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Sustainability challenges of artificial intelligence and Citizens' regulatory preferences

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ABSTRACT

Following the idea that citizens' regulatory preferences matter for the acceptance and success of policy measures, this paper investigates citizens' support for the regulation of Artificial Intelligence (AI). The focus lies on the transparency and the ecological sustainability of AI as two key challenges tied to possible long-term impacts on societies. Findings from survey data representative of the German population show overall moderate to strong support for the government regulating AI. Perceived regulatory competence of policymakers is positively associated with citizens' support for soft regulation. Lower trust in tech companies is linked to a lower readiness to rely on soft regulation, but not to more demand for hard regulation. While regulatory preferences barely map on political conflict lines, people's future orientation emerges as a strong correlate of support for both hard and soft regulation. Citizens thus seem to perceive a clear sustainability dimension in the development and governance of AI.

1. Introduction

Information technologies and applications of Artificial Intelligence (AI), both in government and in the private sector, offer novel solutions for addressing sustainability challenges (Estevez & Janowski, 2013; Vinuesa, Azizpour, Leite, et al., 2020; Zuiderwijk, Chen, & Salem, 2021). However, they also create problems of their own in regard to sustainability (Kankanhalli, Charalabidis, & Mellouli, 2019; Nishant, Kennedy, & Corbett, 2020; van Wynsberghe, 2021). Governing the trajectory of technological and societal change with a view toward the sustainability of emerging technology, like AI, demands a suitable choice of regulatory instruments by policymakers. This paper focuses on the issue of regulation for sustainable AI from a perspective that centers on citizens' views. It studies regulatory preferences concerning aspects of AI for mass consumer markets that are linked to long-term impacts of the technology use. In this way, it offers insights on the question of what form of regulation – if any – do citizens want from their governments and for what reasons.

This perspective is rooted in the central assumption, drawn from the existing literature on regulatory preferences, that the extent to which policies align with citizens' preferences matters for whether policies are successfully adopted and effective (e.g. Ingold, Stadelmann-Steffen, & Kammermann, 2019; Wüstenhagen, Wolsink, & Bürer, 2007). Previous research has shown that there is often considerable variation in what regulation citizens want and that this variation is linked to citizens dispositions, including their personal values and political attitudes (e.g. Dietz, Dan, & Shwom, 2007; Harring, 2016; Harring & Jagers, 2013; Kallbekken, Garcia, & Korneliussen, 2013; Leiserowitz, 2006; Steg, Dreijerink, & Abrahamse, 2005; Stoutenborough, Bromley-Trujillo, & Vedlitz, 2014, 2014; Tosun, Schaub, & Fleig, 2020). Looking at citizens' regulatory preferences can yield insights into which policies are expected to be supported – and thus likely to meet with compliance – and for what reasons. This is especially relevant in fields addressing emerging technology, such as AI, where a political debate on suitable regulation is ongoing and regulation is inchoate.

Empirical evidence on citizens' preferences concerning the regulation of AI, particularly regarding sustainability, is still sparse. Studies on the European Union (EU; European Commission, 2017), the United States (Zhang & Dafoe, 2019), the United Kingdom (Ada Lovelace Institute & The Alan Turing Institute, 2023), and Germany (Kieslich, Keller, & Starke, 2022) suggest that citizens generally want AI to be carefully managed, but we lack knowledge about what this means more precisely in terms of support for different regulatory instruments and with regard to specific aspects of AI that may create regulatory demand.

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Additionally, we do not know which citizens are more supportive of hard (i.e., binding, coercive) versus soft (i.e., non-binding, voluntary) regulation, and whether there are latent conflicts over the governance of AI in society that may even become entangled with political divides. For instance, AI's impact on labor markets generates losers mainly among routine works, while also producing a large group that profits economically from the technological change – with consequences for welfare policy preferences and voting behavior (Gallego & Kurer, 2022). Further divisions could arise from how people want risks associated with digital technologies, like AI, to be governed.

However, attitudes toward emerging technologies are usually not yet consolidated and firmly embedded into political conflict dimensions (Pidgeon, Harthorn, & Satterfield, 2011: 1695). While attitudes toward AI regulation could parallel those for other risk technologies, like nuclear energy and nanotechnology, it is an empirical question as to what extent previous findings on regulatory preferences pertain to AI regulation. AI differs from other risk technologies since many AI applications are already or will become widespread among consumers who will enjoy the various benefits linked to AI. Existing survey evidence suggests that people see various benefits to AI, such as greater convenience and novel services, but also several risks, such as undesirable biases and unfair discrimination of opaque applications (Araujo, de Vreese, Helberger, et al., 2018; European Commission, 2020a; Grzymek & Puntschuh, 2019; Zhang & Dafoe, 2019). Therefore, citizens may have conflicted views about AI, leaving it an open question as to how much and what kind of regulation they support. Citizens who have formed positive views of AI systems and the tech companies behind them may be skeptical of regulation. These companies, intend to cultivate a positive image and try to avoid constraining regulation by presenting regulation as a barrier to innovation and better services for consumers (see e.g. Kalyanpur & Newman, 2019; Nemitz, 2018). Hence, tech companies may enjoy considerable trust among consumers to the extent that they offer widely used AI-based products and services that consumers cherish. At the same time, given the novelty and complexity of the topic, governments may lack regulatory competence in the eyes of the public. Under these circumstances there might be a notable reluctance among citizens to support regulation, particularly hard regulation.

Due to the widespread use of consumer applications, systemic effects of AI become especially important. Besides very direct and palpable possible harms, such as erroneous decisions and unfair discrimination in settings with high stakes, like credit ratings or recidivism assessments, AI can also have more long-term and diffuse impacts on society that are less palpable. It is especially an open question what citizens think about AI regulation when it comes to aspects of AI that matter for such long-term systemic impacts. As one survey on citizens' views about AI and environmental sustainability has shown, people perceive AI's benefits to outweigh the risks and harms, but they also see the responsibility to address risks lying with politicians (Akyürek, Kieslich, Došenović, et al., 2022). This could mean that they want little regulation, but also that they want substantial regulation even though they have an overall positive view about the technology itself.

Based on these considerations, the present paper focuses on attitudes toward AI regulation concerning aspects that are particularly relevant for long-term systemic impacts. It draws on survey data representative of the German population to study how much citizens support soft and hard regulation of AI. By asking about regulatory preferences regarding (i) the transparency and (ii) the ecological sustainability, specifically regarding the use of energy use of AI, the survey was designed to include questions on aspects of AI that concern two central sustainability dimensions involving systemic and long-term impacts of AI on society. The first challenge is that consumers may face opaque AI systems that increasingly intervene in or govern their lives, thus impairing their personal autonomy (Krafft, Zweig, & König, 2020; Lepri, Oliver, Letouzé, et al., 2018; Mittelstadt, Allo, Taddeo, et al., 2016). A second major challenge is the growing resource and energy use of AI (Cowls, Tsamados, Taddeo, & Floridi, 2021; Dauvergne, 2021), particularly in light of the growing energy consumption of data centers (IEA, 2020) and the exponential energy demand of advanced forms of machine learning (Schwartz, Dodge, Smith, et al., 2019; Thompson, Greenewald, Lee, et al., 2020). As a result, regulating the transparency and the ecological sustainability of AI will be crucial in preventing the emergence of an unsustainable information infrastructure. Therefore, evidence on regulatory preferences in these domains are of particular value to both scholarly and policymaking debates.

2. Theoretical assumptions and hypotheses

2.1. Regulating AI as an emerging technology

Emerging technologies create uncertainty for policymakers and demand the partial establishment of novel regulatory frameworks to address possible short- and long-term risks (Lewallen, 2021; Mandel, 2009; Taeihagh, Ramesh, & Howlett, 2021). Regarding AI, important legislation is already under way to deal with the risks of this technology. The most far-reaching set of policies regulating AI to date, which has been proposed and adopted by the EU, includes strong rules that protect people from harm and safeguard their autonomy when interacting with certain AI systems. The EU's General Data Protection Regulation (Art. 22) guarantees an opt-out from automated decisions made about an individual. Furthermore, the EU's Data Services Act aims to provide transparency of the algorithms operating on online platforms by stipulating user-facing transparency obligations as well as third-party auditing for large platforms (Leistner, 2021). The policy most directly and comprehensively covering AI, however, is the EU's AI Act, which entails a risk-based regulation that demands more far-reaching requirements regarding the transparency and testing of AI systems (European Commission, 2022).

This policy bans certain AI systems that can manipulate individuals or exploit their vulnerabilities and it stipulates strong transparency and risk management requirements for so-called high-risk AI systems. These are systems that pose a significant risk to the health, safety, or fundamental rights of persons, meaning they are commonly used for high-stakes decisions about individuals, such as in recruitment or for credit default assessments. However, even for these high-risk systems, the mechanisms to ensure transparency are rather general and leave room for interpretation. For applications with lower risks ("limited" and "minimal or no risk"), more basic transparency obligations or no obligations at all apply. Consequently, many applications developed for consumer markets that entail low direct risks, such as recommender systems, are likely to avoid stronger transparency rules.

