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Public Perception of Technologies in Society: Mapping Laypeople's Mental Models in Terms of Risk and Valence

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Abstract

Technological advancements profoundly shape individuals, society, and the planet. As we continue to innovate, it is essential to assess how the public perceives both the benefits and risks of new technologies. This study explores the mental models of N = 111 laypeople from a convenient sample mainly from Germany and Bulgaria regarding a wide range of technologies and technology-driven trends, focusing on valence, familiarity, perceived risk, and the desire for societal debate. The article presents: (1) a ranking of various technologies and trends based on their valence (or perceived value), risk, familiarity, and societal debate demand; (2) a detailed analysis and visual mapping of the strong correlation between risk and valence ($r^2 = 89\%$) and the moderate association between familiarity and the desire for societal debate ($r^2 = 33\%$); and (3) an examination of the limited impact of user diversity on these perceptions. These findings underscore the importance of understanding public perceptions to guide responsible technological development and policy-making, highlighting key areas for fostering public acceptance and guiding governance of technology. Based on this, we derive actionable policy recommendations.

Highlights

- Technological advancements have substantial impacts on individuals, society, and the environment.
- Careful consideration of the benefits and risks of emerging technologies is essential for society.
- This study maps laypeople's mental models of various technologies, analyzing them based on valence, familiarity, perceived risk, and interest in societal debate.
- Findings include a ranking of technologies and societal trends by valence, risk, familiarity, and desire for public discourse.
- The analysis reveals strong correlations between risk and valence, familiarity and desire for debate, with user diversity having only a minor impact on these perceptions.

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1 Introduction

Technological advancements have had profound impacts on individuals, society, and the planet, raising significant ethical dilemmas. While technologies hold the promise of enhancing our lives, improving well-being, increasing productivity, and fostering connections, they also pose threats such as job insecurity, physical risks, and unforeseen consequences. These dilemmas are evident not only in ongoing and future technological innovations but also in those of the past.

Historical examples highlight this duality. Mechanization and industrialization, for instance, led to increased productivity but also contributed to poor working and living conditions for laborers (Engels, 1845; Watt, 1769), with deindustrialization later leaving lasting socio-economic consequences (Brey & Rueda, 2024). Similarly, the development of nuclear energy created significant benefits yet presented enduring challenges, such as the lack of suitable repositories for radioactive waste (Vandenbosch & Vandenbosch, 2007). The printing press, while promoting literacy, also facilitated the spread of misinformation through pamphlets (Beckwith, 2009; Eisenstein, 1980; Steinberg, 1974). Likewise, the invention of clothing improved protection and warmth, but the rise of fast fashion has led to severe ecological damage (Kvavadze et al., 2009; Niinimäki et al., 2020). These examples underscore the ethical complexities that accompany technological progress, a pattern likely to persist as future innovations unfold.

The assessment of new technologies and their societal impact is an instance of a "Collingridge dilemma" (Collingridge, 1982): On the one hand, the impact of a technology can be better assessed when the technology is more advanced or already in use. But then it becomes more difficult to control and regulate it. On the other hand, it is difficult, if not impossible, to predict the impact of a technology in the beginning of its development. At this stage, however, it is easier to manage and regulate from the outset.

Balancing technology development with human needs and values requires interdisciplinary cooperation among the stakeholders: engineers and developers can contemplate about foreseeable technologies whereas a legal and philosophical perspective can clarify what is legally allowed or prohibited, or if legally allowed pathways actually should be pursued. Integrating the public is equally crucial to avoid technological determinism (meaning that advancements in technology shape social change (Bimber, 1990; Smith & Marx, 1994)), to bridge technological divides, and to ensure that the developments are in line with peoples norms and values. Ultimately, people are the biggest stakeholders and determine whether a technology is accepted in the first place (Devine-Wright, 2008).

For the later and as a basis for the discourse among the stakeholders, we need to understand how the general public or laypeople perceives different technologies, how they are weighted against each other and how they contrast to big and technology driven trends of our time. This information can then be used to identify topics that are perceived as critical and which should be addressed through, for example, information campaigns, open discourses, and referendums on the topic, or governance measures and regulation.

This work contributes to this understanding by providing an empirical modelling of people's perception of different and currently discussed technologies and topics like climate and demographic change or blockchain technology that is visualized as a spatial map.

For a broad set of current and future topics it visualizes people's perception in regard to their *perceived risk* (do people associate lower or higher risk with it?), the *familiarity* with the given technology or topic (low to high familiarity), their *valence* (is the technology or topic perceived as positive or negative?) and if there is a desire for a *societal debate* on it (low to high desire). This map can inform the public, researchers, and policy makers on topics that are perceived as controversial and may thus serve as a basis for a public discourse or future research or governance measures.

The structure of this article is as follows: Sect. 2 reviews the relevant literature on risk perception and technology assessment. Section 3 outlines the design and structure of the questionnaire used to evaluate perceptions of various technologies and topics, as well as the characteristics of the survey sample. In Sect. 4, we present an analysis of the data through a general risk perception map, followed by a discussion of the influence of user diversity factors. Section 5 elaborates on the findings, addresses the limitations of the study, and identifies areas for future research. Finally, Sect. 6 offers policy recommendations for researchers, policymakers, and society at large.

2 Related Work

In 2000 Bill Joy published the equally controversial and influential article "*Why The Future Doesn't Need Us*" warning about the dangers of several 21st-century technologies (Joy, 2000). Reviewing the development of nuclear weapons and the ensuing arms race, he urges greater responsibility and reflection on the implications and possible downsides of new and potentially self-replicating technological developments like genetics, nanotechnology and robotics. While his work sets the stage for justifying research on the up- and downsides of technologies, other approaches and frameworks are needed that provide actionable and reproducible guidelines on how to perform these assessments.

Technology assessment is a multidisciplinary process that evaluates the social, economic, ethical, and environmental impacts of a technology or innovation (Grunwald, 2018; van den Hoven, 2013). It involves analyzing the implications of introducing or adopting a new technology, considering factors such as feasibility, desirability, risks, benefits, and potential consequences. The goal of technology assessment is to inform decision-making, policy development, and public understanding of technological advancements.

There are different models and frameworks for technology assessment that are commonly used in social science and policy research. Some of these models include:

- *Ethical Technology Assessment (ETA)*: ETA examines the ethical implications of a technology, including issues related to privacy, autonomy, informed consent, and social responsibility (Palm & Hansson, 2006). It seeks to identify and address ethical dilemmas and concerns arising from the development and use of a technology.
- *Social Impact Assessment (SIA)*: SIA focuses on evaluating the social consequences and implications of a technology on individuals, communities, and societies (Burdge, 2015). It considers factors such as equity, justice, human rights, and cultural values in assessing the social impacts of technology.
- *Participatory Technology Assessment (PTA)*: PTA involves engaging various stakeholders, including policy-makers, experts, industry representatives, and members of the public, in the assessment of a technology (Sclove, 2016). It aims to incorporate diverse perspectives, values, and knowledge into the decision-making process.
- *Social Construction of Technology (SCOT)*: SCOT theory focuses on how social factors shape the development, implementation, and perception of technology (Wiebe et al., 2012). It highlights the influence of social groups, power dynamics, and cultural values on technology assessment and decision-making processes.
- *Multi-Criteria Decision Analysis (MCDA)*: MCDA is a structured decision-making approach that considers multiple criteria or attributes when evaluating technologies or risks (Belton & Stewart, 2002). It involves quantifying and prioritizing criteria such as cost, safety, environmental impact, and social acceptability to support informed decision-making and risk assessment.

Recent models emphasize the incorporation of diverse stakeholders, including the public and their perceptions of technologies, in the assessment process (Sclove, 2016; Wiebe et al., 2012). This inclusion is crucial, as disparities in values attributed to a technology by the public compared to experts can lead to inconsistencies and conflicting views, resulting in potential rejection, conflicts, or protests (Peters, 2005).

