
MISALIGNMENTS IN AI PERCEPTION: QUANTITATIVE FINDINGS AND VISUAL MAPPING OF HOW EXPERTS AND THE PUBLIC DIFFER IN EXPECTATIONS AND RISKS, BENEFITS, AND VALUE JUDGMENTS

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ABSTRACT

Artificial Intelligence (AI) is transforming diverse societal domains, raising critical questions about its risks and benefits and the misalignments between public expectations and academic visions. This study examines how the general public (N=1110)—people using or being affected by AI—and academic AI experts (N=119)—people shaping AI development—perceive AI’s capabilities and impact across 71 scenarios, including sustainability, healthcare, job performance, societal divides, art, and warfare. Participants evaluated each scenario on four dimensions: expected probability, perceived risk and benefit, and overall sentiment (or value). The findings reveal significant quantitative differences: experts anticipate higher probabilities, perceive lower risks, report greater utility, and express more favorable sentiment toward AI compared to the non-experts. Notably, risk-benefit tradeoffs differ: the public assigns risk half the weight of benefits, while experts assign it only a third. Visual maps of these evaluations highlight areas of convergence and divergence, identifying potential sources of public concern. These insights offer actionable guidance for researchers and policymakers to align AI development with societal values, fostering public trust and informed governance.

Keywords Risk Perception • Societal integration of technology • Valence • Expert-layperson comparison • AI Governance • Public Perception • Psychometric Model

1 Introduction

Although the origins of Artificial Intelligence (AI) date back decades (McCarthy et al. 2006; Hopfield 1982; Rumelhart, Hinton, and Williams 1986), recent developments, driven by advancements in algorithms, computing power, and availability of training data (Deng et al. 2009), yielded transformative breakthroughs and rise in funding (Lecun, Bengio, and Hinton 2015; Statista 2022). AI becomes increasingly integrated in many sectors such as education (Chen, Chen, and Lin 2020), healthcare (Amunts et al. 2024), journalism (Diakopoulos 2019), forestry and farming (Holzinger et al. 2024), as well as production and manufacturing (Brauner et al. 2022) and offers benefits in terms of convenience, efficiency, and innovation (Bouschery, Blazeovic, and Piller 2023).

However, AI also raises concerns—such as privacy infringements, job displacement (Acemoglu and Restrepo 2017), algorithmic bias (Brauner et al. 2019), and ethical challenges (Awad et al. 2018)—that affect individuals, organizations, and society as a whole. Consequently, the expectations regarding AI seem divided: Some view AI as a revolutionary tool that will improve our lives (Brynjolfsson and McAfee 2014; Makridakis 2017), others express concerns about ethical implications and potential risks (Cath 2018; Bostrom 2003).

For decades, it has been known that computers and algorithms are not value-neutral but inherently reflect embedded values and potential biases (Friedman and Nissenbaum 1996; Nissenbaum 2001; Sadek, Calvo, and Mougnot 2024). These embedded values can influence decisions and outcomes, potentially perpetuating inequality or reinforcing existing biases. Furhter, Crawford (2021) argues that artificial intelligence is neither artificial nor intelligent. It is not artificial, as it relies on vast, hidden cloud infrastructure, consumes enormous amounts of energy for training and inference, and depends heavily on invisible human labor—primarily from the Global South—for labeling training data (Hern 2024). Nor is it intelligent because, though it mimics intelligent behavior, it lacks independent thought, genuine understanding, and self-awareness. Instead, it is a product of human design, shaped by the developers goals, assumptions, and biases. This underscores the importance of examining both the similarities and differences in AI perception between experts and developers, who shape these technologies, and the general public, who ultimately use or are affected by them.

In this article, we therefore queried the opinions of both academic experts in AI and the general public regarding AI's future using 71 micro scenarios. As individual risk and benefit perceptions shape attitudes, usage intentions, and actual usage across various domains Huang, Dai, and Xu (2020), we measured the expected likelihood of occurrence, perceived risks and perceived benefits, as well as the overall valence (value, or sentiment) towards these topics. We analysed the responses for similarities, differences, and patterns and provide visual maps of the findings. The study aims to inform about similarities and differences in AI perception and evaluation between experts and the public to support the development of a research agenda for AI's future, identify which AI fields may require stronger regulation, and highlight areas where accessible education on AI and its implications is needed to enhance public understanding.

2 Related Work

The structure of the related work is as follows. First, we outline related work on the perception of AI. Second, we present work on the similarities and differences in AI and technology perception between experts and the general public. Third, we introduce the psychometric model of risk perception and works on risk perception, as this approach serves as the basis of our work.

2.1 Public Perception of AI

While AI has been around for decades, the public release and rapid adoption of ChatGPT at the end of 2022 (Hu 2023) sparked unprecedented academic interest regarding broader implications and public perceptions of AI across various tasks and domains. As research on this topic is still evolving, many findings remain preliminary, and knowledge about AI perception is yet to be fully consolidated. Consequently, the following section provides a brief and necessarily selective overview of this rapidly developing field.

Public perception of artificial intelligence (AI) is multifaceted and influenced by various factors, including media representation, personal experiences, and societal context.

Media plays a significant role in shaping public opinion about AI. Fast and Horvitz (2017) conducted an extensive analysis of three decades of AI coverage in the New York Times, observing a marked rise in public interest after 2009. Their findings indicate that coverage has generally been more positive than negative, balancing optimism with growing concerns over control and ethical issues, while recent years reflect heightened enthusiasm for AI's potential in fields like healthcare. News coverage often emphasizes the benefits of AI while downplaying potential risks, leading to a perception of AI as superior to human capabilities and fostering anthropomorphization of technology (Puzanova, Tertyshnikova, and Pavlova, n.d.). Cave, Coughlan, and Dihal (2019) explored common AI narratives in the UK, identifying four optimistic and four pessimistic themes. These narratives often involve anxiety, with only two emphasizing benefits over risks, such as making life easier. Sentiment analysis of WIRED articles shows a trend towards

polarized views, with both positive and negative sentiments increasing over time (Moriniello et al. 2024). Sanguinetti and Palomo (2024) investigated how news outlets portray “AI anxiety”, often depicting AI as an autonomous and opaque entity beyond human control. Using an AI anxiety index, the study analyzed newspaper headlines before and after ChatGPT’s launch, finding increased coverage and heightened negative sentiment.

Perceived Risks and Benefits influence the perception of AI. Surveys indicate that the public views AI as both a risk and an opportunity. Concerns include privacy invasion and cybersecurity threats (Brauner et al. 2023), while benefits are seen in areas like urban services and disaster management Yigitcanlar, Degirmenci, and Inkinen (2022). Neri and Cozman (2019) argue that experts play a significant role in shaping public perception of AI risks. Their public positioning can amplify the perception of certain risks by the public, such as existential threats, which may not be based on actual disasters but rather on expert discourse. Lee et al. (2024) found that individuals with higher education levels, interest in politics, and knowledge about ChatGPT tend to perceive greater risks associated with AI. This finding challenges the conventional “knowledge deficit” model and indicates that negative perceptions can stem from a critical mindset approaching AI technology with caution.

Trust in AI varies by context and demographic factors. People generally trust AI in personal lifestyle applications but are more sceptical about its use by companies and governments (Yigitcanlar, Degirmenci, and Inkinen 2022). Willingness to use AI is influenced by the perceived balance of risks and opportunities, which varies across different application domains such as medicine, transport, and media (Schwesig et al. 2023).

There is a significant gap in public understanding of AI, often leading to irrational fears and control beliefs. Promoting AI literacy is essential for informed decision-making and responsible innovation (Brauner et al. 2023).

Further, public perception of AI can vary significantly based on local context, political ideology, and exposure to science news. For instance, the people from the US generally expects more benefits than harms from AI, with a significant portion supporting regulation to mitigate potential risks (Elsy and Moss 2023). However, existential risks are not a prominent concern for most people, who tend to worry more about concrete issues like job loss. Sindermann et al. (2022) explored cross-cultural differences in AI attitudes among Chinese and German participants, linking fear of AI to neuroticism in both groups and highlighting cultural variations in AI acceptance and fear. Kelley et al. (2021) surveyed over 10,000 participants across eight countries to examine public attitudes toward AI (Australia, Canada, USA, South Korea, France, Brazil, India and Nigeria), finding that developed nations predominantly expressed worry and futuristic expectations, while developing nations showed excitement about AI’s potential, with South Korea emphasizing AI’s usefulness and future applications, amid widespread uncertainty about its societal impact. In Taiwan, science news consumption and respect for scientific authority positively influence AI perceptions (Wen and Chen 2024).

The public discourse on AI frequently features either fears and inflated expectations, especially concerning artificial general intelligence (AGI), which remains largely speculative and fictional as of today (Jungherr 2023). Ipsos (-@ Ipsos 2022) conducted a survey revealing that the general population frequently lacks a nuanced understanding of AI’s technical capabilities and limitations. Similarly, Pew Research (2023) found that only a small percentage of Americans could accurately identify AI in everyday scenarios, underscoring widespread confusion about AI’s scope and capabilities. The Alan Turing Institute (2023) similarly noted that public understanding of AI varies significantly by education level and context, with common concerns centered on automation and robotics, particularly in employment and security applications. This limited awareness fosters misconceptions and simplistic views of AI’s impact, hindering informed public discourses on societal implications.

In summary, public perception of AI is complex and shaped by a combination of media influence, perceived risks and benefits, trust levels, and cultural context.

In a comment, four AI researchers (Russell et al. 2015) Stuart Russell warns against lethal autonomous weapons, arguing for an international ban to prevent an arms race. He stresses ethical concerns and argues that the AI community must take a clear stance, as in past cases with nuclear and chemical weapons. Sabine Hauert advocates for researchers to engage the public and counter misconceptions about AI. She highlights the importance of balanced communication to shape perceptions and policies. Coordinated efforts could unify communication strategies across AI stakeholders. Russ Altman emphasizes AI’s transformative potential in healthcare but warns of inequitable access. Without careful implementation, AI could widen disparities, creating unjust systems. Clinicians also need AI systems they can understand and trust. Manuela Veloso: Envisions a collaborative future where robots complement humans and how robots and humans can mutually assist one another. Practical challenges remain, including improving communication and robot capabilities in real-world settings. She sees robots enhancing, not replacing, human productivity.

