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Government regulation or industry self-regulation of AI? Investigating the relationships between uncertainty avoidance, people's AI risk perceptions, and their regulatory preferences in Europe

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Abstract
Artificial Intelligence (AI) has the potential to influence people's lives in various ways as it is increasingly integrated into important decision-making processes in key areas of society. While AI offers opportunities, it is also associated with risks. These risks have sparked debates about how AI should be regulated, whether through government regulation or industry self-regulation. AI-related risk perceptions can be shaped by national cultures, especially the cultural dimension of uncertainty avoidance. This raises the question of whether people in countries with higher levels of uncertainty avoidance might have different preferences regarding AI regulation than those with lower levels of uncertainty avoidance. Therefore, using Hofstede's uncertainty avoidance scale and data from ten European countries ($N = 7.855$), this study investigates the relationships between uncertainty avoidance, people's AI risk perceptions, and their regulatory preferences. The findings show that people in countries with higher levels of uncertainty avoidance are more likely to perceive AI risks in terms of a lack of accountability and responsibility. While people's perceived AI risk of a lack of accountability exclusively drives their preferences for government regulation of AI, the perceived AI risk of a lack of responsibility can foster people's requests for government regulation and/or industry self-regulation. This study contributes to a better understanding of which mechanisms shape people's preferences for AI regulation.

Keywords AI regulation · AI risks · Cultural dimensions · Uncertainty avoidance · Quantitative methods · Mediation analysis

1 Introduction

Artificial Intelligence (AI) has the potential to influence people's lives in various ways as it is increasingly integrated into crucial decision-making processes in key areas of society, such as governance, finance, healthcare, or journalism. While AI offers opportunities, it is also associated with risks (Buhmann and Fieseler 2023; Diakopoulos 2019; Faroldi 2024; Schepman and Rodway 2020; Sindermann et al. 2021). These risks have sparked debates about how AI should be regulated, whether through government regulation or industry self-regulation (Ferretti 2022).

Jurisdictions worldwide have been working on regulations, such as the European Union with the AI Act (Novelli et al. 2024a, b), which is a comprehensive legal framework on AI that aims "to promote the uptake of human-centric and trustworthy artificial intelligence" (European Union 2024; see also Helberger and Diakopoulos 2023; Schuett 2023). At the same time, industries have been following self-regulatory practices such as the Association for Computing Machinery's Code of Ethics and Professional Conduct, which states that AI designers and developers should ensure that AI systems align with ethical standards such as diversity and responsibility.

Risk perceptions and, ultimately, regulatory preferences regarding AI can be shaped by national cultures (Eitle and Buxmann 2020; Gerlich 2023), specifically, "the extent to which the members of a culture feel threatened by ambiguous or unknown situations" (Hofstede et al. 2010, 191), called *uncertainty avoidance*. Previous research has found that people from countries with a strong tendency toward

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uncertainty avoidance approach new technologies with apprehension and are, therefore, more critical of their adoption (Uğur 2017). Accordingly, people in countries with higher levels of uncertainty avoidance might have different preferences regarding AI regulation than those with lower levels of uncertainty avoidance. However, international-comparative research on people's preferences for AI regulation remains scarce (Kieslich et al. 2022), and the influence of uncertainty avoidance on people's regulatory preferences regarding AI has, to our knowledge, not been investigated.

Therefore, using Hofstede's (2015) uncertainty avoidance scale and data from ten European countries ($N=7.855$), this study investigates the relationships between uncertainty avoidance, people's AI risk perceptions, and their regulatory preferences. Regarding people's AI risk perceptions, we consider a lack of accountability, a lack of responsibility, and discrimination. Moreover, we consider government regulation and industry self-regulation regarding people's preferences for AI regulation.

2 Literature review

2.1 Uncertainty avoidance and AI

The decisions made by AI systems have "moral consequences" (Martin 2019, 835) for social coexistence. Accordingly, public debates on responsible AI and the informed use of AI systems are increasing. In these debates, critical voices emphasize the risks of "individual and societal harms that the misuse, abuse, poor design, or unintended negative consequences of AI systems may cause" (Leslie 2019, 4). Previous studies have shown that cultural dynamics can be relevant in this context, as they can influence people's risk perceptions associated with the use of AI (e.g., Ismatullaev and Kim 2024)—a finding that is consistent with research on the relationship between culture and people's willingness to engage with new information technologies (Erumban and de Jong 2006; Lekhanya 2013; Uğur 2017). In a literature review, Hagerty and Rubinov (2019) summarized findings on the differences in the perception of AI systems and the consequences of their implementation for societal development in five global regions. Their findings show that people's "perceptions and understandings of AI are likely to be profoundly shaped by [their] local cultural and social context" (2), as AI applications can "have a pattern of entrenching social divides and exacerbating social inequality, particularly among historically marginalized groups" (2). Similar points have been raised in other studies (e.g., Lee 2018). Cultural dynamics also affect technological (e.g., efficiency, process integration, commercial tools), organizational (e.g., talent acquisition, financial resources, organizational structures), and environmental (e.g., regulations, market competition, vendor selection criteria) determinants of AI adoption as they are directly related to management decisions (Eitle and Buxmann 2020).

According to the dimensionality model of national cultures, culture is "the collective programming of the mind that distinguishes the members of one group or category of people from others" (Hofstede et al. 2010, 6). Hofstede et al. (2010) proposed six cultural dimensions of which uncertainty avoidance has been most intensely investigated in relation to new technology engagement (Uğur 2017). Uncertainty avoidance refers to "the extent to which the members of a culture feel threatened by ambiguous or unknown situations" (Hofstede et al. 2010, 191). Research has found that people living in countries that score high on uncertainty avoidance are less open to engaging with new technologies (Uğur 2017). Studies investigating algorithm aversion, which refers to people's distrust of algorithmic decision-making, have drawn similar conclusions (Logg et al. 2019). For instance, Dietvorst and Bharti (2020) have found that people disapprove of algorithmic decision-making in uncertain situations and prefer human decision-making despite its less precise and often worse forecasting. These findings align with other studies that showed people's skepticism toward the trustworthiness of algorithms as decision-making entities (Dietvorst et al. 2015).

2.2 Risk perceptions and AI

Typically, people encounter AI with strong positive or negative emotions (Hou and Jung 2021)—a phenomenon likely boosted by the media hype regarding AI and the accompanying "ebullient mysticism […] around all of the possibilities algorithms create" (Diakopoulos 2019, 3). Some scholars argue that there is a "preponderance of negative views" (Schepman and Rodway 2020, 1) in public discussions about AI that feature various potential risks related to AI engagement and that emphasize the "exceptionally broad and intractable uncertainties about benefits, risks, and future trajectories [of AI]" (Wallach and Marchant 2019, 505). These views elicit mixed public opinions about AI systems' potential usefulness or fairness (Araujo et al. 2020) as well as risk perceptions that motivate people to request ethically acting AI systems (Fast and Horvitz 2017; Helberger, Araujo et al. 2020).

AI risks refer to "the anticipation of likely negative consequences related to the variety of applications of AI as a technology" (Neri and Cozman 2020, 663). Such negative consequences may vary in terms of their severity and probability (Faroldi 2024). AI risk perceptions (Helberger, van Drunen, et al. 2020) can be driven by personality traits (Wissing and Reinhard 2018), socioeconomic standing, or technology literacy (Zhang and Dafoe 2019). A negative relationship between perceived AI risks and people's willingness to engage with AI can be found in several domains, including professional environments (Bhargava et al. 2021), politics and government (Rufín et al. 2014; Yu et al. 2018), lifestyle (Sindermann et al. 2021), or media and psychology (Schwesig 2023).

As the need for AI that makes transparent decisions based on human moral standards becomes pressing (Boddington 2017; Greene et al. 2019; Hagendorff 2020), scholars have explored the possibility of implementing ethical standards into the design of AI systems (Müller 2020). However, the complexity of the concept of ethics aggravates a uniform solution. Approaches have become manifold, ranging from suggestions to inherently program ethical decision-making into the AI models' designs to taking a machine learning approach and leaving it to the AI to learn ethical decision-making from its environment (Baum 2020; Loreggia et al. 2018). Nevertheless, it has been argued that designing AI systems that entirely act ethically and can be used outside controlled environments remains "mostly intangible" (Martinho et al. 2021, 487).