A challenge here is that we as humans are not rational agents. Kahnemann and Tversky introduced the dual mode hypotheses that assumes two distinct cognitive operation modes: One is slow, laborious, and energy-consuming but enables rational decision making. The other one is build on fast, unconscious, and energy-efficient heuristics, but is prone to errors and biases (Gilovich et al., 2002; Kahneman, 2012). Thus, when conducting technology assessments in the absence of detailed information about the technology, common heuristics may come into play. Some examples that may be used are: (1) the *availability heuristic* which means that people tend to overestimate the probability of events that they can easily remember because they were very present in the media. (2) *confirmation bias* means that people tend to look for information or interpret it in a way that supports their beliefs and assumptions (Plous, 1993) (3) the *affect heuristic* states that people are quick to make judgements based on their affective impressions, underestimating the risks of things they like and overestimating the risks of thinks they do not like (Gilovich et al., 2002) and as a final example (4) the *delay discounting* which in the context of technology assessment means that people tend to value present benefits or risks more highly than those that lie in the future (Gold & Brown, 2009). While the use of heuristics is necessary to interact reasonably efficiently with our environment (Gigerenzer & Brighton, 2009), they can also be biased and lead to misjudgements and adverse actions. This emphasises the importance of unterstanding how cognitive processes influence perception and decision-making in technolgy assessment.

Another insight into cognitive processes in the evaluation of technology is provided by mental models. Mental models are simplified internal representations of real-world objects, processes, or structures (Moray, 1999). These models are understood as a cognitive structure that forms reasoning, decision-making and behaviour on basis of humans personal life experience, learning and socialization processes (Jones et al., 2011). They help animals and humans alike to evaluate the consequences of their actions and they influence our behavior (Craik, 1943; Johnson-Laird, 2010; Jones et al., 2011). When aligned with reality, they enable effective and efficient interactions with our surroundings (Gigerenzer & Brighton, 2009). However, mental models are limited due to each humans ability to represent the world accurately. Therefore they are characterized as incomplete or even inconsistent represenations of reality which are context-dependant and can change depending on the situation in which they are used (Jones et al., 2011). This means that incorrect mental models hinder accurate assessment of the environment and impede accurate inferences (Breakwell, 2001; Gilovich et al., 2002). Hence, studying mental models provides insights into fundamental attitudes and perspectives. In the context of technology assessment, this may aid in pinpointing areas where the mental models of the general public diverge or contrast from those held by experts, or where they do not align accurately with reality.

It is important to note that current approaches to technology and risk assessment primarily center around evaluating individual technologies, with limited emphasis on conducting comprehensive assessments across multiple technologies.

Rare counter-examples includes Slovic's milestone work on risk assessment and risk perception (Slovic, 1987). First, it shows that risk assessment is subject to heuristics and biases. Second, it provides an overview of the different risk perceptions for different technologies. Third, a cornerstone of Slovic's work is the decomposition of perceived risk into the two dimensions *dread risk* (how severe is the risk) and *unknown risk* (how predictable is the risk). Prior work also showed individual and possibly avoidable risks (e.g., skiing) have different trade-offs than external risks and difficult to avoid risks (e.g., such as food preservatives) (Starr, 1985).

Boudet (2019) reviewed the public perception and responses to various new energy technologies. Instead of focussing on specific technologies, the review encompasses both large-scale energy projects (e.g., utility-scale wind and solar, fossil fuel extraction, marine renewables) and smaller-scale consumer-oriented technologies (e.g., electric vehicles, rooftop solar, smart meters). Result of the review is not a weighting of the technologies against each other but an overview of each technology's specific risks and benefits, as well as an overview of factors contributing to public perception.

Brauner et al. surveyed the public perception of artificial intelligence as a novel technology but applied and contrasted it in various fields (e.g., impact on the job market, creation of art, or the downfall of society). The participants rated for each topic if the development will likely happen (expected likelihood) and their personal evaluation should the topic become a reality (if it is perceived as positive or negative) (Brauner et al., 2023). Those results are visually presented in a scatter plot, allowing the identification of topics where expectations and evaluations are in line and where discrepancies occur, thus lending itself to easily derive points of interest.

2.1 Research Objective

The previous section highlighted extensive research on mental models, risk perception, biases, and approaches for measuring technology acceptance. However, there is a scientific lacuna in research that compares multiple technologies simultaneously to enable pragmatic comparisons, such as overall perceived risk or valence. To address this gap, we adopt an exploratory research approach.

Given the intertwining of technologies with contemporary societal challenges such as climate change, demographic shifts, and social equity, the impact of technologies can either mitigate or exacerbate existing issues (Grübler, 1998; Huesemann, 2006). To understand the relationship between these technologies and impending societal changes, we aimed to investigate how various technologies and societal trends are comparatively weighted against four dependent variables: overall perceived valence, risk, familiarity, and the resulting desire for societal debate. Exploring these variables can provide valuable insights into public perceptions of different technologies and highlight whether there is a need for further public discourse.

- *Perceived Valence*: Affect significantly influences cognitive processes such as perception, learning, communication, and decision-making (Pessoa, 2008).[1] Understanding emotional responses toward different technologies can help researchers determine whether a technology is viewed positively, negatively, or neutrally by the public (i.e, a valence or the perceived value or sentiment ranging from posirtive to negative), which in turn can affect adoption rates, acceptance, and overall attitudes toward the technology (Ozturk et al., 2017). In fact, the Value-based Adoption model incorporates valence as a core variable for studying perceived value of technology, though it is limited in its focus on individual technologies within single studies (Kim et al., 2007).
- *Perceived Risk*: Investigating the perceived risk of a technology allows researchers to identify potential concerns or barriers to its adoption (Fischhoff, 2015). Understanding these risk perceptions enables policymakers and developers to address concerns and potentially enhance technology acceptance (Covello, 1983; Fischhoff, 2015).
- *Perceived Familiarity with Topics*: Assessing individuals' familiarity with a technology offers insights into their knowledge, experience, and understanding of it. Familiarity can shape their likelihood of adopting the technology and influence their overall perceptions and attitudes toward it (Idemudia & Raisinghani, 2014).
- *Desire for Societal Debate*: Exploring individuals' desire for societal debate on a technology can reveal the need for stakeholder engagement in public discourse. It may also explain individual participation in discussions, advocacy, and decision-making processes related to the technology. Understanding this can help researchers and policymakers assess public interest and involve the public in shaping the technology's development and integration in the society (Habermas, 1986).

[1] We thank a referee at this journal for suggesting this point.

Beyond examining the distribution of individual assessments, we also aimed to analyze their interrelationships, as these assessments can be connected in various ways:

- *Familiarity and Perceived Risk*: People who are more familiar with a technology may perceive it as less risky. This familiarity can come from personal experience, knowledge, or exposure to the technology. On the other hand, individuals who are unfamiliar with a technology may perceive it as riskier due to uncertainties or lack of understanding. Increased familiarity can lead to decreased perceived risk, and vice versa (Alraja et al., 2019).
- *Valence and Perceived Risk*: The emotional response or valence people have towards a technology can influence their perceived risk. For example, individuals who have a positive attitude towards a technology may perceive it as less risky, while those with a negative attitude may see it as more risky. Valence and perceived risk can be closely linked, as emotions can shape perceptions of risk (Sjöberg, 2007).
- *Familiarity and Desire for Societal Debate*: Individuals who are more familiar with a technology may be more likely to wish for societal debates and discussions surrounding it. Familiarity could provide individuals with the confidence and knowledge to participate in debates and share their opinions themselves or the reasons why a public discourse is necessary. Conversely, individuals who are less familiar with a technology may be less inclined to engage in societal debates themselves or acknowledge the need for a public discourse due to their limited understanding (Mast & Stehle, 2016).
- *Valence and Desire for Societal Debate*: The emotional response or valence people have towards a technology could influence their desire for societal debate. Individuals who feel strongly about a technology, either positively or negatively, may wish for representatives in politics, media or science to provide support for the individuals' valence towards a specific topic. Furthermore, they might be be more likely to engage in debates themselves as well, driven by their emotional response.

