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Abstract

This paper examines an often overlooked yet significant threat to survey validity and epistemic justice: the unequal communication of opinion. We discuss research that signals the presence of this threat when studying public opinion about AI. Furthermore, we apply Bourdieu's theoretical framework as a potential explanation of the inequality in communicating an opinion about AI.

We describe this inequality and test our explanation by performing a multilevel analysis on four questions about AI governance from the Eurobarometer 92.3 and two questions on its implications on our way of life and jobs from the Eurobarometer 95.2. Our results suggest that there is inequality in communicating opinions: higher social positions are more likely to communicate an opinion. We also find evidence to support the claim that the habitus is the underlying mechanism mediating this inequality in opinion Our results suggest significant effects of self-perceived social class, external political efficacy, internal political and scientific efficacy, and relevant cultural capital regarding science and technology. Lastly, we do not find consistent results regarding the effect of the selected contextual level variables across the two surveys.

This paper examines an often overlooked yet significant threat to survey validity and epistemic justice: the unequal communication of opinion. We discuss research that signals the presence of this threat when studying public opinion about AI. Furthermore, we apply Bourdieu's theoretical framework as a potential explanation of the inequality in communicating an opinion about AI. We describe this inequality and test our explanation by performing a multilevel analysis on four questions about AI governance from the Eurobarometer 92.3 and two questions

on its implications on our way of life and jobs from the Eurobarometer 95.2. Our results suggest that there is inequality in communicating opinions: higher social positions are more likely to communicate an opinion. We also find evidence to support the claim that the habitus is the underlying mechanism mediating this inequality in opinion Our results suggest significant effects of self-perceived social class, external political efficacy, internal political and scientific efficacy, and relevant cultural capital regarding science and technology. Lastly, we do not find consistent results regarding the effect of the selected contextual level variables across the two surveys. Our findings suggest that inequality in communicating an opinion is widely present when studying public opinion about AI. Future studies should check for this inequality before widely distributing their surveys. Should such inequality be detected, corrective measures should be taken to preserve research validity and mitigate epistemic injustice.

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Keywords: survey research, AI, public opinion, inequality in communicating opinion**,** epistemic injustice

1) Introduction

Artificial intelligence (AI) has woven itself into the fabric of everyday life, manifesting in both leisurely activities, such as navigating social media platforms like Facebook, and public services exemplified by the implementation of predictive policing (Brayne & Christin, 2021), and spanning areas of finance, hiring, surveillance and marketing (Brayne & Christin, 2021; Feldstein, 2019; OECD, 2019). The recent revolution in generative AI, symbolized by ChatGPT has accelerated the penetration of AI in society and flared up the public discussion surrounding it (Christiaens, 2024; D'Amato, 2024).

Understanding public opinion about AI is pivotal, given the public's role as a key stakeholder in AI development (Züger & Asghari, 2023). Stimulating dialogue between the public and experts implementing AI can foster mutual understanding (Selwyn & Gallo Cordoba, 2022). This is particularly critical for minorities and marginalized communities, who are disproportionately affected by AI's adverse effects according to research (Bircan & Korkmaz, 2021; Brayne & Christin, 2021; Lei & Kim, 2024; O'Neil, 2016; Selwyn & Gallo Cordoba, 2022; Weng et al., 2024). Christiaens (2024) for example argues that '*LLMs are just the latest weapon of mass obsolescence that capital has developed against the bargaining power of the working class*'.

Surveys are pivotal for gauging the public's opinions about AI, prized for their ability to capture a representative snapshot of societal views (Gurkan & Suchow, 2024; Kozyreva et al., 2021; Zhang & Dafoe, 2020). However, using surveys for studying public opinion about AI comes with notable challenges.