2.2 Similarities and Differences in Risk Perception between Experts and the Public

The perception of risk varies significantly between experts and the general public or novices across various domains. We outline findings outside outside the technology context to findings on AI in particular.

Health experts and the public differ in their risk assessments of health hazards (Krewski et al. 2012). Experts tend to perceive behavioral health risks (e.g. smoking, obesity) as more significant, while the public may have different priorities. This discrepancy highlights the need for effective risk communication strategies to align public perception with expert assessments. Public perception of risks of production facilities is often more subjective and emotional compared to the objective evaluations by safety professionals (Botheju and Abeysinghe 2015). This misalignment necessitates two-way communication to prevent public concerns from escalating. In different context, Siegrist et al. (2007) contrasted the public perception of nanotechnology between 375 laypeople and 46 experts using the psychometric model. In the context of environmental hazards, such as nuclear waste, experts and laypeople have different perceived risks and risk perception is influenced more by attitudes and moral values than by cognitive factors (Sjöberg 1998). Laypeople, who generally have less technical knowledge, tend to assess risks based on intuitive and emotional factors. In contrast, experts rely more on evidence-based, technical assessments. This difference often leads to divergent views on policy and regulation, with members of the public perceiving higher levels of risk than experts. The research also highlighted that the public prioritize ethical and societal implications, while experts focus primarily on scientific and technical risks (Siegrist et al. 2007).

In contrast, in the context of natural hazards like hurricanes and cyclones, there is often a good deal of consistency between expert risk assessments and public perceptions, especially in high-risk areas (Peacock, Brody, and Highfield 2005; Sattar and Cheung 2019). However, public risk perception can be influenced by factors such as trust in authorities and previous disaster experience

In the realm of autonomous vehicles (AVs), public risk perception is heavily influenced by trust in technology and authorities. Knowledge about AVs can improve trust, which in turn reduces perceived risk, emphasizing the importance of trust-building initiatives (Robinson-Tay and Peng 2024). In aviation, experts generally have a more accurate perception of relative risks compared to novices, whose perceptions can be influenced by overconfidence and lack of experience (Thomson et al. 2004).

Elena and Johnson (2015) examined expert and public perceptions of cloud computing services. The findings indicate that experts generally have a more nuanced understanding of risks, especially concerning data security and integrity, while members of the public are more likely to experience a generalized “dread risk” related to unfamiliar or abstract technological threats. Perceptions were also shaped by factors like trust in regulatory bodies and the perceived benefits of the technology.

About a decade ago, Müller and Bostrom (2016) surveyed AI experts on their expectations for AI’s future capabilities, finding that most anticipated the development of “superintelligence” between 2040 and 2050. Notably, a third of these experts viewed this development as “bad” or “extremely bad” highlighting significant concerns even within the expert community.

Crockett et al. (2020) compared trust and risk perceptions of AI between the general public and computer science students, people with above average expertise in AI. The findings suggest differences in risk and trust perceptions with education playing a crucial role in building trust and mitigating perceived risks. Novozhilova et al. (2024) found that higher technological competence and familiarity with AI increases trust in AI.

Comprehensive expert and novice comparisons are comparatively rare. Recently, Jensen et al. (2024) interviewed 25 individuals from the general public and 20 AI experts in the United States to assess their perceptions of AI. Experts and the public emphasized that AI reflects its creators, with inherent biases and limitations. Ethical worries include AI’s lack of transparency, profit-driven development, and potential to exacerbate inequalities. Both groups advocate for human oversight, particularly in high-stakes scenarios like healthcare. Despite its efficiency, AI’s inability to replicate human empathy raises trust issues. In both groups, ideas about humanness and ethics were central.

These studies highlight the importance of integrating both expert and public perspectives when shaping policies for AI as an emerging technology, as differing perceptions of risk can significantly influence technology design, public acceptance, and regulatory decisions.

Despite the growing body of literature on the perception and use of AI, the similarities and differences in expert and public perception of AI and its potential implantations are still not sufficiently understood. On that account, the present study addresses these gaps and is guided by the following research questions:

1. What are the similarities and differences in the perception of AI and AI’s likely capabilities and impacts between AI experts, as creators of AI-based systems, compared to the general public or potential users of these systems?
2. In which fields are these expectations similar or different?
3. Which value do both groups attribute to AI’s? In which areas is AI perceived as positive or negative and which areas do these attributions differ between both groups?

4. Is the attribution of value to AI driven by the perceived risks or the perceived benefits? How do these risk-benefit trade-off vary between experts and the general public?

3 Method

The studies' goal is to identify similarities and differences in how the general public and academic AI experts perceive AI, focusing on the underlying trade-offs between perceived risks, benefits, and value.

3.1 Risk Perception and the psychometric model

In this work, we build on the psychometric model that focusses on an individuals' subjective perception of risk by, for example, quantifying risk through subjective rating scales Slovic, Fischhoff, and Lichtenstein (1986). This model is suitable to study risk perception of emerging technologies and offers a framework to describe how individuals perceive and balance their risk and benefits. It has been applied in a variety of contexts, such as gene technology (Connor and Siegrist 2010), genetically modified food (Verdurme and Viaene 2003), nuclear energy (Slovic et al. 2000), climate change (Pidgeon and Fischhoff 2011), and Carbon Capture and Utilization technology (Arning et al. 2020). A common pattern in technology perception is the inverse relationship between perceived risk and perceived benefits: technologies viewed as highly useful are typically seen as safer, while those perceived as risky are often regarded as less beneficial (Alhakami and Slovic 1994).

To achieve this, we designed two closely related surveys: one targeting the general public and the other directed at academic AI experts. Both surveys centered on a core where participants evaluated a randomized subset of 15 out of 71 micro-scenarios (to mitigate fatigue), describing potential AI developments across five assessment items (Brauner 2024). This approach provides two distinct perspectives for interpreting the data collected: First, responses can serve as a reflexive measure of underlying dispositions or individual differences among participants. Second, responses can be interpreted as topic or technology attributions, allowing for the analysis of common patterns or visual mapping of the data.

To develop the list of scenarios, we first identified potential capabilities and impacts that AI might have in the near future. Drawing on expert workshops and prior research (Brauner et al. 2023), we compiled an initial set of potential topics for the survey. Through several iterations, we refined the selection by removing redundancies and optimizing the labels for clarity and conciseness. The final list of topics encompasses both straightforward and more speculative statements, such as AI "creates many jobs", "promotes innovation", "acts according to moral concepts", or "considers humans as a threat". A complete list of items is provided in Table 4 in the Appendix.

We chose five dependent variables to assess each of the topics, measuring each on a single 6-point semantic differential scale.

- Expectation: How likely is the projection to occur in the next 10 years ("will not happen—will happen")?
- Personal risk: How do you evaluate the risk of this development/aspect for you personally ("low-risk – high-risk")?
- Social risk: How do you evaluate the risk of this development/aspect for the society as a whole "socially harmful—socially harmless"¹?
- Benefit: How do you evaluate the benefits or utility of the respective development/aspect ("useful—useless")?
- Valence: How do you consider this development, should it come true, to be positive or negative ("positive–negative")?

With the last item, we assessed the participants' general evaluation of each topic using the Value-Based Adoption Model (VAM), which proposes overall value or valence—ranging from positive to negative—as a suitable target variable for technology evaluations (Kim, Chan, and Gupta 2007).

In addition to the topic evaluations, participants were asked to provide their age (in years) and gender (male, female, diverse, or no answer).

In the survey for the AI experts, participants were additionally asked to self-report their level of AI expertise (*no expertise in the field of AI, basic knowledge, well-informed, expert, recognized authority in the field of AI*). Further questions included their years of experience in the field, the number of scientific publications, current country of residence, and scientific discipline.

In the survey for the the general public, participants were asked about their education and employment status, along with several personality factors that could influence their perception of AI. These included measures such as Technology

¹This item exhibited very strong correlations with the personal risk assessment across all topics and in both samples, leading us to exclude it from further analysis. Scholars interested in this particular variable are encouraged to analyze the data independently.

Readiness, an AI Readiness Scale, and interpersonal trust. Another article presents a focussed analysis of the role of individual differences in the general public (Brauner et al. 2024).

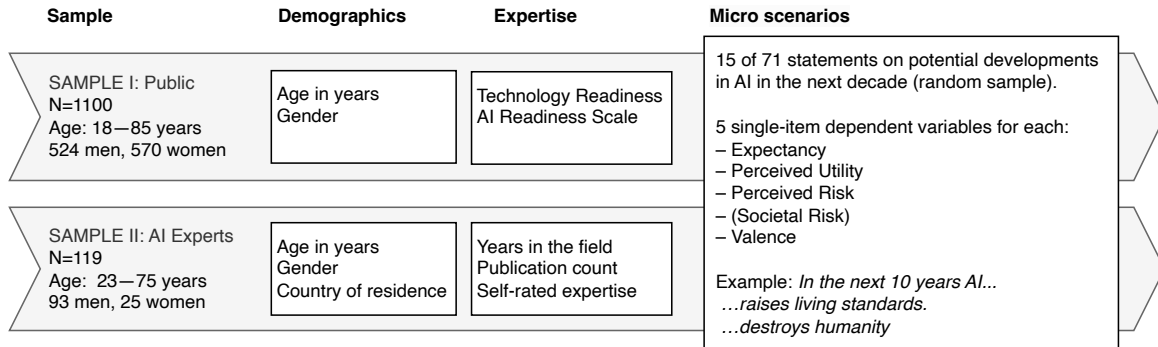


Figure 1: Overview of the experimental design for both surveys. In each survey, participants evaluated 15 randomly selected micro-scenarios from a pool of 71. The measured explanatory user factors differed between experts and the members of the public.

