between those that agree, disagree, or neither agree or disagree in regard to the use of AI for enrollment and decision-making in welfare and social security programs (Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024). In regard to tax assessments, 40% of UK respondents agree AI should be used for this task, while 28% disagree, and the rest are torn. In the United States, the public is again evenly split between the three response options.
- The same survey finds that there is stronger support for the use of AI to identify misuse and wrongdoing in the public sector. For example, 53% of UK and 48% of US respondents agree that AI should be used to identify potential fraud in the administration of public sector services. But in both countries, approximately one in five respondents disagree with this use case.
- A survey conducted between November-December 2022, found that 48% of British adults thought that use of AI to assess welfare

eligibility would be somewhat or very beneficial, while 32% said they thought it not be very or at all beneficial. In turn, 44% said they are somewhat or very concerned about such use, while 43% said they were not very or at all concerned about it (Ada Lovelace Institute and The Alan Turing Institute, 2023).

- In an experimental series of studies on public sector decision-making, respondents preferred giving some weight to AI systems in these processes, but they generally wanted less weight given to AI systems than other human decision-makers. Overall, 69% preferred politicians outweighed AI in terms of the weight given to them in policy decisions, 11% wanted them to be given equal weight, and 20% had a preference for AI systems being given more weight than politicians for making policy decisions. In one study, 53% of UK adults would accept a public sector decision-making model that placed 50% of the decisional weight on AI and the other 50% on human politicians. 24% of UK adults would accept a government decision making model that placed 75% of the decisional weight on AI and 25% on human politicians (Haesevoets et al., 2024).[25]
- A European survey conducted by the Center for the Governance of Change at IE University found that a quarter of Europeans (25%) were in favour of letting an AI system make important decisions about running a country (Center for the Governance of Change, 2019).
- In another iteration of the survey in 2021, around half of respondents (51%) across the eleven countries said they would support reducing the number of national parliamentarians in their country and giving those seats to an artificial intelligence algorithm that would have access to your data to maximise your interests (Center for the Governance of Change, 2021). Across the European countries surveyed, 49% were against the proposal.
- Of course, in practice, when AI politicians have stood for elections or candidates that promised they would use AI systems to make their decisions, they have not yet succeeded in garnering many votes (Pettit, 2017; Grierson, 2024; Christou, 2018).
- Indeed, academic research has found that there is much higher support for the use of AI in government and politics to perform administrative tasks or assist in making decisions, rather than take decisions for politicians or compete in elections (König, 2023).

[25] These numbers were extrapolated from Figure 1 in the paper by Haesevoets et al. (2024) but are not labelled by the researchers, meaning they may be off by a few percentage points.

Military use of AI and AI weapons More people oppose autonomous weapons than support them, but there is higher support for military use of AI than autonomous weapons; particularly in the US where the military remains among the most trusted institutions even if trust in the military has been declining in recent years (Jones, 2022; Younis, 2023).

- Only 43% of UK adults surveyed in December 2022 believed that using AI in autonomous weapons would be very (13%) or somewhat (30%) beneficial; and 71% were concerned about such use (Ada Lovelace Institute and The Alan Turing Institute, 2023).
- In early 2021, Ipsos reported that 61% of adults across 28 countries opposed the use of lethal autonomous weapons systems, with only 21% supporting such use (Ipsos and Human Rights Watch, 2021). The majority of women and men oppose autonomous weapons, although there are some geographic differences. But only India shows a majority (56%) supporting their use.
- In March 2023, 9% of US adults said they were comfortable with AI making a decision about killing an enemy soldier (rising to 14% if it is only being used to advise). 7% were comfortable with AI choosing whether to launch a nuclear weapon (rising to 8% if being used only to advise) (Public First, 2023b).
- 63% of US adults believe that armed military search drones that distinguish between enemy combatants and civilian bystanders and decide which buildings to attack are a bad idea (Monmouth University Poll, 2023).
- The majority of US respondents (64%) think it is ethically permissible for the US military to continue to invest in AI technology for military use (Morgan et al., 2020).
- Human control is a key determinant of whether respondents felt that autonomous weapons that could search and kill were considered ethically permissible: agreement that the US military using missiles that autonomously search for and destroy enemy targets in war zones dropped from 72% to 17% when no human authorisation was needed (Morgan et al., 2020).
- A study looking at public opinion of military AI in Estonia also found that human control and trustworthiness were important desiderata for AI technology used by the military (Lillemäe et al., 2023).
- A survey conducted by O'Shaughnessy et al. (2023) found lower opposition for autonomous weapons and a more polarised and uncertain picture of US public opinion on the issue. The description of the item may have played a role in this by starting with a benefit with broad appeal for the US public: "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."

Caveats There is still limited data available on public perceptions of military use of AI. This is underlined by the AI SHARE database, where currently only 2.5% of survey question on domain-specific AI applications were related to the military. In addition, longitudinal data on public attitudes gathered alongside ongoing conflicts and coverage thereof would also be useful to improve our understand of public opinion in this area. Indeed, behaviour of adversaries may affect people's support for AI military development as well (West, 2018b).

Applied AI attitudes research

Topics, constructs, and frameworks

There is a growing academic literature looking at AI attitudes towards the use of AI in various sectors and domains such as public administration (e.g., Ingrams et al., 2022; Haesevoets et al., 2024; Gesk and Leyer, 2022), political decision-making (e.g., Starke and Lünich, 2020; König, 2023), health (e.g., Yang et al., 2024; Liu and Tao, 2022), education (e.g., Chai et al., 2021; Kashive et al., 2020), journalism (e.g., Moravec et al., 2024; Toff and Simon, 2023), and many other domains (see, for example, Kelly et al., 2023). Such research often focuses on specific tasks, systems, decisions, processes, or actions of an AI system, or their applied use in a given domain or function. Such research spans various academic disciplines and motivations. Overarchingly, it tries to systematically answer questions such as:

- **Attitudes:** What perceptions do people have of AI systems? What do people think of the use of AI in different tasks and domains?
- **Antecedents and consequences:** What are the antecedents and consequences of such perceptions? What drives use, perceptions, and acceptance of or resistance to AI in a given field or function? What is the impact of the use of AI on people's perceptions of AI-related decisions and processes?
- **Use:** How do people use, interact, take advice from, and cooperate with AI systems? How do system, task, individual, and contextual characteristics affect such behaviours and use-related attitudes?

Many of these studies apply or are influenced by classic theories in attitudes and behaviour research in psychology (e.g., Theory of Reasoned Action, Theory of Reasoned Behaviour), usually in the form of descendents which are commonly used to understand technology acceptance such as the Technology Acceptance Model (TAM), and in turn, its extensions (see Table 1).

But, of course, the constructs and conceptual frameworks used are not limited to these. For example, the literature on moral psychology of AI, human-robot interactions, and research looking at attitudes in relation to robots and mind perception, anthropomorphisation, and moral beliefs have their own sets of theories and frameworks they commonly draw on (e.g., Ladak et al., 2024; Gasteiger et al., 2023; Yogeeswaran et al., 2016; Stock-Homburg, 2022). The algorithmic decision-making and algorithm aversion literature has also explored AI-related attitudes for many years and comes with its own research traditions, constructs, and frameworks (Dietvorst et al., 2014; Mahmud et al., 2022). As such, studies also often investigate factors which can be specific to theory in the academic discipline or domain in question but can also be borrowed from others.

Table 1: Some of the common frameworks used to explain attitudes and behaviours in relation to technology attitudes. There are others that have been developed for AI specifically, for example, the AI device use acceptance model (AIDUA), designed to explain customer willingness to accept AI device use in service encounters (Gursoy et al., 2019). Yang et al. (2022) also capture a variety of different factors explored in relation to attitudes towards AI devices in Table 1 of their paper. See for example, Ho et al. (2023), for an overview of why TAM on its own is not seen as sufficient by researchers.

	Key reference	Upstream factors	Downstream factors
Theory of reasoned action (TRA)	Fishbein and Ajzen (1975)	Attitudes Subjective norms	→ Intention → Behaviour
Theory of planned behaviour (TPB)	Ajzen (1991)	Attitudes Subjective norms Perceived behavioural control	→ Intention → Behaviour
Technology acceptance model (TAM)	Davis (1985, 1989)	Perceived usefulness Perceived ease of use	Attitude towards using Behavioural intention to use Actual system use
Unified theory of acceptance and use of technology (UTAUT and UTAUT 2)	Venkatesh et al (2003, 2012)	Performance expectancy Effort expectancy Social influence Facilitating conditions (Price value) (Habit)	Behavioural intention Use behaviour

Examples of other features studied include[26]:

- **Features of the AI system** (e.g., transparency, accountability, effectiveness, performance, human-likeness, interpretability, explainability, reliability, fairness, predictability, privacy, security) and perceptions thereof.
- **Other attitudinal measures** (e.g., trust, satisfaction, perceived risks and benefits, moral judgements, perceived fairness).
- **Individual characteristics**, including *psychographics* (e.g., expertise, familiarity with or knowledge of AI, computers, etc; general trust, institutional trust, media trust, or trust in technology; per-

[26] For a quick picture of the various frameworks and additional variables used in more user-centred research, see Tables 3 through 8 in the meta-analysis conducted by Kelly et al. (2023) of the factors contributing to AI acceptance.

sonal norms and values; the person's innovativeness or tendency to adopt technology;[27] media consumption), *socio-demographics* (e.g., age, gender, political affiliation, income, and education), and *cross-cultural differences*.

- **Effects of the use of AI on perceptions of outputs, processes and institutions** (e.g., perceptions of fairness or input, output, and throughput legitimacy; news credibility) (Tandoc, Edson C. Jr. et al., 2020).
- **Additional aspects of how the AI system is used or interacted with** (e.g., the level of human involvement in the decision-making process, whether the AI system takes an advisory role or is integral to the decision-making process, and other characteristics related to human-AI cooperation).

[27] To measure innovativeness in the realm of technology attitudes, researchers sometimes use non-systematically chosen sets of items adapted from other researchers (e.g., Mohr and Kühl, 2021), adapt domain-specific scales (e.g., Goldsmith and Hofacker, 1991) or use scales such as the Technology Readiness Index (TRI; Parasuraman and Colby, 2015), the Personal Innovativeness in the Domain of Information Technology (PIIT; Agarwal and Prasad, 1998), or Adopter Category Innovativeness (ACI; Yi et al., 2006).

Insights

Some key overarching findings across such studies looking at what determines AI attitudes, trust, and acceptance are detailed below (for some reviews and meta-analyses see, Kelly et al., 2023; Starke et al., 2022; Glikson and Woolley, 2020; Kaplan et al., 2023; Mahmud et al., 2022; Machado et al., 2023). We present these in a somewhat different style to the AI public opinion insights discussed in the previous sections, due to the difference in the kind of results reported in academic studies, often more systematic research and reviews conducted, and the more top-level statements that need to be made to capture insights across academic disciplines, AI domains, and studies.