Firstly, the response rate to surveys querying public opinion about AI is low (Araujo et al., 2020; Yigitcanlar et al., 2022). Additionally, a substantial proportion of the people who do take part in these surveys abstain from communicating an opinion (Gillespie et al., 2021; Lillemäe et al., 2023; Selwyn & Gallo Cordoba, 2022; Vu & Lim, 2021). Typically, these nonresponses are then coded as missing and removed from the analysis. However, the number of missing values is substantial. For example in (Vu & Lim, 2021) the sample size is reduced from 27,901 to 16,672. Moreover, this refrainment from communicating an opinion is not random but seems to be related to demographic and socio-economic characteristics of participants (Eurobarometer, 2017; Lillemäe et al., 2023). Inequalities in communicating an opinion about AI are also observed across countries (Eurobarometer, 2017; European Commission, Brussels, 2020) and across regions (Neudert et al., 2020).

The inequality in communicating an opinion about AI poses an important threat to the validity of surveys. It might be a sign of *epistemic injustice*, implying that some people are excluded from the discussion surrounding the topic (Fricker, 2013). Given that surveys are an indispensable yet expensive instrument in research (Yigitcanlar et al., 2022; Züger & Asghari, 2023), this threat to their validity warrants further investigation.

This research applies Bourdieu's sociological theories to understand inequalities in public opinion about AI governance, exploiting his insights on social fields, habitus, and capital. We have chosen Bourdieu's theories for their robust capacity to describe the complexities that shape interactions in the evolving domain of AI, particularly useful for examining the distinct ways in which different generations engage with these technologies. Older individuals may approach AI with more scepticism and less intuitive digital fluency compared to younger people, who are typically more embedded in digital culture. This generational gap informs our survey methodology, prompting us to include measures of digital literacy and political efficacy alongside traditional demographic variables to capture a wide array of factors that shape AI opinions.

Through this theoretical and methodological approach, we aim to offer a nuanced understanding of public opinions on AI, guiding more inclusive and effective AI governance policies, and mitigating epistemic injustice in this field of research.

Theoretical background

1) Peril and promise of The Survey

Surveys are widely recognized as a crucial tool to map the public opinion about various topics, offering the unique capacity to make generalized statements about a population's thoughts and sentiments (De Leeuw et al., 2012; Mays et al., 2022). However, this utility is not without its drawbacks. Unlike qualitative research, which emphasizes researchers' efforts to comprehend participants, surveys require participants to interpret the intent behind the researchers' questions.

Indeed, surveys function as a top-down approach in capturing people's perspectives. Researchers are guided by existing literature in developing their surveys; thus determining what is deemed significant enough to inquire about (Yigitcanlar et al., 2022).

Surveys that delve into the public's opinion about an emerging topic such as AI are therefore vulnerable to what Bourdieu (2000) calls the *scholastic barrier*. This barrier arises when the language and concepts used by researchers are drawn from an academic discourse that may not be universally comprehensible. The scholastic barrier is bifurcated by the field-specific competence necessary to decipher the questions asked (Bourdieu, 2000b). In the following paragraph we discuss how the scholastic barrier and the field specific competence required to overcome it might lead to epistemic injustice.

2) Field-specific competence: the requirement to break through the scholastic barrier

To communicate a valuable opinion through a survey requires that you read the question through the discourse of the field and that you can place the answer options according to the divisions characterizing the field (Bourdieu, 1993). To do so requires field-specific competence (Bourdieu, 1984, 1993). Field-specific competence provides the respondent with the right key to decipher the meaning of field-specific questions, like aesthetic competence provides people with the right key to decipher the meaning behind a work of art (Bourdieu, 1984, 1993; Bourdieu & Darbel, 1991).

Inequalities in field-specific competence translate into differences in *modes of production* of opinion (Bourdieu, 1993). Some people indeed read field-specific questions through the fitting discourse and answer accordingly, hence using the field's schemes of perception (Bourdieu, 1984, 1993). Others do not read these questions using the field's discourse because they did not acquire its schemes of perception (Bourdieu, 1993). When respondents read field-specific questions without having the required competence, this can lead to frustration and refrainment from answering the question. But it can also lead to misinterpretation of the question-and-answer options.

Questions that require field-specific competence and are hence characterized by a scholastic barrier are prone to what Fricker (2007) has termed *hermeneutical injustice*. Hermeneutical injustice occurs when people experience unfair obstacles, like the scholastic barrier, in communication (Medina, 2017). Applied to the context of this study, this scholastic barrier is drawn by AI literacy.