Overall, existing regulation primarily addresses the more concrete and directly palpable effects, such as wrong decisions (e.g., in the case of autonomous vehicles) or unfair discrimination, which have been discussed in public debate and have, at times, received considerable media attention. Yet, beyond the more substantial potential harms of AI and even with comparatively harmless consumer applications, AI systems can still have diffused adverse effects on people's autonomy. By gradually becoming normalized in people's lives and providing convenience through recommending or making decisions for them, AI systems may successively induce a soft paternalism (Laitinen & Sahlgren, 2021). Furthermore, negative environmental impacts of AI applications, as another more indirect and systemic potential impact, especially of widely used applications, is hardly covered by existing or planned regulation of AI. Notably, the EU AI Act mentions environmental risks of AI use only in passing and envisages voluntary measures.

Due to their prevalence, AI applications for mass consumer markets are highly relevant with regard to the potential systemic and long-term impacts of AI regarding creeping paternalism and environmental harms. At the same time, it is these applications and impacts that are least covered by existing regulatory efforts. Their regulation is also the most likely to be malleable in the context of ongoing political debates on how to regulate AI. This makes the study of citizen attitudes toward AI regulation concerning long-term systemic impacts on society particularly pertinent, especially since public support for policies can become a key resource for political movements and policymakers (Dietz et al., 2007: 187). Policymakers also tend to be reluctant to adopt policy instruments if the public does not support them. Low support for policies in the populace will also mean reduced compliance, in turn decreasing the effectiveness of policies (Tosun et al., 2020: 137). These considerations motivated the focus on citizen attitudes toward AI regulation.

2.2. Citizens' regulatory preferences

Although regulatory preferences regarding AI is a scarcely researched area, it can directly build on extensive research on regulatory preferences in the larger public concerning other policy areas, such as nanotechnology, genetically modified organisms, and energy. A common approach in this work is to study correlations between the support for different regulatory instruments, with a particular focus on differing support for soft regulation (e.g., information or positive incentives) and hard regulation (e.g., strict regulation through laws or bans). This approach will also guide the analysis of regulatory preferences concerning the transparency and energy efficiency of AI.

Contributions on citizens' regulatory preferences are not only scattered over different policy areas, but also show heterogeneity in the hypothesized determinants on which they focus. For the purpose of a coherent analytical framework underlying the analysis, we systematize predictors examined in the literature according to the element of regulatory action that they concern as shown in Fig. 1. Regulatory preferences can depend on (1) people's attitudes toward policymakers who are responsible for the regulation (e.g. Cho & Moon, 2019; Hammar & Jagers, 2006; Harring, 2016; Kitt, Axsen, Long, et al., 2021; Tosun et al., 2020), (2) their general disposition on different forms of regulation and the role of the state, mainly market-based versus command-and-control (e.g. Dietz et al., 2007; Ingold et al., 2019; Stadelmann-Steffen & Eder, 2021; Stoutenborough et al., 2014), (3) the target of the regulation (e.g. Aghion, Algan, Cahuc, et al., 2010; Cho & Moon, 2019; Harring, 2016; Kitt et al., 2021; Pinotti, 2012), and (4) their attitudes toward the desired goals and possible impacts of the regulatory action – or a lack thereof (e.g. Dietz et al., 2007; Graham, Bland, Cookson, et al., 2017; Tosun et al., 2020). The hypotheses formulated in the following section include relevant variables covering all four aspects.

When investigating how different predictors are associated with regulatory preferences, it is not enough to simply look at the absolute support (or refusal) for different forms of regulation. If, for example, some personal disposition is not related to support for hard regulation, but is negatively related to soft regulation, this still means that hard regulation becomes relatively more acceptable to some people. We thus formulate the hypotheses in a way that also focus on the relation between hard and soft regulation, mirroring previous studies on regulatory preferences and allowing for more direct ties to other findings in existing research.

2.3. Correlates of regulatory preferences regarding AI

Turning first to the role of attitudes toward the regulating actors, we follow the argument that the perceived competence of the political actors responsible for devising suitable regulation shapes the support for regulatory measures (Cho & Moon, 2019; Kitt et al., 2021). If perceived competence is low, we would expect citizens to be more reluctant to accept any regulation. To the extent that they do support any regulation, they will be more welcoming of soft instruments, which effectively leaves regulation to the market and those operating within it, while being less likely to support hard regulation by the state, which depends on competent political actors.

H1a. The lower the perceived regulatory competence of policy actors, the more that person supports no or soft rather than hard regulation of AI.

Besides their regulatory capacity, trust in the main institutions responsible for finding adequate regulatory institutions may also affect the regulation citizens that want. Following the seminal work on political support by Easton (1975), one can distinguish the evaluations of actors' performance and competence as a form of specific political support from a more fundamental trust in political institutions, which Easton deemed diffuse political support. From this follows that even if citizens are not satisfied with policymakers' actions and do not attest them high competence, they may still have trust in the working of the political system. Research in other policy areas has argued that people who have little trust in policy actors and political institutions are less likely to support far-reaching regulation (Hammar & Jagers, 2006; Harring, 2016; Kitt et al., 2021; Tosun et al., 2020). A lack of trust in core institutions involved in policymaking, i.e. mainly the government and parliament, is therefore likely to translate into citizens supporting no or soft and voluntary regulation of AI, such as information-based instruments and positive incentives, rather than hard regulation, such as laws.

H1b. The less a person trusts core political institutions involved in policymaking, the more that person supports no or soft rather than hard regulation of AI.

How much citizens support market-based or state-based regulation also generally depends on their preference regarding the extent of state intervention versus reliance on the market (Cho & Moon, 2019; Dietz et al., 2007; Ingold et al., 2019; Stadelmann-Steffen & Eder, 2021; Stoutenborough et al., 2014). This argument can be applied to the regulation of AI as much as to any other domain of regulation. Accordingly, one would expect that a market-liberal stance means a

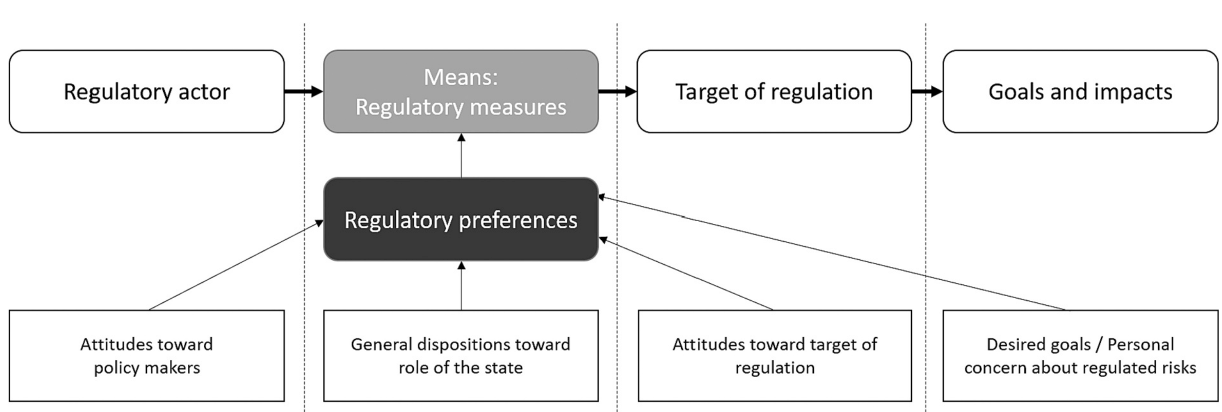

Fig. 1. Analytical framework.

stronger support for no or soft regulatory instruments that do not constrain market actors rather than hard regulation that imposes rigid restrictions on businesses.

H2. The more market-liberal a person is, the more that person supports no or soft rather than hard regulation.

Although policymakers are primarily responsible for establishing a regulatory framework, the perceived adequacy of different regulatory instruments also depends on those who form the target of the regulation, typically businesses or citizens depending on the concrete regulatory domain (Aghion et al., 2010; Cho & Moon, 2019; Harring, 2016; Harring & Jagers, 2013; Kitt et al., 2021; Pinotti, 2012): If low trust reflects a perceived risk of defection, then information and positive incentives are inadequate and insufficient as they will allow non-compliance, whereas state intervention becomes more suitable in relation to soft measures. Transferring this argument to the regulation of AI, we would expect that a lack of trust in technology companies developing and operating AI would lead to greater reluctance among citizens to rely on non-regulation or self-regulation and voluntary measures as opposed to hard regulation.

H3. The lower the trust in technology companies, the higher support is for hard regulation rather than no or soft regulation of AI.