Overall, these dependent variables are often interconnected and can influence each other in complex ways. By examining their relationships and interactions, researchers and policymakers can gain deeper insights into how individuals perceive and engage with technologies in society. The following section outlines the selection of topics, the implementation of the online survey, the study sample, and the methods used for data analysis.

3 Method

This section presents how we identified and selected possible topics and technologies for our study. We then describe the design of the final study, the procedure, and the sample.

3.1 Collection of Topics for the Study

We employed a multi-stage approach in designing the survey as Fig. 1 illustrates: The first stage involved collecting potential survey topics through a brainstorming session with academic experts from various disciplines that were involved in research projects on the future of mobility, manufacturing and healthcare. We asked them to collect topics that are likely to have an impact on how we life or work in the future. Subsequently, we consolidated the outcomes while eliminating any duplicate entries.

In the second stage, a brief questionnaire was distributed to 29 colleagues who ranked the 40 resulting topics according to their perceived importance. This ranking process enabled the identification and selection of the top 24 topics chosen for inclusion in the final survey.

In the third stage, we iteratively refined the terminology and descriptions of the selected topics to ensure optimal understanding by participants. This process enhanced the clarity and structure of the survey, resulting in the development of a comprehensive and well-structured questionnaire for the final stage.

3.2 Survey Construction and Distribution

Figure 2 depicts the three sections of the final survey: Initially, demographic data such as age, gender (male, female, other, no answer), and country of origin are gathered. Subsequently, participants are presented with the 24 topics and are asked to

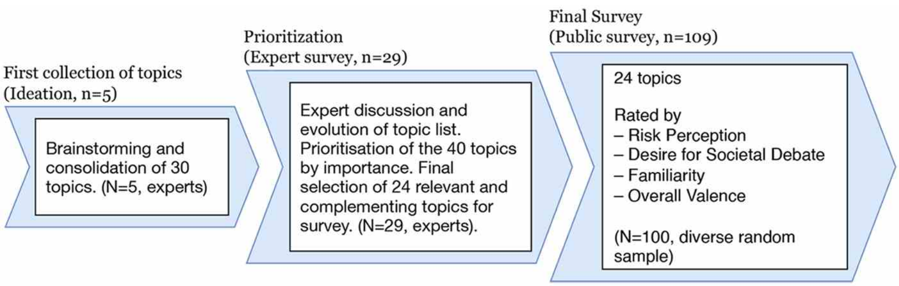

Fig. 1 Iterative definition of the investigated topics and technologies

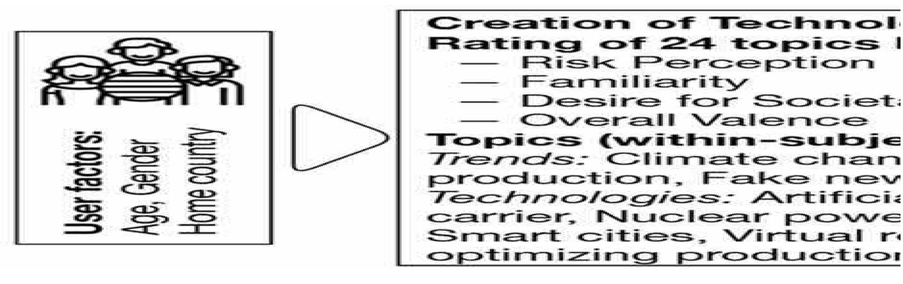

Fig. 2 Design of the survey with user demographics and the technology and trend evaluation using micro scenarios

evaluate each based on overall valence, perceived risk, familiarity, and desire for societal debate about the topic. The survey is structured around the micro scenario approach, with each topic accompanied by a brief explanation and participants providing assessments using single-item scales for each dimension (Brauner, 2024).

Table 1 presents a summary of the chosen topics, accompanied by brief rationales for their inclusion. The topics listed can be broadly classified into two primary groups: *past and emerging technologies* (e.g., nuclear power or blockchain technologies) and *general trends* (such as climate change or demographic shifts).

Participants evaluated each of the 24 topics along four dimensions: *Risk perception* (ranging from low risk to high risk), personal *perceived valence* towards the topic (varying from very negative to very positive), *perceived familiarity* with the topic (ranging from very familiar to never heard of the topic), and *desire for societal debate*, indicating whether society should address the issue (ranging from fully agree to do not agree at all). The participants responded to each item on a 6-point semantic differential scale, which we scaled from −100% (e.g., very negative attitude towards the topic) to +100% (e.g., very high risk associated risk).

We employed Qualtrics to administer the online survey and collect responses. To mitigate bias, we randomized the order of topics presented to participants. However, the sequence of the four target dimensions was kept consistent for test efficiency. Utilizing convenience sampling, we distributed the survey via personal (e.g., personal email) and technology-mediated social networks (e.g., Facebook, LinkedIn). Leveraging the international social network of the research team, the questionnaire was available in English, Bulgarian, and German languages. Participants were not offered any incentives for participation, and they were informed that their involvement was voluntary with the option to withdraw at any time (informed consent). The median survey completion time was approximately 16 min.

3.3 Participants of the Study

Of the 111 participants in the study, 51 identified themselves as male (46%) and 60 as female (54%). The age range is between 18 and 70 years with a mean age of (M=37.0, SD=13.5) years. We observed no significant correlation between age and gender (r=0.081, p=0.416). For the data collection process, we concentrated on recruiting participants from Bulgaria and Germany by utilizing personal connections to enhance the recruitment efforts (convenience sample). Nevertheless, there were no restrictions imposed on participation based on nationality or country of origin. As a result, the majority of our participants were from Bulgaria (67, 60%) and Germany (38, 34%).

3.4 Analysis

We first cleaned the dataset and removed records with more than single missing values. Following the micro scenario approach (Brauner, 2024), we then formed two variables for each of the four dimensions of the topic assessments: On the one hand, as participant variable as arithmetic mean over all topics for each participant (horizontally through the data set). This first perspective can be viewed as a reflexive measurement of an individual's evaluation of the specific dimension through iterative