3) The obstacle to surveying the public opinion on AI: AI literacy

The comprehension of AI-related survey questions requires a certain level of AI literacy (the key necessary to unpack the meaning behind the questions-and-answer options about AI). However, AI literacy is in general low and unequally distributed across social space. Individuals' self-reported knowledge about AI is low (Horowitz et al., 2023; Scantamburlo et al., 2023). Awareness about when AI is present is low (Balaram et al., 2018; Gillespie et al., 2021; Gran et al., 2021) and understanding about AI is distorted in a significant proportion of the population (Cave et al., 2019). Research also shows that many people believe in radical narratives surrounding AI which indicates that people overestimate AI's abilities (Cave et al., 2019).

The disparities in AI literacy often reflect broader socio-economic inequalities. Research indicates that younger, higher educated, financially better-off people, and men report greater familiarity with AI (Eurobarometer, 2017; Gillespie et al., 2021; Snaphaan et al., 2020). The democratization of AI tools and technologies has made AI more accessible to a broader audience, yet this accessibility has not necessarily translated into improved literacy across all demographics (Arguedas & Simon, 2023; Seger et al., 2023). Recent studies further demonstrate that higher education attainment correlates with both increased awareness of, and a more critical attitude towards AI (Gran et al., 2021; O'Shaughnessy et al., 2023). Furthermore, Wang and colleagues (2024) find that the most vulnerable people (i.e., older, lower education, and with weaker privacy protection skills than average) were also the ones with the lowest levels of AI knowledge. Lastly, research in medical students also shows significantly lower AI literacy in women compared to men, but also a significantly lower literacy about the technicalities of AI systems compared to the critical assessment of AI systems (Laupichler et al., 2024). Emerging research suggests that while more people engage with AI-enabled services, the understanding of AI's ethical and societal implications remains limited, necessitating targeted educational initiatives to bridge this knowledge gap (Akter et al., 2023; Stix & Maas, 2021).

4) *The role of the opinionated habitus*

Why individuals from lower social positions may be less inclined to develop AI literacy and communicate their opinions about AI can be illuminated through Bourdieu's *Habitus* concept. Habitus, as articulated by Bourdieu (1984, 1990), is a system encompassing all our dispositions, i.e., durable, generative schemes of perception, appreciation, and action. The habitus is a product of socialization, systematically conditioned according to one's social position (Bourdieu, 1990). Its dispositions are generative, they produce actions, opinions, and perceptions (Bourdieu, 1984). This way, social position and opinions are linked (people in the same social position, evolve similar dispositions, which lead to similar opinions).

Children internalize these dispositions throughout their upbringing, making them more likely to act in accordance with their social background (Bourdieu, 1984). This results in different expressions of social inequality. Even though there are not many formal barriers in our societies (e.g., education is financially accessible for everyone), people nonetheless select or exclude themselves from institutions according to their social background (Bourdieu & Passeron, 1979).

This principle also applies to the communication of opinions (Bourdieu, 1984). The probability of answering for example complex political questions shows a strong relation with the political power that people objectively have (Bourdieu, 1984). The dominant explanation for this phenomenon is political competence: those who are more politically competent are more likely to answer political questions. However, this does not fully capture the situation. What happens is a cyclical process in which people who enjoy social status (e.g., someone with a master's or a PhD) are more inclined to inform themselves, become acquainted with the political discourse, and develop an opinionated habitus, because they will be expected to have an opinion by society and their peers. Furthermore, they possess *the right to speak*, feeling more entitled to have an opinion, and are listened to with more respect (Bourdieu, 1984). They will also have an interest in having an opinion since they will be more likely to have actual power to implement their opinion (Bourdieu, 1984).

People with low social status (e.g., no secondary degree) will be less likely to inform themselves (Beaumont, 2011; Bourdieu, 1984; Kraus et al., 2015; Laurison, 2012, 2015, 2016). They are less likely to experience the incentives to produce an opinion, less often expected to have an opinion by their peers, and lack the political power necessary to implement their opinions. Consequently, they are more likely to be disinterested in politics (Bourdieu, 1984). Having developed less political competence, they will be less likely to have the necessary key to read politics and hence, with the associated frustration, conclude that politics is not for them (Bourdieu, 1984). They are generally more demotivated to develop an opinion because they have less favourable cards to play the political game (Bourdieu, 1984).