Finally, the dimension of goals and impacts of regulation can also play a role for citizens' evaluations of regulatory action. As noted above, the focus of the analysis is on the two aspects of transparency and energy efficiency of AI, which are both tied to sustainability concerns. Unlike with other regulatory action, the impacts of the regulation regarding those two domains are indirect and systemic rather than affecting citizens directly, e.g., in terms of distributional consequences and the allocation of risk. This means that differences regarding citizens' expected impacts of the regulation itself – e.g., consequences for fairness, liberties, and costs (see e.g. Harring & Jagers, 2018; Jakobsson, Fujii, & Gärling, 2000; Schade & Schlag, 2003) – are not as relevant for the purpose of our analysis. However, citizens' perceived importance of the goals and the risks that regulation is supposed to deal with can be presumed to inform their evaluation of regulatory instruments. If the general goals of regulating transparency and energy efficiency of AI are felt as deeply important to citizens, we would expect them to show support for more far-reaching, i.e. for hard rather than no or soft regulation.

Since the goals are domain-specific, we will test two dispositions that can be presumed to lie behind the felt importance of regulating the transparency of AI and the energy of AI respectively. First, since a lack of transparency means less control over AI systems, desire for control (Burger & Cooper, 1979) is a strong candidate for shaping citizens demand for effectively regulating transparency of AI (Gaudiello, Zibetti, Lefort, et al., 2016; Syahrivar, Gyulavári, Jászberényi, et al., 2021): If a person values self-reliance and being in control, they are unlikely to accept conditions under which decision-making is opaque and particularly non-transparent automated decision-making by AI. Second, in the same vein, support for more far-reaching and stricter regulation of the energy efficiency of AI is likely to depend on how much citizens value the protection of the environment – and thus how much they are concerned about environmental harms. Hence, if citizens show strong environmental concern, they are likely to demand hard rather than no or soft regulation. We will thus test the following two hypotheses.

H4b. The stronger a person's desire for control, the more that person supports hard rather than no or soft regulation regarding the transparency of AI.

H4b. The more strongly a person is concerned about the environment, the more that person supports hard rather than no or soft regulation regarding the ecological sustainability of AI.

These two additional dispositions are potentially even more relevant than political policy positions. At the same time, it is possible that they are both interrelated. For instance, a stronger market-liberal stance is likely to run counter to a strong environmental concern. It remains to be seen which of these variables emerges as important predictors of support for no, soft, or hard regulation of AI in the areas of transparency and energy use.

3. Data and method

3.1. Sample

The study uses original survey data collected from participants in Germany. The sample has been drawn from an online panel that is hosted by respondi AG and is representative of the German population aged 18 to 74 based on quotas for gender, age, and region (see Annex A1 for sample composition). On the one hand, existing evidence suggests that AI perceptions in Germany are comparable to those in other European countries (Grzymek & Puntschuh, 2019). On the other hand, the German population seems to be, on average, more risk averse and skeptical toward new technologies than other societies (Metag & Marcinkowski, 2014; Mundorf, Dholakia, Dholakia, et al., 1996), and environmental concern is very pronounced among Germans (Franzen & Meyer, 2010; Gellrich, 2021; Wurster, 2010). This context therefore makes it more likely to register support for stricter regulation of AI, specifically with regard to transparency and ecological sustainability.

3.2. Measures

Dependent variables. Since we asked respondents about the regulation of the rather unfamiliar issues of AI transparency and energy use, the survey included two introductory pages on AI systems. This established what AI is in simple terms and illustrated, with the example of AI assistants (an application that understands natural language commands and performs tasks for the user), how AI can differ with regard to transparency and to energy use – not only of the devices that run the AI, but also in external data use, mainly through data centers. The introduction familiarized respondents with the topic of AI and referred to concrete challenges introduced by AI.

It is important to note that while AI comes in many different forms that entail very different purposes and risks, our focus lies on a specific group of consumer-oriented AI applications, specifically in the form of AI assistants. While these may be less contested than other AI systems, like recidivism risk assessments, we chose them precisely because regulatory preferences are less clear and because these systems, as they are intended for mass-markets, are more likely to have less palpable long-term aggregate effects on societies.

The formulation of the questions to measure citizens' regulatory preferences is based on the distinction between (1) binding regulation, (2) incentives, and (3) persuasion – or sticks, carrots, and sermons – with the extent of coercion of the target of regulation decreasing from the first to the last (Sager, 2009; Vedung, 1998).[1] While the first of three categories clearly refers to hard regulation the third refers to soft regulation. Incentives, in turn lies somewhat between the two and, depending on the concrete instruments, could be closer to hard or to soft regulation. It is an empirical question whether citizens discriminate between these categories.

Drawing on the distinction between the three categories, we use a set of rating items for overall six regulatory instruments in both examined areas of regulation (i.e., transparency and energy use): bans, legal measures, negative incentives, positive incentives, labels, and

[1] While the governance literature also conceptualizes further dimensions for distinguishing policy instruments (e.g. Treib, Bähr, & Falkner, 2007) we follow previous work on regulatory preferences by focusing on the extent to which policies are coercive, reflecting a continuum from state-versus-marked-based and voluntary governance.

information (see Annex A2 for details). Rather than relying on bipolar measures directly capturing trade-offs between forms of regulation, as they are regularly used in related research, the chosen measures aim at shedding light on the absolute level of support for different forms of regulation. In doing so, we can show for each instrument whether there is support for its use, and if so, to what extent. This is particularly instructive with this hardly researched topic of AI, as empirical evidence on regulatory preferences is scarce and it allows us to examine whether citizens, on average, show clear differences in their absolute support for a variety of instruments. At the same time, by studying and comparing support for policies that range from soft to hard regulation, we can also examine to what degree relevant predictors are associated with different forms of regulation and regulatory intensity.

To create the dependent variables, preferences regarding the regulation of (i) the transparency and (ii) the environmental sustainability of AI, we first inspect the dimensionality of our items. People may show a preference for several regulatory instruments that is (partly) independent from their preference for other instruments – and their preference might not reproduce the distinction between the three categories mentioned above. Using exploratory factor analysis (oblique rotation) based on maximum likelihood estimation over the six items, we obtain two dimensions (Table 1). The pattern is overall very clear with little overlap between factors. Hence, empirically, we do not obtain a third form of regulation, but instead find two dimensions that correspond largely to a difference between soft and hard regulation. It is plausible that the variable for negative incentives show the worst separation between factors in both analyses as this instrument is restrictive, while still being clearly softer than legal standards or bans – i.e. lies between hard and soft regulation. Based on these results, we generate additive scales for soft and hard instruments in the two studied domains, i.e., transparency and energy efficiency of AI (for mean and standard deviation, see results section). The reliability of the resulting scales is good, with a Cronbach alpha of 0.76 and higher.

Independent variables. Trust in government (M = 3.97, SD = 1.81) and trust in parliament (M = 4.07, SD = 1.77) are each measured with a rating item scaled from 1 (do not trust at all) to 7 (trust a lot). An identically scaled rating item serves to measure trust in technology companies, i.e. the target of regulation (M = 3.80, SD = 1.51). To measure the perceived competence of policymakers, we included items in the survey that asked about the competence of the parties in parliament in regulating AI with regard to (a) transparency and (b) environmental sustainability. For both dimensions, a competence perception variable has been created in the form of the mean over all seven parties in parliament (missing values have been imputed with the mean, (M = 2.54, SD = 1.05 and M = 2.52, SD = 0.98, respectively).

Respondents' socio-economic political position, capturing their market-liberal versus pro-state orientation, is measured by means of a rating item from the German Longitudinal Election Study (Roßteutscher, Schmitt-Beck, Schoen, et al., 2018) on a seven-point scale (M = 2.95, SD = 1.65). Desire for control is based on a validated scale developed by Burger (1989). As the entire scale is relatively long and not all subscales are equally relevant for our purposes, we use only the items for the dimension of desire for self-control according to the analysis by Parker (2009). The six items we use to construct this subscale show a Cronbach's Alpha of 0.74 (M = 3.80, SD = 0.87). The items for environmental concern are based on a scale developed by the German Environment Agency, which could be used without translation (Geiger & Holzhauer, 2020). The seven items refer to different aspects of environmental concern. In an exploratory factor analysis, they yield three dimensions, with the third dimension consisting of a single item. We thus discard this singular item and use the first two dimensions. While the second captures a concern for harms to the environment, the items of the first dimension indicate a future orientation, with the highest-loading item reflecting concerns for future generations and their living conditions (for details, see Annex A3). Although Cronbach's Alpha for all seven items amounts to 0.81, we use the more differentiated measures in the form of two subscales. Their reliability scores are 0.73 and 0.78 (M = 3.68, SD = 1.02 and M = 4.14, SD = 0.87, respectively).