Table 1 Topics from the study and a motivation for their consideration

Topic	Description
Climate change	Refers to Earth's warming due to human actions and studying how individuals and communities respond to it is relevant for climate communication, policy development, and collective action (Merk et al., 2019; Dabla-Norris et al., 2023; Chang-Brahim et al., 2024).
Wind power	Is is a form of renewable energy generated by converting kinetic energy of moving air to electricity. Studying the public perception of wind energy drives is important to facilitate informed decision-making, address concerns, and promote sustainable renewable energy solutions (Devine-Wright, 2005).
Hydrogen power	Hydrogen as an energy carrier involves the generation and utilization of hydrogen gas. An application is using hydrogen as fuel for propulsion engines in motor vehicles which raises questions regarding efficiency, safety, and overall environmental impact (Scovell, 2022; Emodi et al., 2021; Huijts, 2018).
Nuclear power	Nuclear power is a potential energy source that is associated with risks for the people and the environment (Slovic et al., 2000; Siegrist et al., 2006).
Artificial intelligence	Artificial intelligence reproduces human thought structures so that computers can deal with problems relatively independently. The associated collection of data and the influence of AI-based automation affects our lives (Brauner et al., 2024; Fast & Horvitz, 2017; Grace et al., 2018; Russell & Norvig, 2020).
Demographic change	The ageing society changes the population structure and brings cultural, economic, social, political, and workforce challenges and opportunities (Beard et al., 2011; World Bank, 2015).
Digital transformation of work	Companies are increasingly utilizing new technological tools based on computers and communication, which not only assist them but also facilitate the automation of various processes (Cherry, 2016; Trenerry et al., 2021; Hildebrandt et al., 2020).
Digital transformation of medicine	The digitization of medicine entails the convergence of medicine and computer science. Digital medicine applications serve a wide range of purposes, including prevention, diagnosis, treatment, monitoring, and management of various health conditions (Stoumpos et al., 2023; Iyawa et al., 2016; Khullar et al., 2022).
Human-robot interaction	With human-robot interaction and teaming, humans and robots share a workspace in production and work closely together (Villani et al., 2018; Onnasch & Roesler, 2020; Rahwan et al., 2019; Biermann et al., 2021).
Fake news	"Fake News" denotes the spread of manipulated, fake and false information, in particular on the Internet and social media platform (Zhou & Zafarani, 2019; Tandoc et al., 2021).
Care robotics	Nursing robots are used to support human nursing staff by performing nursing tasks such as washing, handing over food or taking over communication in parts (Andrade et al., 2014; Maibaum et al., 2022).
Work from home	Modern telecommunication technologies, such as e-mail and video conferences, along with accessible server infrastructure via the Internet, enable individuals to work from home (Tønnessen et al., 2021; Neirotti et al., 2019).
Urbanization	Urbanization is the process of increasing the proportion of a population living in urban areas, leading to the growth and expansion of cities and towns (National Research Council, 2003).
Autonomous driving	Autonomous driving entails vehicles moving independently, guided by intelligent control systems, and operating without the need for human drivers' direct influence (Becker & Axhausen, 2017; Azad et al., 2019; Brell et al., 2019).
5G radio standard	5G represents the most recent generation of cellular standards, significantly enhancing connection speeds for mobile devices (Siegrist et al., 2006; Herrera-Contreras et al., 2020).
Smart home	Smart home means the networking of technical processes and systems in living spaces and houses to increase the quality of living (e.g. programmable lamps) (Balakrishnan et al., 2018; Brauner et al., 2017; Huijts et al., 2023).

Table 1 (continued)

Topic	Description
Virtual reality	Virtual Reality (VR) denotes an artificial reality that is computer-generated and displayed through VR glasses or similar devices, enabling individuals to perceive and interact with this simulated environment (Xiong et al., 2021; Schmitz et al., 2018).
Blockchains	Blockchain technology is a decentralized digital ledger that records transactions in cryptographically secured blocks, which are linked in a chain. This technology supports various applications, including digital currencies like Bitcoin, smart contracts, and secure data management systems (Ahram et al., 2017; Bader et al., 2021; Casolari et al., 2023).
Smart cities	Smart cities are development concepts with a view to a more efficient, technologically advanced, green and socially inclusive design of cities (Dustdar et al., 2017; Dirsehan & van Zoonen, 2022; Calzati & van Loenen, 2023).
Social equality	Social justice pertains to the just and equitable allocation of rights, opportunities, and resources, irrespective of gender, cultural, religious background, or other individual factors (United Nations, 2015).
Cyber crime	Cybercrime not only inflicts substantial damage but also exhibits a growing level of professionalism among its perpetrators. A report by Cyjax highlights that factors such as holiday regulations and sick pay play a significant role in the recruitment of prospective female workers within this domain (Bada et al., 2015; Cyjax, 2022).
Electric vehicles	Electric vehicles represent a sustainable mode of transportation for both people and goods, relying on electric power as their source of propulsion (Becker & Axhausen, 2017; Baum et al., 2019).
Self-optimizing production	Autonomous technical systems are integrated into classic production processes, enabling them to independently adapt to current conditions and objectives, thereby optimizing their operations (Martins et al., 2020; Schlick et al., 2017).
Digital Transformation of production	Industry 4.0 encompasses the digitization of industrial production, facilitated by interconnected and collaborative machines. Data analysis and artificial intelligence play crucial roles in increasing automation within this context (Kagermann, 2015; Holzinger et al., 2024; Brauner et al., 2022).

assessments across different technologies. On the other hand, as average evaluation of the topics as the arithmetic mean for each topic over all participants (vertically through the data set). This second perspective captures the overall evaluation of the various technologies by participants for each of the four assessment dimensions.

We then analysed the data with descriptive methods (mean, median, standard deviation, confidence intervals) and inference statistics (correlation analysis using Person's or Spearman's correlation coefficient r resp. s, r^2 as an indicator of the predictive power of one variable on another, and linear regression analyses). We set the level of statistical significance to $\alpha = 5\%$.

4 Results

The results section is structured into three main sections. First, we present the participants' evaluations of the different topics individually, focusing on four evaluation criteria: valence, familiarity, perceived risk, and desire for societal debate on each topic. Subsequently, we delve into an exploration of the interrelationships between these evaluations, aiming to identify any prevalent patterns. Lastly, we conduct an assessment of how user diversity influences the evaluations of the topics.

4.1 Evaluation of the Different Topics

In the following, we iterate through the evaluations of the different topics on the four evaluation dimensions and point out some particular findings. Figure 3 (and Table 4 in the Appendix) presents the full results with the participants' evaluations of the queried aspects' valence, perceived risk, familiarity, and desire for societal debate on the topics as a profile plot.

It should be noted that the distributions of the four evaluation dimensions vary: For both perceived valence (–20.1% to +69.7%) and perceived risk (–56.5% to +70.8%) the participants report both negative and positive evaluations and use a large portion of the available scale. For perceived familiarity (+7.9% to +66.8%) and the desire for societal debate (+28.0% to +77.6%), the participants report only positive values (meaning they are at least somewhat familiar with each queried topic or having a more than average interest in a societal debate) and the responses are more compact.

4.1.1 Valence or Perceived Value

First, we examined the general valence or perceived value of the queried topics, assessing whether participants held a predominantly positive or negative basic sentiment or attitude towards each topic.

The average perceived valence of the topics queried was M = 27% (SD = 23%) and thus, on average, the participants had a slightly positive valance towards the topics as

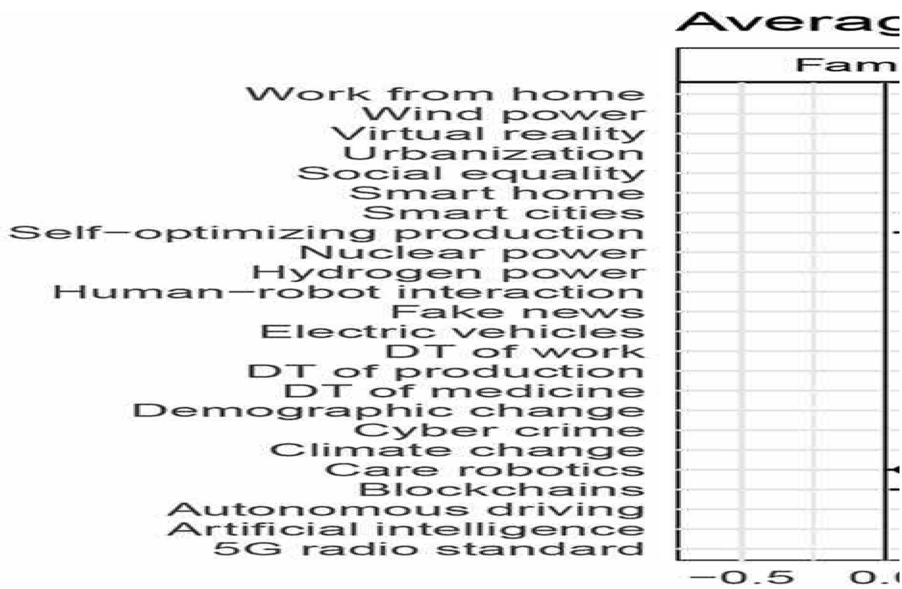

Fig. 3 Average perception of the queried topics by each of the four evaluation dimensions. Error bars indicate the 95%-CI

a whole. However, there is considerable variation in the valence ratings: Among the topics, wind energy received the most positive rating (M=70%, SD=37%), closely followed by electric vehicles (M=53%, SD=47%), and the digital transformation of medicine (M=53%, SD=46%). On the other hand, participants expressed the lowest valence towards the topics of climate change (M=–2%, SD=78%), cyber crime (M=–15%, SD=74%), and, notably, fake news (M=–20%, SD=79%).