Central risks associated with AI deployment discussed by scholars include a lack of accountability, a lack of responsibility, and discrimination (Buhmann and Fieseler 2023; Hagendorff 2020). The first two concepts—accountability and responsibility—are often used synonymously in the literature, although they have relevant differences (McGrath 2022). As Bivins (2006, 21) summarizes: "If responsibility is defined as a bundle of obligations, functional and moral, associated with a role, then accountability might be defined as'blaming or crediting someone for an action–normally an action associated with a recognized responsibility". Put differently, while accountability refers explicitly to the potentially negative outcome of an action and usually involves tracing that outcome back to the responsible actor, i.e., holding them to account, responsibility refers to the actor and their assigned role in an action in general. Thus, differentiating between responsibility and accountability entails separating "the obligation to satisfactorily perform a task (responsibility) from the liability to ensure that it is satisfactorily done (accountability)" (McGrath 2022, 299).

Novelli et al. (2024a, b) state that *accountability* is a cornerstone of AI governance, as it concerns identifying the actors involved in developing and deploying AI systems and holding them accountable for the consequences of the systems' use. As Dignum (2017, 5) puts it, "accountability in AI requires both the function of guiding action (by forming beliefs and making decisions), and the function of explanation (by placing decisions in a broader context and by classifying them along moral values)". Therefore, the risk of a lack of accountability relates to situations where there is nobody to hold accountable for adverse outcomes of AI systems (Buhmann and Fieseler 2023; Busuioc 2020; Novelli et al. 2024a, b). Conversely, positively perceived accountability benefits AI's perceived trustworthiness, usefulness, and convenience (Shin 2020).

However, technologically complex AI systems that draw on machine learning make it challenging to trace the responsible actors in AI decision-making processes (Leppänen et al. 2020). Some scholars argue that due to the opaque operating logic of these AI systems and their increasing autonomy as collaborative agents in certain situations, it may become increasingly difficult to hold humans accountable for the (adverse) outcomes of AI-based processes (Santoni de Sio and Mecacci 2021). In some settings (e.g., autonomous driving), research about perceived responsibility suggests that participants assign more responsibility to robots than humans (Hong et al. 2020).

Discrimination caused by AI systems may occur "when data-driven decision-support systems serve to perpetuate existing injustices related to ethnicity or gender, either because these systems are biased in their design or because human biases are picked up in the training data used for algorithms" (Buhmann and Fieseler 2023, 150). Barocas and Selbst (2016) differentiate between unintentional discrimination, which can stem from incorrect data labels, partial or non-representative training data, and proxies for social class membership, and intentional discrimination, which, for instance, relates to "intentionally bias[ing] the data collection process, purposefully mislabel[ling] examples, or deliberately [using] an insufficiently rich set of features" (712).

2.3 Preferences for AI regulation

International-comparative research on people's preferences for AI regulation remains scarce (Kieslich et al. 2022). One exception is a comparative study by Ehret (2022) that investigated people's preferences for AI public policy in Germany, the UK, India, Chile, and China. Findings show that people may request AI regulation by the government when its use could cause employment uncertainty. Thus, when threatened to be replaced by technology in the labor market, "citizens might prefer to use regulatory power [of the government] to prohibit certain types of AI" (Ehret 2022, 1792).

Findings in studies with national samples vary, supporting arguments about the cultural context's relevance (Hagerty and Rubinov 2019). For instance, Zhang and Dafoe (2019) found that in the US—a country that scores rather low on uncertainty avoidance (Hofstede 2015)—citizens lack confidence in government institutions to tackle the challenges of AI for society and, therefore, prefer industry-led regulation. Findings from a representative survey of citizens in Germany—a country that scores rather high on uncertainty avoidance (Hofstede 2015)—show a stronger preference for AI regulation by the government. More specifically, in Germany, "citizens want policymakers to govern the transparency and energy efficiency of AI" (König et al. 2023).

Aside from surveys with citizens, national agendas of AI regulation might also indicate culturally influenced public requests for AI regulation. Examining the two national contexts of the US and Germany (the latter being part of the European Union), a comparative analysis of regulation agendas showed that the US government takes much less precautionary action to regulate AI, which includes having a more lenient approach to data protection laws, compared to Germany (Eitle and Buxmann 2020). The authors explain their results with the "different degree[s] of uncertainty avoidance" (1) in the two countries.

3 Conceptual model and research questions

Research suggests that people from countries with higher levels of uncertainty avoidance are more skeptical of new technology adoption (Uğur 2017). This skepticism—expressed, among other things, as risk perceptions associated with the use of AI, for instance, regarding lacking accountability and responsibility or increased discrimination (Buhmann and Fieseler 2023; Hagendorff 2020)—has spurred calls for AI regulation to ensure the technology's ethical use (Helberger, Araujo et al. 2020; Chinen 2023). Although parts of the relationship between cultural predispositions, AI risk perceptions, and regulatory preferences regarding AI have been discussed in other studies, it has, to our knowledge, not yet been empirically investigated in its entirety.

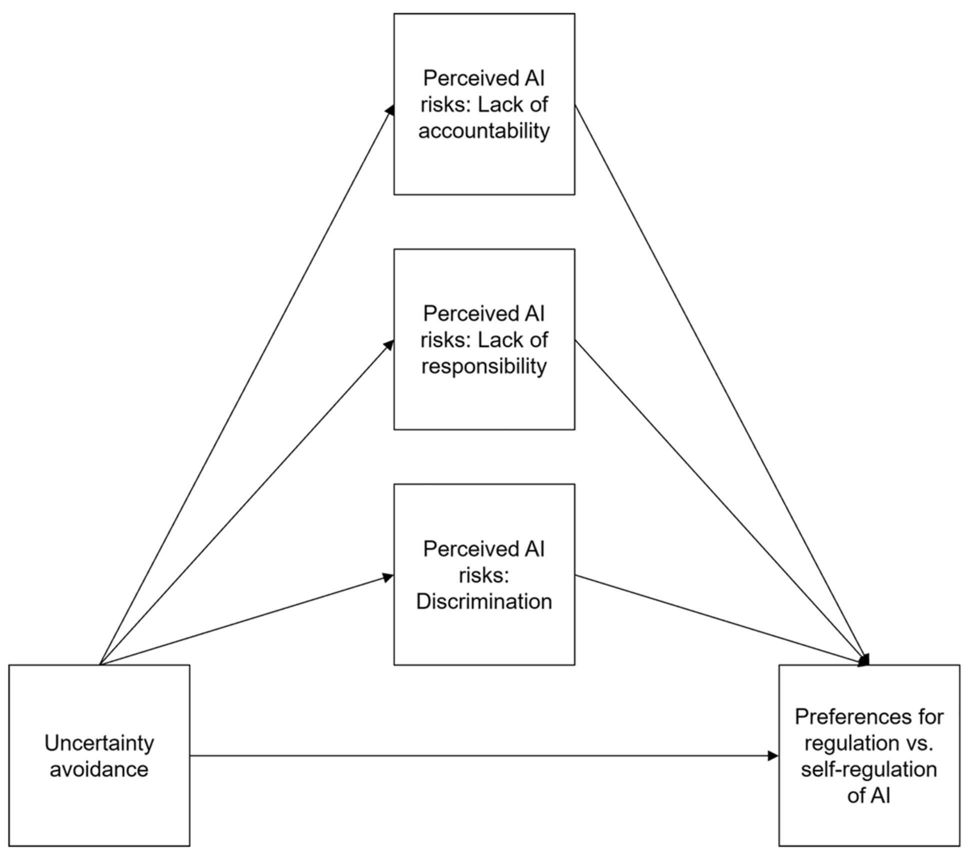
Therefore, this study presents a conceptual model (see Fig. 1) that draws on the above-reviewed literature regarding uncertainty avoidance and AI, risk perceptions and AI, and preferences for AI regulation to investigate the following overall research question: How are uncertainty avoidance, people's AI risk perceptions, and their preferences for AI regulation related? In addition, we raise the following specific research questions:

1%1 How does uncertainty avoidance relate to people's perceived AI risks regarding (a) a lack of accountability, (b) a lack of responsibility, and (c) discrimination?