The analysis also includes a range of control variables. Since support particularly for more restrictive regulation could be driven by a general fear of technology, we include a variable for technophobia (Rosen & Weil, 1995) that is based on a scale established in previous studies (Nimrod, 2018; Sinkovics, Stöttinger, Schlegelmilch, et al., 2002). In light of the length of the full scale, we included only items belonging to the dimension "human versus machine ambiguity" (Sinkovics et al., 2002: 486) to avoid respondent fatigue while still collecting relevant information on technophobia for our analysis. The ten items show a Cronbach's Alpha for this scale of 0.92 (M = 1.98, SD = 0.87, five-point scale). We also include a measure of self-reported AI knowledge, ranged from 1 (no knowledge) to 6 (very good knowledge), in the analysis (M = 2.83, SD = 1.28). Finally, standard sociodemographic control variables for political interest (scaled from 1 to 5, M = 3.47, SD = 1.08), age (M = 47.62, SD = 15.65), education (coded as 1 if a person has attained upper secondary tier education and 0 if not), and gender (1 = female, 0 = male or diverse) are also included.[2] An overview of all independent variables is provided in Table 2.

Table 1
Results from exploratory factor analyses.

	Transparency		*Energy use*	
Policy instrument	*Factor 1*	*Factor 2*	*Factor 1*	*Factor 2*
Information	**0.762**	0.008	**0.829**	−0.061
Labels	**0.933**	−0.120	**0.885**	−0.084
Positive incentives	**0.612**	0.058	**0.682**	0.060
Negative incentives	0.172	**0.458**	0.269	**0.484**
Hard provisions (legal standards)	0.222	**0.641**	0.248	**0.659**
Bans	−0.196	**0.953**	−0.161	**0.999**
Eigenvalue	1.943	1.548	2.095	1.681
Cumulative explained variance	0.324	0.582	0.349	0.628
Cronbach's Alpha	0.79	0.76	0.82	0.84

Notes: Maximum likelihood factor analysis with oblique rotation. Cronbach's Alpha has been calculated for the respective items marked in bold.

Table 2
Overview of the measures for the independent variables.

Measure	n	Range	Mean	Std. deviation
Trust in government	1025	[1;7]	3.97	1.81
Trust in parliament	1025	[1;7]	4.07	1.77
Perceived regulatory competence of policymakers: transparency	1025	[1;5]	2.54	1.05
Perceived regulatory competence of policymakers: energy efficiency	1025	[1;5]	2.52	0.98
Trust in technology companies	1025	[1;7]	3.80	1.51
Market-liberal	1025	[1;7]	2.95	1.65
Desire for control	984	[1;5]	3.80	0.87
Environmental concern: harm to nature	977	[1;5]	3.68	1.02
Environmental concern: future orientation	977	[1;5]	4.14	0.87
Technophobia	966	[1;5]	1.98	0.87
AI knowledge (self-assessed)	1025	[1;6]	2.83	1.28
Political interest	1025	[1;5]	3.47	1.08
Age	1025	[18;74]	47.62	15.65
Gender: female	1025	[0;1]	0.50	0.50
High formal education	1025	[0;1]	0.58	0.49

[2] Gender was asked with three response categories, but as the number of respondents self-categorized as diverse (2) was too low for statistical analyses, we coded the mode (female) as 1 and combined the other two categories.

3.3. Analytical approach

To ease interpretation, all variables are normed to a scale from 0 to 1 for the analysis. Before performing the analysis, we also apply an attention check included in the desirability of control item battery and a control question confirming the usability of the responses. After these filters, 1025 cases remain in the analysis. As the dependent variables are metric, we use OLS regressions to estimate the association of our predictors with those variables. We also perform additional analyses for individual instruments and with other model specifications. To more directly test a preference for hard regulation (i.e. negative incentives, legal standards, and bans) over soft regulation (i.e. information, labels, and positive incentives), we construct additional dependent variables that directly measure how much respondents prefer the former over the latter by subtracting the scores for soft regulation from the scores for hard regulation. A further variant of the dependent variables tested in further analyses is all regulatory instruments taken together into combined scales (Cronbach's Alpha = 0.83 and 0.87 for transparency and energy efficiency respectively). We also estimate models with perceived effectiveness of regulation as the dependent variable as this allows us to examine whether a lack of association with support for regulation of some predictors is tied to a lack of perceived effectiveness. Results from these are detailed in the Annex.

4. Results

4.1. Description of the dependent variables

Looking at the distribution of the dependent variables, they are all clearly skewed toward the right and above the mid-point of the scale. Support for soft regulation both regarding AI transparency and energy efficiency lies at 3.9 and 3.8 (both SD = 0.9) respectively on the five-point scale. Support for hard regulation is lower, but still moderate with scores of 3.5 and 3.6 (both SD = 1.0) for transparency and energy efficiency respectively.[3] Overall, these findings indicate that citizens more strongly support regulation of AI. Citizens willingness to support soft regulation somewhat more than hard regulation of AI is similar to what has been found in research on renewable energy policies (Ingold et al., 2019; Stadelmann-Steffen & Eder, 2021), as well as the regulation of other risk technologies, such as nano foods (Chuah, Leong, Cummings, et al., 2018). Only with respect to climate change policies and the prevention of environmental pollution do studies find stronger support for hard than for soft regulation (Harring, 2016; Huber, Wicki, & Bernauer, 2020; Tosun et al., 2020). Further research is needed to shed light on what lies behind such differences. However, when contextualizing the findings from the preceding section in the broader literature, it seems at least plausible that citizens see AI – similar to renewable energy – as an issue that is less directly associated with an immediate threat than climate change. Thus, people may not see an acute need for hard measures but are willing to accept regulations that go beyond mere reliance on free markets. This is notable considering other survey evidence from Germany which indicates that people's perceived potential positive effects of AI on environmental sustainability clearly outweigh the perceived negative effects (Akyürek et al., 2022).

Regressing the dependent variables on the set of predictors included in the analysis yields the results shown in Fig. 2 (for table, see Annex A4). The findings from this analysis, specifically how these relate to theoretical assumptions and previous research on regulatory preferences, will be described in the following sections.

[3] Paired *t*-tests yield highly significant differences between soft and hard regulation (two-sided tests, $t = 9.74$, df = 1023 and $t = 12.33$, df = 1022, for transparency and energy efficiency respectively).

4.2. Testing predictors of regulatory preferences

Attitudes toward regulating actors. The results are only partly in line with H1a and suggest that the perceived regulatory competence of policymakers does matter, but is only linked positively with soft regulation – which parallels findings by Cho and Moon (2019) in the area of environmental policy.[4] It appears that perceived competence of policymakers translates into more support for soft measures, but that it is not enough to encourage citizens to demand stricter measures. Only acute reasons may lead citizens to demand hard instruments.[5] Therefore it shows that policymakers can, through evoking an image of competence, only engender support for soft regulation based on the expected effectiveness of regulation.[6] One should note that the perceived average competence of German parties in the Bundestag regarding AI regulation in the examined areas is below the mid-point of the five-point scale (2.54 for transparence and 2.52 for energy efficiency). Consequently, there is plenty of headspace for policymakers to increase support for soft regulation based on their image of being competent in regulating AI.

Trust in government and in parliament, in turn, play no role in influencing citizens' support of hard and soft regulation of AI in the areas of transparency and energy use, leading us to reject H1b. This confuting finding adds to the negative evidence among largely positive evidence on the role of trust in regulating actors. While some contributions found trust in policymakers to go along with greater support for stricter regulation (Davidovic & Harring, 2020; Hammar & Jagers, 2006; Harring, 2016; Tosun et al., 2020), others did not find this association (Dietz et al., 2007). At least with regard to AI, perceived competence of policymakers is clearly a better predictor, which is in line with findings on climate policy acceptance by Kitt et al. (2021).

General orientation toward state intervention. Economic policy preferences are found to be a relevant predictor in the regression models depicted in Fig. 2, similar to what has been established in various other contributions on regulatory preferences (Dietz et al., 2007; Ingold et al., 2019; Stadelmann-Steffen & Eder, 2021; Stoutenborough et al., 2014). While a market-liberal stance is not linked to lower support for soft regulation, it does show a significant negative association with hard regulation, supporting H2. However, overall, the regulatory preferences regarding transparency and energy efficiency of AI are not markedly aligned with political ideology, which suggests that they are not (yet) politicized.[7]

Attitudes toward the target of regulation. According to the evidence, the more people trust the technology sector, ceteris paribus, the greater their readiness to support soft regulation transparency and energy

[4] Additional analyses show that when using the perceived competence of the government parties instead of all parties, there is not even any significant association with the dependent variables (Annex A5).

[5] Additional analyses with perceived effectiveness of the regulatory measures as the dependent variable show a clear positive association between perceived competence and perceived effectiveness of both hard and soft regulation (Annex A6). This means that although perceived competence does translate into perceived effectiveness of hard regulation, this does not suffice to urge higher support for such regulation.

[6] Although one also obtains a positive coefficient for perceived regulatory competence when estimating models with overall support for regulation (soft plus hard) as the dependent variable, this relationship can be attributed to the positive association with soft regulation (see Annex A7).