4.1.2 Risk

Next, we analysed how the perceived risk differed between the covered topics, assessing whether and which topics were perceived as relatively risk-free or high-risky by the participants.

The average perceived risk of the topics queried was M=8% (SD=31%), indicating a neutral overall perception of risk across all topics. However, the range in perceived risk across the various topics is substantial, spanning from (71%) to (–56%): The topic with the highest perceived risks are fake news (M=71%, SD=51%), cyber crime (M=67%, SD=49%), and climate change (M=63%, SD=55%). The topics perceived to have the lowest level of risk were work from home (M=–25%, SD=58%), electric vehicles (M=–28%, SD=54%), and wind energy (M=–56%, SD=45%). These findings highlight the variability in participants' risk perceptions across the various topics, indicating significant disparities in the perceived level of risk associated with each topic.

Moreover, the level of agreement among participants also exhibited variability. For example, the standard deviation for the perceived risk of wind power (45%) is considerably lower than the standard deviation of the risk assessment for the 5G mobile standard (65%).

4.1.3 Familiarity

In this section, we evaluate participants' familiarity with the topics under consideration, examining their subjective perception of familiarity with each topic. The average reported familiarity with the queried topics was M=36% (SD=16%), suggesting that participants generally indicated being acquainted with the majority of the topics surveyed.

The topics with the highest reported familiarity were work from home (M=67%, SD=35%), climate change (M=58%, SD=36%), and fake news (M=57%, SD=34%). The topics the participants were least familiar with were self-optimizing production (M=12%, SD=46%), blockchains or distributed ledger technologies (M=11%, SD=48%), and health care robots (M=8%, SD=44%). Despite the average familiarity being always positive on the scale ranging from –100% to +100%, these topics were perceived as less familiar compared to others.

4.1.4 Desire for Societal Debate

Lastly, we examined the participants' wish for societal debates on the topics. The average reported desire for such discussions concerning the topics was M=55%

(SD=14%), with a range spanning from 28% for blockchain technologies to 78% for climate change.

It is essential to acknowledge that all topics in the survey garnered some degree of desire for societal debate (the scale ranging from −100% indicating no desire to +100% indicating strong desire, with all average ratings being positive), reflecting participants' desire for a social debate on each topic. However, discernible discrepancies emerged as participants showcased diverse levels of urgency in advocating for a societal debate, which were influenced by the particular topic at hand.

The topics that appear to be most crucial for social discussion are climate change (M=78%, SD=46%), cyber crime (M=77%, SD=36%), fake news (M=76%, SD=44%), and the demographic change (M=74%, SD=39%). The topics for which our participants expressed the least desire for a public debate were virtual reality applications (M=29%, SD=57%), health care robotics (M=40%, SD=59%), and block chain technologies (M=28%, SD=52%).

The examination of the four dimensions (valence, perceived risk, familiarity, and desire for societal debate) unveiled pronounced differences in participants' assessments of the topics. In the subsequent section, we delve into investigating the connections and interactions among these dimensions across the diverse topics surveyed.

4.2 Relationships Between the Perceptions of the Topics

After examining the topics individually, this section now delves into analyzing the relationships between the average evaluations of the topics (aggregate evaluation of each topic by all participants), considering overall valence, perceived risk, familiarity, and the desire for societal debate. In this context, we calculated the correlations among the four evaluation dimensions across the 24 topics. As illustrated in Table 2, two of these correlations are not only statistically significant but also strong.

The correlation analysis indicates a significant negative and strong relationship between perceived risk and overall valence of a topic ($r=-0.945$, $p<0.001$), which translates to a strong effect size of $r^2=89\%$. This suggests that as individuals associate higher risk with a topic, its valence tends to be lower, and conversely. Figure 4 illustrates the strong relationship between an individuals' valence towards a topic and its perceived risk. For instance, topics like fake news, cyber crime, and climate change are perceived negatively and as significant risks, while wind energy or electric vehicles are evaluated positively with lower perceived risk.

The correlation between perceived familiarity with a topic and the desire for a societal debate regarding the topic reveals a lower, yet strong and significant relationship ($r=0.572$, $p=0.0035$) with a moderate effect size of $r^2=33\%$.

Figure 5 illustrates that when participants are less familiar with a topic, like health care robotics, blockchain technologies, or self-optimizing production, they demon-

Table 2 Average evaluations of and correlations between the evaluation dimensions of the 24 topics by N=111 participants

Dimension	M (SD)	2	3	4
1. Valence	26.7% (22.6%)	–0.945	–0.164	–0.172
2. Percieved risk	8.5% (30.9%)	–	0.166	0.326
3. Familiarity	36.0% (16.5%)	–	–	0.572
4. Societal debate	54.8% (14.2%)	–	–	–

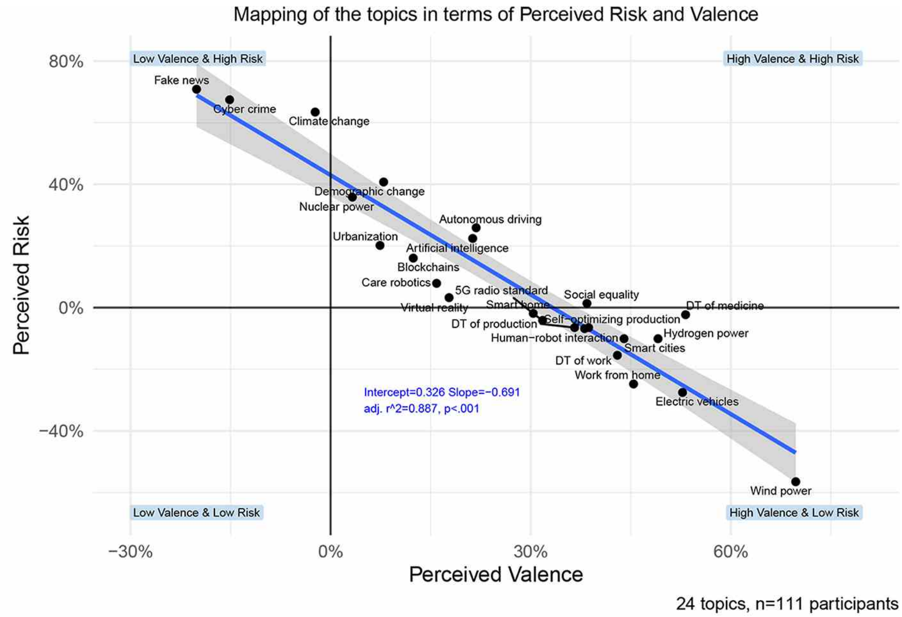

Fig. 4 Association between perceived risk and the overall valence (or perceived value) of the topics. The blue line shows the estimated regression line. The gray shaded area represents the confidence interval within which the true regression line is likely to fall