Context matters Attitudes are generally found to be highly context-dependent (e.g., by task, application, domain, system), with the effect of system characteristics on acceptance and other attitudes also depending on the context.

- **Variation across domains and task contexts** AI attitudes and what drives them vary significantly depending on the domain of use and task context (e.g., Grimmelikhuijsen, 2023). For example, in a systematic review of 58 studies, Starke et al. (2022) found that perceived fairness of algorithmic decision-making systems was dependent on the domain within which the system was used (e.g., hiring vs. judicial decision-making) but also varied by task within a given domain. Features such as whether the implementation involves high stakes or scarce resources have also been found to play a role in one study (Nussberger et al., 2022). Even within one industry, different technology factors can have differential effects depending on the context (Kurt et al., 2022).

- **Task characteristics** One contributing factor to this is that preference for the use of AI systems varies by task characteristics and perceived agent-task fit (Hertz and Wiese, 2019). Studies have found that AI systems can be perceived as less suited for tasks which are more subjective, involve moral decisions, or require more human emotional skills and characteristics (e.g., Peng et al., 2022b; Waytz and Norton, 2014; Castelo et al., 2019; Grimmelikhuijsen, 2023; Bigman and Gray, 2018; Lee, 2018) or tasks that are more ideological (Haesevoets et al., 2024). Task complexity[28] and perceived expertise of the AI system compared to humans may also contribute to use behaviours (e.g., Xu et al., 2020), but may be differentially related to different kinds of attitudes. For example, Kaplan et al. (2023) find that task complexity does not consistently predict trust across three studies considered in their meta-analysis, while Mahmud et al. (2022) suggest it contributes to algorithm aversion based on their systematic review of the literature.
- **Cross-cultural differences** There are cross-cultural differences in attitudes towards AI systems and how factors interact to drive AI attitudes and perceptions (e.g., Mantello et al., 2023; Edelmann et al., 2021; Sindermann et al., 2022; Barnes et al., 2024; Araujo et al., 2022; Liu et al., 2023) although it is difficult to draw out consistent trends across studies. This means readers of AI attitude research should be cautious about simply transferring findings between countries and regions.

[28] For example, a study published in Scientific Reports found that people relied more on algorithmic advice when task difficulty increased (Bogert et al., 2021).

System characteristics and perceptions thereof shape responses The AI system's features and perceptions thereof such as performance, fairness, accountability, transparency, interpretability, explainability, dependability, reliability, predictability, and anthropomorphisation or human-likeness play a role in determining reactions, trust, and preferences for AI systems and their outputs.

- **Transparency** Transparency is important for trust in AI systems (Glikson and Woolley, 2020; Wanner et al., 2022; Liu, 2021; Shin, 2021; Shin and Park, 2019; Grimmelikhuijsen, 2023; Tomlinson and Schnackenberg, 2022; Aysolmaz et al., 2023). It generally is a feature valued by the public (König et al., 2022; König et al., 2024; Schiff et al., 2022; Shin and Park, 2019). Automation transparency has also been found to positively influence human-automation interactions (Sargent et al., 2023).
- **Perceived fairness** Fairness perceptions matter in terms of the implementation of AI systems (for a review see Narayanan et al., 2024) and can be an important mediator between transparency and trust (e.g., Aysolmaz et al., 2023). In a meta-analysis, Starke et al. (2022) found that four of the five studies they looked at saw perceived fairness positively predict trust in AI systems. Other stud-

ies also found that there can be a relationship between perceived fairness and use satisfaction, protest or litigation intention, and productivity. Schiff et al. (2022) found that citizens had significant negative reactions to governments using algorithmic decision-making tools when fairness and transparency were not part of the implementation.

- **Performance preference** Accuracy and performance is highly weighted by the public as a feature of AI systems. Studies find that the public is often happy to trade off other features such as explainability,[29] interpretability, and transparency in return for increased accuracy (e.g., Nussberger et al., 2022; König et al., 2024) even if they do value such features. Indeed, accuracy can be more influential than human involvement in increasing acceptance of AI (e.g., Horvath et al., 2023). In a meta-analysis looking at the antecedents of trust perceptions of AI systems, performance-based attributes of the AI system generally had higher effect sizes than non-performance related attributes (Kaplan et al., 2023).
- **Anthropomorphisation and human-likeness** There is a long-standing literature on anthropomorphisation and mind perception of digital technologies including robots and the effects such characteristics have on people's views of using such technologies and threats they perceive from them, including in fields such as human-computer interaction and psychology. Overall, the evidence of the effect of human-likeness is mixed, perhaps interacting with capability assessments (Stein et al., 2020) and threat perceptions of AI systems, which may also be differentially affected by technological vs. human replacement (Granulo et al., 2019).

  Anthropomorphism appears to be able to increase positive attributions of (e.g., trust, competence perceptions) and behaviours towards (e.g., social responses) robots, chatbots and AI applications such as autonomous vehicles (e.g., Adam et al., 2019; Gong, 2008; Li and Sung, 2021; Waytz et al., 2014; Glikson and Woolley, 2020). Such anthropomorphic cues often involve adding faces or voices to interfaces. However, such anthropomorphic technology designs do not necessarily invariably result in favourable outcomes either (Cornelius and Leidner, 2021; Kontogiorgos et al., 2019; Li and Sung, 2021) and can, for example, increase the likelihood of the uncanny valley phenomenon (e.g., Mara et al., 2022; Kim et al., 2019; Wang et al., 2015; Mori, 1970).
- **Training data** Some research points to the fact that preferences for AI can be related to information about the amount of data the system was trained on, with larger datasets associated with higher trust in systems (Waggoner et al., 2019; Kennedy et al., 2022). This factor has been studied less than the others noted above but may become increasingly relevant.

[29] How this desire for explainability plays out in practice may depend on the AI application and performance. For example, there are many domains where the general public may not expect an explanation of how the output of automated systems was calculated (e.g., ad servers, postal code sorting, aircraft collision avoidance systems).

Individual differences exist Individual differences in terms of people's socio-demographics and psychographics can influence attitudes towards AI as well as the relationship between predictive factors, perceptions, and behaviours.

- **Socio-demographics** There is mixed evidence on whether demographic factors such as gender, age, and education are associated with AI attitudes, dispositions, and behaviours consistently (e.g, Mahmud et al., 2022; Kaufmann et al., 2023; Kaplan et al., 2023; Kieslich et al., 2022b). Kaplan et al. (2023), for example, found that men trust AI systems more than women in a meta-analysis, but that age and education did not significantly predict trust reliably. Meanwhile, Mahmud et al. (2022) found mixed evidence on whether gender is related to algorithm aversion, the tendency to accept advice on a decision from an algorithm.
- **Psychographics** Psychographics such as personality traits (e.g., Kaya et al., 2024; Mahmud et al., 2022; Glikson and Woolley, 2020; Schepman and Rodway, 2023; Kaplan et al., 2023), political leanings (e.g., Araujo et al., 2022; Grgic-Hlaca et al., 2018; Grgić-Hlača et al., 2022; Cui and Van Esch, 2022), trust in AI (Kieslich et al., 2022b; Molina and Sundar, 2024; Schepman and Rodway, 2023), innovativeness (Goli et al., 2023), and knowledge of AI (Krieger et al., 2024; Horvath et al., 2023; Araujo et al., 2020; Starke et al., 2022; Kaplan et al., 2023; Mahmud et al., 2022) can be associated with different AI attitudes, predispositions, perceptions, and preferences.
- **Knowledge is important to consider but is not a reliable predictor across attitudes** There is mixed evidence on whether AI knowledge, literacy, and familiarity are related to the attitude measured in question (e.g., Krieger et al., 2024; Horvath et al., 2023; Araujo et al., 2020). Araujo et al. (2020), for example, found that knowledge was associated with expectations of the usefulness of automated decision-making, but was not related to fairness and risk perceptions. In a systematic review of 64 studies, Krieger et al. (2024) found familiarity to be a predictor of risk perceptions of narrow AI applications. In a meta-analysis of studies on fairness perceptions, Starke et al. (2022) also found that studies found mixed evidence of the association between familiarity with AI and algorithms on fairness perceptions.

  In regard to trusting AI systems (Kaplan et al., 2023) and relying on them as decision aids (Mahmud et al., 2022), familiarity is more consistently found to play a role. The type of attitude (e.g., risk perceptions, trust, usefulness, acceptance), the kind of AI knowledge (domain-specific, general, AI-relevant education or work experience, awareness about algorithms' expertise), and application context will likely matter in determining the association between AI knowledge and attitudes.

- **Associations of socio-demographics and psychographics may differ by contextual factors** One driver for such inconsistent findings is that the relationships of socio-demographic variables may vary by task: Araujo et al. (2022) found that age, gender, education and income are differentially related to preferences for use of AI (vs. humans) depending on the type of media task asked about (news recommendation or creation, content or user moderation). The association of different individual difference measures may vary country by country as well (Liu et al., 2023).
- **There may be clusters of AI attitudes and perceptions** Work in the line of Kieslich et al (2022b) could be useful to further disentangle what socio-demographic and psychographic variables differentiate AI attitudes: the authors found that there are clusters of preference models for ethically designed systems for tax fraud detection in the German population set-apart by both demographic variables (age, education) and AI attitudes (interest, awareness, risk awareness, benefit awareness, and trust in AI). This means that only looking at the association of specific variables separately may be insufficient to understanding the psychology of AI attitudes and relevant individual differences.

The role of individual and group characteristics

Topics and questions

Surveys that look beyond just specific AI applications often include demographic questions, such as, as respondents about their age, gender, education, income, employment status, political affiliation, and ethnicity or race as well. Research on attitudes towards other emerging technologies and risks has also found that such factors can play a strong role (e.g, Wildavsky and Dake, 1990; Slovic et al., 1991; Flynn et al., 1994; Finucane et al., 2000), and AI attitudes also appear to differ by demographic and psychographics.

In polls such variables are usually used to present cross tabulations of the result by demographic categories (e.g., Tyson and Kikuchi, 2023; Beets et al., 2023), but in addition to this, in more academic studies, researchers often also examine these differences further using statistical methodologies to determine whether these differences between groups are significant. Some studies have focused specifically on investigating the association of AI attitudes with demographic individual differences (e.g., Grassini and Ree, 2023; Vu and Lim, 2022; Zhang and Dafoe, 2019) as well as country-level differences (e.g., Vu and Lim, 2022). Psychographics are less commonly asked about in societal AI public opinion research, though some research has examined the association of AI attitudes with worldviews and values (e.g., O'Shaughnessy et al., 2023; Većkalov et al., 2023), trust (e.g., Araujo et al., 2022), and personality (e.g., Wissing and Reinhard, 2018).