[7] The explanatory power of policy preferences is absorbed by variables expressing environmental concern. Without these variables, the variable for a market-liberal policy stance is more clearly significant in the models for hard regulation and becomes significant in the models for soft regulation (see Annex A8). A more market-liberal position is also negative and statistically significant under alpha <0.05 when using soft and hard support taken together as the dependent variable (see Annex A7).

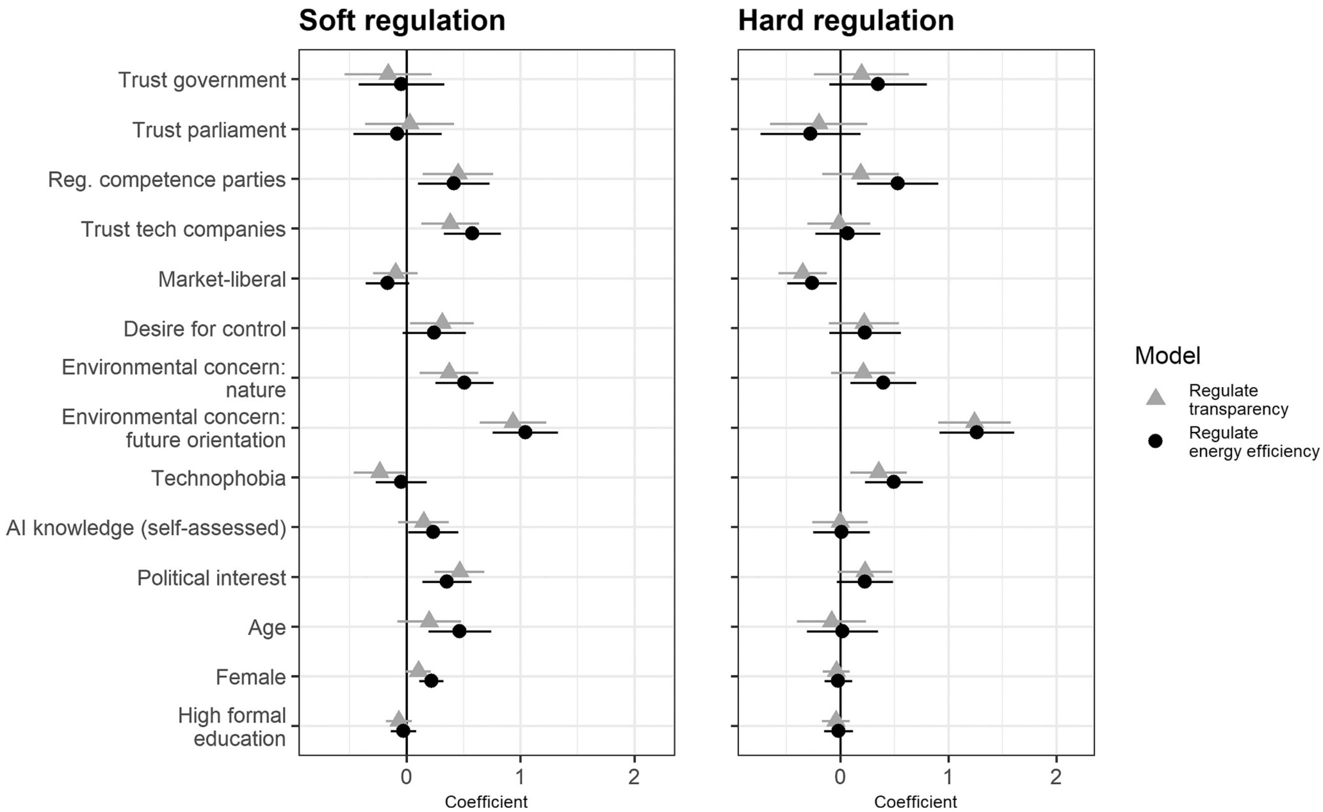

Fig. 2. Results from OSL regressions. Models with main political variables and control variables. Unstandardized regression coefficients with 95%-confidence intervals. Independent variables are normed to a range from 0 to 1. R^2 is 0.18 and 0.25 for the models estimated for soft regulation and 0.12 and 0.16 for hard regulation (N = 948 for regulation of transparency, N = 947 for regulation of energy efficiency).

efficiency of AI.[8] For hard regulation, however, the coefficients are not significant under conventional levels.[9] While this goes partly against H3, the findings also imply that greater trust in tech companies translates into a higher support for soft regulation in relation to hard regulation, which is still in line with H3 and mirrors findings by Dietz et al. (2007) on climate policy.[10] The results suggest that the tech sector is capable of convincing citizens that market-based, soft regulation is the suitable approach to AI through fostering a positive image among the larger public. At the same time, they seem to be able to avoid public calls for hard regulation if they do not have or lose trust among citizens.

Attitudes toward the importance of the goals of regulation. Desire for control and environmental concern have been included in the analysis to capture how much citizens value the goals at which regulation is aimed in the two areas of transparency and energy efficiency of AI. Based on the findings in Fig. 2, we have to reject the hypothesis H4a that desire for control is predictive of preferences toward the regulation of AI transparency.[11] On the other hand, environmental concern stands as the single most important construct in the analysis, a finding that adds to previous evidence on preferences for environmental and health policies (Dietz et al., 2007; Graham et al., 2017; Tosun et al., 2020).

Strikingly, environmental concern is associated with more support for both soft and hard regulation, not only regarding energy efficiency, which supports H4b, but also regarding transparency of AI. The clearest association emerges with the variable reflecting concern for future generations and their environment. The coefficient of concern for harms to nature is weaker and reaches conventional levels of statistical significance in three of the four models shown in Fig. 2.[12] These findings suggest that concern for the environment of future generations captures more than merely environmentalism and concern for human harms to nature.[13] The variable that reflects a future orientation shows a very clear positive association with the dependent variables in all four models, even while simultaneously including concern for harms to nature: For soft and hard regulation of both transparency and the energy

[8] Additional models (see Annex A6) also show that trust in tech companies has a very clear positive association with perceived effectiveness of soft instruments. The coefficient for hard instruments, although still significant under 0.05, is less than half that size. Trust thus seems to imply the expectation that businesses will behave accordingly under regulation that stresses information, labels, and positive incentives – and this translates into support for such regulation.

[9] In additional regression models using overall support (hard plus soft regulation) as the dependent variable, trust in tech companies shows no consistent relationship with the dependent variables (see Annex A7).

[10] This interpretation is corroborated by additional estimated models expressly using support for hard minus soft regulation as the dependent variable (see Annex A9).

[11] Additional regression models for individual instruments (Annex A10 and A11) show that desire for control is only consistently linked to support for information measures and is otherwise irrelevant.

[12] Additional regression analyses (not tabled) show that when removing the variable for environmental concern capturing a future orientation, concern for damages to nature has a significant positive coefficient that is almost the size of the former variable.

[13] When using only the item that most directly asks about concern for future generations, the results are substantively identical (see Annex A12).

efficiency of AI.[14]

All in all, citizens seem to perceive AI as a technology that can have far-reaching, undesirable consequences for humankind regarding environmental aspects, but also other dimensions. This is because a general concern for the future of society and social development (not only for environmental harms) means citizens are calling for more – soft as much as hard – regulation of AI in general. It is important to note that this variable on a future orientation is skewed toward higher values, meaning that it is uncommon not to care about future generations. It is those who do not show a clear concern for future generations who are, ceteris paribus, less supportive of AI regulation.

Control variables and discussion of limitations. Turning, finally, to the control variables, political interest seems to lie behind higher support for soft regulation, and women, ceteris paribus, are more supportive of soft regulatory instruments. Otherwise, there are consistent associations of a control variable with the dependent variables. Overall, the models can explain a respectable portion of variance that is comparable to what has commonly been obtained in other studies on regulatory preferences (e.g. Pitlik & Kouba, 2015; Stoutenborough et al., 2014; Tosun et al., 2020). The adjusted R^2 is 17.7 and 24.5%, respectively, for the models estimated for soft regulation as the dependent variable. Support for hard regulation appears to be harder to predict. The adjusted R^2 is 12.3 and 16.1, respectively, for the corresponding models.

We should also take into consideration the limitations of our study. First, while the analysis has uncovered a central importance of a future orientation for the regulation of not only ecologically sustainable, but also of transparent AI, this finding should be further corroborated with alternative measures that completely delink future orientation from environmental concern. Second, like in many other studies on regulatory preferences, the findings come from a single case, Germany, and may not hold equally in other contexts. Although the studied relationships are of a rather general sort and Germany does not seem to differ from other European countries regarding AI attitudes in the populace, varying political conditions could mean that some political variables show different associations with the dependent variables. Third, the analysis has been designed around AI systems that are consumer-oriented and provide services, e.g., in the form of assisting with certain tasks and decisions. The long-term systematic impacts of an increasing prevalence of such AI systems are particularly relevant with such applications that are likely to have very broad usage. Nonetheless, one should bear in mind that AI cannot be defined as a singular thing because AI comes in many different forms and can be used for many different purposes and with different risks involved. Citizens' attitudes toward AI may thus look different when looking at other risks and forms of AI than those focused on in the analysis above. Fourth, we note that the data does not permit a causal interpretation of the registered association. Like previous studies on citizens' regulatory preferences, our findings primarily shed light on which individual characteristics are related to regulatory preferences and accordingly, on the question of which kinds of citizens are more supportive of soft or hard regulation. To study more in depth the causal relevance of the predictors examined above, experimental studies are an important alternative approach that could complement and corroborate the presented findings. Finally, it is important to observe that, over time, policies may also shape attitudes rather than just the other way around. However, studying such trends will require long-term observations via regular surveys within larger projects such as the project MeMo:KI for the context of Germany.