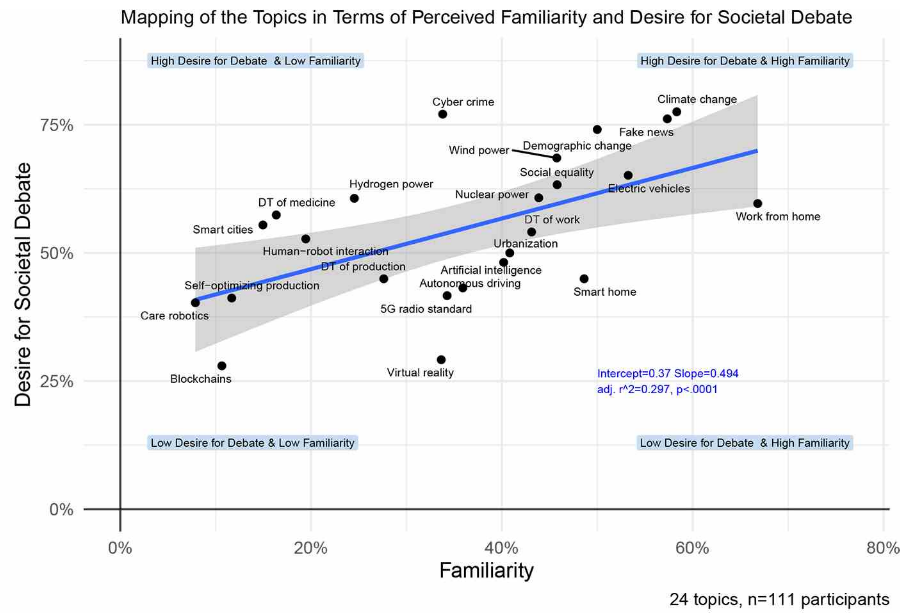

Fig. 5 Association between familiarity and the desire for societal debate about the topic. The blue line shows the estimated regression line. The gray shaded area represents the confidence interval within which the true regression line is likely to fall

strate less desire for societal debate on that topic. Conversely, when participants are more acquainted with a topic, such as climate change, remote work, or fake news, they express a heightened desire for a societal debate. This highlights the connection between familiarity with a topic and the wish for societal discussions related to that topic.

The other evaluation dimensions did not exhibit statistically significant correlations in our sample. Specifically, there was no significant relationship observed between familiarity and perceived value or valence of the topics (r=–0.164, p=0.445), nor was there a relationship between perceived risk and the desire for a societal debate on the topic (r=0.326, p=0.12).

4.3 The Influence of User Diversity on the Assessment of the Topics

Lastly, we analyse how individual differences or the diversity of the participants are associated with the evaluations of the topics in this study. While the previous analysis focused on correlations within the topic ratings (e.g., riskier topics being perceived more negatively), here we investigate whether the average ratings are linked to other user factors such as participants' age, gender, or country of origin and if the ratings are correlated among respondents. For this, we calculated an average score for valence, risk, familiarity, and desire for public discussion for each participant as his or her average evaluation across the queried topics. These scores can be interpreted as an individual assessment if the participants finds the queried topics as a whole, for example, more or less favourable. Table 3 shows the results of the correlation analysis.

In this sample, age is not linked to neither of the four evaluation dimensions familiarity, perceived risk, desire for societal debate, or overall valence. However, the participants gender is correlated with the perceived familiarity with the topics and, with men generally reporting higher familiarity with the topics compared to women (r=–0.31, p<0.001). Nonetheless, there was no significant association between gender and average valence, desire for a societal debate, or perceived risk. Therefore, age did not show an influence on the evaluation of the topics.

Table 3 Average evaluations of and correlations between the evaluation dimensions of the 24 topics by N=111 participants[a]

Dimension	M (SD)	2	3	4	5	6	7
1. Age (in years)	33.0 (13.5)	0.077	–0.366	0.178	0.019	0.044	0.082
2. Gender	51 male, 60 female	–	–0.195	–0.290	0.097	–0.310	–0.137
3. Country	38 Germany, 67 Bulgaria	–	–	–0.054	0.045	0.136	0.266
4. Valence	0.3 (0.2)	–	–	–	–0.435	0.262	0.658
5. Percieved Risk	8.3% (29.4%)	–	–	–	–	–0.182	–0.235
6. Familiarity	36.5% (22.8%)	–	–	–	–	–	0.389
7. Desire Societal Debate	54.7% (27.0%)	–	–	–	–	–	–

[a]Gender and country are dummy-coded (1=male, 2=female; 1=Bulgaria, 2=Germany)

There is a moderate negative association between an individual's average perception of the risks associated with the topics surveyed and the average perceived valence (r=–0.435, p<0.001). This suggests that if a person views the topics in this study as more risky, their reported valence is lower, and vice versa.

Remarkably, the strongest association is observed between the perceived valence of a technology and the desire for a societal debate about the topic (r=–0.435, p<0.001). This suggests that the higher the positive valuation of a technology, the greater the desire for public discussions over its implementation.

Further, there is a medium association between the familiarity with a technology and its overall evaluation (r=–0.435, p<0.001). The more a technology is perceived as familiar, the more positive is its evaluation and conversely.

5 Discussion

In this work, we queried the public perception of various technology and technology related trends in terms of perceived risk, familiarity, desire for societal debate, and overall valence.

5.1 Differences in Perceptions

The results imply that people perceive the queried topics differently, therefore suggesting diverging underlying attributions: While some of the projected developments are seen as positive (e.g., using wind power drives as a sustainable source for energy), others are not (e.g., fake news, misinformation, or cyber crime). Likewise, the study revealed pronounced differences in the perceived risk of the queried topics, with some topics being perceived as safer (e.g., wind power, electric vehicles, or work from home) and others as risky (e.g., fake news, cyber crime, and the climate change). In terms of familiarity, the participants report to be very familiar with some of the queried topics (e.g., work from home, climate change, and fake news) and less familiar with others (e.g., care robotics, self-optimizing production, and block chains). Regarding the desire for a societal debate, the participants report the least desire for social debate on blockchain or distributed ledger technologies, virtual reality, and care robotics, whereas they want social debates on other topics, such as climate change, cyber crime, and fake news. At this point we will not go deeper into the reasons for individual technology and topic assessments but instead refer readers to works that offer more detailed analyses focusing on specific topics, such as discussions of fake news (Lazer et al., 2018), climate change (Delistavrou et al., 2023), or wind power (Linzenich et al., 2020).

5.2 Overview on Public Perception of Technologies and Trends

The visual mappings of this relationships provide a comprehensive overview of how the public perceives the queried topics and societal trends and allows an interpretation of the absolute placement of the topics and their relative positions in the resulting maps (see Figs. 4 and 5). The maps show that only few of the topics are perceived negatively by the participants, while the majority of the queried topics were rated neutral to positively. Similarly, the majority of the topics are perceived as somewhat risky (with only few receiving high scores in perceived risk), whereas only few are perceived as rather safe. In contrast, familiarity with the topics and the desire for a societal debate received only positive scores. Hence, we can conclude that the participants feel to be at least somewhat familiar with all of the queried topics and expressed at some to higher desire for a societal debate about these. This is astonishing, as some of the queried topics are not directly related to the everyday life of our participants (e.g., block-chain technology may be interesting for some people, but is certainly not for the majority).

5.3 Correlations Among the Evaluations

Beyond this unidimensional perspective, the evaluation dimensions show systematic connections: The findings of this study suggest that individuals' perceptions of various topics in the realm of technology and society are interconnected and that the perceptions of risk, valence and familiarity influence each other. The strong relationship between perceived risk and valence highlights the importance of understanding how individuals assess and prioritize potential risks associated with different topics. First and foremost, the perceived risk the participants associate with the queried topics is strongly coupled with the overall perceived valence. Topics perceived as less risky were associated with a more positive attitude and topics with higher perceived risk, with a considerably more negative attitude.

Additionally, the link between familiarity and desire for a societal debate emphasizes the role of societal discourse in shaping public perceptions and attitudes towards emerging technologies but it also opens the door for familiarity to be used as a potential predictor for future public discourses. If a technology is seen as more familiar, there is a stronger desire for a societal debate about it and vice versa.