The survey began with obtaining informed consent and informing participants that their participation was voluntary, no personal information was collected, and the data would be shared as open data. The expert questionnaire was in English, while the questionnaire of the public was in German.

The study was approved by our university’s institutional review board (IRB) under ID [REDACTED]. The full survey design, all materials, data, and the analysis can be found in the data repository on OSF ([REDACTED]).

3.2 Sample Acquisition

The sample of public was gathered in collaboration with a panel provider Consumerfieldworks. The sample of 1354 participants was selected to be representative of the population in terms of age, gender, socio-economic status, and distribution across the federal states in Germany. Participants received a monetary compensation of approximately 1 Euro for their participation. For the expert sample, we utilized convenience sampling through our personal social networks from joint projects and project proposals. We also gathered publicly available email addresses from prominent journals and conferences in the field and asked for further dissemination of the survey (snowball sampling). In total, we reached out to approximately 450 experts to participate in the survey of which 139 passed beyond the first page.

3.3 Data Analysis and Cleaning

We analyzed the data using R version 4.3.2 (2023-10-31) using both parametric and non-parametric methods, including the Bravais-Pearson (r) and Kendall’s Tau (τ) correlation coefficients, Chi-square (χ^2) tests, multiple linear regressions, and multivariate analysis of variances (MANOVA). We used Pillai’s trace (V) as the test statistic for the MANOVA omnibus tests. We evaluated the assumptions underlying each test and report any violations. Missing responses were handled on a test-wise basis. Consistent with social science standards, we set the Type I error rate at 5% ($\alpha = .05$) to determine statistical significance (Field 2009). All data, calculations, and this reproducible manuscript are publicly available in the open data repository.

We filtered the data from both surveys for incomplete or low quality responses based on a) the participant must have completed the survey b) has passed the attention item (“please select ‘rather agree’”; only in the survey for the members of the public), c) reported at least basic knowledge and more than a year in AI (only in the experts’ survey), and d) the participant is not a speeder (less than 1/3 of the median survey duration); while the latter is usually considered sufficient for detecting meaningless data (Leiner 2019). The median completion time for laypeople was 9.8 minutes and 9.5 minutes for the experts. Based on these criteria, we excluded 254 of the 1354 participants in the sample of laypeople (equals an exclusion rate of 18.8%) and 20 of the 139 participants in the sample of experts (equals an exclusion rate of 14.4%). The unfiltered datasets and the filtering procedures are available in the data repository.

3.4 Sample 1: General Public

After cleaning, the sample of the general public consists of 1100 people, 524 reporting to be male and 570 reporting to be female. The participants’ age ranged from 18–85 years with a median age of 51 years (SD 14.2) years. There is no significant correlation between age and gender in the sample ($\tau = -0.031, p = 0.210 > .05$).

Table 1: The average assessment of the four evaluation dimensions across all queried topics was compared between experts and the public. A MANOVA revealed a significant overall effect as well as individual significant effects on the four dependent variables expectancy, risk, benefit, and valence.

Dimension	Experts				Public				Sig.
	M	SD	CI-95	N	M	SD	CI-95	N	p
Expectancy	25.2%	67.4%	[13.1%,37.3%]	119	12.7%	66.7%	[8.8%,16.7%]	1100	<0.001
Perceived Risk	19.3%	63.1%	[7.9%,30.6%]	119	34.7%	56.4%	[31.4%,38.1%]	1100	<0.001
Perceived Benefit	15.3%	62.1%	[4.1%,26.4%]	119	-5.2%	59.0%	[-8.7%,-1.7%]	1100	<0.001
Valence	-4.0%	60.9%	[-14.9%,7.0%]	119	-19.7%	57.8%	[-23.2%,-16.3%]	1100	<0.001

Note:

Measured on 6 point Likert scales and rescaled to -100% to +100%. Negative values indicate a negative evaluation of the respective dimension (i.g., low valence, low perceived risk, low perceived benefits, or low expectancy) and positive values indicate a high evaluation.

3.5 Sample 2: Experts on Artificial Intelligence

After cleaning, the expert sample has 119 people with 93 reporting being male and 25 reporting being female. The age ranged from 23—75 years with a median age of 36.5 years (SD 13.4 years). Again, there is no significant association between age and gender ($\tau = -0.113, p = 0.143 > .05$). The majority of the experts were from Germany (N = 77), followed by the Netherlands (N = 10). All other countries received less than 10 mentions. The years of AI experience ranged from 1 to 40 years with an arithmetic mean of 10.3 and a median of 5 years. In total, the participants wrote 2713 academic publications with an arithmetic mean of 22.8 and a median of 5 publications per expert. As indicated by the high Gini coefficient ($G = 0.771$), the number of publications is unevenly distributed among the experts—many have few, few have many—which suggests that both visible figures from the field as well as junior researchers have participated in the survey. When asked for their expertise, 11 participants reported having basic knowledge and 51 participants reported being well-informed, 48 reported being experts, and 9 said they are a “recognized authority in the field of AI”.

4 Results

In this section, we first analyze differences in the overall attributed risk, benefit, and valence, as well as the average expectancy between the general public and academic AI experts. Next, we interpret the individuals’ responses as reflexive measurements of latent constructs of expectancy, risk, benefit, and overall valence towards AI and analyse the different risk and benefit trade-offs between both AI experts and the public. Following, we switch the perspective and interpret how the many AI-related statements are evaluated and how experts and the public differ in their evaluation in terms of expectancy and valuation, as well as the different risk and benefit attributions towards the queried statements (Table 4 provides the ratings for all statements for both groups).

4.1 Differences in the Grand Mean of the Evaluations

First, we analyse how both samples rate the topics in regard to the queried dependent variables risk, benefit, valence, and expectancy. As the boxplots in Figure 2 illustrate, there are differences in the evaluation between both samples. A one-way MANOVA with group as independent variable showed a small but statistically significant difference between both samples on the combined dependent variables ($V=0.057, F(4, 1214) = 18.332, p < 0.001$). Further analysis revealed that each of the dependent variables—expected likelihood of occurrence, risk, benefit, as well as overall valence—showed significant differences based on the group membership (expectancy: $F(1, 1217) = 18.572, p < 0.001$; risk: $F(1, 1217) = 26.716, p < 0.001$; benefit: $F(1, 1217) = 43.443, p < 0.001$; valence: $F(1, 1217) = 21.929, p < 0.001$). These findings suggest that academic AI expertise significantly impacts the overall multivariate response as well as on each individual dependent variable.

In particular, the AI experts, on average, report the queried projections to be more likely to come true within the next decade (25.2%), less risky (19.3%), more useful (15.3%), and more positive (-4.0%) compared to the members of the public (expectancy: 12.7%, risk: 34.7%, benefit: -5.2%, valence: -19.7%). Table 1 details these findings.

Table 2: Correlation analysis of the assessment dimensions across the 71 topics for experts and the public.

Variable 1	Variable 2	Experts (N=119)			Public (N=1100)		
		r	95%-CI	p	r	95%-CI	p
Expectancy	Risk	0.144	[-0.04,0.32]	0.118	0.212	[0.15,0.27]	<0.001
Expectancy	Benefit	0.401	[0.24,0.54]	<0.001	0.143	[0.08,0.20]	<0.001
Expectancy	Valence	0.393	[0.23,0.54]	<0.001	0.039	[-0.02,0.10]	0.193
Risk	Benefit	-0.295	[-0.45,-0.12]	0.002	-0.639	[-0.67,-0.60]	<0.001
Risk	Valence	-0.418	[-0.56,-0.26]	<0.001	-0.749	[-0.77,-0.72]	<0.001
Benefit	Valence	0.712	[0.61,0.79]	<0.001	0.869	[0.85,0.88]	<0.001

Note:

Correlations of the average evaluations of the 71 queried topics (perspective 1).

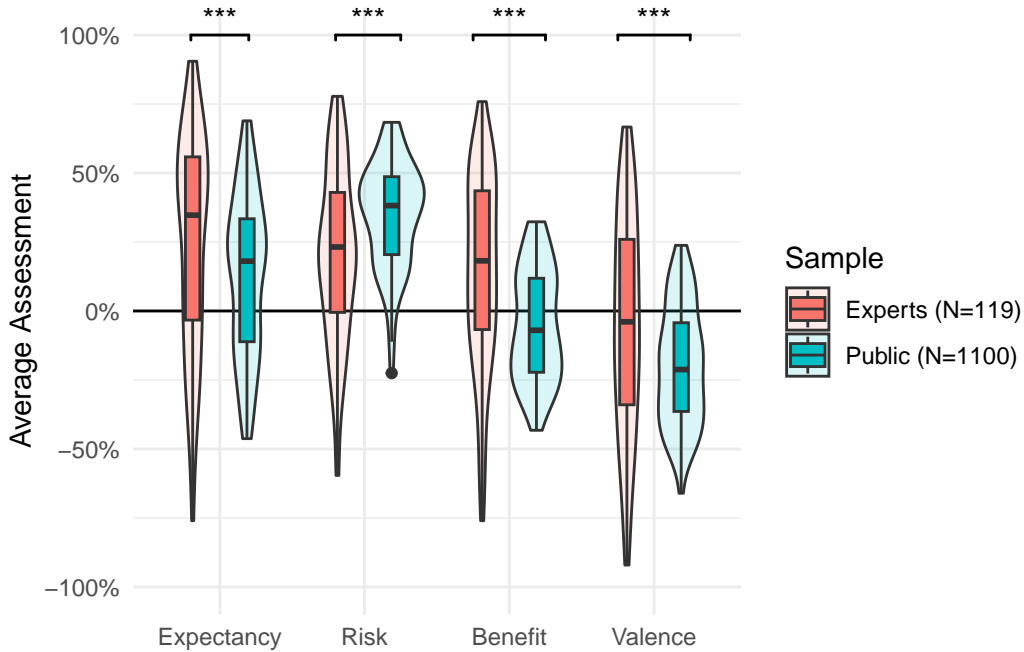


Figure 2: Overall average evaluations of all 71 topics per assessment dimension by sample as boxplots. The underlying shadow shows the shape of the data’s distribution. The stars signify the significant differences for the four assessment dimensions between experts and the public.