[14] When estimating additional models with dependent variables measuring overall support for regulation, adding up support for soft and hard regulation, the variable for future orientation again shows clearly the strongest association with demand for regulation (see Annex A7).

5. Discussion

AI is an emerging general-purpose technology that promises to bring new and improved products and services in a vast number of areas. It is, however, also a risk technology as its adoption and use can have unintended – or even intended – harmful consequences and may entail negative, long-term effects on society. Whereas risks associated with AI may lead citizens to demand far-reaching regulation of the technology, the benefits that they already reap from its use today or potentially in the future may well depress demand for strong regulation.

The findings presented above suggest that citizens support moderate to strong regulation of AI for dealing with two core challenges that are tied to the potential long-term societal impacts of AI on personal autonomy and the environment: the transparency and the energy efficiency of AI, respectively. The analysis of German survey data has yielded evidence of moderate to strong support for regulation in both of these areas. Citizens want policymakers to govern the transparency and energy efficiency of AI. This support for AI regulation is notable when considering that consumers seem to show little concern for transparency and especially energy efficiency of AI in their personal choices, even if they state those issues to be important (König, Wurster, & Siewert, 2022). However, support for hard regulation (bans, legal standards, negative incentives) is lower than for soft regulation (information, labels, positive incentives).

Compared to regulatory preferences regarding climate change policy, citizens appear to be somewhat reluctant to call for strict regulation of the technology regarding its transparency and environmental footprint. In this sense, the current regulatory approach on the EU level may strike a balance that is well aligned with citizens' regulatory preferences – as it involves voluntary governance, but also, to some degree, moves toward binding legislation (Smuha, 2021: 75). Yet, its differentiated risk-based regulation of transparency requirements (European Commission, 2020) and its emphasis on soft instruments in the area of green IT (European Commission, 2021) may ultimately not be enough to meet citizens' demand for AI regulation. At the same time, stronger regulation can hinder innovation and reduce possibilities of creating value from data. Strict rules governing AI may also impede the uptake of AI in public administration and constrain its ability to leverage AI to produce value for society (Mikalef, Lemmer, & Schaefer, 2022).

What kind of regulation citizens see fit depends, in some part, on the image of tech companies. The evidence suggests that higher trust in these companies, while not reducing support for hard regulation, is associated with greater support for market-based regulation and soft instruments, such as information and labels. This puts the tech sector in a politically and rhetorically strong position. Citizens appear to find soft instruments less acceptable the less they trust tech companies and doubt their compliance with these measures. At the same time, gambling away people's trust may not induce demand for stricter regulation. Additionally, the perceived regulatory competence of policymakers only translates into support for soft regulation. Not only is the average perceived competence of policymakers low, but even if it rises, it does not lead citizens to demand stricter regulation involving binding rules or even bans – again indicating a certain reluctance among citizens to demand corresponding measures.

AI and its regulation are furthermore discernibly, but weakly, linked to citizens' positions on an economic policy dimension, indicating that AI is, thus far, not politicized and attitudes toward its regulation are hardly induced by ideological affinities. The most important predictor in the analysis, both regarding support for hard and soft regulation, is a concern for future generations and their living conditions. The findings suggest that citizens do perceive a sustainability dimension in the development and governance of AI and recognize risks of the technology for the future of humankind. A considerable part of the population see AI regulation as a political task to shape the future trajectory of societies and is thus likely to expect expressly future-oriented action by policymakers in their governance of the technology.

Overall, the findings are, in part, similar to what has been found for regulatory preferences regarding other risk technologies, although there are also some particularities to AI. It is notable that trust in political institutions showed to be irrelevant in the analysis, which differs from findings from other policy areas and for other technologies (Davidovic & Harring, 2020; Hammar & Jagers, 2006; Harring, 2016; Tosun et al., 2020). It is also unexpected, based on previous research on regulatory preferences, that ideology plays only a weak role for attitudes toward the regulation of sustainable AI (e.g., Ingold et al., 2019). A reason for this could be that attitudes toward AI are anchored on the level of the personal values that we included in the model (importance of control and environmental concern) and that reduce the predictive power of political ideology to which these values are related (see also Dietz et al., 2007). Most remarkably, the findings not only add to limited existing evidence that a future orientation matters for regulatory preferences (Dietz et al., 2007; Graham et al., 2017; Tosun et al., 2020), but also suggest that a future orientation is even extremely important for how people think about regulation for sustainable AI. It emerges clearly as the most important predictor in the analysis, more so than in studies on micropollutants (Tosun et al., 2020) and environmental policy (Dietz et al., 2007).

The findings contribute novel evidence to a growing literature on how citizens think about AI and its regulation, thereby also complementing research on regulatory preferences on other issues, such as emerging technologies. One should be careful when drawing conclusions from these findings about suitable policies since adequate regulation does not merely depend on the wants and needs of citizens. Nevertheless, the results do suggest that citizens generally support regulation of AI, even hard regulation, and that this is in considerable part due to their concerns about long-term impacts on the environment and humanity – besides the more direct and visible harms that AI may cause. As democratic politics, governed by the rhythm of regular elections, tends to have a short-time horizon (Wurster, 2013), policy on AI may well lack a strong emphasis on dealing with long-term effects.

Overall, the findings thus have several implications for policymaking. To align policies with citizens' views, injecting a citizen perspective on sustainable AI could correct for the short-time horizon in democratic policymaking. Indeed, the presented evidence on citizen attitudes suggests that policymakers have a mandate to adopt policies specifically to ensure the sustainability of AI and prevent long-term harms. Furthermore, the evidence also indicates that citizens would show even stronger support for soft regulatory measures, such as positive financial incentives, if policymakers appeared more competent to citizens regarding AI regulation. There is therefore room for policymakers to improve their reputation on the issue and devise innovative, soft regulatory instruments that orient the development and adoption of AI toward avoiding long-term systematic harms to society and the environment. Finally, policymakers' regulatory efforts may also have to consider the public image of tech companies. According to the findings, lower trust in tech companies among citizens translates into less legitimacy of soft regulation, while not increasing acceptance of hard regulation. An erosion of public trust in these companies may thus constrain the space for acceptable policy action.

Policymakers face no small task as regulating AI has even more far-reaching implications than is the case with other emerging and risk technologies given the importance of AI for the future prosperity and competitiveness of national economies. There is not only a race for leadership in AI technology, but also for AI regulation that establishes standards which promote the competitiveness of domestic industries (Smuha, 2021), and various countries, including the EU, have issued AI strategies that differ in the policy mix they envisage (e.g. Cath, 2018; Djeffal, Siewert, & Wurster, 2022; Filgueiras, 2022; Radu, 2021). Whether fostering sustainable AI is part of the winning formula remains to be seen.

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Data availability

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Appendix A. Supplementary data

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References

Ada Lovelace Institute & The Alan Turing Institute. (2023). *How do people feel about AI? A nationally representative survey of public attitudes to artificial intelligence in Britain*. London: Ada Lovelace Institute. Available at: https://www.adalovelaceinstitute.org/report/public-attitudes-ai/ (last accessed 3 August 2023).

Aghion, P., Algan, Y., Cahuc, P., et al. (2010). Regulation and distrust. *Quarterly Journal of Economics, 125*(3), 1015–1049. https://doi.org/10.1162/qjec.2010.125.3.1015

Akyürek, S. Y., Kieslich, K., Došenović, P., et al. (2022). *Nachhaltigkeit und Künstliche Intelligenz*. Düsseldorf: Meinungsmonitor Künstliche Intelligenz. Available at: https://www.cais.nrw/wp-94fa4-content/uploads/MeMoKI_Facts_heets/factsheet-6-ai-nachhaltigkeit.pdf (accessed 6 February 2023).

Araujo, T., de Vreese, C., Helberger, N., et al. (2018). *Automated decision-making fairness in an AI-driven world: Public perceptions, hopes and concerns*. Amsterdam: Digital Communication Methods Lab. Available at: http://www.digicomlab.eu/reports/2018_adm_by_ai/.