Overall, surveys that have examined demographic individual differences and the person's cultural context have found that they matter in determining AI attitudes, although no meta-analyses or detailed reviews exist to our knowledge. O'Shaughnessy et al. (2023) summarise some of these findings from other research and find evidence in their favour in their own study: those who are younger, men, more educated, or residing in urban areas appear to show higher comfort and support for AI, and those who are more educated, work in white collar jobs, and have a higher income tend to think that AI holds more personal and societal benefits.

This should caution a careful reader in terms of making general statements across individuals and geographic regions when it comes to AI public opinion without considering such differences. Especially global surveys underline the stark differences that exist between countries on a variety of different AI public opinion topics (see, for example, Ipsos, 2022b, 2023b, 2024b; Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024; Gillespie et al., 2023; World Risk Poll, 2019, 2021, 2024; Funk et al., 2020).

Insights

Geographic differences There can be notable differences between countries in terms of their attitudes towards AI and associated beliefs. For many questions, countries like China and India are more positive and optimistic about AI than Western countries like the United States and Great Britain. However, this does depend on the type of question asked in terms of the strength of the association.

- The percentage who agree that AI products and services have more benefits than drawbacks is substantially higher in China (78%) and India (71%) than in the United States (35%) and Great Britain (38%). There are substantial other cross-country differences across the questions asked on the survey (Ipsos, 2022b).
- 66% of Indian respondents and 36% of US respondents say that using AI products and services make them excited. By contrast, in terms of whether they make them nervous, India (58%) and the United States (63%) have more similar levels of agreement (Ipsos, 2023b).
- In a global survey of 32 countries fielded between April and May

2024, Asian countries were found to be similarly nervous about AI products and services as European countries, but far more excited. Anglosphere countries, on the other hand, were more nervous about AI products and services than both European countries and Asian countries (Ipsos, 2024b).

- India has the highest percentage of respondents that strongly support the development of AI (36%), with both the United States (10%) and United Kingdom (7%) showing lower levels of strong support. Indian respondents also had the highest percentage of respondents saying they felt very positive about AI (43%), including in comparison to China (18%), the United States (12%), and the United Kingdom (8%). There is cross-country variation across questions including questions on self-reported understanding of AI, personal automation concern, and trust (Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024).
- A global survey fielded in October 2022 found that India and China show some of the highest trust in AI systems, along with substantial variation between countries (Gillespie et al., 2023).
- When asked whether AI would mostly help or harm people in the country. North Americans and North/West Europeans were relatively equally divided between those who said AI would do more harm than help. Only in East Asia did a majority say that AI would mostly help (World Risk Poll, 2019).
- There is substantial variation between countries on whether they think the development of AI will be a good or bad thing: 67% of Indian respondents, 47% of US respondents, and 46% of UK respondents thought it would be a good thing for society in 2020. Respondents from France showed the least optimism with only 37% saying it would be a good thing (Funk et al., 2020).
- Out of all global regions, East Asia had the highest level of trust in AI systems and decision-making, with 59% of survey respondents believing it will mostly help, and only 11% believing that it will mostly harm. This contrasts significantly to the region of Europe, where 38% believe AI decision-making will mostly help, and 43% believe it will mostly harm (Neudert, Lisa-Maria et al., 2020).
- In a qualitative poll, 14% of responses from South Korea described AI as "worrying," compared to 30% of respondents in the US (Kelley et al., 2019).
- Cultural differences have also been found to exist in technology acceptance studies for other technologies and may in part pertain to differences in values and other culture related variables (e.g., Peng et al., 2022a; Rojas-Méndez et al., 2017; Blut et al., 2016; Nistor et al., 2013; Steenkamp et al., 1999).

Age Younger generations tend to view AI more favourably than their older counterparts and use AI more.

- In a global survey in October 2022, those aged 18-39 expressed more trust (42%) and acceptance (40%) of AI than those aged 56+ (33% and 22%, respectively), with 40-55 lying somewhere in between (37% and 31%, respectively) (Gillespie et al., 2023).
- In May 2023, 18-24 year olds in the UK expressed slightly more optimism (28%) about the impacts of AI than pessimism (25%), while older generations expressed notably more pessimism: 15% of 50-64 year olds expressed optimism while 37% expressed pessimism about AI's impacts (YouGov, 2023a).
- A November 2021 survey found 79% of US adults aged 50-64 were concerned about AI making important life decisions for people, vs. 63% of 18-24 year olds. Across various other possible AI developments, such as handling customer service calls, diagnosing medical problems, and performing repetitive work tasks, older generations noted more concern than younger generations (Pew Research Center, 2022).
- A January 2023 survey found that 51% of Americans over 55 thought that AI would do more harm than good, in comparison to 42% of 35-44 year olds, and 27% of 18-34 year olds (Monmouth University Poll, 2023).
- In the UK in June 2023, Ofcom found 74% of online 16-24 year olds said they used a generative AI tool, but only 50% of 25-34 year olds, 35% of 35-44 year olds, and just 14% of those aged 45+. This was calculated based on asking about use of LLMs such as ChatGPT, image generators such as Midjourney, and Snapchat My AI (Ofcom, 2023).
- A US survey found that 22% of Gen Z and 23% of millennials feel very familiar with AI, compared to only 8% of Gen Xers and 4% of baby boomers (Axios and Morning Consult, 2023).

Political affiliation Political affiliation is sometimes a reliable predictor of AI support and optimism – as well as of a desire to regulate AI – but not always. In the US, Democrats are more likely to support AI and be optimistic about it, and are more likely to support AI regulation. Republicans are more likely to oppose both AI and its regulation than Democrats. In the UK, political affiliation may not be an as clear cut predictor of optimism and pessimism about AI, nor of regulatory appetite.

There is likely cross-cultural variation in how political leanings relate to views on AI and technology. The construct or question asked also appears to determine whether there are differences between people in terms of political affiliation. We focus below on optimism and concern about AI along with general regulatory appetite.

- In November 2021, Republicans were more concerned (45%) than Democrats (31%) about the increased use of AI in daily life. Republicans were generally more likely to express concern about a range of possible AI uses than democrats were. (Pew Research Center, 2022).
- In January 2023 a survey of US adults found that 55% of Democrats favour an FDA-like regulatory agency for AI vs. just 36% of Republicans (Monmouth University Poll, 2023).
- In October 2023, more democrats were supportive of the Executive Order on AI than republicans (78% vs. 64%), and slightly more republicans than democrats were opposed to it (17% vs. 11%) (The AI Policy Institute, 2023b).
- In July 2023, Democrats were more excited than Republicans about AI (26% vs. 26%) and less concerned (59% vs. 68%). Democrats also favoured regulating AI federally akin to the DFA at much higher rates than Republicans (71% vs. 41%) (The AI Policy Institute, 2023a).
- In the US, those who rated themselves higher on conservatism (vs. liberalism) were slightly less likely to support the regulation of AI (O'Shaughnessy et al., 2023).
- Optimism about AI's impact overall was similar amongst conservatives (18%) and labour supporters (20%) in the UK. So was pessimism (39% vs. 35%, respectively) (YouGov, 2023a).
- In a UK survey fielded in October 2023, 48% of conservatives and 46% of labour supporters thought the UK government should be doing more to tackle the risks from AI. 61% of conservatives and 57% of labour supporters thought governments should be providing oversight of super-human AI (YouGov and AISCC, 2023).
- Across green energy, AI, gene-based medicine, and GMO foods, the Edelman Trust Barometer found that right leaning US adults were far more likely to reject such innovations (53%) than those who were left leaning (12%). The effect was less strong in the UK (35% vs. 22%) (Edelman, 2024).

AI knowledge and awareness Better understanding can lead to more optimism about AI. It depends on the application, risk, or issue whether higher familiarity leads to increased optimism or concern. Those with more exposure and understanding of AI can favour increased care in terms of its governance than those with less in some cases, though evidence is more limited.

- In May 2023, a survey of UK adults found that 40% of those claiming to understand 'a great deal' about AI issues were optimistic, vs. 27% of those who understood 'a fair amount', 15% of those who responded 'not very much' and only 5% of those that self-reported no understanding of the issues surrounding AI were fairly or very optimistic about AI (YouGov, 2023a; Smith, 2023).
- Pessimism rates also increased with self-reported level of understanding, but this increase was less pronounced: 43% of those understanding AI issues 'a great deal' were pessimistic, 37% 'a fair amount', 35% 'not very much' and 28% 'not at all'. This suggests that as people learn more about AI they are somewhat more likely to switch their views from neutral/don't know to feeling optimism rather than pessimism. It also means that those who report knowing a great deal about AI are also the group that is most polarised in their views (YouGov, 2023a; Smith, 2023).
- Higher familiarity and expertise with AI was associated with higher support of autonomous vehicles, autonomous AIs surgeries, and autonomous AI cyber defence, but not autonomous weapons in a survey of the US public conducted in 2018 and 2020 (Horowitz et al., 2024).
- Those with higher subjective and objective knowledge of AI were found to be significantly more likely to perceive the benefits of AI. Subjective knowledge of where AI is used showed some association with perceived risks as well, but to a far lesser extent (Gillespie et al., 2023).
- Those who have computer science or programming experience were significantly more likely to express support for the development of AI: 31% of those who said they had no such experience said they somewhat or strongly supported AI development and 58% of those who said that they did have computer science or programming experience (Zhang and Dafoe, 2019).
- In a survey of over four thousand respondents conducted at the end of 2022, UK adults surveyed who were more aware of the use of AI for facial recognition were significantly less likely than those who felt less informed to believe that the benefits of facial recognition outweigh concerns relating to the technology. This suggests higher awareness is linked to greater concern about the use of facial

recognition (Ada Lovelace Institute and The Alan Turing Institute, 2023). However, those which had higher awareness of the use of AI in science, education, healthcare, and robotics were more likely to think such applications were more beneficial rather than concerning. In the case of targeted social media advertising, increased awareness was associated with higher concern.

- Subjective knowledge and technological efficacy were associated with a small increase in trust in AI systems in a global survey conducted in 2022 (Gillespie et al., 2023).
- A UK survey found that those with higher digital familiarity were more likely to believe that governments need to carefully manage certain applications of AI: self-driving cars, education, hiring and recruitment (Department for Science, Innovation and Technology and Centre for Data Ethics and Innovation, 2023c).
- AI users were more supportive than non-AI users of a range of risk mitigation measures including pre-deployment security testing, information sharing, investment in cybersecurity to secure model weights, third-party vulnerability discovery and reports, and other measures (Ipsos, 2023c).