4.2 Perspective 1: Different Risk-Benefit Tradeoffs between Academic AI Experts and the Public

In this section, we analyse how individuals of both samples perceive AI in terms of expectancy, risk, benefit, and valence and interpret the subjects’ responses as reflexive measurements of latent constructs.

Table 2 presents the correlation patterns between individuals’ AI expectancy, AI risk and benefit dispositions, and their overall valence towards AI for the two samples: academic AI experts and the general public.

Among experts, the expected likelihood of occurrence is positively associated with both the perceived benefit of AI and the overall valence. However, there is no significant relationship between perceived risk and expectancy regarding whether projections will come true within the next decade. Risk and benefit are moderately negatively correlated, while risk is also negatively associated with valence. Conversely, perceived benefit exhibits a strong positive relationship with overall valence towards AI.

For the general public, AI expectancy is positively correlated with *both* an individual’s perceived AI risks and benefits but shows no significant association with perceived valence: Individuals who view AI as either riskier *or* more useful are more likely to believe that projections will materialize within the next decade, and vice versa. Overall valence towards AI is strongly and positively correlated with perceived benefits, while it is strongly and negatively associated with perceived risks.

For both the general public and AI experts, overall valence towards AI is negatively associated with perceived risks and positively associated with perceived benefits. Additionally, individuals’ perceptions of AI risks and benefits are mutually correlated.

To disentangle these mutual influences and assess the strength of each predictor in the risk-benefit tradeoff, we conducted three multiple linear regression analyses: The first two regressions were performed separately for each sample, with perceived AI risks and AI benefits as independent variables and overall AI valence as the dependent variable. The third regression was conducted on the combined sample, incorporating a sample identifier as a third predictor. Table 3 presents the details of all three significant regression models.

The third regression model (right side of the table), which also includes the factor distinguishing the two samples, was significant and explained 80% of the variance in overall valence ($F(3,1215)=1704.018, p < 0.001, R^2 = 0.807$). This factor was significant, indicating small but significant differences in the risk-benefit trade-offs between academic AI experts and the general public ($\beta = 0.044, p < 0.003$). Given these significantly different trade-offs, we analyze the two samples separately.

For the sample of academic AI experts (left side of the table), the regression model was significant, explaining over 54% of the variance in AI valence ($F(2, 116) = 72.2, p < 0.001, R^2 = 0.547$). The intercept was significant and negative ($I = -0.101$), suggesting a slightly negative baseline evaluation—if an expert holds a neutral attitude towards AI risks and benefits, their overall perceived valence would be slightly negative. Perceived AI risk had a moderate negative influence ($\beta = -0.195$) while perceived AI benefits had a strong positive influence on overall valence ($\beta = 0.623$). Compared to the influence of risk, the influence of the perceived benefits is about three times as large ($\times 3.19$).

For the general public (middle part of the table), the regression model was also significant, with an even stronger fit, explaining 82% of the variance ($F(2, 1097) = 2483.4, p < 0.001, R^2 = 0.819$). Unlike the experts, the valence intercept for the general public was not significantly different from zero, suggesting an absence of baseline variation. Overall valence towards AI was significantly related to both perceived risk ($\beta = -0.361$) and perceived benefit ($\beta = 0.703$), with the the influence of perceived benefit being about two times as large ($\times 1.95$). Apparently, the negative influence of risk is substantially larger for the general public compared to the experts.

Table 3: Regression table for three multiple linear regressions with an individuals perceived AI risk, AI benefit (for the experts and the general public), and sample (combined sample) as independent variables and overall valence as dependent variable.

Independent variables	Dependent variable: Overall valence		
	Experts (N=119)	Public (N=1100)	Combined
(Intercept)	-0.101***	-0.036	-0.085***
(SE)	(0.022)	(0.007)	(0.015)
Perceived Risk β	-0.195***	-0.361***	-0.346***
(SE)	(0.056)	(0.018)	(0.017)
Perceived Benefit β	0.623***	0.703***	0.704***
(SE)	(0.063)	(0.018)	(0.017)
Sample β	—	—	0.044*
(SE)			(0.015)
F	F(2,116)=72.218	F(2,1097)=2483.360	F(3,1215)=1704.018
p	<0.001	<0.001	<0.001
adj. R^2	0.547	0.819	0.807

4.3 Differences in Expectancy between Experts and the Public

As the previous analysis indicates, experts and the public differ in their expectations regarding what AI will likely achieve in the next 10 years (referred to as expectancy hereafter). To illustrate these differences at the topic level, Figure 3 presents the average expectancy evaluations for each topic as a scatter plot. The figure can be read as a visual map and interpreted as follows (Brauner 2024): Each point represents a question item, with its coordinates corresponding to the experts’ (x -axis) and the public’s assessment (y -axis). Points farther to the left or right indicate lower or higher expert expectations for a given statement. Similarly, points lower or higher on the plot reflect lower or higher public expectations. Points on or near the dashed diagonal represent topics where experts and the public have congruent assessments, meaning both groups assign similar expectancy evaluations to the statements. In contrast, points far from

the diagonal highlight differences between the groups: topics above the diagonal are considered more likely by the public, while those below the diagonal are deemed more likely by experts. Finally, the blue line represents the maximum likelihood estimation of the regression line, while the gray area shows the 95%-confidence interval, indicating the range within which the true regression line is expected to fall.

The figure displays several similarities and distinct differences in the expectancy assessment between the public and experts in AI. First, overall there is a strong and positive correlation between the expectations regarding AI of experts and the public ($r = 0.734$, $p < 0.001$). This suggests that, at least for many topics, there is an agreement on the perceived expectancy on AI's capabilities and impact. Second, however, the distribution of the expectancy of the public is much narrower than the expectancy distribution of the experts. This suggests that the experts may have a more nuanced and differentiated view on the potential of AI than the public. This is also reflected by the flatter slope of the regression line. Third, despite the general agreement on many topics, there are various aspects with a strong discrepancy between experts and the public. Topics where the experts had much lower expectations than the public were the statement that *AI will destroy humanity*, *AI leads to personal loneliness*, and that *AI can no longer be controlled by humans*. Statements where the experts had much higher expectations were that *AI will improve our health*, *AI will prefer certain groups of people*, and that *AI will become humorous*. Table 4 presents the expectancy evaluations for all topics for the experts and public.

4.4 Differences in Attributed Valence between Experts and the Public

Next, we analyse the similarities and differences between academic AI experts and the public in terms of attributed valence or AI sentiment. Again, we created a scatter plot in Figure 4 with the average valence attributed to a topic by experts on the x -axis (horizontally) and by the public on the y -axis (vertically). Apparently, the average attributed valence between both groups is tighter correlated ($r = 0.855$, $p < 0.001$) compared to the expectancy, which suggests that the agreement of both groups is higher.

Overall, experts exhibit a more positive outlook on AI compared to public. However, the analysis reveals notable differences in the valence evaluations of AI projections between the two groups, with sentiments diverging significantly on specific topics. Specifically, the public expresses greater negativity toward projections where AI is perceived as dividing society, destroying humanity, or AI viewing humans as a threat. Conversely, experts are more positive about scenarios where AI acts according to moral principles, contributes to a more sustainable society, or makes decisions about medical treatments. These differences underscore varying levels of optimism and concern, reflecting contrasting perceptions of AI's potential risks and benefits across the two groups.

4.5 Illustration of risks and benefits attributed to the statements for experts and the general public

As the overall sentiment towards AI-related statements appears to differ between academic AI experts and the general public, we analyze the attributed risk and benefit for each group independently. The left panel of Figure 5 illustrates the risk-benefit attributions for AI experts, while the right panel represents these attributions for the general public.

The x -axis (horizontal) represents the perceived risk attributed to each topic, and the y -axis (vertical) represents the perceived benefit. Note that these plots do not depict the relationship between risk, benefit, and the overall valence of the topics. A regression analysis examining the relationship between attributed risk, benefit, and the overall valence is provided in Section A.2 in the Appendix.

Data points in the plots illustrate where the perceived risks and utilities of evaluated statements fall. Items below the horizontal axis are considered less useful, while items above are seen as more useful. Similarly, items to the left of the vertical axis are perceived as more risky, whereas items to the right are viewed as safer. Items in the top-right quadrant are perceived as both risky and useful, while those in the bottom-left quadrant are considered neither risky nor useful. Items in the top-left quadrant are seen as risky but not useful, and items in the bottom-right quadrant are evaluated as not risky but useful.

The evaluations provided by AI experts display greater distribution compared to those of the general public, suggesting more nuanced assessments. Experts' risk and benefit attributions span a broader range, with a substantial proportion of topics deemed useful and a smaller proportion assessed as useless. Experts perceive topics as both risky and safe across the spectrum. In contrast, the general public's evaluations are concentrated, with most topics viewed as relatively risky.