5) A model about communication of opinions

Figure 1 summarizes the ideas discussed above. It shows that we can explain opinions (i.e., whether they are produced, communicated, or their content) based on one's social position. The relationship between both is mediated by the habitus.

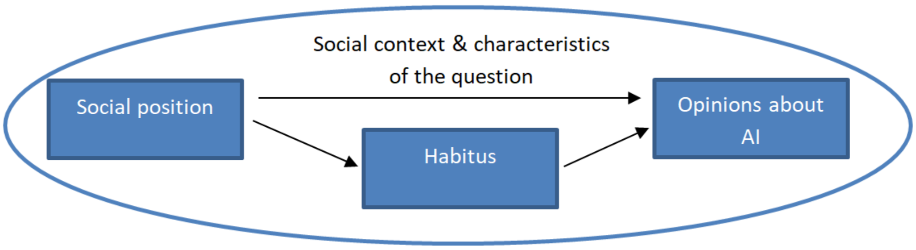

Figure 1: Theoretical model explaining the production of opinions. Based on (Bourdieu, 1984).

In our analysis, we will test this theoretical model. More specifically, we will test the inequality in political opinions by statistically analysing the inequality in communicating 'Don't Know'. Participants also had the option to select *'none of the above'* and some also answered *'other'*, implying that if they state DK they do not abstain from communicating an opinion because their answer option is not provided.

Hypothesis 1: the more abstract the question posed; the less respondents will communicate their opinion.

Hypothesis 2: there is inequality between social positions (i.e., your position on the dimensions of age, gender, economic and cultural capital) and between countries in communicating an opinion about AI governance.

Hypothesis 3: The relationship between social position and communicating an opinion is mediated by relevant dispositions of the habitus.

6) The role of country context

Since our study uses hierarchical data (citizens clustered within European member states), we will use a multilevel analysis (Heck et al., 2013; Hox, 2010). This affords to study whether certain country characteristics are related to the development of a more or less opinionated habitus. Previous research suggests that contextual variables can shape individual-level opinions (Turja & Oksanen, 2019; Vu & Lim, 2021). Contextual level variables create a social context that could support or discourage the formation and communication of opinions about AI. However, extant research on public opinion about AI is in general negligent about institutional context (Zhang, 2021).

Based on the theoretical framework outlined above, we hypothesize that inequality results in a less opinionated population. The underlying rationale is that countries with greater equality offer a context with smaller status differences (Wilkinson & Pickett, 2010). Since we anticipate that the reluctance to communicate an opinion stems from a low self-perceived social status relative to others (Bourdieu, 1984; Kraus et al., 2015; Laurison, 2015), we expect that countries with smaller status differences will have more citizens who are willing to communicate their opinions.

However, other contextual factors could also influence the communication of opinions. We might expect societies that fulfil more conditions for a smooth operation of democracy in contemporary digital societies, to be more opinionated. This implies that we expect that populations in member states will more often communicate an opinion if they: (1) perceive themselves as digitally literate, (2) spend more time on the internet (as a proxy for digital inclusion), (3) have high media literacy (since it would be logical that citizens, in that case, are better informed about the development of AI), (4) perceive themselves as understanding the contemporary world (which is a proxy for internal political efficacy but then aggregated on a population level), (5) perceive the governments (of their country of residence) as more responsive to their opinions and (6) have a higher Human Development Index (HDI).

Secondly, also economic conditions could play a role in whether or not a population is opinionated. Countries with more economic welfare possibly have a more opinionated population about AI.

To test our theory, we will test the following hypotheses:

Hypothesis 4.1: Countries with lower inequality, have a more opinionated population. Even if we control for other variables.

Hypothesis 4.2: Contextual factors that point to a more highly developed digital democracy and economy, are also related to a more opinionated population.