Caveats An important caveat to consider is that few surveys evaluate objective knowledge and awareness of AI with most asking respondents to self-report. It is also important to keep in mind that the issue or construct asked about in the question can influence the effect of having a better understanding of AI.

Beyond surveys

Until this point we have focused on survey-based research that tells us what the public thinks about AI. But, of course, ascertaining what the public thinks about AI should not be limited to survey-based approaches alone. Done well, surveys can excel in asking well designed and thoughtful questions to representative samples of the public that can help us better model the world and be reactive to the public's preferences with low effort from those participating. But survey based methods have their limitations and there is a wealth of nuance, diversity, and complexity that ends up being left out that we can attempt to capture with other methods. Additionally, survey methods often do not give us insight into the public's views under ideal democratic conditions, not laying the groundwork for both informed and deliberative elicitation of views that have democratic legitimacy (Fishkin, 1991; Goodin and Dryzek, 2006). In this section we canvas some additional approaches that exist for understanding public opinion on AI and what shapes it.

Participatory and deliberative methods and tools

A variety of participatory and deliberative democratic processes have been developed to enhance the quality and legitimacy of decision-making by engaging citizens directly in informed discussion, preference elicitation, and policy formation on complex public issues. In turn, they can give an insight into the public's views under better information environments and while engaging deliberatively with other members of the public. One example, are mini-publics (Dahl, 1987; Escobar and Elstub, 2017), such as, deliberative polling (e.g., Fishkin, 1991; 1995; 2018), citizen assemblies (e.g., Gibson, 2002; Reuchamps et al., 2023), citizen juries (Crosby, 1995; 1996), planning cells (e.g., Dienel, 1999), and consensus conferences (e.g., Joss and Durant, 1995).[30]

Key to the process of a mini-public is the (stratified) random selection of respondents, the presentation of information that allows the public to make informed decisions, and a deliberation process between the participants. Mini-publics have been conducted across issues and geographies (OECD, 2020). They have been suggested to lead to preference changes, increase legitimacy and public trust, improve decision quality, and enhance civic engagement, but their limitations have also been noted such as not being immune to partisan politics, methodological challenges, as well questions around their representativeness and legitimacy (e.g., Germann et al., 2024; Curato and Böker, 2016; Lafont, 2015).

Recent mini-publics on AI have explored a variety of AI topics. For example, Atwood and Bozentko (2023) conducted a deliberative assembly with 40 US participants focusing on high-risk AI and included survey

[30] These approaches can differ in terms of their emphasis on measuring opinion change pre and post deliberation, whether consensus is a goal of deliberation, sample size, approach to choosing the sample, the output and its destination, and the length of deliberation (see, for example, Table 1 in Escobar and Elstub, 2017). Where there is a survey element, the process usually involves a first survey that elicits information about the participant and often their pre-deliberative views, the presentation of evidence and information about the question at hand (e.g., through expert presentations on the topic), a deliberation period where participants come together to discuss the issue, and a final survey that is able to measure post-deliberative views. Ovadya (2023b) details further differences and similarities between deliberative polling and citizen assemblies.

questions on which actors should be held accountable for AI harms and who should determine who is held responsible as well as what constitutes an AI harm in a variety of scenarios. In 2022, a project led by André Bächtiger organised a citizen assembly with 200 participants to discuss AI applications in sectors like nursing and hiring (Bürgerrat, 2022). The Belgian presidency of the Council of the European Union convened a 60-person panel to provide recommendations on AI and the final report compiled key messages on technological replacement, innovation, the environment, deepfakes and the information environment, the role of humans, and global agreements (Belgian Presidency of the Council of the European Union, 2024). Meta announced that they would conduct a series of community forums in 2022 (Harris, 2022). Meta held a community forum that involved 1,545 participants from the US, Germany, Spain, and Brazil to discuss principles for the use of AI chatbots (Chang et al., 2024; Clegg, 2023), following a previous effort focused on the metaverse (Ovadya, 2023b; Ovadya, 2023c; Chang et al., 2023).

There are a number of innovative tools, platforms, voting procedures, and analysis approaches that have been developed to aid in gathering and distilling collective intelligence. These include wiki surveys (Salganik and Levy, 2015) that allow participants to submit questions themselves and vote on them, algorithms and aggregation methods that extract and cluster submitted information using language-driven or language agnostic algorithmic processes, AI-enabled collective dialogues, redesigned voting and decision-making methods such as liquid democracy and quadratic voting (Lalley and Weyl, 2018;Paulin, 2020), as well as prediction markets (see Ovadya, 2023a and Konya et al., 2023a for overviews, and for examples see Polis, n.d. AllOurIdeas, n.d. City, n.d. Kosmo, n.d. Remesh, n.d. Konya et al., 2023b).[31] Indeed, researchers have suggested that AI can play a role in scaling up high quality deliberation to the masses, and that this will be essential to face the risks of AI and other collective challenges (Landemore, 2024; Ovadya, 2023d; Konya et al., 2023a).

[31] Interestingly, one study found that predictions markets can be enhanced by applying aggregation algorithms to self-reported beliefs and combining them with prediction markets (Dana et al., 2019).

The Collective Intelligence Project (n.d.) has conducted five alignment assemblies on the topic of AI, including two run in cooperation with the frontier AI labs OpenAI and Anthropic. The study conducted by the Collective Intelligence Project in collaboration with OpenAI, aimed to understand public concerns about AI risks (The Collective Intelligence Project, 2023). It involved one thousand Americans using the AllOurIdeas wiki-survey platform to rank and submit AI safety concerns and a follow-up roundtable discussion was held with six participants and OpenAI to further explore the identified issues and concerns. The key findings were that the public desires AI regulation and governance and rejects a "Wild West" model, cautions against overreliance on misunderstood technologies, and had significant concerns about AI misuse and spreading misinformation. In the study conducted in cooperation with Anthropic, roughly one thousand Americans helped to draft a constitution for an AI system via the Polis platform (Anthropic, 2023). The public's input focused on transparency, accessibility, and avoiding harmful behaviours, resulting in a constitution that emphasised balanced and objective information, and which resulted in the AI system showing less bias when trained on these public principles compared to an internally developed constitution.

The OpenAI non-profit organisation ran a funding program to run experiments in setting up democratic processes to determine what rules AI systems should follow (2023), with many resulting projects that tested innovative approaches to eliciting democratic and deliberative input to AI (e.g., Konya et al., 2023b; Dembrane, 2023; Klingefjord et al., 2024; Fish et al., 2023; Fish et al., 2024). Top-level findings noted by the organisers included that 1) public opinion could change frequently, 2) that representative recruitment was hampered in some cases by selection effects and difficulty recruiting across the digital divide, 3) it was possible in several projects to design processes that find support for certain policies across the political spectrum bridging polarised groups, and 4) that there is a need to find a balance between representing the breadth of views of participants and reaching consensus when implementing such processes. One interesting result was that strong support (85%) emerged in one project for the position that policies should be "expanded on and updated regularly as new issues arise, better understanding is developed, and AI's capabilities evolve" (OpenAI, 2024).

Interviews, focus groups, and other qualitative methods

Qualitative interviews, focus groups, mixed method, and ethnographic approaches have been used to understand views on the use of AI in a variety of applied contexts or functions such as healthcare (e.g., Amann et al., 2023; Viberg Johansson et al., 2024; Gould et al., 2023; Dlugatch et al., 2023), care homes (e.g., Paluch and Müller, 2022), education (e.g., Bobrytska et al., 2024), autonomous vehicles (e.g., Hilgarter and Granig, 2020), and leadership positions (e.g., Petrat, 2022). Such research also is a more bottom-up approach to understanding what someone thinks about a topic in comparison to starting with set-out survey items which more strongly reflect the researcher's views of what is important to consider.

We were unable to find much research that was more focused on broader AI public opinion that used such methodologies (though see, for example, Hick and Ziefle, 2022; Hadlington et al., 2024; Centre for Data Ethics and Innovation and Department for Science, Innovation and Technology, 2023), but our literature review did not focus on finding such research nor did it use systematic approaches to surfacing this literature. One approach we found that has been used to understand the impacts people expect AI to have is scenario writing (Kieslich et al., 2024a; Kieslich et al., 2024b). In one study, for example, respondents were asked to write short stories about the future impacts personal chatbots they envisaged and to tie these stories back to their values and why they thought such impacts were important (Kieslich et al., 2024b).

Media, social media, and content analysis

Our information environment can shape our reality (McCombs and Shaw, 1972). Communications sciences and other disciplines have studied the public communication of science, technology, and risks, especially in regard to controversies, looking at things such as media coverage, framing, and narratives and their relationship to public perceptions, how to communicate science and strategies for including the public in science, the effect of digital literacy and media use on perceptions, as well as social media content analysis as a way of getting an insight into public perceptions.

There is a growing literature looking at the framings used, sentiments expressed, and topics covered by the media in relation to AI (e.g., Chuan, 2023; Luo et al., 2023; MeMo:KI - Media analysis, n.d.). Generally these studies find that media coverage of AI has increased (Nguyen and Hekman, 2024; Fast and Horvitz, 2017; MeMo:KI - Media analysis, n.d.) and is more optimistic than pessimistic about AI, contrary to assumptions about predominantly negative "Terminator Syndrome" media coverage (Garvey and Maskal, 2020; Chuan et al., 2019; Fast and Horvitz, 2017; Cools et al., 2024; Korneeva et al., 2023). More critical media discourse has emerged (Nguyen and Hekman, 2024; Fast and Horvitz, 2017; Cools et al., 2024), although some researchers also highlight that the ethical, social, and legal implications of AI do not receive sufficient attention in comparison to more optimistic topics and frames (Frost and Carter, 2020; Bunz and Braghieri, 2022).

Others have pointed out that media coverage vacillates between pointing out the benefits and extreme risks from AI, sometimes tending towards sensationalist news coverage (e.g., Roe and Perkins, 2023). Other reviews of media coverage have found that ethical issues were treated in a more level-headed way that shows less propensity for hype (Ouchchy et al., 2020). As with survey-based research, where explored, it appears there are notable cross-cultural differences in how the media covers AI (e.g., Suerdem and Akkilic, 2021) and that there can be differences in issues highlighted by right- vs. left-leaning outlets (Brennen et al., 2018).

Such studies give us an insight into the media environment which likely contributes to public opinion on AI, but we could not find studies that directly tracked media coverage and related it to changing publication perceptions. Research from other related fields has found that media coverage can correlate significantly with public perceptions of nuclear power as well as biotechnology controversies (Neresini and Lorenzet, 2016; Bauer, 2005; Gamson and Modigliani, 1989). Where survey-based methodologies were used, there was generally support for a relationship between an individuals' media consumption and perceptions of AI (e.g., Cui and Wu, 2021; Nader et al., 2024). Nader et al. (2024), for example, found that people's beliefs about AI in entertainment media were related to people's beliefs about AI, with those that believed the media depicted AI realistically being more likely to see AI as a potential companion or apocalyptic robot in comparison to automating jobs or being used in surveillance.