Burger, J. M., & Cooper, H. M. (1979). The desirability of control. *Motivation and Emotion, 3*(4), 381–393. https://doi.org/10.1007/BF00994052

Cath, C. (2018). Governing artificial intelligence: Ethical, legal and technical opportunities and challenges. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 376*(2133), 20180080. https://doi.org/10.1098/rsta.2018.0080

Cho, B., & Moon, M. J. (2019). The determinants of citizens' preference of policy instruments for environmental policy: Do social trust, government capacity, and state-society relations matter? *International Review of Public Administration, 24*(3), 205–224. https://doi.org/10.1080/12294659.2019.1643101

Chuah, A. S. F., Leong, A. D., Cummings, C. L., et al. (2018). Label it or ban it? Public perceptions of nano-food labels and propositions for banning nano-food applications. *Journal of Nanoparticle Research, 20*(2), 36. https://doi.org/10.1007/s11051-018-4126-5

Cowls, J., Tsamados, A., Taddeo, M., & Floridi, L. (2021). The AI gambit — Leveraging artificial intelligence to combat climate change: Opportunities, challenges, and recommendations. *AI & Society, 38*(1), 283–307. https://doi.org/10.1007/s00146-021-01294-x

Dauvergne, P. (2021). The globalization of artificial intelligence: Consequences for the politics of environmentalism. *Globalizations, 18*(2), 285–299. https://doi.org/10.1080/14747731.2020.1785670

Davidovic, D., & Harring, N. (2020). Exploring the cross-national variation in public support for climate policies in Europe: The role of quality of government and trust. *Energy Research & Social Science, 70*, Article 101785. https://doi.org/10.1016/j.erss.2020.101785

Dietz, T., Dan, A., & Shwom, R. (2007). Support for climate change policy: Social psychological and social structural influences*. *Rural Sociology, 72*(2), 185–214. https://doi.org/10.1526/003601107781170026

Djeffal, C., Siewert, M. B., & Wurster, S. (2022). Role of the state and responsibility in governing artificial intelligence: A comparative analysis of AI strategies. *Journal of European Public Policy, 29*(11), 1799–1821. https://doi.org/10.1080/13501763.2022.2094987

Easton, D. (1975). A re-assessment of the concept of political support. *British Journal of Political Science, 5*(4), 435–457. https://doi.org/10.1017/S0007123400008309

Estevez, E., & Janowski, T. (2013). Electronic governance for sustainable development — Conceptual framework and state of research. *Government Information Quarterly, 30*, S94–S109. https://doi.org/10.1016/j.giq.2012.11.001

European Commission. (2017). *Special Eurobarometer 460: Attitudes towards the impact of digitisation and automation on daily life*. Brussels: European Union.

European Commission. (2020). *White paper on artificial intelligence - a European approach to excellence and trust*. Brussels: European Commission.

European Commission. (2020a). *Eurobarometer 92.3 (2019)Eurobarometer 92.3 (2019): Standard Eurobarometer 92: Standard Eurobarometer 92. GESIS Data Archive*. https://doi.org/10.4232/1.13564

European Commission. (2021). *Declaration on a green and digital transformation of the EU*. Brussels: European Commission. Available at: https://digital-strategy.ec.europa.eu/en/news/eu-countries-commit-leading-green-digital-transformation (accessed 17 July 2021).

European Commission. (2022). *Regulatory framework proposal on artificial intelligence*. Brussels: European Commission. Available at: https://digital-strategy.ec.europa.eu/en/policies/regulatory-framework-ai (accessed 6 February 2023).

Filgueiras, F. (2022). Artificial intelligence policy regimes: Comparing politics and policy to National strategies for artificial intelligence. *Global Perspectives, 3*(1), 32362. https://doi.org/10.1525/gp.2022.32362

Franzen, A., & Meyer, R. (2010). Environmental attitudes in cross-National Perspective: A multilevel analysis of the ISSP 1993 and 2000. *European Sociological Review, 26*(2), 219–234. https://doi.org/10.1093/esr/jcp018

Gallego, A., & Kurer, T. (2022). Automation, digitalization, and artificial intelligence in the workplace: Implications for political behavior. *Annual Review of Political Science, 25*(1). https://doi.org/10.1146/annurev-polisci-051120-104535. annurev-polisci-051120-104535.

Gaudiello, I., Zibetti, E., Lefort, S., et al. (2016). Trust as indicator of robot functional and social acceptance. An experimental study on user conformation to iCub answers. *Computers in Human Behavior, 61*, 633–655. https://doi.org/10.1016/j.chb.2016.03.057

Geiger, S., & Holzhauer, B. (2020). *Weiterentwicklung Einer Skala Zur Messung von Zentralen Kenngrößen Des Umweltbewusstseins*. Dessau-Roßlau: Umweltbundesamt.

Gellrich, A. (2021). *25 Jahre Umweltbewusstseinsforschung Im Umweltressort*. Dessau-Roßlau: Umweltbundesamt.

Graham, H., Bland, J. M., Cookson, R., et al. (2017). Do people favour policies that protect future generations? Evidence from a British survey of adults. *Journal of Social Policy, 46*(3), 423–445. https://doi.org/10.1017/S0047279416000945

Grzymek, V., & Puntschuh, M. (2019). *What Europe knows and thinks about algorithms results of a representative survey*. Gütersloh: Bertelsmann Stiftung.

Hammar, H., & Jagers, S. C. (2006). Can trust in politicians explain individuals' support for climate policy? The case of CO2 tax. *Climate Policy, 5*(6), 613–625. https://doi.org/10.1080/14693062.2006.9685582

Harring, N. (2016). Reward or punish? Understanding preferences toward economic or regulatory instruments in a cross-National Perspective. *Political Studies, 64*(3), 573–592. https://doi.org/10.1111/1467-9248.12209

Harring, N., & Jagers, S. (2013). Should we Trust in Values? Explaining public support for pro-environmental taxes. *Sustainability, 5*(1), 210–227. https://doi.org/10.3390/su5010210

Harring, N., & Jagers, S. C. (2018). Why do people accept environmental policies? The prospects of higher education and changes in norms, beliefs and policy preferences. *Environmental Education Research, 24*(6), 791–806. https://doi.org/10.1080/13504622.2017.1343281

Huber, R. A., Wicki, M. L., & Bernauer, T. (2020). Public support for environmental policy depends on beliefs concerning effectiveness, intrusiveness, and fairness. *Environmental Politics, 29*(4), 649–673. https://doi.org/10.1080/09644016.2019.1629171

IEA. (2020). *Data centres and data transmission networks*. Paris: International Energy Agency. Available at: https://www.iea.org/reports/data-centres-and-data-transmission-networks (accessed 12 July 2021).

Ingold, K., Stadelmann-Steffen, I., & Kammermann, L. (2019). The acceptance of instruments in instrument mix situations: Citizens' perspective on Swiss energy transition. *Research Policy, 48*(10), 1–11. https://doi.org/10.1016/j.respol.2018.10.018

Jakobsson, C., Fujii, S., & Gärling, T. (2000). Determinants of private car users' acceptance of road pricing. *Transport Policy, 7*(2), 153–158. https://doi.org/10.1016/S0967-070X(00)00005-6

Kallbekken, S., Garcia, J. H., & Korneliussen, K. (2013). Determinants of public support for transport taxes. *Transportation Research Part A: Policy and Practice, 58*, 67–78. https://doi.org/10.1016/j.tra.2013.10.004

Kalyanpur, N., & Newman, A. L. (2019). The MNC-coalition paradox: Issue salience, foreign firms and the general data protection regulation. *JCMS. Journal of Common Market Studies, 57*(3), 448–467. https://doi.org/10.1111/jcms.12810

Kankanhalli, A., Charalabidis, Y., & Mellouli, S. (2019). IoT and AI for smart government: A research agenda. *Government Information Quarterly, 36*(2), 304–309. https://doi.org/10.1016/j.giq.2019.02.003

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 & Society*, 1–15. https://doi.org/10.1177/20539517221092956 (online version).

Kitt, S., Axsen, J., Long, Z., et al. (2021). The role of trust in citizen acceptance of climate policy: Comparing perceptions of government competence, integrity and value similarity. *Ecological Economics, 183*, Article 106958. https://doi.org/10.1016/j.ecolecon.2021.106958

König, P. D., Wurster, S., & Siewert, M. B. (2022). Consumers are willing to pay a price for explainable, but not for green AI. Evidence from a choice-based conjoint analysis. *Big Data & Society, 9*(1), 1–13. https://doi.org/10.1177/20539517211069632

Krafft, T. D., Zweig, K. A., & König, P. D. (2020). How to regulate algorithmic decision-making: A framework of regulatory requirements for different applications. *Regulation & Governance*. https://doi.org/10.1111/rego.12369 (online first).