Contrary to expectations, our study did not find any evidence linking a topic's perceived risk to a desire for societal debate: One might have assumed that higher perceived risk would lead to a greater desire for debate and potential regulation, but our results did not support this hypothesis. Similarly, familiarity with the topic did not appear to influence overall valence. One may have suspected that, either because individuals would try to get informed and familiar with topics they like, or based on the mere exposure effect that postulates that people like things more if they are repeatedly exposed to it (Bornstein & Craver-Lemley, 2022; Montoya et al., 2017). We hypothesize that these results may be attributed to the limited sample size of 24 technologies and societal trends as well as the mix of both trends and technologies.

5.4 The Role of User Diversity

The influence of user diversity on the evaluations wassmall but nevertheless important to consider. We found a correlation between the gender of the participants' and their familiarity with the queried topics, with men reporting to be more familiar with the queried technologies than women. This pattern has been observed in many studies, spanning from interactions with computers (Galyani Moghaddam, 2010; Jokisch et al., 2020), to other technologies such as the willingness to adopt automated driving (Weigl et al., 2022), and across various age groups (Brauner et al., 2018; Jokisch et al., 2020). This effect is often referred to as the “gender technology gap” or “digital gender divide” (Marzano & Lubkina, 2019). Surprisingly and in contrast to other studies (e.g. Brown et al., 2021), there was neither an influence of gender on risk perception nor on overall valence across the whole set of queried technologies. Here, further research on gender and technology perception is needed to explore the complex interplay between individual characteristics and societal perceptions of technology-related issues, as effects may have been occluded by averaging the many risk perceptions of the different topics into one score.

5.5 Micro Scenarios for Quantifying Mental Models

The results presented here do not stem from a rational weighing of the advantages and disadvantages of the technologies. Instead, they are based on a swift affective evaluation influenced by heuristics and the participants’ mental models across four dimensions: valence, risk, familiarity, and desire for societal debate.

Humans are not purely rational agents; heuristics and mental models significantly shape our attitudes and behavior (Gilovich et al., 2002; Kahneman, 2012). In areas where mental models are not aligned with technical risk assessments, conflicts may arise that impact the use of new technologies by individuals or the society. Future research should aim to conduct a more in-depth analysis of public perception in conjunction with integrating experts’ evaluations and risk assessments. This comprehensive approach will help identify and visualize any discrepancies that exist, allowing for the development of more effective strategies to address and mitigate conflicting risk attributions in the development and regulation of new technologies.

5.6 Policy Recommendations

Based on the empirical findings, we stress the following recommendations aimed at supporting the development of a socially responsible, human-centered digital society.

First, despite covering a wide range of topics, two digital issues emerged as particularly high-risk and negative: fake news and cybercrime. These were perceived as more critical than even the highly visible and tangible threat of climate change. In light of this, efforts to address these issues must be intensified within the framework of existing regulatory regimes, such as the EU’s Digital Services Act and General Data Protection Regulation (GDPR) (European Parliament and Council of the European Union European Parliament, Council of the European Union, 2016), which provide guidelines for platform responsibility and data security. However, our findings suggest that stricter regulations are needed to govern the creation and dissemination of fake news by individuals and platforms. In line with international efforts, such as the United Nations’ Global Programme on Cybercrime, policies must extend beyond regulations and integrate educational initiatives that empower individuals to protect themselves from misinformation and cyber threats (Nurse, 2018; Williams et al., 2016). Educational campaigns can complement existing legal frameworks like the Council of Europe's Budapest Convention on cybercrime, which calls for cross-national cooperation and capacity building.

Second, to address the rapid pace of technological innovation, particularly in fields such as digitalization and artificial intelligence, which often evolve through disruptive revolutions rather than gradual change, we underline the need for value-oriented and participatory development frameworks (van den Hoven, 2013; van den Hoven et al., 2015). The European Union's AI Act and similar international initiatives, such as the OECD's AI Principles, recognize the need for responsible innovation. However, our findings support the call for a more proactive approach—one that goes beyond mere compliance and centers on co-designing technologies that align with societal norms and values. We propose three foundational components:

1. *Empower individuals to cope with (digital) transformations:* The rapid pace of digital innovation may outstrip individuals' capacity to understand, adapt to, and control the impact of these changes on their personal and professional lives. This presents a challenge to the social fabric of society. It is therefore essential to equip people with the tools to better navigate these transformations. This recommendation aligns with ongoing efforts within the European Union's Digital Education Action Plan (European Commission, 2021), which emphasizes integrating digital literacy, technological innovation, and ethics into public school, university, and vocational curricula. The goal is to ensure individuals are equipped with critical thinking skills and a positive mindset to assess and adapt to technological shifts.
2. *Increase openness to innovation:* To effectively assess and anticipate the implications of technological advances, organizations and societies should promote public science initiatives through experimental spaces and living labs where new technologies can be tested in real-world settings. This recommendation aligns with the European Commission's New European Bauhaus and Horizon Europe programs, which prioritize participatory design and experimentation. These experimental spaces should be coupled with forums that bring together diverse stakeholders—government, academia, civil society, and industry—to debate the benefits, risks, and societal impacts of emerging technologies. By fostering a participatory "enabling culture", this approach would build on existing frameworks, such as the Responsible Research and Innovation (RRI) agenda, to promote greater public acceptance and understanding of socio-technological innovations.
3. *Continuous technology assessments and impact monitoring:* To ensure that technological advancements remain aligned with societal needs, we recommend implementing ongoing technology assessments and impact monitoring. Similar to the role of the "canary in a coal mine", this approach could serve as an early warning system for emerging risks. Current frameworks, such as the OECD Guidelines for AI (Lorenz et al., 2023) and European Parliamentary Technology Assessment network (EPTA, 2024), recognize the importance of technology assessment and monitoring the societal impacts of technologies. By extending static technology assessment by regularly applying methodologies like the one used in this study, policymakers can track evolving societal and individual perceptions of technology, understand how different groups perceive risks and

benefits, and monitor how social events or crises (e.g., pandemics, wars) influence technology assessments. This would strengthen the evidence base for policy decisions, ensuring that regulations and governance strategies are informed by empirical data and evolving societal contexts. Without systematically integrating public perceptions—including their hopes, fears, and anxieties—it will be difficult to guide the transition toward a thoughtful, socially responsible, and human-centered digital society.

5.7 Limitations and Future Work

Of course, this work is not without limitations. First, the sample is biased towards younger people and not representative for the general public, especially, as the majority of participants originated from Bulgaria and Germany. However, the skewed sample towards younger individuals from specific countries can provide valuable insights into potential generational or cultural differences in risk perception, offering a unique perspective that warrants further investigation and comparison with more diverse populations. Hence, future work should expand the study to include a more diverse European or global sample, so that we can gain a deeper understanding of how cultural differences may impact the acceptance of technology on a broader scale.

This study used the micro scenario approach and we introduced each topic briefly before the participants evaluated each of the four dimensions on a single item (Brauner, 2024). Obviously, this brief evaluation may oversimplify nuanced opinions of participants. Taking the risk perception of electric vehicles as an example, different people may see different causes for risk of these cars that are summarized in a single score. For sure, this leads to higher variance in the data that is impossible to explain using our approach. Nevertheless, from a methodological perspective, this broader approach has worked well, as evidenced by the systematic and plausible effects. Also, this approach allowed us to present an overview of the perceptions of many different topics and their relations in a single study. For future studies we suggest to use these findings and focus on particular topics and analyse these individually in detail.

The variance in the data indicates that participants evaluate technologies differently, with some technologies garnering higher levels of agreement than others. This finding aligns with previous research that has shown significant variations in public attitudes towards technologies such as nuclear power (Slovic, 1996) and wind power (Wolsink, 2007). Therefore, the limited agreements observed in this study should be viewed as an indicator for the plurality of opinions rather than a flaw in the measurement model.