Studies have also analysed social media content as another way of accessing public perceptions of and sentiments towards AI (e.g., Qi et al., 2023; Kim et al., 2022; Quid, 2023 cited in Maslej et al., 2024; Zeng et al., 2022; , 2024; Leiter et al., 2024). An analysis of almost 7 million social media posts, for example, found that GPT-4 dominated online discussions of AI systems and that the ratio of positive to negative conversations about GPT-4 was close to equal with a slight preponderance of negative sentiment most quarters in 2023 (Quid, 2023). In line with findings from other approaches, there appear to be cross-cultural differences when sentiments of tweets are analysed (Kim et al., 2022; Leiter et al., 2024).

Public imaginaries and futurity

Sociotechnical perspectives on AI examine the complex interactions between artificial intelligence technologies and the broader social, cultural, and institutional contexts in which they are developed and deployed (e.g., Sartori and Theodorou, 2022). Sociotechnical imaginaries are part of two key scholarly approaches that offer a lens to understanding how public and expert future visions and imagined ideals shape the course of scientific practice (e.g., Borup et al., 2006; Beckert, 2016) and the role forecasting has in controlling or protesting potential futures (e.g., Brown et al., 2017; Andersson, 2012; Vieille Blanchard, 2010; Mitchell, 2014).

Researchers in this discipline have explored the sociotechnical imaginaries, framings, and narratives – influencing and emanating from public discourse – that shape and offer broad organising visions for understanding how the public thinks about AI and its future (e.g., Jasanoff and Kim, 2015; Cave et al., 2020; Cave and Dihal, 2019; Sartori and Bocca, 2023). Such work has, for example, explored fictional and non-fictional writing on AI, and extracted the fundamental fears and hopes they express (Cave and Dihal, 2019). Cave and Dihal's (2019) analysis revealed four primary hopes (immortality, ease, gratification, dominance) and four primary fears (dehumanisation, obsolescence, uprising, displacement) associated with AI in the popular imagination. Techniques such as looking at media discourse frames (e.g., Köstler and Ossewaarde, 2022) and scenario writing (Kieslich et al., 2024b) have also been used to understand the public's visions of AI futures.

Where next for AI attitudes and public opinion research?

Areas for cross-disciplinary learning and inspiration

We think there are a number of areas that those interested in AI attitudes and public opinion could look to for cross-disciplinary learning and inspiration for future studies, where researchers are not doing so already anyway. In particular, those conducting more descriptive surveys can look to these to help systematise future polling and surveying efforts. And readers of such findings may find them useful in terms of contextualising what such results may mean in practice.

Examples of these include: looking at research on attitudes and behaviours towards other emerging technologies and risks, such as climate change or nuclear technology, further exploring the literature on risk perceptions, reasoning, and decision-making, considering general attitudes towards science and technology, and taking into account relevant political science and communications research. We go into more detail on each of these in the Appendix.

An overview framework

The AI public opinion research field as we have described it is in need of further synthesising efforts and currently can be difficult to get an overview of the field. It is also not well integrated with the findings from the more academic applied AI attitudes literature that has focused on specific uses and applications of AI.

To that end, over the course of conducting the above broad and non-systematic literature review we tried to collect the kinds of variables that previous research on AI attitudes and public opinion research, as well as what related fields, have investigated. A broad collection of variables that have been used to investigate attitudes and public opinion of AI and emerging technologies.

We have put these together in an overview framework that can be seen in Figure 16. We hope the framework offers a top-level view for those thinking about options and approaches to studying and thinking about public opinion of AI and AI attitudes and can help in efforts to gain a systematised understanding of these.

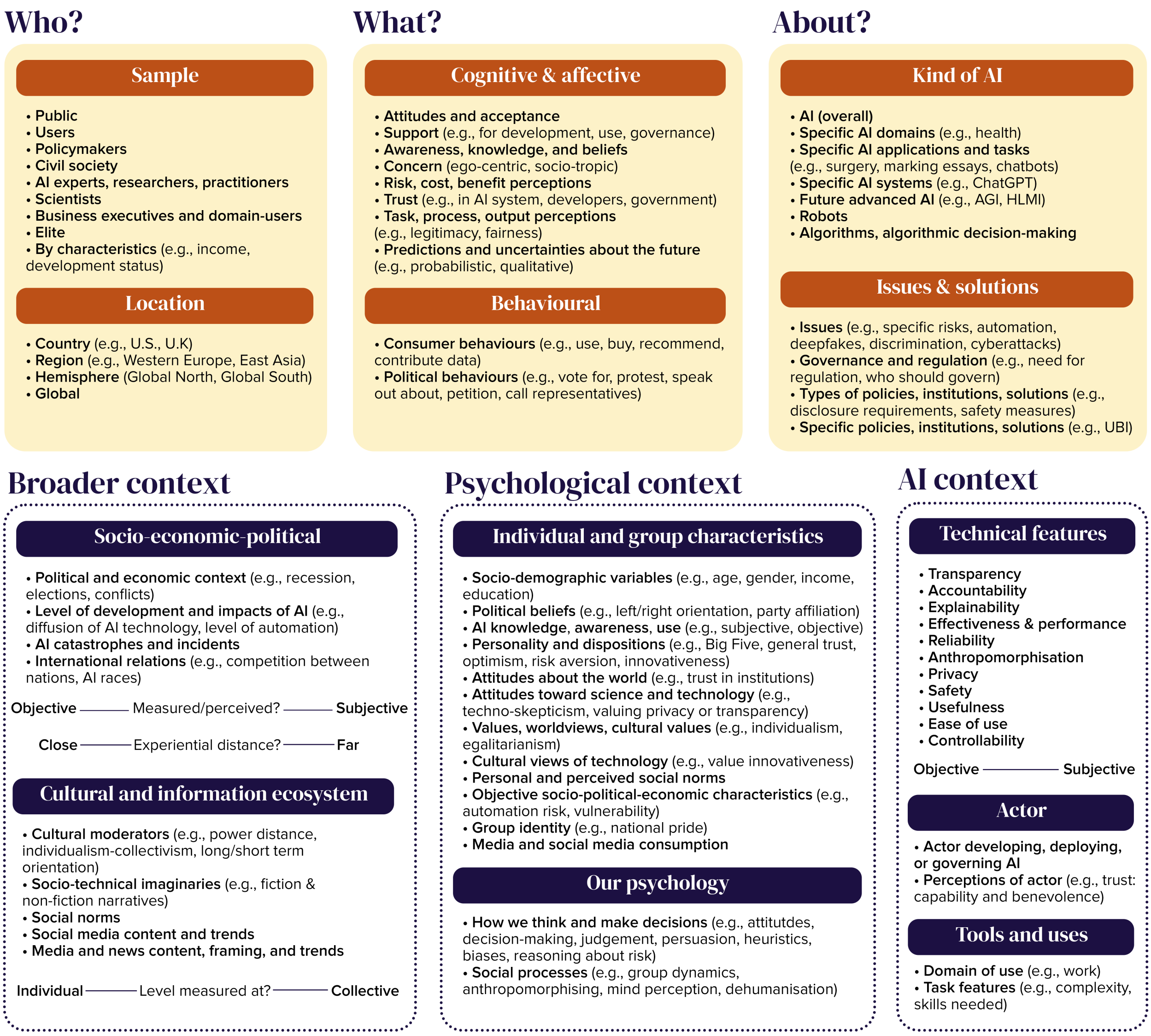


Figure 16: Overview framework for AI attitudes and public opinion.

The framework makes no assumptions about causality; the causality and direction of how constructs relate to one another are ongoing areas of discussion in most fields (e.g., Siegrist, 2021) and so we make no specific claims here on these relationships though they are important to gain a better understanding of.

Recommendations

In addition, we believe that our report motivates a number of funding, research, policy, and consumption recommendations (see Figure 17). These are particularly focused on improving our understanding and use of AI public opinion research and addressing the various limitations we have identified in the research field. We divide the recommendations into those addressed at:

1. Policymakers, civil society, and other funders and consumers of AI public opinion
2. Researchers from academia, think tanks, government, and other institutions

Policymakers, civil society, funders, and other consumers		Researchers in academia, think tanks, government, and industry	
1	Fund and set up high-quality longitudinal public opinion trackers.	6	Advance hypothesis-driven AI public research agendas.
2	Establish infrastructure to monitor and forecast AI impacts.	7	Develop and use reliable and validated AI attitude constructs.
3	Consume survey findings with care, considering their limitations.	8	Conduct systematic reviews and meta-analyses of the field.
4	Examine complete survey results instead of relying on editorialising.	9	Coordinate and collaborate across research teams.
5	Fit survey findings into broader evidence-based models of the world.	10	Address open questions in AI governance and public opinion.

Figure 17: AI attitude and public opinion funding, research, policy, and consumption recommendations.

How policymakers and civil society can help improve our understanding of public opinion of AI

Fund and set up high quality longitudinal public opinion trackers. Governments and researchers should set up high-quality trackers of public opinion and attitudes towards AI now. There is a lack of these in most countries, including the United States. This will require upfront long-term commitment from funders and government programs that are dedicated to creating longitudinal data that can inform policy and our broad understanding of AI attitudes. In addition, existing high-quality regular surveys and infrastructure such as the European Social Survey and International Social Survey could consider adding regular AI-related items to aid in these efforts.

Fund and set up surveying infrastructure and research agendas to help monitor and forecast the impacts of AI. Governments should set up the infrastructure to collect data, including survey data, that aids in monitoring and forecasting the societal, economic, and personal impacts of AI. Research should take the long view on their research agendas, considering what data will be needed to create high quality insights into the impacts AI will have on individuals and our society at large. Topics that may be of interest here include: use of AI systems in personal (e.g., AI companions)[32] and work contexts (by industry, job, task, see, for example, Humlum and Vestergaard, 2024), exposure to misinformation and disinformation, automation and economic impacts, and the impact of AI on mental health and wellbeing.

[32] AI companion companies are valued in the billions and have millions of users (Ludlow et al., 2023) . Character AI, for example, has 20 million users with 37% of traffic coming from the United States according to Demandsage (Kumar, 2024).

Consume surveys with care, considering their limitations and context. Readers and users of AI attitudes and public opinion research need to keep in mind the complexities, challenges, and nuances of measuring and interpreting AI attitudes. While AI attitudes and public opinion research can fulfil many functions (Figure 1), it can also lead such outputs astray and pollute the information environment if not done rigorously and with sensitivity to the various issues that merit consideration and we have discussed (see The challenges of understanding AI public opinion and attitudes), and the many others we did not have space for. It is also important to remember that there can be substantial cross-cultural differences (Liu et al., 2023; Vu and Lim, 2022; Ipsos, 2022b, 2023b; Policy, Elections, and Representation Lab and Schwartz Reisman Institute for Technology and Society, 2024; Gillespie et al., 2023; World Risk Poll, 2019, 2021, 2024; Funk et al., 2020) and to consider the point in time the survey occurred. Ultimately, a single survey is never going to give you a final answer when trying to understand public opinion of AI.