2%1 How do people's perceived AI risks regarding (a) a lack of accountability, (b) a lack of responsibility, and (c) discrimination relate to people's preferences for government regulation of AI?

3%1 How do people's perceived AI risks regarding (a) a lack of accountability, (b) a lack of responsibility, and (c) discrimination relate to people's preferences for industry self-regulation of AI?

Fig. 1 Conceptual model



4 Methods

4.1 Data

This study investigates ten European countries: Austria, Germany, Denmark, Sweden, Ireland, the UK, France, Italy, the Czech Republic, and Poland. We selected these countries since their cultures are characterized by varying degrees of uncertainty avoidance (Hofstede et al. 2010). We obtained corresponding data from Hofstede (2015).

To obtain information about people's perceptions of AI risks, their preferences for government regulation or industry self-regulation of AI, as well as their gender, age, education, political ideology, and internet use, we used data from wave 92.3 of the Eurobarometer survey, which was conducted in November 2019. The data, thus, reflect people's opinions leading up to the EU AI Act negotiations, which took several years (Novelli et al. 2024a, b). To establish representativity, participants of the Eurobarometer survey were sampled in each country using a randomized, multi-stage approach. More specifically, in each country, "a number of sampling points was drawn with probability proportional to population size (for a total coverage of the country) and population density" (European Commission and European Parliament 2019, 76). Respondents with missing values were excluded from the analysis. This resulted in a final sample of $N = 7.855$ for the ten European countries (Austria: $N = 848$; Germany: $N = 853$, Denmark: $N = 880$, Sweden: $N = 937$, Ireland: $N = 760$, the UK: $N = 726$, France: $N = 682$, Italy: $N = 709$, Czech Republic: $N = 854$; Poland: $N = 606$).

4.2 Measurement

4.2.1 Independent variable

As indicated above, Hofstede (2010, 191) defines uncertainty avoidance as "the extent to which the members of a culture feel threatened by ambiguous or unknown situations". To measure the degree of uncertainty avoidance in a national culture, Hofstede (2015) developed the *Uncertainty Avoidance Index* (UAI) with a range between lower (toward 0) and higher (toward 100) extent of uncertainty avoidance. Based on this index, we measured uncertainty avoidance ($M = 56.73$; $SD = 23.947$) on an ordinal scale, with Denmark having the lowest extent of uncertainty avoidance and Poland the highest: Denmark ($UAI = 23$), Sweden ($UAI = 29$), the UK ($UAI = 35$), Ireland ($UAI = 35$), Germany ($UAI = 65$), Austria ($UAI = 70$), Czech Republic ($UAI = 74$), Italy ($UAI = 75$), France ($UAI = 86$) and Poland ($UAI = 93$).

4.2.2 Mediator variables

People's perceptions of AI risks were measured using three items: lack of accountability, lack of responsibility, and discrimination. In wave 92.3 of the Eurobarometer survey, these risks were queried as follows: "Which statements below, if any, would you select to finish the statement: You are concerned that the use of Artificial Intelligence could lead to …". In the case of a lack of accountability, the following option was given: "… situations where there is nobody to complain to in case of problems" (yes = 1; no = 0; yes = 39.34%); in the case of a lack of responsibility, the following option was given: "… situations where it is unclear who is responsible, for example in case of accidents caused by self-driving cars" (yes = 1; no = 0; yes = 50,40%); in the case of discrimination, the following option was given: "… discrimination in terms of age, gender, race or nationality, for example in taking decisions on recruitment, creditworthiness, etc." (yes = 1; no = 0; yes = 44,14%).

4.2.3 Dependent variables

People's preferences for government regulation or industry self-regulation of AI were queried in wave 92.3 of the Eurobarometer survey using the following question: "Which statement below do you agree most to finish the statement: To ensure that Artificial Intelligence applications are developed in an ethical manner …". In the case of government regulation of AI, the following option was given: "… public policy intervention is needed" (yes = 1; no = 0; yes = 58,41%); in the case of industry self-regulation of AI, the following option was given: "… industry providers of Artificial Intelligence can deal with these issues themselves" (yes = 1; no = 0; yes = 17,71%).

4.2.4 Control variables

As news may shape people's perceptions of AI risks and consequently their preferences for AI regulation (Diakopoulos 2019), we controlled for the media system of the investigated countries at the macro level following the approach by Hallin and Mancini (2004). The sample includes countries with a democratic corporatist media system, namely Austria and Germany (yes = 1; no = 0; yes = 21,66%) as well as Denmark and Sweden (yes = 1; no = 0; yes = 23,13%); Ireland and the UK (yes = 1; no = 0; yes = 18,92%) are countries with a liberal media system, and Italy and France (yes = 1; no = 0; yes = 17,71%) are countries with a polarized pluralist media system. Furthermore, the Czech Republic and Poland (yes = 1; no = 0; yes = 18,59%) belong to a central cluster within Eastern European media systems with high media ownership concentration, strong public service media, and low foreign ownership (Castro Herrero et al. 2017). For the statistical analyses, we used these two countries as the reference group.

At the micro level, we controlled for gender (1 = male; 0 = female; male = 49,39%), age (M = 51,08; SD = 17,99), education (0 = no full-time education; 3 = more than 20 years or still studying; M = 2,41; SD = 0,79), political ideology (1 = left; 9 = right; M = 5,18; SD = 2,09), and internet use (1 = never/no access; 6 = everyday/almost everyday; M = 5,2; SD = 1,63).

The descriptive statistics are summarized in Table 1. The bivariate correlations are presented in Table 2.

4.3 Data analysis

To answer our overall research question, we performed mediation analyses based on the approach introduced by Baron and Kenny (1986). Initially, the authors suggested sequentially verifying four conditions: first, the independent and dependent variables (c-paths) must be significantly related; second, the independent and mediator variables (a-paths) must be significantly related; third, the mediator and dependent variables (b-paths) must be significantly related (when controlling for the independent variable); fourth, the relationship between the independent and dependent variables must be significantly reduced when controlling the effect of the mediator variable (c'-paths).

However, since Baron and Kenny (1986) introduced the four-step approach, many scholars–among them, Kenny (2008)—have argued that only the second and third conditions are essential, i.e., mediation can occur even though the first and fourth conditions are not met (Pardo and Tabanera 2013). We follow this notion in our analysis but also report the other paths of the four-step approach. As this study's mediator and dependent variables have nominal scales, we tested the conditions using logistic regressions in SPSS. The dataset analyzed in this study can be obtained from the corresponding author upon request.

5 Findings

5.1 Logistic regressions: a-paths

Regarding RQ1, the findings show that uncertainty avoidance is significantly and positively related to the perceived AI risk of a lack of accountability (B = 0.015**) and the perceived AI risk of a lack of responsibility (B = 0.010*) but not to the perceived AI risk of discrimination (see Table 3). This indicates that respondents in a national culture with higher levels of uncertainty avoidance are more likely to perceive AI risks regarding a lack of accountability and a lack of responsibility.

5.2 Logistic regressions: b-paths

Regarding RQ2, the findings show that all three perceived AI risks are significantly and positively related to a preference for government regulation of AI, namely lack of accountability (B = 0.319***), lack of responsibility (B = 0.326***), and discrimination (B = 0.736***) (see Table 4). This indicates that respondents' perceptions of all three types of AI risks positively affect their preferences for the government to take on AI regulation.