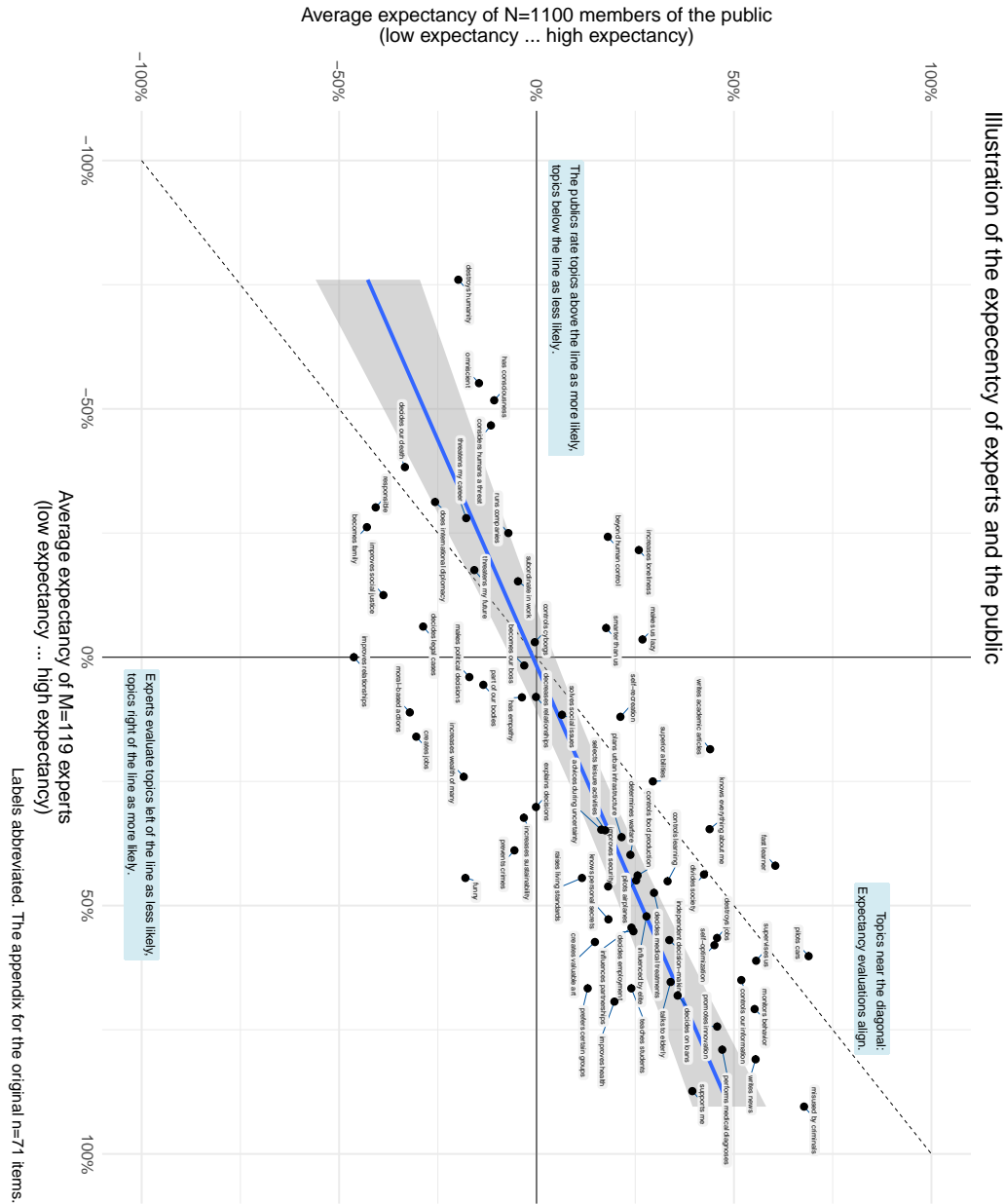


Figure 3: Scatter plot of the expectancy evaluations for the 71 topics by experts (x -axis) and the public (y -axis). The black line shows the regression line and the gray area signifies the 95%-CI of the regression line. Many topics show congruent evaluations, with a few exhibiting notable differences.

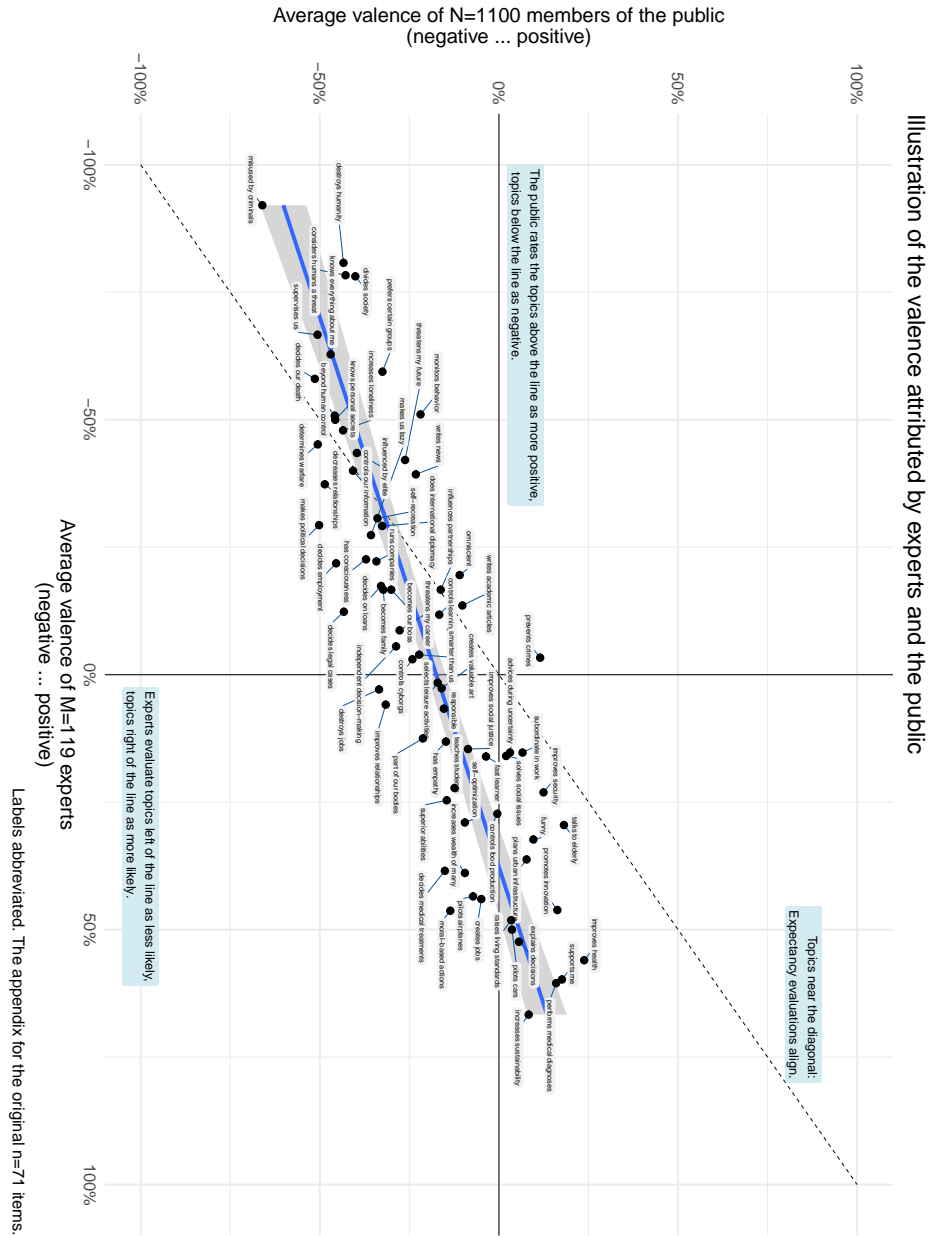


Figure 4: Scatter plot of the valence attributed to the 71 topics by experts (x -axis) and the public (y -axis). The black line shows the regression line and the gray area signifies the 95%-CI of the regression line. For most topics the evaluations are congruent, with only a few notable differences.

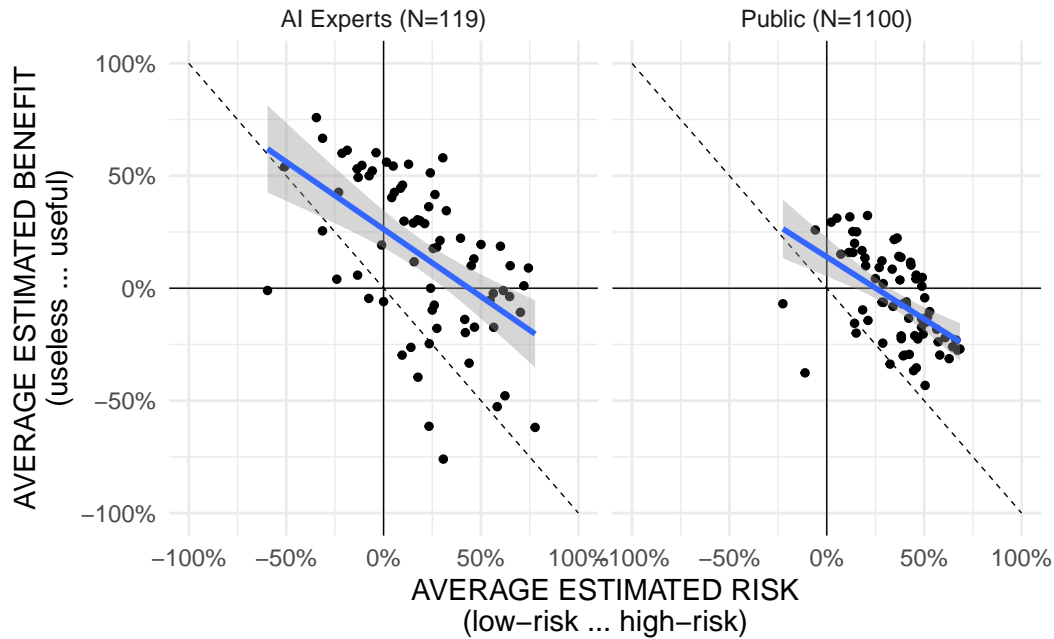


Figure 5: Illustration of perceived risk and utility between the experts (left) and general public (right). The black lines show the regression line and the gray area signifies the 95%-CI of the regression lines.

5 Discussion

As AI is reshaping our world, we explored the similarities and differences in the perceptions of those who use or are affected by AI technology and those who design or advance AI. Drawing on the psychometric paradigm (Slovic, Fischhoff, and Lichtenstein 1986), we conducted a survey based study involving both a representative sample of the German general public and academic AI experts from Germany and the Netherlands. Both groups evaluated a diverse set of AI-related projections based on their perceived probability of occurrence, associated perceived risks and benefits, and their overall valence or the value towards these many topics.