When reading the findings of a survey try to look at the full percentage breakdowns of a question and do not rely only on the editorialising of the results. For example, if a survey[33] reports that only 28% of people think AI has more risks than benefits, you may think this points to low pessimism about AI. If you were then told that 14% of respondents said there were more benefits than risks, you would conclude that people are twice as likely to be pessimistic than optimistic about AI. But missing out that 43% of respondents said the risks and benefits were equal, would mean you overlook a key aspect of this study's findings – the largest fraction of people in this survey expressed the belief that AI will have similar levels of risks and benefits!

[33] These percentages are taken from a study of British adults conducted by the Office for National Statistics (2023c).

Consider carefully how the survey findings fit into your world model. Even if the survey is excellent in various technical aspects, this does not yet tell you how this links to other things you may care about and whether this question is measuring something useful in that regard. For example, knowing how concerned someone is about AI does not yet tell you how this may relate to their other attitudes or behaviours, for example, their voting intentions. Support for an AI system may not translate directly to use intentions. Horowitz et al. (2024), for example, found that willingness to use a range of autonomous AI applications was consistently lower than policy support for them. In turn, this may be different to real-world adoption rates and behaviour. In reality, understanding how such findings actually matter often requires additional empirical investigation.

How researchers can help improve public opinion of AI research

Create research agendas that can better illuminate AI attitudes and their impacts. Researchers who are looking at the societal adoption of AI should work towards producing more systematic, hypothesis-driven research agendas which 1) move more towards connecting AI attitudes with relevant variables such as political behaviours, AI use, voting, policy support, and wellbeing, 2) transfer and integrate learnings from other disciplines and studies of other technologies and risks to avoid sisyphean re-inventing of the wheel (Orben, 2020) and to motivate high-quality empirical work. When researchers then run studies to test their hypotheses, they should where possible employ sampling best practices, since the AI SHARE database reveals these are not yet broadly used across all studies.

Create and use reliable and validated AI constructs and understand their validity. Researchers can help surveying efforts by designing, testing, and advocating for reliable and validated measures of AI attitudes and behaviours and the factors we may be interested in in relation to them. Those who want to measure AI attitudes should use such constructs to increase the quality of their data collection and to increase comparability between datasets. For example, it would be useful to better understand the effect of different sentiment questions on AI attitude measurement. Using existing research on trust to help shape questions around trust would be helpful (see, for example, Gillespie et al., 2023; McKnight et al., 2009; Mcknight et al., 2011; Mayer et al., 1995). In turn, having better and consistent ways to measure both objective and subjective AI knowledge could be immensely helpful when integrating across survey findings.

Researchers should also consider composite indices for measuring AI attitudes and offering “don’t know” options when assessing AI knowledge or familiarity. Both are best practices in public opinion research but are not common in current AI attitudes research. Currently, the AI SHARE database finds that only 35% of AI-related surveys use composite index variables and only 11% offer “don’t know” options.

To that end, a number of AI related scales have already been developed by psychologists (e.g., AI attitude scale, AIAS-4, Grassini, 2023; Negative Attitude toward Robots Scale, NARS, Nomura et al., 2006; General Attitudes towards Artificial Intelligence Scale, GAAIS, Schepman and Rodway, 2020; Schepman and Rodway, 2023; Threats of Artificial Intelligence Scale, TAI, Kieslich et al., 2021), although their practical benefits are not yet clear and each needs to be critically evaluated on their own merits before use. More work on how the micro and macro aspects of AI attitudes relate to one another and their relationship to key impacts and behaviours will be particularly helpful in the coming years.

Gain better understanding of the state of knowledge by conducting more systematic reviews and meta-analyses of the field. As research in the fields of AI attitude and public opinion research continues, especially research on broad AI public opinion will continue to be in need of better systematic attempts of understanding the literature and summarising across it. Our efforts above were non-systematic and therefore only preliminary. Capturing the nuances of different questions, the time the survey was fielded, and other considerations will require substantial efforts to collect and categorise existing surveys. The AI SHARE database will hopefully aid such efforts.

Coordinate and collaborate across research teams. Researchers should coordinate and collaborate in order to conduct comparative analyses and to measure the development of AI attitudes over time. One important area for coordination and collaboration is in expanding the geographic reach of public opinion research on AI. Our current understanding of AI attitudes reflects a bias towards North America and Europe. Based on public opinion survey questions of AI from 2014 to 2023 compiled in the AI SHARE database, 31% survey individuals in the United States specifically and 10% focus on the United Kingdom specifically, while various other surveys address individuals in numerous EU countries, China, South Korea, Australia, the Netherlands, and elsewhere. Overall, approximately 75% of survey questions in the database focus exclusively on individuals in the Global North, while less than 10% focus exclusively on individuals in the Global South. This mirrors findings from other research that has found that the Global South is underrepresented in AI-related survey research samples (Tahaei et al., 2024). Significant efforts should be devoted to measuring AI attitudes in other countries and contexts, as opinions of AI can vary substantially across space and place.

A second important area for coordination and collaboration pertains to longitudinal research. We do not yet have a good sense of how AI attitudes are evolving over time. Of the AI SHARE surveys and polls, over half (52%) were conducted in 2022 and 2023 alone. AI SHARE can support both efforts by providing common survey questions on AI opinions that can be asked across different countries and across time.

Finally, we also recommend that researchers make their data and codebooks available to promote open science best practices and replication. At the initial compilation stage of AI SHARE, only 17% of publications provided raw data and only 16% provided access to a codebook. Sharing such resources will promote coordination and collaboration over time and space, will support replication and meta-analyses, and will enable the expansion of the AI SHARE resource and other resources.

Address open questions on the relationship between AI governance and public opinion and other key topics. There are many open questions that will require cross-disciplinary efforts to answer. These include questions on the effects of automation or AI harms on people's attitudes and behaviours, whether AI attitudes will become increasingly polarised, and what people think about AI companions and how we can monitor their impacts on people more broadly. A full list of potential open questions are included in the Appendix: open questions in AI public opinion research.

Conclusion

Understanding public attitudes towards AI will become increasingly crucial as the technology continues to reshape society. Our analysis reveals both the complexity of public views and the challenges in studying them systematically. While surveys have captured some aspects of public opinion towards AI, the interconnections between people's beliefs, experiences, and behaviours across personal, professional, and political contexts require more nuanced investigation in the future.

This report provides a foundation for such work by synthesising current research, identifying key challenges, and offering concrete recommendations for improvement. Of course, our review of the literature had its limitations: it was limited in geographical scope, non-systematic, and non-comprehensive. However, while synthesising such a broad field necessarily requires sacrificing much detail, our analysis highlights critical gaps in current research and methods. New tools and resources like the AI SHARE database can help address these gaps, but improving our understanding of public attitudes will require coordinated effort from researchers, policymakers, and industry leaders.

While our analysis focuses primarily on North America and Europe, it highlights the pressing need for more surveys and similar synthesis of research from other regions, particularly the Global South. As AI systems become more prevalent and powerful, understanding and responding to public attitudes – across all populations and contexts – will be essential for responsible development and governance. We encourage all organisations with a stake in AI's impacts to engage meaningfully with public opinion, using the frameworks and recommendations presented here as a starting point for more comprehensive and systematic approaches.

Appendix

Considerations when conducting and evaluating surveys

Below we list a range of considerations and challenges to keep in mind when considering individual survey findings generally.[34] These, in turn, highlight the need for carefully designed studies as well as systematic reviews and meta-analyses that help average across such issues to help us make more concrete claims about attitudes and public opinion.

[34] This list is by no means comprehensive, the interested reader could also consider work such as those by: Berinsky (2017); Fowler (2014); Tourangeau et al. (2000); Traugott (2012).

Question wording and order Respondents are influenced by the information they read over the course of answering survey questions and by the construction of the questions themselves. Issues here include context effects, like how a query on personal health can sway answers on healthcare policy; priming, as when a crime rate question affects feelings on safety; question fatigue leading to hasty answers in long surveys; and consistency pressure pushing respondents to maintain early survey stances even if they change their mind later.

Readers should also take care to consider if additional information is given to the reader, such as arguments on both sides of an issue, where the results are then often later simply cited without reference to this. Definitions or descriptions given of items should also be considered in terms of the effect they could have, as well as lack thereof, which may leave ambiguous how someone has interpreted an item if multiple interpretations are possible.

Dynamic nature of attitudes Public attitudinal surveys are a snapshot of what people think at a given moment in time. Opinions about a political leader, for example, might change after a significant policy announcement or a notable public event. For AI, a major event like the calls to pause AI development may significantly impact views on AI governance in the immediate aftermath of the news cycle covering the story. That being said, attitudes also correlate across time in any given individual.

Inherent noise in data Public attitudes bake in a degree of noise. This challenge is illustrated by the 'Lizardman's Constant,' (Alexander, 2013) which originates from a reference to the fraction of people in any given poll who seem to give unexpected or bizarre answers. It is named after surveys that have included questions about whether respondents believe in "lizardmen" controlling the world to which a consistent, small percentage of people (around four per cent) tend to affirmatively respond. Pew Research has also found that 4-7% of respondents from online opt-in polling sources give systematically positively skewed bogus responses, introducing bias into the data (Kennedy et al., 2020).

The level of specificity or abstraction of items and aggregation methods matters It can be difficult to know how much weight to give to any specific survey result. A handful of short questions are rarely suitable for capturing perspectives about particularly nuanced issues (including many of those related to AI development, deployment, and governance). Often multiple ideas are compressed into questions, which presents challenges for understanding which specific idea a respondent is reacting to. Another challenge is the sometimes found instability of micro-level attitudes compared with more stable macro-level attitudes.

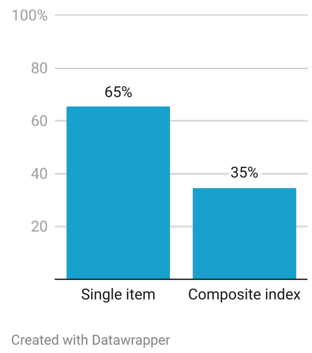


Figure 18: AI SHARE database finding: What percentage of AI-related surveys use single-items and composite index variables?