Table 1 Descriptive statistics

	M	SD	%
Uncertainty avoidance (ordinal scale)	56,73	23,947	
Perceived AI risks: lack of accountability (1 = yes; 0 = no)			39,338
Perceived AI risks: lack of responsibility (1 = yes; 0 = no)			50,401
Perceived AI risks: discrimination (1 = yes; 0 = no)			44,137
Preferences: government regulation of AI (1 = yes; 0 = no)			58,409
Preferences: industry self-regulation of AI (1 = yes; 0 = no)			17,708
Democratic corporatist media system (Austria and Germany) (1 = yes; 0 = no)			21,655
Democratic corporatist media system (Denmark and Sweden) (1 = yes; 0 = no)			23,132
Liberal media system (1 = yes; 0 = no)			18,918
Polarized pluralist media system (1 = yes; 0 = no)			17,708
Eastern European media system (1 = yes; 0 = no)			18,587
Gender (1 = male; 0 = female)			49,395
Age (metrical scale)	51,08	17,955	
Education (ordinal scale)	2,41	0,795	
Political ideology (ordinal scale)	5,18	2,087	
Internet use (ordinal scale)	5,20	1,632	

N = 7.855

Table 2 Bivariate correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Uncertainty avoidance (ordinal scale)	–															
Perceived AI risks: lack of accountability (1 = yes; 0 = no)	0,024 *	–														
Perceived AI risks: lack of responsibility (1 = yes; 0 = no)	0,020	− 0,149 ***	–													
Perceived AI risks: discrimination (1 = yes; 0 = no)	− 0,031 **	− 0,14 ***	− 0,119 ***	–												
Preferences: government regulation of AI (1 = yes; 0 = no)	− 0,143 ***	0,083 ***	0,058 ***	0,188 ***	–											
Preferences: industry self-regulation of AI (1 = yes; 0 = no)	0,097 ***	− 0,055 ***	0,082 ***	− 0,037 ***	− 0,55 ***	–										
Democratic corporatist media system (Austria and Germany) (1 = yes; 0 = no)	0,236 ***	− 0,051 ***	0,051 ***	0,008	− 0,017	0,019	–									
Democratic corporatist media system (Denmark and Sweden) (1 = yes; 0 = no)	− 0,702 ***	0,03 **	− 0,055 ***	− 0,002	0,122 ***	− 0,134 ***	− 0,288 ***	–								
Liberal media system (1 = yes; 0 = no)	− 0,438 ***	− 0,047 ***	0,036 **	0,039 ***	0,035 **	0,048 ***	− 0,254 ***	− 0,265 ***	–							
Polarized pluralist media system (1 = yes; 0 = no)	0,458 ***	0,099 ***	− 0,066 ***	0,022 *	0,043 ***	− 0,02	− 0,244 ***	− 0,254 ***	− 0,224 ***	–						
Eastern European media system (1 = yes; 0 = no)	0,502 ***	− 0,028 *	0,034 **	− 0,067 ***	− 0,191 ***	0,096 ***	− 0,251 ***	− 0,262 ***	− 0,231 ***	− 0,222 ***	–					
Gender (1 = male; 0 = female)	− 0,054 ***	− 0,001	0,004	0,005	0,054 ***	− 0,004	0,007	0,05 ***	− 0,001	− 0,003	− 0,058 ***	–				
Age (metrical scale)	− 0,156 ***	0,039 ***	− 0,054 ***	0,008	0,088 ***	− 0,112 ***	− 0,047 ***	0,204 ***	− 0,034 **	− 0,023 *	− 0,115 ***	0,055 ***	–			
Education (ordinal scale)	− 0,121 ***	− 0,004	− 0,01	0,049 ***	0,089 ***	− 0,019	− 0,083 ***	0,194 ***	− 0,059 ***	− 0,025 *	− 0,039 ***	0,016	− 0,327 ***	–		
Political ideology (ordinal scale)	0,078 ***	0,028 *	0,022 *	− 0,077 ***	− 0,07 ***	0,039 ***	− 0,09 ***	− 0,036 ***	− 0,023 *	− 0,002	0,16 ***	0,015	0,043 ***	− 0,089 ***	–	
Internet use (ordinal scale)	− 0,146 ***	0,024 *	0,02	0,058 ***	0,074 ***	0,016	− 0,027 *	0,149 ***	− 0,004	− 0,049 ***	− 0,081 ***	0,004	− 0,411 ***	0,33 ***	− 0,052 ***	–

N = 7.855

*$p < 0{,}05$

**$p < 0{,}01$

***$p < 0{,}001$

Table 3 Logistic regressions—relationships between uncertainty avoidance and AI risk perceptions (a-paths)

	Perceived AI risks: lack of accountability		Perceived AI risks: lack of responsibility		Perceived AI risks: discrimination	
	B	Odds ratio	B	Odds ratio	B	Odds ratio
Uncertainty avoidance	0,015**	1,015	0,010*	1,010	− 0,002	0,998
Democratic corporatist media system (Austria and Germany)	0,140	1,150	0,227*	1,255	0,202*	1,223
Democratic corporatist media system (Denmark and Sweden)	1,008***	2,741	0,295	1,343	−0,051	0,951
Liberal media system	0,620**	1,859	0,512*	1,668	0,276	1,318
Polarized pluralist media system	0,568***	1,765	−0,386***	0,680	0,306***	1,357
Gender	−0,021	0,979	0,039	1,040	0,004	1,004
Age	0,006***	1,006	−0,005***	0,995	0,007***	1,007
Education	−0,022	0,978	−0,043	0,958	0,123***	1,131
Political ideology	0,027*	1,027	0,022*	1,022	−0,065***	0,937
Internet use	0,063***	1,065	0,018	1,018	0,083***	1,087
Constant	−2,475***	0,084	−0,575	0,563	−1,003*	0,367
	X^2 = 140,825; df = 10; p < 0,001		X^2 = 104,970; df = 10; p < 0,001		X^2 = 127,477; df = 10; p < 0,001	
	Nagelkerke R^2 = 0,024		Nagelkerke R^2 = 0,018		Nagelkerke R^2 = 0,022	
	Log-likelihood = 10,388,583		Log-likelihood = 10,783,867		Log-likelihood = 10,653,629	

N = 7.855

Regarding RQ3, the findings show that all three perceived AI risks are also significantly related to a preference for industry self-regulation of AI. However, the perceived lack of accountability ($B = -0.263^{***}$) and discrimination ($B = -0.163^{**}$) are negatively related, while the perceived lack of responsibility ($B = 0.358^{***}$) is positively related (see Table 5). This indicates that if respondents fear a lack of responsibility, they are more likely to accept industry self-regulation of AI. However, if respondents fear a lack of accountability or discrimination, they are more likely to disapprove of industry self-regulation of AI.

5.3 Logistic regressions: c′-paths

Moreover, as Table 4 further indicates, uncertainty avoidance is not significantly related to a preference for government regulation of AI when controlling for the perceived AI risks, namely lack of accountability, lack of responsibility, and discrimination. However, as Table 5 further shows, uncertainty avoidance is significantly related to a preference for industry self-regulation of AI when controlling for the perceived AI risks, namely lack of accountability ($B = 0.017^{**}$), lack of responsibility ($B = 0.015^{**}$), and discrimination ($B = 0.016^{**}$).

5.4 Logistic regressions: c-paths

Finally, as Table 6 indicates, uncertainty avoidance is not significantly related to a preference for government regulation of AI. However, as Table 7 shows, uncertainty avoidance is significantly and positively related to a preference for industry self-regulation of AI ($B = 0.016^{**}$).

6 Discussion

AI is integrated into crucial decision-making processes in key areas of society (Greene et al. 2019), influencing people's lives in various ways. While AI offers opportunities, it is also associated with risks (Buhmann and Fieseler 2023; Diakopoulos 2019; Foffano et al. 2023; Schepman and Rodway 2020; Sindermann et al. 2021). This has sparked debates regarding how AI should be regulated, whether through government regulation or industry self-regulation (Ferretti 2022).