Overall, both groups acknowledge that AI is likely here to stay, as the majority of queried statements received above-average scores for their expected likelihood of occurrence. Across the diverse statements, participants from both groups reported risk scores higher than neutral. However, experts consistently perceived more benefits compared to the public. Notably, the public's overall evaluation was lower than that of the experts. Given the broad range of topics in the statements—spanning from plausible to speculative—the absolute scores are less informative than the relative differences between groups.

The experts and the public differed in the expected likelihood of occurrence. Compared to the public, experts generally perceive most of the AI projections as more probable. However, the variance among experts is significantly higher, indicating a more nuanced evaluation by experts, with many topics assessed as substantially more likely than by public. Conversely, there are some topics that experts consider markedly less likely than public does. The absolute placements of the expectancy should not be over interpreted, as both experts and laypeople often struggle with accurately predicting future events (Recchia, Freeman, and Spiegelhalter 2021). While experts perform better, their forecasts are only slightly more accurate, which reflects inherent challenges in forecasting complex, uncertain phenomena even with domain knowledge (Recchia, Freeman, and Spiegelhalter 2021). Nevertheless, the relative differences are of interest: the experts' expectancies shape future research directions and actual implementations of AI and the public's may yield unmatched expectations, political over regulation, or failing technology adoption despite of potential benefits.

In terms of value attributed to AI, measured as valence or sentiment, experts generally perceive these scenarios as more positive compared to members of public. But again, the experts' assessments are not uniformly more positive; they display greater variance with stronger ratings in both positive and negative directions compared to the public. It is possible that experts were more critical and deliberate in their evaluations, likely due to their specialized knowledge and ability to discern complexities in AI-related scenarios. While they recognize significant opportunities, they also identify potential risks or limitations that may not be as apparent to public (Russell et al. 2015). The general public often relies on simplified narratives or media portrayals of AI (Puzanova, Tertyshnikova, and Pavlova (n.d.) that often frames AI more negatively. This indicates a potential communication gap: For policymakers and communicators, this underscores

the need to address both experts' optimism and public scepticism while fostering an informed dialogue that bridges these perspectives.

For both groups, perceived risk and perceived benefits were inversely correlated, aligning with previous findings (Alhakami and Slovic 1994). While this relationship appears intuitive, it is not necessarily inevitable. As seen with technology perception broadly, certain AI developments may simultaneously be regarded as highly beneficial *and* risky. We propose that this inverse correlation may stem from individuals' desire for cognitive consistency, which helps reduce dissonance when forming evaluations of technology (Alhakami and Slovic 1994).

Beyond the absolute evaluations, we also analysed the participants' relative importances of the perceived risks and benefits in the individual risk-benefit balancing process. For both groups, perceived benefits exerted a stronger influence on the overall valuation of AI than perceived risks. Similar findings have been reported in other contexts, such as nanotechnology hazards (Siegrist et al. 2007). In our study, the impact of perceived benefits on the overall valuation of AI was comparable across both groups. However, a notable divergence emerged in the influence of perceived risk: among experts, the influence of risk was significantly smaller than it was for the general public. The experts' deeper understanding or familiarity with AI may mitigate the influence of perceived risk. Conversely, the general public might have heightened concerns about potential risks, possibly due to less familiarity or more exposure to negative narratives.

Consequently, our findings suggest that the discrepancies between experts and the public emerge a) on the level of the absolute evaluations and b) in the individual risk-benefits trade-offs, with the public focussing more on the risks than the experts that perceive AI as safer. These divergent views between the academic AI experts—people that shape research, research agendas, and development—and the general public—people using AI or being affected by it—might hinder the development and deployment of (socially accepted) AI technologies or create technology that is misaligned with individual and societal values.

These divergent findings emphasize the importance of fostering dialogue between AI creators and developers, the general public, and regulatory bodies, enhancing AI education and transparency, and promoting interdisciplinary approaches to AI development and implementation. The visual maps of AI perception across different contexts and applications—that should be extended and continuously updated—can serve as an actionable tool to support AI experts, practitioners, and regulators to identify topics with diverging evaluations that prompt for critical reflections, societal discussions, or governance measures. Otherwise, these gaps can result in research and development activities that are misaligned with the public interest.

In Greek mythology, Procrustes offered a bed to travelers, but instead of providing a bed that fit his guests, he forced his guests to fit the bed—either by stretching or cutting them to size (the “bed of Procrustes”). Similarly, our work highlights a misalignment between the public's individual values and expectations of AI and those of the experts shaping technological progress and societal transformation. This suggests we raise the risk of creating “Procrustean AI technology” forcing people to conform to systems rather than designing systems that adapt to their wants and needs. Accordingly, it is crucial to enhance the alignment process through transparency and participation, ensuring that AI development and policy-making prioritize the needs of individuals and society Decker, Wegner, and Leicht-Scholten (2024). This includes fostering equity, safety, inclusivity, and responsiveness to societal values, which are essential for the responsible advancement of AI.

6 Limitations

This work is not without its limitations.

Firstly, while the first sample is large and diverse in terms of age, gender, and education, we only surveyed participants from Germany. While we reached out for a global audience in the expert survey, most participants came from Germany and the Netherlands. Future work may therefore extend the second sample by including AI experts from other, and especially non-European and non-Western countries, and mirror the public sample with subjects from other countries. This would allow to study the perception of AI and the risk-benefit trade-offs in relationship to the individual's cultural backgrounds.

Secondly, while significant differences were observed between academic AI experts and the general public across all evaluation dimensions, the effect sizes were small. We attribute this to the breadth and diversity of topics in the micro-scenario-based study, where evaluations of individual scenarios are influenced by personal perspectives, introducing variance unaccounted for in this study. We hypothesize that these differences in public and expert perceptions will become more pronounced in studies focusing on specific phenomena.

Thirdly, although the selection of queried topics is based on existing research, it may be biased, potentially leading to spurious findings due to Berkson's paradox (Berkson 1946)². Future research should compile the topics more thoroughly

²A selection bias where uncorrelated traits appear negatively correlated because the sample excludes cases lacking these traits.

or address areas that are currently under-explored in the spatial maps. Despite this potential bias, the identified patterns between topic evaluations and individual evaluations of AI are consistent. Since biases in topic selection do not translate to biases in individual differences, this suggests that the selection was sufficiently well-chosen.

Lastly, participants evaluated a set of brief micro-scenarios illustrating potential imaginary futures of AI. This also contributes methodologically to the understanding of technology and AI perception. Recent studies indicate that results from conventional surveys may not solely be shaped by the participants' judgements but also by linguistic properties of the questions items, such as word co-occurrences in the administered scales (Gefen and Larsen 2017). Instead of relying on psychometric scales of similarly phrased items, the micro scenario approach addresses this challenge by employing reflexive measurements across many topics (Brauner 2024). Instead of a potentially biased but detailed and cognitively demanding assessment of benefits, barriers, and implications, we captured an affective evaluation of each topic. Yet, as the results show strong and systematic patterns, this suggests reliable measurements that may offer a novel tool for triangulating cognitive phenomena in technology perception. However, we know little about the specific motives behind the evaluation of individual topics. As AI continues to reshape individual lives and society, future research should deepen our understanding of these evaluations through qualitative and quantitative methods. This would help practitioners, researchers, and policy-makers better align AI with human needs.

7 Acknowledgements

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A Appendix

A.1 Survey items and responses

Permission to translate, use, and adapt the survey items is granted, provided the work is properly cited.

Table 4: Question items from the survey and average responses to each item from the experts (N=119) and the public (N=1100) ordered by the differences in valence between experts and the public.

In 10 years, AI...	Expectancy		Risk		Benefit		Valence	
	M Experts	M Novices	M Experts	M Novices	M Experts	M Novices	M Experts	M Novices
destroys humanity.	-76.0%	-19.8%	30.7%	42.3%	-76.0%	-29.4%	-80.8%	-43.4%
leads to personal loneliness.	-21.6%	25.9%	17.6%	39.8%	-39.6%	-29.8%	-47.9%	-43.5%
can no longer be controlled by humans.	-24.2%	18.1%	43.9%	57.2%	-33.3%	-23.8%	-50.8%	-45.8%
has its own consciousness.	-51.7%	-10.7%	27.4%	51.0%	-17.9%	-15.1%	-22.6%	-37.1%
is omniscient.	-55.2%	-14.6%	21.1%	38.1%	28.7%	13.7%	-19.5%	-11.0%
considers humans as a threat.	-46.7%	-11.6%	23.3%	39.3%	-61.4%	-30.1%	-78.3%	-42.8%
makes society lazy.	-3.6%	26.8%	9.5%	38.2%	-29.8%	-22.4%	-27.4%	-35.7%
independently writes scientific articles.	18.5%	44.0%	42.0%	33.6%	-19.8%	8.5%	-13.6%	-10.2%
is more intelligent than humans.	-5.9%	17.6%	15.7%	49.0%	11.8%	4.8%	-3.9%	-22.3%
learns faster than humans.	42.0%	60.5%	8.6%	34.6%	44.4%	21.6%	16.0%	-3.6%
runs companies.	-25.0%	-7.1%	25.0%	48.6%	-9.7%	-17.3%	-22.2%	-34.2%
is always subordinate to us in working life.	-15.3%	-4.7%	15.3%	13.4%	29.0%	15.9%	15.3%	6.6%
threatens my professional future.	-28.0%	-17.8%	-13.3%	15.1%	5.8%	-20.0%	-8.7%	-27.7%
can recreate itself.	12.0%	21.2%	60.0%	51.8%	18.7%	-12.7%	-30.7%	-33.9%
knows everything about me.	34.6%	43.8%	74.4%	60.8%	9.0%	-22.0%	-62.8%	-47.0%
independently drives automobiles.	60.2%	68.9%	-11.1%	36.1%	54.6%	22.3%	50.0%	3.6%
conducts international diplomacy.	-31.2%	-25.7%	26.0%	49.5%	-7.5%	-20.4%	-29.2%	-32.6%
decides about our death.	-38.3%	-33.3%	23.5%	50.5%	-24.7%	-43.2%	-58.0%	-51.4%
is ahead of humans in its abilities.	25.0%	29.5%	9.7%	43.3%	45.8%	10.2%	24.6%	-14.6%
controls hybrids of humans and technology.	-3.0%	-0.4%	27.3%	40.9%	18.2%	-7.4%	-3.0%	-24.1%
threatens my private future.	-17.5%	-15.8%	14.0%	14.2%	-26.3%	-15.6%	-42.1%	-26.2%
divides society.	43.8%	42.4%	58.3%	46.7%	-52.7%	-22.6%	-78.1%	-40.1%
occupies leadership positions in working life.	1.7%	-3.1%	45.0%	40.8%	10.0%	-6.1%	-16.7%	-30.1%
contributes to solving complex social problems.	11.6%	6.4%	23.2%	28.3%	36.2%	12.2%	15.9%	2.0%
supervises our private life.	61.1%	55.6%	64.7%	67.1%	-3.7%	-27.6%	-66.7%	-50.6%
reduces our need for interpersonal relationships.	8.0%	-0.1%	46.7%	44.5%	-17.3%	-36.7%	-37.3%	-48.6%
has a sense of responsibility.	-30.2%	-40.7%	10.5%	39.0%	29.8%	-7.0%	6.7%	-15.4%
destroys many jobs.	56.5%	45.7%	46.4%	48.7%	13.0%	-13.6%	2.9%	-33.5%