Both in political science and psychology an approach used to gain a more stable and informative measure is to aggregate across multiple items to create a single measure that creates a better signal with less noise (e.g., Ansolabehere et al., 2008; Diamantopoulos et al., 2012; Song et al., 2013). Currently, based on the AI attitudes questions in the AI SHARE database, single item approaches (65%) are more common than composite index variables (35%). Another key way survey designers can address these issues is to make sure the questions are pitched at the right level of specificity for the question at hand (see Berinsky, 2017 for discussion, solutions, and their tradeoffs).

Dealing with lack of knowledge and opinions One view in political science holds that individuals average across immediately salient considerations based on their personal experiences and characteristics when answering a survey question (Zaller, 1992). One concern one can have, however, is that respondents will give an answer to questions, even if they don't know about a given issue or they do not hold an opinion. This makes it important to offer "I don't know" options and evaluate respondents' level of knowledge about the surveyed topic. The latter allows for later subgroup and statistical analyses of the role awareness and knowledge play. The other lets people 'opt out' of giving a response and signal their lack of knowledge, opinion, or uncertainty. Currently, too few surveys in the AI public opinion literature offer "I don't know" options: only 11% of survey questions in the AI SHARE database have them, while 89% do not.

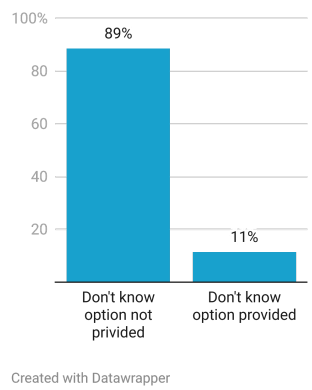


Figure 19: AI SHARE database finding: What percentage of AI-related surveys have I don't know options?

Response biases There are a variety of response biases (Lohr, 2021) that survey designers and readers have to contend with. For example, social desirability bias is the phenomenon whereby some people might provide answers they believe are socially acceptable rather than their true opinion. Social desirability bias represents the gap between what people genuinely think or do and what they report in surveys due to the influence of societal norms and the desire for approval. In 2022, for example, Ipsos found that 6% of respondents claimed to know "a great deal" and a further 6% "a fair amount" about a made-up political candidate that they regularly add to such polls (Ipsos, 2022a).

Sample size Sample size is also an important factor to consider, with two ideas particularly relevant for making sense of attitudinal data: the margin of error and the confidence level associated with the results. In this context, a confidence level of 95% means that if we were to repeat the sampling process many times and calculate the confidence interval each time, about 95% of these intervals would contain the true population parameter. The confidence interval itself is fixed once calculated from a single sample - it either contains or doesn't contain the true parameter (we just don't know which).[35] The margin of error, meanwhile, tells us how much we'd expect the actual results to vary from what the results of the poll show. At a basic level, we can think of the confidence level as how sure we are, and the margin of error as the range around our poll's result where the true answer lies.

[35] A 95% confidence level indicates the reliability of our method, not the probability that the true parameter falls within any single calculated interval. A 95% confidence level is commonly used because it strikes a balance between precision and certainty and is widely accepted in research and statistics for making inferences about populations.

Generally speaking, with proper sampling techniques a sample of one thousand respondents should provide a fairly accurate representation of general public opinion. The key factor here is randomness, which ensures that every individual in the population has an equal chance of being selected. With a sample size of one thousand respondents, we typically get a margin of error[36] of around ±3% with perfect sampling assuming a confidence level of 95%. However, analyses of subpopulations, such as those based on education level, political affiliation, or gender, will have larger margins of error and lower statistical power due to the smaller effective sample sizes within each subgroup. This reduction in precision means that larger overall sample sizes or oversampling of key subgroups are often necessary to obtain reliable estimates for these smaller populations.

[36] **Calculating the margin of error**

$$MoE = Z \times \sqrt{\frac{p(1-p)}{n}}$$

$$MoE = 1.96 \times \sqrt{\frac{0.5 \times (1-0.5)}{1000}}$$

$$= 1.96 \times \sqrt{\frac{0.25}{1000}}$$

$$= 1.96 \times 0.016 = 0.031$$

Sample representativeness The technical ideal for drawing a sample that represents a population would entail that each member of a population has an equal chance of being randomly selected to be in the survey (this is known as simple random sampling). In practice, this is prohibitively difficult and expensive to achieve. Instead, those conducting surveys aim to ensure that their sample is representative of the underlying population in terms of relevant characteristics such as age, gender, political affiliation, ethnicity, and so on. Researchers use a variety of methods to achieve representativeness and overcome sampling biases (Lohr, 2021). These include sampling design techniques, such as stratification, clustering, and quota sampling, and post-sampling adjustments, particularly weight adjustments, such as raking, post-stratification, and propensity score weighting.

Funding sources and conflicts of interest Studies have generally focused on the effect of research funding sources in the fields of medicine and pharmaceuticals, where industry funding has been found to be associated with stronger pro-industry conclusions (Bekelman et al., 2003), misleading titles (Bero et al., 1992), publication delays (Blumenthal et al., 1997), and failure to report negative studies (Krimsky, 2013). For consumers of survey research, it is worth considering that financial and other interests could lead to "cherry-picking" of results and the foregoing of publishing results that go against the organisation's agenda. Available funding can also affect the topics of surveys if it is made available only for specific kinds of research. It is also worthwhile to consider question wording carefully, since surveyors can easily add bias into questions and items even inadvertently. Looking at results and question wording carefully instead of relying on the narrative of articles is always well advised.

Constructs Things quickly become complex in terms of defining terms within and across fields, the measurement of constructs, and determining what phenomena are actually being studied. It can be surprisingly difficult to ascertain consensus definitions for a specific construct and standard way to ask about it in a survey. In addition, researchers sometimes do not clarify the empirical and theoretical backgrounds to the terms they use, or do not strictly hold to any definition in particular since they also often reflect natural language use of terms. Illustratively, for example, one can look at how, in even more established fields examining views towards emerging technologies, there are a variety of ways researchers have approached defining acceptance, support, and acceptability and their differing beliefs about whether they should include evaluative and/or behavioural elements (compare, for example, Dreyer et al., 2017; Dreyer and Walker, 2013; Schade and Schlag, 2003; Huijts et al., 2012).

Things are not clear cut or simple when looking at the emotion or affect literature either, with non-consistent definitions and measurement approaches, and lack of consensus remaining an issue in understanding the affective components of our mental lives (see, for example, Walle and Dukes, 2023; Lerner et al., 2015;[37] Munezero et al., 2014; Gervais and Fessler, 2017; Scherer, 2005). If you expect that terms such as, attitudes, affect, trust, emotion, and sentiment are consistently used terms, measured using consistent approaches across disciplines or even within one field, you would often be disappointed.

[37] The supplementary materials of Lerner et al., 2015 contain useful primers on emotions as well decision-making processes.

More detail on areas for cross-disciplinary learning and inspiration

Attitudes and behaviours towards other emerging technologies and risks have been studied more systematically and extensively. There is a broad literature looking at attitudes towards other emerging technologies and risks that the field of AI can learn from, with some research already using such paradigms for automated driving (Ward et al., 2017; Liu et al., 2019). Such research can be particularly useful because they are closer to the behavioural frontier than AI attitude research is currently. Areas where policy preferences and people's behaviour have already been examined for several years since they have mattered in terms of interventions and regulatory success (e.g., climate change), will be helpful places to look to when conducting high-quality research on public opinion on AI in the coming years as AI enters the political arena. Research looking at public perceptions of other technologies and risks investigates similar questions that we will want to investigate in relation to AI, such as looking at the role of awareness and understanding, how risk and benefit perceptions determine attitudes, and how views change over time or react to events or informational treatments.

Much like AI-related research conducted so far, such research has also found that factors such as trust in the institutions, trust in the technology, prior knowledge, awareness, individual differences, attitudes, and risk and benefit perceptions can matter for the acceptance of other emerging technologies and associated policies (e.g., De Groot et al., 2020; Dreyer et al., 2017; Howell et al., 2017; Visschers et al., 2011; Bearth and Siegrist, 2016; Emodi et al., 2021; Siegrist, 2000; Siegrist and Cvetkovich, 2000; Dreyer and Walker, 2013; Gupta et al., 2012; Stoutenborough et al., 2013; Bogert et al., 2024). Many of these fields offer frameworks with many constructs and their interrelationships to consider backed up by a broader evidence-base that has been more exhaustively reviewed. In turn, there has been more work connecting attitudes to behaviours in these strands of research. For example, in a meta-analysis of 693 articles in the technology acceptance research, Marikyan et al. (2023) identified 21 factors that had different relationships with attitudes, intentions, and use behaviour.

Some potential fields to consider include:

- **Climate change** There is a substantial research base that has been reviewed and meta-analysed in the realm of climate change related to public opinion and related behaviours, as well as informational treatments that affect support for climate policies (e.g., Bergquist et al., 2022; Dasandi et al., 2022). Bergquist et al. (2022) for example, conducted a meta-analysis of the determinants of public opinion on climate change policies. The meta-analysis of 89 datasets found that perceived fairness and effectiveness of climate change policies were the two most important determinants of public opinion of the policies investigated. Knowledge about climate change only showed a weak relationship with views, while demographic variables had weak to no associations. They also evaluated factors such as climate change evaluations (e.g., concern, risk perception, seriousness, belief) and psychological factors (self-transcendent values, trust, ideology, self-enhancement values).

  While climate change risk may differ to AI risk in some ways, it also has some characteristics which make it a useful reference class: international cooperation and competition, benefit sharing, inequalities and differences in terms of those who create, benefit, and suffer from the risk. It may also be useful to consider if there are lessons from research on rising climate anxiety (Ballew et al., 2024; Whitmarsh et al., 2022; Hickman et al., 2021; Clayton, 2020), and whether parallel AI anxiety will be an issue that needs to be considered in terms of our mental health and political behaviours.

- **Nuclear technology** The dual-use nature of nuclear technology reflects some of the concerns that arise in relation to AI as well. Research that looks at the factors that are associated with public acceptance and perceptions of the benefits and risks of nuclear technology could therefore also be informative for thinking about public opinion of AI (e.g., Ho et al., 2019; De Groot et al., 2020; Ansolabehere and Konisky, 2009; Stoutenborough et al., 2013; Baron and Herzog, 2020).

  There may also be useful touchpoints for understanding the effect of large-scale extreme AI harms from studies looking at the effects of nuclear disasters such as Fukushima (e.g., Siegrist and Visschers, 2013; Visschers and Siegrist, 2013; Huang et al., 2013; Kim and Kim, 2023). Such research has found that there is a negative effect on public opinion of nuclear technology due to such accidents and that they are related to people's risk and benefit perceptions, but that prior beliefs and trust matter in determining these effects. Modelling the long-term effects of such disasters, especially in terms of the direct and indirect effects in relation to other competing issues such as climate change, can be more complex (Kim and Kim, 2023).