In this context, international-comparative research on people's preferences for AI regulation remains scarce (Kieslich et al. 2022), which is surprising as research suggests that national cultures, especially the cultural dimension of uncertainty avoidance, potentially affect people's regulatory preferences (Eitle and Buxmann 2020). Against this

Table 4 Logistic regressions—relationships between AI risk perceptions and preferences for government regulation of AI (b- and c'-paths)

	Preferences: regulation of AI		Preferences: regulation of AI		Preferences: regulation of AI	
	B	Odds ratio	B	Odds ratio	B	Odds ratio
Perceived AI risks: lack of accountability	0,319***	1,376				
Perceived AI risks: lack of responsibility			0,326***	1,385		
Perceived AI risks: discrimination					0,736***	2,088
Uncertainty avoidance (c'-paths)	−0,002	0,998	−0,001	0,999	0,000	1,000
Democratic corporatist media system (Austria and Germany)	0,630***	1,878	0,625***	1,868	0,627***	1,873
Democratic corporatist media system (Denmark and Sweden)	0,825**	2,281	0,883**	2,418	0,951**	2,589
Liberal media system	0,789**	2,202	0,799**	2,223	0,822**	2,276
Polarized pluralist media system	0,865***	2,375	0,940***	2,56	0,878***	2,407
Gender	0,157**	1,170	0,152**	1,164	0,158**	1,171
Age	0,015***	1,015	0,016***	1,016	0,014***	1,015
Education	0,239***	1,269	0,241***	1,272	0,220***	1,247
Political ideology	−0,045***	0,956	−0,045***	0,956	−0,032**	0,968
Internet use	0,099***	1,104	0,102***	1,107	0,092***	1,096
Constant	−1,990***	0,137	−2,142***	0,117	−2,285***	0,102
	X^2 = 544,882; df = 11; p < 0,001		X^2 = 549,281; df = 11; p < 0,001		X^2 = 732,869; df = 11; p < 0,001	
	Nagelkerke R^2 = 0,090		Nagelkerke R^2 = 0,091		Nagelkerke R^2 = 0,120	
	Log-Likelihood = 10,121,245		Log-Likelihood = 10,116,845		Log-Likelihood = 9933,258	

N = 7.855

background, this study investigated *how uncertainty avoidance, people's AI risk perceptions, and their preferences for AI regulation are related.*

As Fig. 2 summarizes, uncertainty avoidance is indirectly related to people's preferences for government regulation of AI in two ways. Here, the second and third conditions of mediation are met (Pardo and Tabanera 2013). First, the higher the level of uncertainty avoidance in a country, the more likely people in such a country perceive a lack of accountability as an AI risk. This, in turn, increases their preferences for government regulation of AI. Second, the higher the level of uncertainty avoidance in a country, the more likely people in such a country perceive a lack of responsibility as an AI risk. This, in turn, also increases their preferences for government regulation of AI.

As Fig. 3 summarizes, uncertainty avoidance is also indirectly related to people's preferences for industry self-regulation of AI in two ways. Here, the second and third conditions of mediation are also met (Pardo and Tabanera 2013). First, the higher the level of uncertainty avoidance in a country, the more likely people in such a country perceive a lack of accountability as an AI risk. This, in turn, decreases their preferences for industry self-regulation of AI. Second, the higher the level of uncertainty avoidance in a country, the more likely people in such a country perceive a lack of responsibility as an AI risk. This, in turn, increases their preferences for industry self-regulation of AI.

In sum, the findings show that, in European countries that score higher on uncertainty avoidance, people are more likely to perceive AI risks regarding a lack of responsibility (i.e., situations where it is unclear who is responsible for AI-related actions). To mitigate such responsibility-related risks, both government regulation and industry self-regulation of AI are considered viable solutions. Moreover, in European countries with higher uncertainty avoidance, people are also more likely to perceive AI risks regarding a lack of accountability (i.e., situations where there is nobody to address in case of problems caused by AI-related actions). To mitigate accountability-related risks, only government regulation is considered a viable option.

These results suggest that uncertainty avoidance as a cultural predisposition evokes AI-related concerns among

Table 5 Logistic regressions—relationships between AI risk perceptions and preferences for industry self-regulation of AI (b- and c'-paths)

	Preferences: self-regulation of AI		Preferences: self-regulation of AI		Preferences: self-regulation of AI	
	B	Odds ratio	B	Odds ratio	B	Odds ratio
Perceived AI risks: lack of accountability	−0,263***	0,769				
Perceived AI risks: lack of responsibility			0,358***	1,430		
Perceived AI risks: discrimination					−0,163**	0,85
Uncertainty avoidance (c'-paths)	0,017**	1,017	0,015**	1,015	0,016**	1,016
Democratic corporatist media system (Austria and Germany)	−0,058	0,944	−0,092	0,912	−0,065	0,937
Democratic corporatist media system (Denmark and Sweden)	−0,145	0,865	−0,251	0,778	−0,225	0,799
Liberal media system	0,651*	1,918	0,552*	1,737	0,609*	1,838
Polarized pluralist media system	−0,446***	0,640	−0,452***	0,636	−0,472***	0,624
Gender	0,058	1,060	0,054	1,056	0,059	1,061
Age	−0,014***	0,986	−0,014***	0,986	−0,014***	0,986
Education	−0,101*	0,903	−0,098*	0,907	−0,097*	0,907
Political ideology	0,040**	1,041	0,036*	1,036	0,035*	1,036
Internet use	0,013	1,013	0,008	1,008	0,013	1,013
Constant	−1,829***	0,161	−1,910***	0,148	−1,731**	0,177
	X^2 = 297,005; df = 11; p < 0,001		X^2 = 314,247; df = 11; p < 0,001		X^2 = 286,756; df = 11; p < 0,001	
	Nagelkerke R^2 = 0,061		Nagelkerke R^2 = 0,065		Nagelkerke R^2 = 0,059	
	Log-Likelihood = 7038,683		Log-Likelihood = 7021,442		Log-Likelihood = 7048,933	

N = 7.855

Table 6 Logistic regression—relationship between uncertainty avoidance and preferences for government regulation of AI (c-path)

	Preferences: regulation of AI	
	B	Odds ratio
Uncertainty avoidance	−0,001	0,999
Democratic corporatist media system (Austria and Germany)	0,639***	1,894
Democratic corporatist media system (Denmark and Sweden)	0,898**	2,456
Liberal media system	0,833***	2,301
Polarized pluralist media system	0,904***	2,468
Gender	0,155**	1,167
Age	0,015***	1,015
Education	0,236***	1,266
Political ideology	−0,043***	0,958
Internet use	0,103***	1,108
Constant	−2,012***	0,134
	X^2 = 502,748; df = 10; p < 0,001	
	Nagelkerke R^2 = 0,083	
	Log-Likelihood = 10,163,378	

N = 7.855

Table 7 Logistic regression—relationship between uncertainty avoidance and preferences for industry self-regulation of AI (c-path)

	Preferences: self-regulation of AI	
	B	Odds ratio
Uncertainty avoidance	0,016**	1,016
Democratic corporatist media system (Austria and Germany)	− 0,068	0,934
Democratic corporatist media system (Denmark and Sweden)	− 0,209	0,812
Liberal media system	0,609*	1,839
Polarized pluralist media system	− 0,483***	0,617
Gender	0,059	1,061
Age	− 0,015***	0,985
Education	− 0,101*	0,904
Political ideology	0,038*	1,038
Internet use	0,009	1,009
Constant	− 1,793***	0,166
	X^2 = 279,749; df = 10; p < 0,001	
	Nagelkerke R^2 = 0,058	
	Log-Likelihood = 7055,940	