Table 4: Question items from the survey and average responses to each item from the experts (N=119) and the public (N=1100) ordered by the differences in valence between experts and the public. (continued)

In 10 years, AI...	Expectancy		Risk		Benefit		Valence	
	M Experts	M Novices	M Experts	M Novices	M Experts	M Novices	M Experts	M Novices
has the ability to recognize, understand and empathize with emotions.	8.1%	-3.7%	-1.0%	29.1%	19.2%	-6.3%	13.1%	-14.8%
controls what and how we learn.	45.1%	33.2%	25.5%	37.6%	17.6%	3.7%	-11.8%	-16.7%
can optimize itself.	58.0%	45.0%	30.4%	43.0%	58.0%	11.6%	29.0%	-9.5%
controls what messages we receive.	65.0%	51.9%	65.0%	56.4%	10.0%	-18.2%	-40.0%	-40.7%
determines the construction and infrastructure of our cities.	36.2%	21.5%	-5.8%	14.3%	52.2%	19.9%	36.2%	7.7%
supervises our behavior in public.	70.8%	55.2%	61.5%	45.8%	-1.0%	4.1%	-51.0%	-21.9%
determines warfare.	39.8%	23.8%	72.0%	66.4%	1.1%	-23.0%	-45.2%	-50.6%
is a family member.	-26.2%	-43.0%	0.0%	28.7%	-6.0%	-24.4%	-16.7%	-32.3%
determines our leisure time activities.	34.8%	17.4%	-7.6%	18.4%	-4.5%	-9.6%	1.6%	-17.1%
decides on medical treatments.	47.4%	29.7%	12.8%	45.9%	55.1%	5.8%	38.5%	-15.1%
advises me in uncertain times.	34.7%	16.4%	17.4%	19.6%	30.4%	13.4%	15.3%	3.1%
controls food production.	43.9%	25.6%	1.5%	19.9%	56.1%	10.0%	27.3%	-0.4%
becomes part of the human body.	5.6%	-13.5%	26.4%	48.8%	41.7%	0.9%	12.5%	-21.2%
autonomously takes off, flies, and lands airplanes.	44.9%	25.2%	-13.0%	37.0%	49.3%	14.2%	43.5%	-7.2%
makes political decisions.	4.0%	-17.0%	54.7%	62.8%	-5.3%	-31.3%	-29.3%	-50.2%
administers justice in legal matters.	-6.2%	-28.7%	39.5%	64.6%	22.2%	-26.0%	-12.3%	-43.3%
is misused by criminals.	90.5%	67.7%	77.8%	68.4%	-61.9%	-27.0%	-92.1%	-66.1%
makes independent decisions that affect our lives.	56.9%	33.6%	50.0%	52.8%	19.4%	-10.4%	-5.6%	-28.7%
is influenced by an elite.	52.2%	27.8%	56.5%	45.1%	-17.4%	-21.1%	-43.5%	-39.7%
independently writes news.	81.0%	55.5%	70.2%	50.3%	-10.7%	-4.3%	-39.3%	-23.2%
increases social justice.	-12.5%	-38.8%	18.8%	28.3%	30.0%	-6.2%	14.6%	-8.6%
improves the security of people.	46.2%	18.1%	24.0%	13.4%	51.3%	25.2%	23.1%	12.4%
promotes innovation.	74.4%	45.7%	-3.8%	11.8%	60.3%	31.7%	46.2%	16.3%
explains its decisions.	30.2%	-0.1%	-50.8%	11.3%	54.0%	15.9%	52.4%	5.6%
controls our search for partners.	54.4%	24.0%	24.1%	21.2%	0.0%	-14.3%	-16.7%	-16.3%
decides on hiring, promotions, and terminations.	55.2%	24.5%	56.3%	58.0%	-2.3%	-29.7%	-21.8%	-45.5%
serves as a conversation partner in elderly care.	65.4%	34.0%	-23.1%	-5.9%	42.7%	25.9%	29.5%	18.1%
carries out medical diagnoses.	79.0%	47.0%	4.9%	20.9%	54.3%	32.3%	60.5%	16.0%

Table 4: Question items from the survey and average responses to each item from the experts (N=119) and the public (N=1100) ordered by the differences in valence between experts and the public. (continued)

In 10 years, AI...	Expectancy		Risk		Benefit		Valence	
	M Experts	M Novices	M Experts	M Novices	M Experts	M Novices	M Experts	M Novices
decides who gets an important financial loan.	68.1%	35.7%	29.0%	42.1%	21.2%	-13.4%	-17.4%	-32.9%
raises our standard of living.	44.4%	11.5%	-13.6%	18.1%	53.1%	16.7%	48.1%	3.4%
knows my secrets.	52.8%	18.2%	41.7%	46.0%	-13.9%	-35.4%	-50.0%	-45.7%
makes our society more sustainable.	32.3%	-3.2%	-31.3%	7.2%	66.7%	15.1%	66.7%	8.3%
increases the wealth of many people.	24.1%	-18.4%	-7.4%	25.0%	50.0%	4.3%	38.9%	-9.5%
creates valuable works of art that are traded for money.	57.3%	14.8%	-24.0%	-11.2%	4.0%	-37.6%	2.7%	-16.0%
teaches students.	66.7%	24.0%	4.2%	26.9%	40.3%	9.2%	22.2%	-12.4%
acts according to moral concepts.	11.1%	-32.1%	5.6%	34.0%	42.6%	-8.1%	46.3%	-13.6%
prevents crimes.	38.9%	-5.6%	32.2%	15.3%	34.4%	25.1%	-3.3%	11.5%
helps us to have better relationships.	0.0%	-46.3%	-31.4%	32.5%	25.5%	-33.8%	5.9%	-31.6%
creates many jobs.	16.0%	-30.5%	-21.3%	29.0%	60.0%	2.0%	44.0%	-4.9%
supports me as a helper in my tasks.	87.4%	39.4%	-34.5%	2.3%	75.9%	29.4%	59.8%	17.6%
improves our health.	69.3%	19.7%	-18.7%	5.2%	61.3%	31.1%	56.0%	23.8%
prefers certain groups of people.	66.7%	13.0%	62.3%	38.2%	-47.8%	-21.2%	-59.4%	-32.5%
is humorous.	44.4%	-18.0%	-59.6%	-22.5%	-1.0%	-6.9%	32.3%	9.6%
Average	25.2%	12.7%	19.3%	34.7%	15.3%	-5.2%	-4.0%	-19.7%

Note:
 Measured on 6 point Likert scales and rescaled to -100% to +100%. Negative values indicate a negative evaluation of the respective dimension (i.g., low valence, low perceived risk, low perceived benefit, or low expectancy) and positive values indicate a high evaluation.

Table 5: Correlations of the topic evaluations across the 71 topics for experts and the public.

Variable 1	Variable 2	Experts (N=119)			Public (N=1100)		
		r	95%-CI	p	r	95%-CI	p
Expectancy	Risk	0.044	[-0.19,0.27]	0.718	0.150	[-0.09,0.37]	0.421
Expectancy	Benefit	0.352	[0.13,0.54]	0.008	0.277	[0.05,0.48]	0.058
Expectancy	Valence	0.272	[0.04,0.48]	0.043	0.054	[-0.18,0.28]	0.655
Risk	Benefit	-0.534	[-0.68,-0.34]	<0.001	-0.524	[-0.67,-0.33]	<0.001
Risk	Valence	-0.754	[-0.84,-0.63]	<0.001	-0.800	[-0.87,-0.70]	<0.001
Benefit	Valence	0.903	[0.85,0.94]	<0.001	0.904	[0.85,0.94]	<0.001

Note:

Correlations of the average evaluations of the 71 queried topics (perspective 2).

A.2 Topic Evaluations and their Associations of Experts and the Public

The micro scenario approach facilitates the interpretation of the data as topic, technology, or projection evaluation or (perspective 2) as reflexive reflexive measurement of an individual difference of the subjects (perspective 1).

In the following, we complement the interpretation as individual differences (perspective 1) from the correlation analysis in Table 2 and the regression analysis from Table 2 by the same analysis interpreted as topic evaluation (perspective 2).

Table 5 presents these correlations, with the results for experts shown on the left and those for the general public on the right. For the experts, the AI projections' expectancy is unrelated to their perceived risks. However, it is significantly associated with perceived benefit, as topics viewed as more useful are also rated as more likely (and vice versa). Expectancy is similarly linked to overall valence, with topics perceived as more positive being rated as more likely. Perceived risk and benefit of the topics exhibit a strong negative relationship, indicating that higher perceived risks are associated with lower perceived benefit. Both perceived risk and perceived benefit are strongly associated with overall valence: risk shows a strong negative correlation with valence, while benefit demonstrates a strong positive correlation (see left side of Table 5). For the general public, expectancy is not significantly associated with perceived risk, benefit, or valence. However, again a strong negative relationship persists between perceived risk and perceived benefit. Similarly, overall valence remains strongly negatively correlated with perceived risk and strongly positively correlated with perceived benefit (see right side of Table 5).