Laitinen, A., & Sahlgren, O. (2021). AI systems and respect for human autonomy. *Frontiers in Artificial Intelligence, 4*, Article 705164. https://doi.org/10.3389/frai.2021.705164

Leiserowitz, A. (2006). Climate change risk perception and policy preferences: The role of affect, imagery, and values. *Climatic Change, 77*(1–2), 45–72. https://doi.org/10.1007/s10584-006-9059-9

Leistner, M. (2021). The Commission's vision for Europe's digital future: Proposals for the data governance act, the digital markets act and the digital services act—A critical primer. *Journal of Intellectual Property Law & Practice*. https://doi.org/10.1093/jiplp/jpab054. jpab054.

Lepri, B., Oliver, N., Letouzé, E., et al. (2018). Fair, transparent, and accountable algorithmic decision-making processes: The premise, the proposed solutions, and the open challenges. *Philosophy & Technology, 31*(4), 611–627. https://doi.org/10.1007/s13347-017-0279-x

Lewallen, J. (2021). Emerging technologies and problem definition uncertainty: The case of cybersecurity. *Regulation & Governance, 15*(4), 1035–1052. https://doi.org/10.1111/rego.12341

Mandel, G. N. (2009). Regulating emerging technologies. *Law, Innovation and Technology, 1*(1), 75–92. https://doi.org/10.1080/17579961.2009.11428365

Metag, J., & Marcinkowski, F. (2014). Technophobia towards emerging technologies? A comparative analysis of the media coverage of nanotechnology in Austria, Switzerland and Germany. *Journalism, 15*(4), 463–481. https://doi.org/10.1177/1464884913491045

Mikalef, P., Lemmer, K., Schaefer, et al. (2022). Enabling AI capabilities in government agencies: A study of determinants for European municipalities. *Government Information Quarterly, 39*(4), 1–15. https://doi.org/10.1016/j.giq.2021.101596

Mittelstadt, B. D., Allo, P., Taddeo, M., et al. (2016). The ethics of algorithms: Mapping the debate. *Big Data & Society, 3*(2), 1–21. https://doi.org/10.1177/2053951716679679

Mundorf, N., Dholakia, R. R., Dholakia, N., et al. (1996). German and American Consumer Orientations to Information Technologies: Implications for marketing and public policy. *Journal of International Consumer Marketing, 8*(3–4), 125–143. https://doi.org/10.1300/J046v08n03_07

Nemitz, P. (2018). Constitutional democracy and technology in the age of artificial intelligence. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 376*(2133), 1–14. https://doi.org/10.1098/rsta.2018.0089

Nimrod, G. (2018). Technophobia among older internet users. *Educational Gerontology, 44*(2–3), 148–162. https://doi.org/10.1080/03601277.2018.1428145

Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *International Journal of Information Management, 53*, Article 102104. https://doi.org/10.1016/j.ijinfomgt.2020.102104

Pidgeon, N., Harthorn, B., & Satterfield, T. (2011). Nanotechnology risk perceptions and communication: Emerging technologies, emerging challenges: Nanotechnology risk perceptions and communication. *Risk Analysis, 31*(11), 1694–1700. https://doi.org/10.1111/j.1539-6924.2011.01738.x

Pinotti, P. (2012). Trust, regulation and market failures. *Review of Economics and Statistics, 94*(3), 650–658. https://doi.org/10.1162/REST_a_00209

Pitlik, H., & Kouba, L. (2015). Does social distrust always lead to a stronger support for government intervention? *Public Choice, 163*(3–4), 355–377. https://doi.org/10.1007/s11127-015-0258-7

Radu, R. (2021). Steering the governance of artificial intelligence: National strategies in perspective. *Policy and Society, 40*(2), 178–193. https://doi.org/10.1080/14494035.2021.1929728

Rosen, L. D., & Weil, M. M. (1995). Adult and teenage use of consumer, business, and entertainment technology: Potholes on the information superhighway? *Journal of Consumer Affairs, 29*(1), 55–84. https://doi.org/10.1111/j.1745-6606.1995.tb00039.x

Roßteutscher, S., Schmitt-Beck, R., Schoen, H., et al. (2018). Nachwahl-Querschnitt (GLES 2017). *GESIS Data Archive*. https://doi.org/10.4232/1.13138

Sager, F. (2009). Governance and coercion. *Political Studies, 57*(3), 537–558. https://doi.org/10.1111/j.1467-9248.2008.00743.x

Schade, J., & Schlag, B. (2003). Acceptability of urban transport pricing strategies. *Transportation Research Part F: Traffic Psychology and Behaviour, 6*(1), 45–61. https://doi.org/10.1016/S1369-8478(02)00046-3

Schwartz, R., Dodge, J., Smith, N. A., et al. (2019). *Green AI*. arXiv:1907.10597 (pp. 1–12).

Sinkovics, R. R., Stöttinger, B., Schlegelmilch, B. B., et al. (2002). Reluctance to use technology-related products: Development of a technophobia scale: Reluctance to use technology-related products. *Thunderbird International Business Review, 44*(4), 477–494. https://doi.org/10.1002/tie.10033

Smuha, N. A. (2021). From a 'race to AI' to a 'race to AI regulation': Regulatory competition for artificial intelligence. *Law, Innovation and Technology, 13*(1), 57–84. https://doi.org/10.1080/17579961.2021.1898300

Stadelmann-Steffen, I., & Eder, C. (2021). Public opinion in policy contexts. A comparative analysis of domestic energy policies and individual policy preferences in Europe. *International Political Science Review, 42*(1), 78–94. https://doi.org/10.1177/0192512120913047

Steg, L., Dreijerink, L., & Abrahamse, W. (2005). Factors influencing the acceptability of energy policies: A test of VBN theory. *Journal of Environmental Psychology, 25*(4), 415–425. https://doi.org/10.1016/j.jenvp.2005.08.003

Stoutenborough, J. W., Bromley-Trujillo, R., & Vedlitz, A. (2014). Public support for climate change policy: Consistency in the influence of values and attitudes over time and across specific policy alternatives: Public support for climate change policies. *Review of Policy Research, 31*(6), 555–583. https://doi.org/10.1111/ropr.12104

Syahrivar, J., Gyulavári, T., Jászberényi, M., et al. (2021). Surrendering personal control to automation: Appalling or appealing? *Transportation Research Part F: Traffic Psychology and Behaviour, 80*, 90–103. https://doi.org/10.1016/j.trf.2021.03.018

Taeihagh, A., Ramesh, M., & Howlett, M. (2021). Assessing the regulatory challenges of emerging disruptive technologies. *Regulation & Governance, 15*(4), 1009–1019. https://doi.org/10.1111/rego.12392

Thompson, N. C., Greenewald, K., Lee, K., et al. (2020). The computational limits of deep learning. ArXiv:2007.05558 [Cs, Stat]. Available at: http://arxiv.org/abs/2007.05558.

Tosun, J., Schaub, S., & Fleig, A. (2020). What determines regulatory preferences? Insights from micropollutants in surface waters. *Environmental Science & Policy, 106*, 136–144. https://doi.org/10.1016/j.envsci.2020.02.001

Treib, O., Bähr, H., & Falkner, G. (2007). Modes of governance: Towards a conceptual clarification. *Journal of European Public Policy, 14*(1), 1–20. https://doi.org/10.1080/135017606061071406

Vedung, E. (1998). Policy instruments : Typologies and theories. In M.-L. Bemelmans-Videc, R. C. Rist, & E. Vedung (Eds.), *Carrots, sticks & sermons: Policy instruments and their evaluation* (pp. 21–58). Available at: https://search.ebscohost.com/login.aspx?direct=true&scope=site&db=nlebk&db=nlabk&AN=1577480 (accessed 25 February 2022).

Vinuesa, R., Azizpour, H., Leite, I., et al. (2020). The role of artificial intelligence in achieving the sustainable development goals. *Nature Communications, 11*(1), 233. https://doi.org/10.1038/s41467-019-14108-y

Wurster, S. (2010). *Zukunftsvorsorge in Deutschland*. Baden-Baden: Nomos. https://doi.org/10.5771/9783845223285

Wurster, S. (2013). Comparing ecological sustainability in autocracies and democracies. *Contemporary Politics, 19*(1), 76–93. https://doi.org/10.1080/13569775.2013.773204

Wüstenhagen, R., Wolsink, M., & Bürer, M. J. (2007). Social acceptance of renewable energy innovation: An introduction to the concept. *Energy Policy, 35*(5), 2683–2691. https://doi.org/10.1016/j.enpol.2006.12.001

van Wynsberghe, A. (2021). Sustainable AI: AI for sustainability and the sustainability of AI. *AI and Ethics, 1*(3), 213–218. https://doi.org/10.1007/s43681-021-00043-6

Zhang, B., & Dafoe, A. (2019). *Artificial intelligence: American attitudes and trends*. Oxford: Center for the Governance of AI, Future of Humanity Institute, University of Oxford.

Zuiderwijk, A., Chen, Y.-C., & Salem, F. (2021). Implications of the use of artificial intelligence in public governance: A systematic literature review and a research agenda. *Government Information Quarterly, 38*(3), Article 101577. https://doi.org/10.1016/j.giq.2021.101577

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