N = 7.855

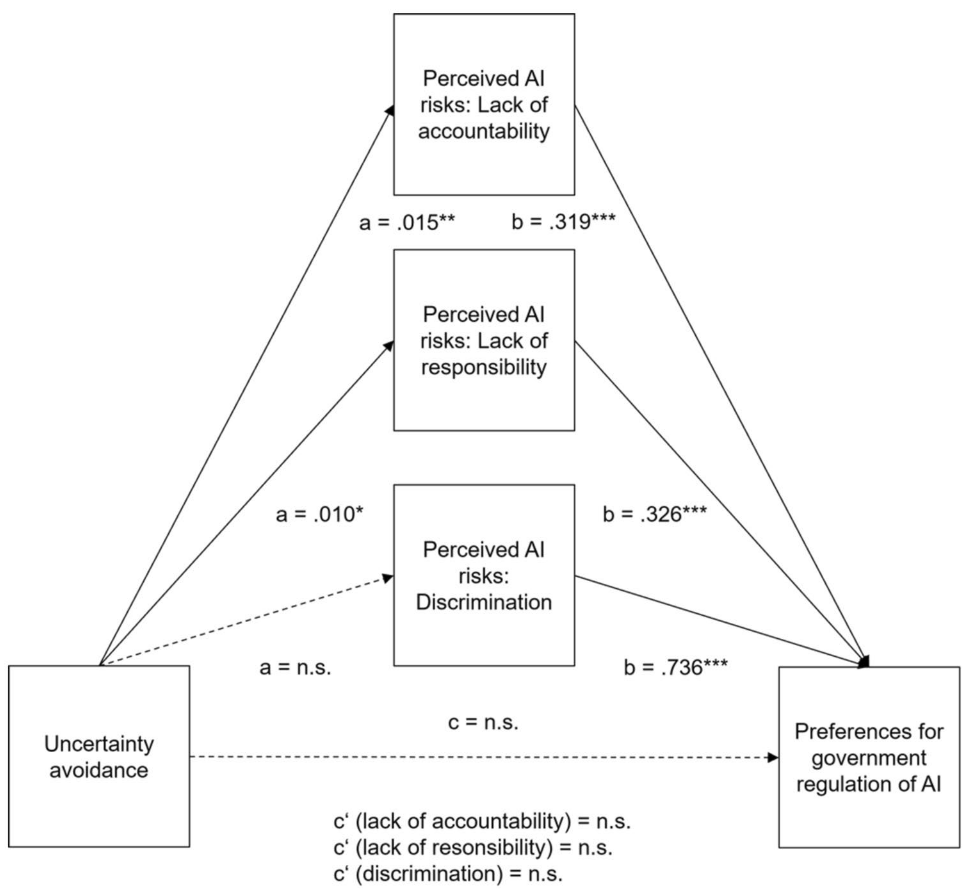


Fig. 2 Summary of the findings—relationships between uncertainty avoidance, people's perceived AI risks, and their preferences for government regulation of AI

people regarding identifying and addressing responsible actors who should have control over AI processes and their outcomes. In cases where the general responsibility of actors plays a role—i.e., in situations where it is unclear who is responsible—both government and industry are seen as possible solution-finding regulatory authorities. However, when

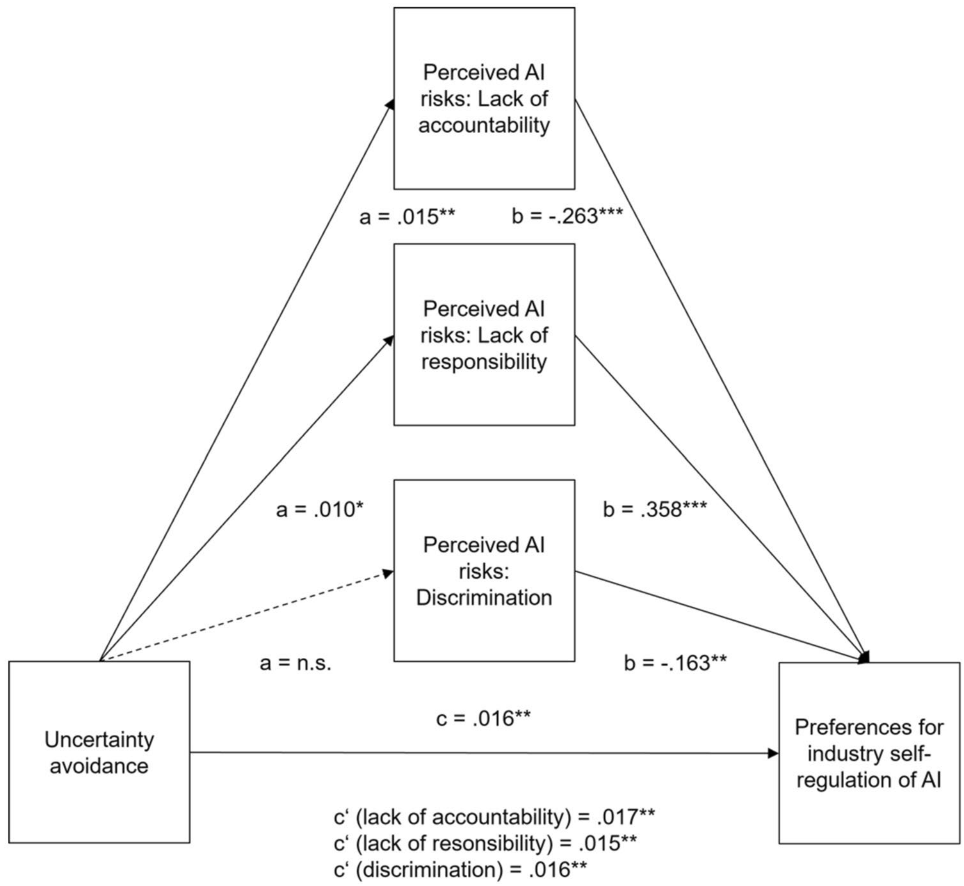


Fig. 3 Summary of the findings—relationships between uncertainty avoidance, people's perceived AI risks, and their preferences for industry self-regulation of AI

accountable entities need to be found—i.e., in situations where there is nobody to complain to in case of problems—the industry is no longer considered a viable solution-finding option in countries that score higher on uncertainty avoidance. Instead, government regulation is desired. This also relates to the journalism sector, where, "typically", the "editor-in-chief" is accountable for the implementation and outcome of journalistic AI (Steering Committee on Media and Information Society of the Council of Europe 2023, p. 13).

These findings support previous research on the relationship between uncertainty avoidance and the perceived risks of new technology engagement (Uğur 2017), including AI (Eitle and Buxmann 2020). Furthermore, these results show which regulatory preferences arise from such risk perceptions. Therefore, this study's results are relevant to academic discussions on AI and provide concrete points of reference for political and economic AI practice.

7 Conclusion

Our findings suggest that culture is a relevant factor that shapes people's preferences for AI regulation. More specifically, the findings show that people in countries with higher levels of uncertainty avoidance are more likely to perceive AI risks in terms of a lack of accountability and responsibility. While people's perceived AI risks of a lack of accountability exclusively drive their preferences for government regulation of AI, the perceived AI risks of a lack of responsibility can foster people's requests for government regulation and/or industry self-regulation. These findings contribute to a better understanding of which mechanisms shape people's preferences regarding AI regulation (Eitle and Buxmann 2020). These findings also provide possible explanations for why differences in national cultures may constrain the development of international public policy interventions, such as the EU AI Act, which underwent several years of negotiations among politicians who represented the culturally diverse EU member states (Novelli et al. 2024a, b).

The perceived "priority of government regulation over self-regulation" (Ferretti 2022, 239) in countries with higher levels of uncertainty avoidance could be explained by the advantages of public policy interventions and the disadvantages of self-regulatory approaches. Government regulation might increase the scrutiny of AI applications and enhance responsible AI innovation and deployment (Buhmann and Fieseler 2023). Moreover, robust regulation by governmental actors such as the European Union (Krarup and Horst 2023;

Novelli et al. 2024a, b) could shape global standards for AI ethics. Companies worldwide might align their AI development and deployment with such regulations to ensure market access. However, such regulatory frameworks for AI must be flexible enough not to restrict AI innovation (Li et al. 2023; Morley et al. 2021). Instead, they should be adapted to the rapid technological advances in the field of AI (Hoffmann and Nurski 2021).