- **And many more** The interested reader can look at research and frameworks that try to capture how public perceptions are determined and the effects they have for fields such as: sustainable and other new energy technologies (e.g., Huijts et al., 2012, see Figure 6 therein; Heiskanen et al., 2008), novel food technologies (e.g., Siegrist and Hartmann, 2020, see Figure 2 therein; Bearth and Siegrist, 2016), GMOs (e.g., Frewer et al., 2013), nanotechnology (e.g., Besley, 2010; Boholm and Larsson, 2019), and synthetic biology (e.g., Pardo Avellaneda and Hagen, 2016; Jin et al., 2019).

Risk perceptions, reasoning, and decision-making are rich fields of inquiry public opinion of AI research can draw on. Understanding and managing risk perceptions of the public have been of interest to academics for many decades (e.g., Fischhoff, 1985). There is research looking at risk and benefit perceptions related to the above noted fields (e.g., Bearth and Siegrist, 2016; De Groot et al., 2020; Poortinga and Pidgeon, 2006; Pidgeon et al., 2005; Bickerstaff et al., 2006), as well as rich veins of research on how we reason, form judgements, make decisions, or are persuaded more generally that can offer insight into how people think (e.g., Fischhoff and Broomell, 2020; Crano and Prislin, 2006; Holyoak and Morrison, 2012). For example, the finding that risk and benefit reactions are inversely related (Bearth and Siegrist, 2016), perhaps due to the affect heuristic (e.g., Slovic et al., 2002; Keller et al., 2006; Skagerlund et al., 2020), may also be useful for understanding responses of surveys on public opinion of AI related to risks and benefits. In general, we believe that far more systematic study designs will be needed to understand how the public thinks about AI risks and that current polls discussed above are not particularly useful yet for gaining a solid understanding of this aspect of AI public opinion.

General attitudes towards science and technology are likely to be at least somewhat predictive of AI attitudes and may merit further exploration. A recent scale constructed to measure attitudes to technologies more generally, the General Attitudes Toward Technology (GATT) scale (Cologna et al., 2024) breaks into three kinds of factors – techno-optimism, techno-pessimism, and techno-fix – which could also be useful for investigating views on AI and their correlates. Techno-optimism and techno-pessimism have been found to be a relevant factor in other areas such as climate change research (e.g., Dentzman et al., 2016; Fletcher et al., 2021) and have been investigated in relation to technology products as well (Kotzé et al., 2016). They can can be differentially related to concerns and behaviours towards technology and risks.

Political science public opinion and communications research beyond AI has grappled with the complexities and impacts of public opinion at length. Public opinion research in political science exists for many issues beyond automation and its findings and approaches may be useful for understanding AI public opinion as well. For example, such research has looked at the stability of public opinion and how micro and macro level attitudes are related and interact with policy support (e.g., McClellan et al., 2018; Zaller, 1992; Page and Shapiro, 1992; Druckman and Leeper, 2012) as well as how people prioritise issues (e.g., Edy and Meirick, 2018). Indeed, it would be useful to determine in more detail how micro-level opinions on AI and associated policies contribute to more macro-level and general attitudes. There are also innovative techniques that can be used to look at the effect of self-chosen information on opinion stability rather than experimenter chosen information treatments, which may be useful in the context of better understanding the public opinion of AI (Druckman et al., 2012).

There is a large amount of research that has been conducted looking at the interplay between public opinion, elite opinion, policymakers, and policy which can help elucidate the relationships between different survey samples' opinions and the impacts of this (e.g., Baum and Potter, 2008; Slothuus and Bisgaard, 2021; Page, 1994; Adams et al., 2004; Levendusky, 2010; Gelpi, 2017; Burstein, 1998; Leeper and Slothuus, 2014; Butler, 2021; Latré et al., 2019). It will be useful to elucidate how different actors' views of public opinion affect AI governance, development and deployment (cf. Van De Grift and Cuppen, 2022; Broockman and Skovron, 2017; Law, 2024) and how elite and expert opinion affects AI public opinion.

Other relevant research includes historical work looking at the impacts of technological change on social movements (Caprettini and Voth, 2020), how public opinion towards nuclear weapons developed and the impacts it had (Capitanchik, 1983; Herron and Jenkins-Smith, 2006), and how technology races unfolded in the past (Barnhart, 2022).

Open questions in AI public opinion research

1. What will the effect of AI automation be on political attitudes and behaviour? How may public reactions differ if cognitive tasks completed by higher educated and higher income members of the public are automatable by AI?
2. How will large-scale AI harms and disasters impact people's views of AI generally and in specific use domains?
3. There is some evidence of growing polarisation of public opinion (e.g., Fiorina and Abrams, 2008; Sunstein, 2009; Gauchat, 2012 though see The Economist, 2021). Will public discourse on AI become more politically polarised and if so how? Will news media framing become more polarised and which topics will fall into different political camps in different countries (Shaikh and Moran, 2024; Flamino et al., 2023)? What are and will be the party cues given on AI in different countries that will influence AI public opinion?
4. How will an AI race framing affect public opinion and support for international cooperation and attitudes towards international governance?
5. What is the general level of people's anxiety towards AI on a day to day basis (see, for example, Elsey and Moss, 2023b)? Will we see a general pessimism and anxiety of the future take hold as climate anxiety and AI anxiety collide? Will this have impacts on young people in particular? How will attitudes towards climate change mitigation and AI risks and benefits collide and affect each other in the public discourse?
6. What will drive the rise of AI social movements and protests and what will their impacts be?
7. What are the key cross-cultural differences in AI attitudes and how will they impact AI issues such as international governance? What is the role of media coverage and broader socio-technical narratives in driving these? Are there useful interventions to bridge attitude

divides?

8. How do consumer AI experiences and attitudes relate to political AI attitudes and behaviours? How should we think about the relationship between more academic findings on AI attitudes towards specific AI applications and uses, and broader AI public opinion results?
9. What will the impacts of widespread proliferation of AI services and extreme automation be on wellbeing, skill development, and people's experiences of meaning in life?
10. What do people think about AI companions, how widespread is their use, and what risks and benefits are there from intensive use of them within society? Are we already seeing any impacts of AI companion use that we are failing to track consistently?
11. How do the risk and benefit perceptions of AI interrelate? What drives people's risk and benefit perceptions and how do they affect political attitudes and behaviour? Can we use previous research of risk perceptions to more systematically understand people's AI risk attitudes?
12. How will attitudes towards AI translate into political behaviour such as voting? How do risk perceptions and policy preferences in the AI realm trade off against other issues on the public's agenda (see, for example, O'Shaughnessy et al., 2023; Zhang and Dafoe, 2019)?
13. What is the role of fairness perceptions in attitudes towards AI and AI policy preferences? (see Jeffrey, 2021; Magistro et al., 2024; Ladreit, 2022 for findings relating to automation concern and policy preferences, and Bergquist et al., 2022 for meta-analytic findings for public opinion of climate change policies)

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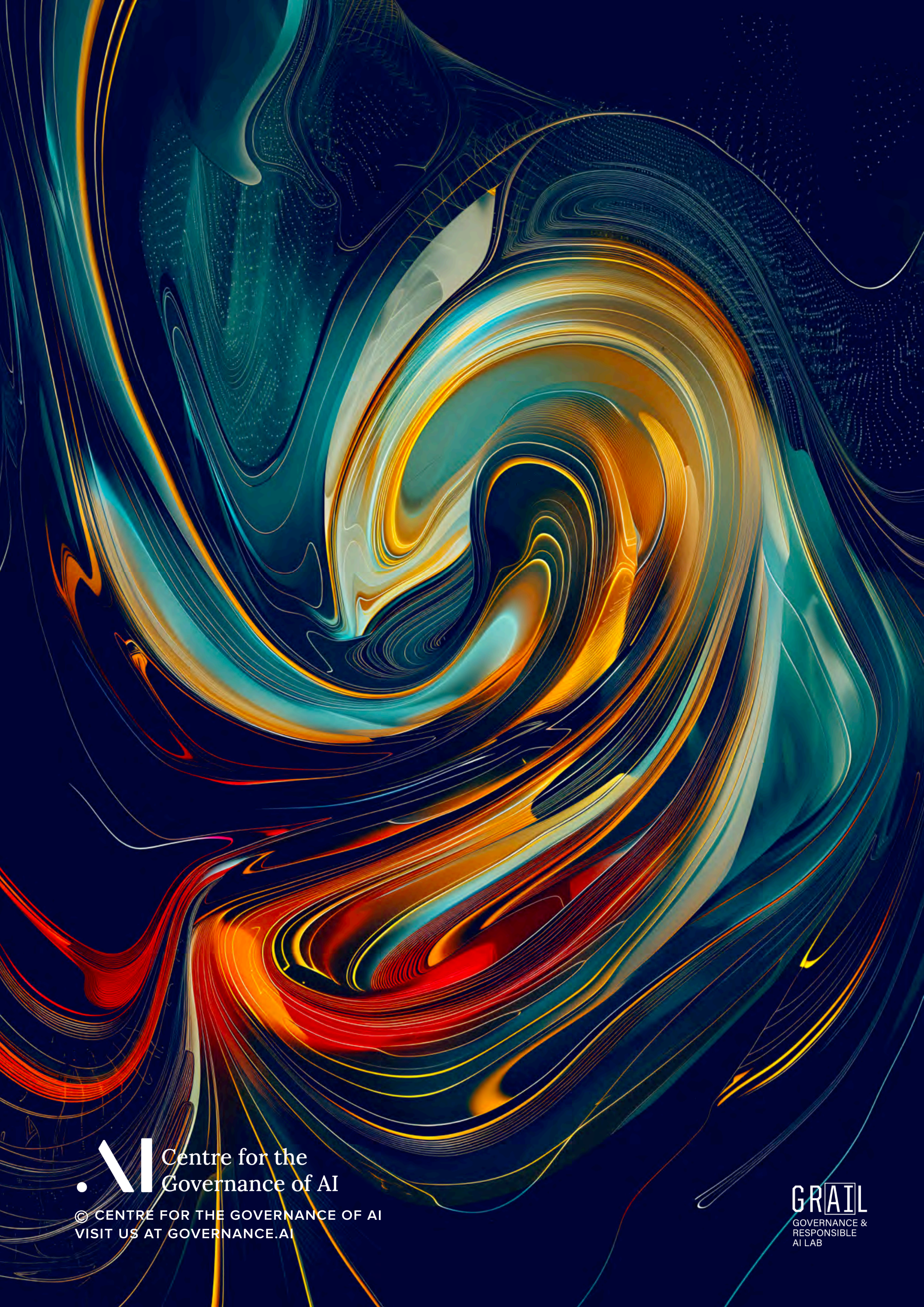

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