In both samples, risk and benefit attributed to the topics are associated with overall valence but are also mutually correlated. To disentangle these mutual influences and determine the strength of each predictor, we performed two multiple linear regressions with risk and benefit as independent variables and overall valence as the dependent variable. Additionally, we examined whether the risk-benefit trade-offs differ between experts and the public using a Chow test (1960). For this analysis, the factor sample was included as an additional factor in the regression model of the combined data. A significant result for this factor indicates that the regression models for the two samples are significantly different. Table 6 presents the results of the three linear regressions.

The Chow test on the combined sample—with risk, benefit, and sample as predictor variables and overall valence as dependent variable—was significant and explained 93% of the variance in overall valence ($F(3,138)=629.166$, $p < 0.001$, $R^2 = 0.930$). In particular, the factor distinguishing both samples was significant, suggesting small but significantly different risk-benefit trade-offs attributed to the topics between academic AI experts and the general public ($\beta = 0.077$, $p < 0.001$). See the right hand side of Table 6 for details of the model.

As both samples have different risk benefit trade-offs, we analyse them separately. Both regression models are significant and explain over 90% of the variance in overall valence (Experts: $F(2, 68) = 384.0$, $p < 0.001$, $R^2 = 0.916$; general public: $F(2, 68) = 916.9$, $p < 0.001$, $R^2 = 0.963$).

Interestingly, for the expert sample, the intercept was significant and negative ($I = -0.070$), suggesting a slightly negative baseline evaluation (if a statements perceived risk and benefit are both neutral). In valence intercept of the general public is not significantly different from zero, hinting at the absence of this baseline variation. In both samples, the predictor perceived risk had a strong negative influence on overall valence and the strengths of the effect is about equal between both samples (experts: $\beta = -0.483$; general public: $\beta = -0.504$). The perceived benefits had a strong positive influence on overall valence for both the experts ($\beta = 0.795$) and the general public ($\beta = 0.710$). Apparently, the positive influence of the benefits is stronger for the experts than for the general public.

Table 6: Regression table for three multiple linear regressions with risk, benefit (for the experts and the general public), and sample (combined sample) as independent variables and overall valence as dependent variable of the topic evaluations (perspective 2).

Independent variables	Dependent variable: Overall valence		
	Experts (N=119)	Public (N=1100)	Combined (Chow test)
(Intercept)	-0.070***	0.014	-0.066***
(SE)	(0.020)	(0.011)	(0.014)
Perceived Risk β	-0.483***	-0.504***	-0.488***
(SE)	(0.052)	(0.030)	(0.033)
Perceived Benefit β	0.795***	0.710***	0.774***
(SE)	(0.046)	(0.029)	(0.030)
Sample β	—	—	0.077***
(SE)			(0.015)
N (topics)	71	71	71
F	F(2,68)=383.993	F(2,68)=916.935	F(3,138)=629.166
p	<0.001	<0.001	<0.001
adj. R^2	0.916	0.963	0.930

A.4 Risk-Benefit Plot of the Experts

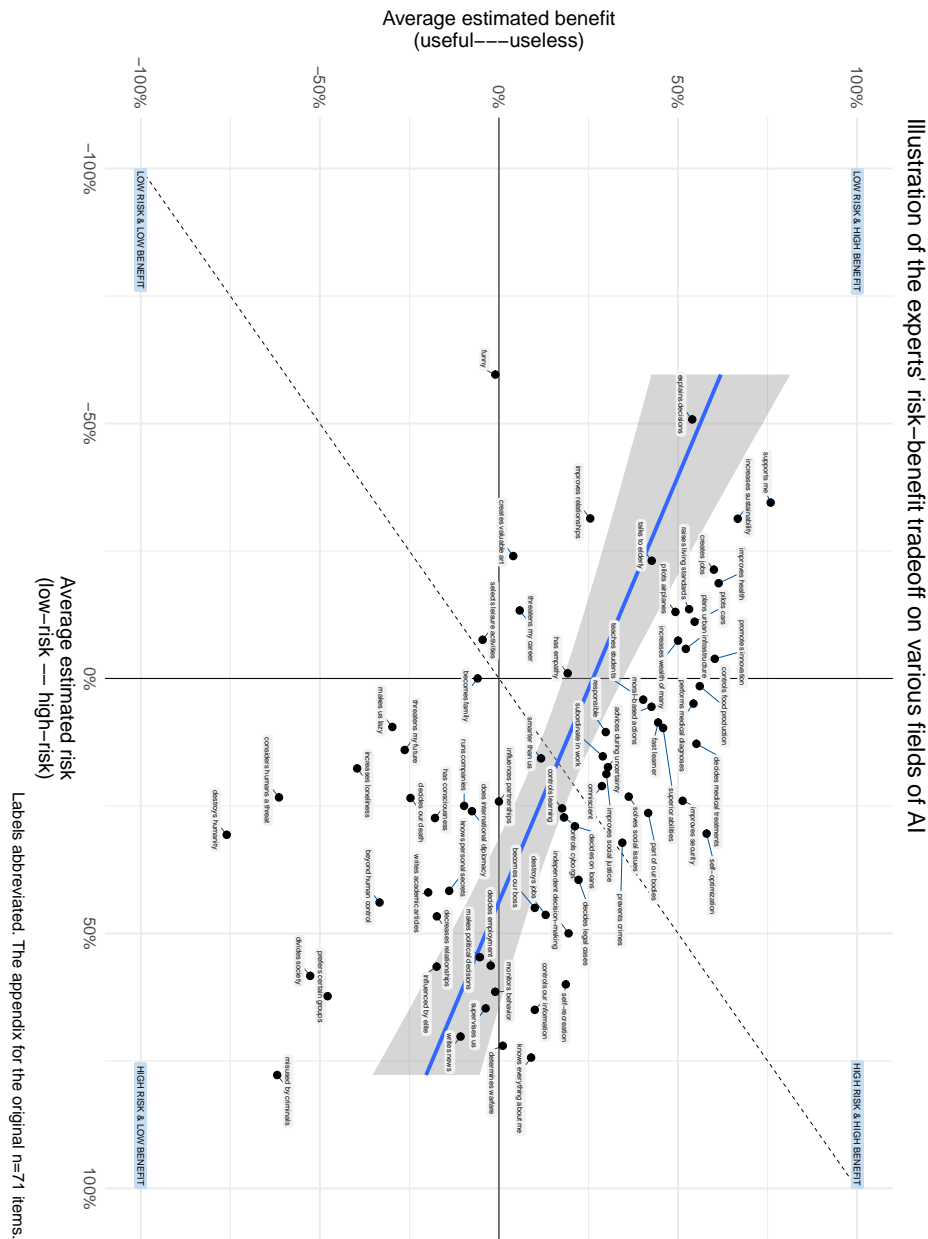


Figure 7: Illustration of the perceived risk (x -axis) by perceived benefit (y -axis) of the experts (risk-benefit tradeoff). The black line shows the regression line and the gray area signifies the 95%-CI of the regression line.

A.5 Location of the participants

Mapping of the geographic location of the participants for the sub-sample of the members of the public (Figure 8) and the experts (Figure 9).

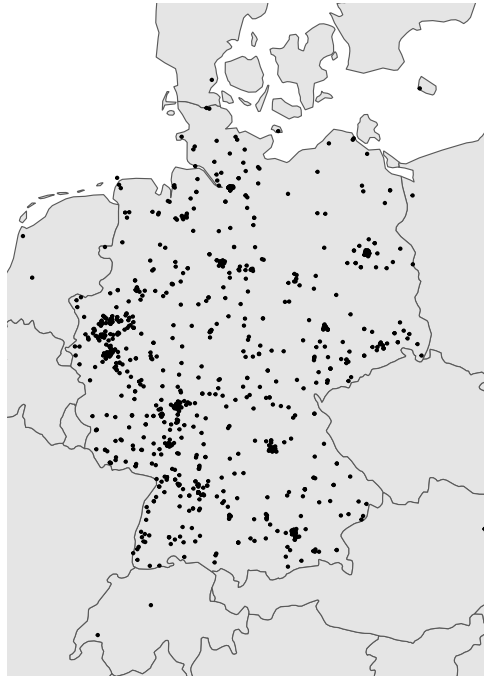


Figure 8: Geographic origin of the participants from the sample of the public.

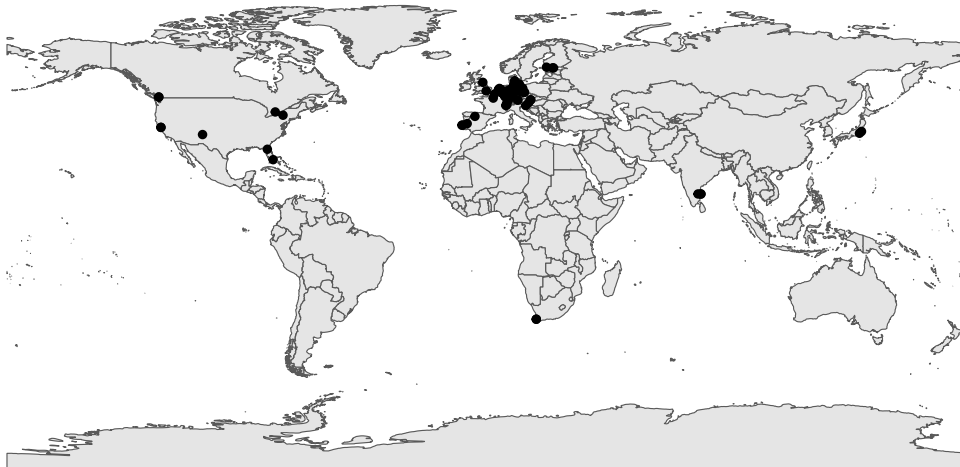


Figure 9: Geographic origin of the participants from the sample of the experts.

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