Conversely, self-regulation relies on the willingness of companies to cooperate, which can be limited by conflicting views about AI governance (Mökander and Floridi 2023) as well as conflicts of interest between commercial objectives and societal well-being (Lancaster et al. 2024). Since the impacts of AI technologies are international, industry self-regulation without international governance, as for example by the EU with the EU AI Act, may lead to fragmented or inconsistent regulatory frameworks, hindering international standardization (Chinen 2023).

The limitations of this study point to possible directions for future research. While this study considered AI risks regarding a lack of accountability, a lack of responsibility, and discrimination, future research could investigate further risks associated with AI and how they relate to people's regulatory preferences (Buhmann and Fieseler 2021). Moreover, future research could compare people's regulatory preferences for specific AI domains such as governance, finance, healthcare, or journalism (Greene et al. 2019; Helberger and Diakopoulos 2023). Finally, while this study focused on European countries, future research could compare countries in different global regions to investigate people's preferences regarding AI regulation.

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Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

Araujo T, Helberger N, Kruikemeier S, de Vreese CH (2020) In AI we trust? Perceptions about automated decision-making by artificial intelligence. AI Soc 35:611–623. https://doi.org/10.1007/s00146-019-00931-w

Barocas S, Selbst AD (2016) Big data's disparate impact. Calif Law Rev 671:671–732. https://doi.org/10.5779/Z38BG31

Baron RM, Kenny DA (1986) The moderator-mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. J Pers Soc Psychol 51:1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173

Baum SD (2020) Social choice ethics in artificial intelligence. AI Soc 35:165–176. https://doi.org/10.1007/s00146-017-0760-1

Bhargava A, Bester M, Bolton L (2021) Employees' perceptions of the implementation of robotics, artificial intelligence, and automation (RAIA) on job satisfaction, job security, and employability. J Technol Behav Sci 6:106–113. https://doi.org/10.1007/s41347-020-00153-8

Bivins TH (2006) Responsibility and accountability. In: Fitzpatrick K, Bronstein C (eds) Ethics in public relations: responsible advocacy. Sage, Thousand Oaks, pp 19–38

Boddington P (2017) Towards a code of ethics for artificial intelligence. Springer, Cham

Buhmann A, Fieseler C (2021) Towards a deliberative framework for responsible innovation in artificial intelligence. Technol Soc 64:101475. https://doi.org/10.1016/j.techsoc.2020.101475

Buhmann A, Fieseler C (2023) Deep learning meets deep democracy: deliberative governance and responsible innovation in artificial intelligence. Bus Ethics Q 33:146–179. https://doi.org/10.1017/beq.2021.42

Busuioc M (2021) Accountable artificial intelligence: Holding algorithms to account. Public Adm Rev 81:825–836. https://doi.org/10.1111/puar.13293

Chinen M (2023) The international governance of artificial intelligence. Edward Elgar Publishing, Cheltenham

Diakopoulos N (2019) Automating the news: how algorithms are rewriting the media. Harvard University Press, Harvard

Dietvorst BJ, Bharti S (2020) People reject algorithms in uncertain decision domains because they have diminishing sensitivity to forecasting error. Psychol Sci 31:1302–1314. https://doi.org/10.1177/0956797620948841

Dietvorst BJ, Simmons JP, Massey C (2015) Algorithm aversion: people erroneously avoid algorithms after seeing them err. J Exp Psychol Gen 144:114–126. https://doi.org/10.1037/xge0000033

Ehret S (2022) Public preferences for governing AI technology: comparative evidence. J Eur Publ Policy 29:1779–1798. https://doi.org/10.1080/13501763.2022.2094988

Erumban AA, de Jong SB (2006) Cross-country differences in ICT adoption: a consequence of culture? J World Bus 41:302–314. https://doi.org/10.1016/j.jwb.2006.08.005

Faroldi FLG (2024) Risk and artificial general intelligence. AI Soc. https://doi.org/10.1007/s00146-024-02004-z

Fast E, Horvitz E (2017) Long-term trends in the public perception of artificial intelligence. Proc Thirty-First AAAI Conf Artif Intell 31:963–969. https://doi.org/10.1609/aaai.v31i1.10635

Ferretti T (2022) An institutionalist approach to AI ethics: justifying the priority of government regulation over self-regulation. Moral Philos Politics 9:239–265. https://doi.org/10.1515/mopp-2020-0056