6 Conclusions

Technologies profoundly influence our personal lives, shaping how we work, interact, and organize societies. The ways technologies are adopted and the necessary regulations for their responsible use should be central to societal discussions. This responsibility cannot be left solely to engineers and entrepreneurs; it requires broader public engagement and oversight.

This study advances the field of participatory technology assessment and participatory responsible research and innovation. By employing an integrated, joint evaluation using the micro scenario approach, it provides crucial insights for researchers, practitioners, policymakers, and the public. Specifically, it highlights which technologies are perceived with little reservation and where greater regulation or government oversight is required.

In conjunction with perspectives from technology developers, ethicists, and legal experts, these findings contribute to a more holistic assessment of (emerging) technologies (Grunwald, 2018; van den Hoven, 2013; van den Hoven et al., 2015). Incorporating the public's mental models enables stakeholders to make more informed decisions, promoting ethical technological development and fostering more inclusive and humane societies that better align with shared norms and values.

Understanding public perceptions is crucial for shaping responsible technological development and informed policy-making. This study highlights the importance of sustained societal dialogue to ensure that technological advancements align with the broader public interest, thereby promoting a more equitable and transparent future.

Appendix

Table 4 The participants' percieved value or valence (negative – postive), percieved risk (low – high risk), familiarity (not familiar – familiar), and desire for societal debate (not neeeded – much needed) for topics in this study[a]

Item	Valence		Perceived risk		Familiarity		Societal debate	
	M	SD	M	SD	M	SD	M	SD
5G radio standard	30.4%	57.8%	−1.9%	65.1%	34.3%	40.8%	41.7%	58.6%
Artificial intelligence	21.3%	49.9%	22.4%	55.5%	40.2%	41.5%	48.1%	53.8%
Autonomous driving	21.8%	54.8%	25.9%	60.5%	35.9%	41.3%	43.2%	59.2%
Blockchains	12.4%	44.2%	16.1%	55.6%	10.6%	48.4%	28.0%	51.6%
Care robotics	15.9%	58.5%	7.9%	59.7%	7.9%	44.4%	40.3%	59.4%
Climate change	−2.3%	77.8%	63.4%	54.5%	58.3%	36.5%	77.5%	45.9%
Cyber crime	−15.1%	74.1%	67.4%	48.8%	33.8%	42.0%	77.1%	35.7%
Demographic change	7.9%	55.4%	40.7%	52.6%	50.0%	36.2%	74.1%	39.0%
Digital Transformation of medicine	53.2%	45.8%	−2.3%	57.5%	16.4%	46.0%	57.4%	47.8%
Digital Transformation of production	36.6%	43.6%	−6.5%	51.2%	27.6%	45.5%	45.0%	49.5%
Digital Transformation of work	43.0%	44.7%	−15.5%	53.2%	43.1%	37.6%	54.1%	48.0%
Electric vehicles	52.8%	46.6%	−27.5%	53.8%	53.2%	36.3%	65.1%	49.8%
Fake news	−20.1%	78.6%	70.8%	50.8%	57.3%	33.9%	76.1%	43.9%
Human-robot interaction	38.1%	43.5%	−6.8%	50.4%	19.4%	44.7%	52.7%	42.2%
Hydrogen power	49.1%	44.1%	−10.1%	56.4%	24.5%	47.1%	60.6%	45.4%
Nuclear power	3.3%	60.4%	35.8%	63.9%	43.9%	39.5%	60.7%	51.9%

Table 4 (continued)

Item	Valence		Perceived risk		Familiarity		Societal debate	
	M	SD	M	SD	M	SD	M	SD
Self-optimizing production	38.7%	45.4%	–6.5%	47.4%	11.7%	45.9%	41.2%	44.2%
Smart cities	44.0%	45.7%	–10.1%	55.2%	15.0%	50.1%	55.5%	47.6%
Smart home	31.8%	51.6%	–4.1%	55.7%	48.6%	35.7%	45.0%	55.3%
Social equality	38.4%	57.0%	1.4%	64.7%	45.8%	36.4%	63.3%	50.8%
Urbanization	7.4%	49.7%	20.2%	53.2%	40.8%	40.9%	50.0%	51.8%
Virtual reality	17.8%	48.2%	3.2%	60.1%	33.6%	43.3%	29.2%	57.2%
Wind power	69.7%	36.7%	–56.5%	45.4%	45.8%	40.9%	68.5%	43.0%
Work from home	45.4%	46.9%	–24.8%	58.0%	66.8%	35.4%	59.6%	47.9%

Items sorted alphabetically

[a]Measured on 6 point semantic differentials and rescaled to –100% to +100%. Negative values indicate a negative evaluiation of the respective dimension (i.e., low valence, low perceived risk, low familiarity, or low desire for society debate) and positive values indicate a high evaluation

Table 5 Correlation of the user factors and the participant's average evaluation across all topics[a]

Variable 1	Variable 2	r	Significance	N
Age (in years)	Gender	0.077	$p>0.999$	103
Age (in years)	Home country	–0.361	$p=0.003$**	103
Age (in years)	Mean Valence	0.178	$p=0.787$	103
Age (in years)	Mean Risk	0.019	$p>0.999$	103
Age (in years)	Mean Familiarity	0.044	$p>0.999$	103
Age (in years)	Mean Desire Societal Debate	0.082	$p>0.999$	103
Gender	Home country	–0.072	$p>0.999$	103
Gender	Mean Valence	–0.284	$p=0.054$	103
Gender	Mean Risk	0.128	$p>0.999$	103
Gender	Mean Familiarity	–0.330	$p=0.011$*	103
Gender	Mean Desire Societal Debate	–0.118	$p>0.999$	103
Home country	Mean Valence	–0.088	$p>0.999$	103
Home country	Mean Risk	0.065	$p>0.999$	103
Home country	Mean Familiarity	0.085	$p>0.999$	103
Home country	Mean Desire Societal Debate	0.250	$p=0.142$	103
Mean Valence	Mean Risk	–0.461	$p<0.001$***	103
Mean Valence	Mean Familiarity	0.292	$p=0.044$*	103
Mean Valence	Mean Desire Societal Debate	0.654	$p<0.001$***	103
Mean Risk	Mean Familiarity	–0.193	$p=0.609$	103
Mean Risk	Mean Desire Societal Debate	–0.258	$p=0.119$	103
Mean Familiarity	Mean Desire Societal Debate	0.396	$p<0.001$***	103

* $p<.05$, ** $p<.01$, *** $p<.001$

[a]Gender and country are dummy-coded (1 = male, 2 = female; 1 = Bulgaria, 2 = Germany)

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the world when you're born is normal and ordinary and is just a natural part of the way the world works. 2. Anything that's invented between when you're fifteen and thirty-five is new and exciting and revolutionary and you can probably get a career in it. 3. Anything invented after you're thirty-five is against the natural order of things." (Adams, 2002). We think this resonates well with the continuous evolution of technology and the ever-changing perspectives that come with it. We utilized Large Language Models (LLMs) for editing assistance with the manuscript and support with R coding. We did *not* use LLMs to write or hallucinate *any* part of the manuscript but to enhance our self-written text and improve the article's readability (typical prompts were "Social scientist here, writing an academic article. Can you edit the following paragraph. Tell me what you have edited and why."). For writing code for the data analysis, LLMs assisted us in expanding our analysis code (refer to the OSF repository) according to our specifications, under our supervision, and through manual validation; we did not use AI/LLMs for automated data analysis. Typical prompts included queries such as, "I am coding in R. I have two data frames, A and B. How do I merge these using the unique ID in tidyverse syntax?". The survey, the analysis, and the RMarkdown document of this article is publicly available: https://osf.io/nj5u4/. All authors state that there is no conflict of interest. Funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy – EXC-2023 Internet of Production – 390621612.

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