Foffano F, Scantamburlo T, Cortés A (2023) Investing in AI for social good: an analysis of European national strategies. AI Soc 38:479–500. https://doi.org/10.1007/s00146-022-01445-8
Gerlich M (2023) Perceptions and acceptance of artificial intelligence: a multi-dimensional study. Soc Sci 12:502. https://doi.org/10.3390/socsci12090502
Hagendorff T (2020) The ethics of AI ethics: an evaluation of guidelines. Mind Mach 30:99–120. https://doi.org/10.1007/s11023-020-09517-8
Hagerty A, Rubinov I (2019) Global AI ethics: a review of the social impacts and ethical implications of artificial intelligence (version 1). arXiv. https://doi.org/10.48550/ARXIV.1907.07892
Hallin DC, Mancini P (2004) Comparing media systems: three models of media and politics. Cambridge University Press, Cambridge
Helberger N, Diakopoulos N (2023) The European AI Act and how it matters for research into AI in media and journalism. Digit J 11:1751–1760. https://doi.org/10.1080/21670811.2022.2082505
Helberger N, Araujo T, de Vreese CH (2020) Who is the fairest of them all? Public attitudes and expectations regarding automated decision-making. Comput Law Secur Rev. https://doi.org/10.1016/j.clsr.2020.105456
Hofstede G (2015) National differences in communication styles. In: Brzozowska D, Chłopicki W (eds) Culture's software: communication styles. Cambridge Scholars, Cambridge, pp 1–14
Hofstede GH, Hofstede GJ, Minkov M (2010) Cultures and organizations: software of the mind: intercultural cooperation and its importance for survival, 3rd edn. McGraw-Hill, New York
Hong J-W, Wang Y, Lanz P (2020) Why is artificial intelligence blamed more? Analysis of faulting artificial intelligence for self-driving car accidents in experimental settings. Int J Hum Comput Interact 36:1768–1774. https://doi.org/10.1080/10447318.2020.1785693
Hou YT-Y, Jung MF (2021) Who is the expert? Reconciling algorithm aversion and algorithm appreciation in AI-supported decision making. Proc ACM Hum Comput Interact 5:477. https://doi.org/10.1145/3479864
Ismatullaev UVU, Kim S-H (2024) Review of the factors affecting acceptance of AI-infused systems. Hum Factors J Hum Factors Ergon Soc 66:126–144. https://doi.org/10.1177/00187208211064707
Kenny DA (2008) Reflections on mediation. Organ Res Methods 11:353–358. https://doi.org/10.1177/1094428107308978
Kieslich K, Keller B, Starke C (2022) Artificial intelligence ethics by design. Evaluating public perception on the importance of ethical design principles of artificial intelligence. Big Data Soc. https://doi.org/10.1177/20539517221092956
König PD, Wurster S, Siewert MB (2023) Sustainability challenges of artificial intelligence and citizens' regulatory preferences. Gov Inf Q 40:101863. https://doi.org/10.1016/j.giq.2023.101863
Krarup T, Horst M (2023) European artificial intelligence policy as digital single market making. Big Data Soc. https://doi.org/10.1177/20539517231153811
Lancaster CM, Schulenberg K, Flathmann C, McNeese NJ, Freeman G (2024) "It's everybody's role to speak up... but not everyone will": Understanding AI professionals' perceptions of accountability for AI bias mitigation. ACM J Responsib Comput. https://doi.org/10.1145/3632121
Lee MK (2018) Understanding perception of algorithmic decisions: fairness, trust, and emotion in response to algorithmic management. Big Data Soc. https://doi.org/10.1177/2053951718756684
Lekhanya LM (2013) Cultural influence on the diffusion and adoption of social media technologies by entrepreneurs in rural South Africa. Int Bus Econ Res J (IBER) 12:1563–1574. https://doi.org/10.19030/iber.v12i12.8250
Leppänen L, Tuulonen H, Sirén-Heikel S (2020) Automated journalism as a source of and a diagnostic device for bias in reporting. Media Commun 8:39–49. https://doi.org/10.17645/mac.v8i3.3022
Leslie D (2019) Understanding artificial intelligence ethics and safety: a guide for the responsible design and implementation of AI systems in the public sector. The Alan Turing Institute, London
Li S, Schütte B, Sankari S (2023) The ongoing AI-regulation debate in the EU and its influence on the emerging economies: a new case for the "Brussels Effect"? In: Findlay M, Ong LM, Zhang W (eds) Elgar companion to regulating AI and big data in emerging economies. Edward Elgar Publishing, Cheltenham, pp 22–41
Logg JM, Minson JA, Moore DA (2019) Algorithm appreciation: People prefer algorithmic to human judgment. Organ Behav Hum Decis Process 151:90–103. https://doi.org/10.1016/j.obhdp.2018.12.005
Martin K (2019) Ethical implications and accountability of algorithms. J Bus Ethics 160:835–850. https://doi.org/10.1007/s10551-018-3921-3
Martinho A, Poulsen A, Kroesen M, Chorus C (2021) Perspectives about artificial moral agents. AI Ethics 1:477–490. https://doi.org/10.1007/s43681-021-00055-2
McGrath SK (2022) Speaking management: how to spot language traps and resolve contested management terms. Springer, Singapore
Mökander J, Floridi L (2023) Operationalising AI governance through ethics-based auditing: an industry case study. AI Ethics 3:451–468. https://doi.org/10.1007/s43681-022-00171-7
Morley J, Elhalal A, Garcia F, Kinsey L, Mökander J, Floridi L (2021) Ethics as a service: a pragmatic operationalization of AI ethics. Mind Mach 31:239–256. https://doi.org/10.1007/s11023-021-09563-w
Müller VC (2020) Ethics of artificial intelligence and robotics. In: Zalta EN, Nodelman U (eds) The Stanford Encyclopedia of Philosophy. Stanford University Metaphysics Research Lab, Stanford
Neri H, Cozman F (2020) The role of experts in the public perception of risk of artificial intelligence. AI Soc 35:663–673. https://doi.org/10.1007/s00146-019-00924-9
Novelli C, Taddeo M, Floridi L (2024a) Accountability in artificial intelligence: what it is and how it works. AI Soc 39:1871–1882. https://doi.org/10.1007/s00146-023-01635-y
Novelli C, Casolari F, Rotolo A, Taddeo M, Floridi L (2024b) Taking AI risks seriously: a new assessment model for the AI act. AI & Soc 39:2493–2497. https://doi.org/10.1007/s00146-023-01723-z
Pardo A, Tabanera MR (2013) Reflections on the Baron and Kenny model of statistical mediation. Anales de Psicología 29:614–623. https://doi.org/10.6018/analesps.29.2.139241
Rufín R, Bélanger F, Molina CM, Carter L, Figueroa JCS (2014) A cross-cultural comparison of electronic government adoption in Spain and the USA. Int J Electron Gov Res 10:43–59. https://doi.org/10.4018/ijegr.2014040104
Santoni de Sio F, Mecacci G (2021) Four responsibility gaps with artificial intelligence: why they matter and how to address them. Philos Technol 34:1057–1084. https://doi.org/10.1007/s13347-021-00450-x
Schepman A, Rodway P (2020) Initial validation of the general attitudes towards artificial intelligence scale. Comput Hum Behav Rep 1:100014. https://doi.org/10.1016/j.chbr.2020.100014
Schuett J (2024) Risk management in the artificial intelligence act. Eur J Risk Regul 15:367–385. https://doi.org/10.1017/err.2023.1
Schwesig R, Brich I, Buder J, Huff M, Said N (2023) Using artificial intelligence (AI)? Risk and opportunity perception of AI predict people's willingness to use AI. J Risk Res 26:1053–1084. https://doi.org/10.1080/13669877.2023.2249927
Shin D (2020) User perceptions of algorithmic decisions in the personalized AI system: perceptual evaluation of fairness, accountability, transparency, and explainability. J Broadcast Electron Media 64:541–565. https://doi.org/10.1080/08838151.2020.1843357

Sindermann C, Sha P, Zhou M, Wernicke J, Schmitt HS, Li M, Sariyska R, Stavrou M, Becker B, Montag C (2021) Assessing the attitude towards artificial intelligence: Introduction of a short measure in German, Chinese, and English language. KI - Künstliche Intelligenz 35:109–118. https://doi.org/10.1007/s13218-020-00689-0

Uğur NG (2017) Cultural differences and technology acceptance: a comparative study. J Media Crit 3:123–132. https://doi.org/10.17349/jmc117310

Wallach W, Marchant G (2019) Toward the agile and comprehensive international governance of AI and robotics [point of view]. Proc IEEE 107:505–508. https://doi.org/10.1109/JPROC.2019.2899422

Wissing BG, Reinhard M-A (2018) Individual differences in risk perception of artificial intelligence. Swiss J Psychol 77:149–157. https://doi.org/10.1024/1421-0185/a000214

Zhang B, Dafoe A (2019) Artificial intelligence: American attitudes and trends. Centre for the Governance of AI, Oxford

Castro Herrero L, Humprecht E, Engesser S, Brüggemann M, Büchel F (2017) Rethinking Hallin and Mancini beyond the West: an analysis of media systems in Central and Eastern Europe. International Journal of Communication. 11: 4797–4823. https://ijoc.org/index.php/ijoc/article/view/6035/2196

Dignum V (2017) Responsible artificial intelligence: designing AI for human values. ITU Journal: ICT Discoveries 1:1–8. http://handle.itu.int/11.1002/pub/8129fdfb-en

Eitle V, Buxmann P (2020) Cultural differences in machine learning adoption: an international comparison between Germany and the United States. In: Proceedings of the 28th European Conference on Information Systems (ECIS)

European Commission and European Parliament, Brussels (2019) Eurobarometer 92.3. https://search.gesis.org/research_data/ZA7601?doi=https://doi.org/10.4232/1.13564

European Union (2024) Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence and amending Regulations (EC) No 300/2008, (EU) No 167/2013, (EU) No 168/2013, (EU) 2018/858, (EU) 2018/1139 and (EU) 2019/2144 and Directives 2014/90/EU, (EU) 2016/797 and (EU) 2020/1828 (Artificial Intelligence Act) Text with EEA relevance. http://data.europa.eu/eli/reg/2024/1689/oj. Accessed 02 Oct 2024

Greene D, Hoffmann AL, Stark L (2019) Better, nicer, clearer, fairer: a critical assessment of the movement for ethical artificial intelligence and machine learning. In: Proceedings of the 52nd Hawaii International Conference on System Sciences. pp. 2122–2131

Helberger N, van Drunen M, Eskens S, Bastian M, Moeller J (2020) A freedom of expression perspective on AI in the media – with a special focus on editorial decision making on social media platforms and in the news media. European Journal of Law and Technology 11. https://ejlt.org/index.php/ejlt/article/view/752/1019

Hoffmann M, Nurski L (2021) What is holding back artificial intelligence adoption in Europe? Policy Contribution 24/2021, Bruegel

Loreggia A, Mattei N, Rossi F, Venable KB (2018) Preferences and ethical principles in decision making. In: Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society. ACM, New Orleans. pp. 222–222

Steering Committee on Media and Information Society of the Council of Europe (2023) Guidelines on the responsible implementation of artificial intelligence systems in journalism. Retrieved 27 Jul 2024, from https://www.coe.int/en/web/freedom-expression/-/guidelines-on-the-responsible-implementation-of-artificial-intelligence-ai-systems-in-journalism.

Yu H, Shen Z, Miao C, et al (2018) Building ethics into artificial intelligence. In: Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence. International Joint Conferences on Artificial Intelligence Organization, Stockholm. pp 5527–5533