2) Methodology

1) The dataset

Our analysis is performed on secondary data from Eurobarometer 92.3 (2019). We use this dataset since it is one of the richest datasets accessible to study the inequality in public opinion about AI, with data about many other interesting variables on the individual level, and the possibility to compare the inequality in public opinion on a country level. We also use data from the Eurobarometer 92.4 (also from 2019. Hence, it is compatible especially since we aggregate it on country level) to operationalize *self-perceived digital literacy* as a country level variable.

The research population are the citizens of European Union member states. We draw on a representative sample of 27382 citizens of the EU aged above 15 (European Commission, Brussels, 2020). Around 1000 people per country are sampled using multi-stage random probability sampling (GESIS, 2020). The dataset contains weights based on figures published by Eurostat. We applied W1 when distinguishing between countries since it reproduces the real number of cases per country. We applied W23 when describing the total population of the EU since it adjusts the sample according to the correct proportion within countries as well as within the EU at large. In the multilevel analysis we did not apply weights. Since we use age, gender, difficulties with paying the bills and age when ending fulltime education as predictors, we already control for all the relevant variables on which the weighting would be based. Difference in weight between countries is solved by implementing a multilevel regression. Furthermore, the package that we use (lme4) does not support the usage of weights. However, we also performed the analysis using the nlme package combined with the MASS package. The correlation between the fitted results of the analysis with and without weights was between 0.96 and 0.975 for the different models we ran.

As a robustness check for our theoretical model, we decided to add an extra analysis on a more recent Eurobarometer, namely the EB95.2 (GESIS, 2021). This data has been collected during the months April and May 2021, and is the most recent Eurobarometer data that asks questions specifically about AI. It contains responses of 27 811 citizens of the EU28 countries. We removed participants who did not identify as man or woman (35 participants) since we use sex as a predictor and 35 participants is too little. Furthermore, we also encountered 11 missing values in the variable measuring age which also had to be removed in order to perform the analysis resulting in a sample of 27 765 participants. In the Eurobarometer 92.3 we did not have to remove any participants. Since we include all DK answers as predictors there are no missing values.

2) Operationalization

In this section, we provide information about operationalization that we deem most important to interpret our findings. For more detailed information, please refer to appendix 1.

We operationalize our dependent variable, communicating an opinion, by creating a dichotomous variable where 0 indicates communicating an opinion (the respondent selects one of the given answer options) and 1 indicates refraining from communicating an opinion (the respondent states "Don't Know" (DK)). This approach is based on the rationale that DK is a good proxy for inequality of opinion due to the scholastic barrier. Individuals who had an opinion that was not provided among the answer options still had the opportunity to choose "none of the above" or "other".

The independent variables are categorized into three categories. We first discuss the operationalization of the variables in the Eurobarometer 92.3 models. The first category contains the demographic variables that operationalize the social position of a respondent. These include: Age, Difficulty with paying the bills, education, sex, and occupation.

The second category of independent variables are the first-level explanatory variables (i.e., explanatory on the individual level). One of these explanatory variables is political self-efficacy which is often used in the political science literature. Morrel defines it as *"citizens' perceptions of powerfulness (or powerlessness) in the political realm."* (Morrell, 2003, p. 589). This definition is very similar to Bourdieu's (1984) notion of *political competence*. Political self-efficacy is often understood as being two-dimensional, with an internal dimension representing the sense of competence of the individual and an external dimension representing the perception that political institutions are responsive to the individual (do they listen, does my voice count?) (Morrell, 2003). Although our data do not allow us to use many established scales, we used the statement: "You understand well what is going on in today's world" as a proxy for internal political efficacy. External efficacy was measured through statements: "My voice counts in the EU" and "My voice counts in (our country)" (as is done in: Mcevoy, 2016; Vincenzo, 2019). The frequency of internet usage and self-perceived social class are also used as explanatory variables within the model.

The last class of independent variables are the explanatory variables on the country level. These entail: self-perceived digital literacy, citizens' average time spent on the internet, media literacy, HDI, real GDP per capita (divided by 1000), and Gini index. All contextual level variables are centred around their grand mean to facilitate the interpretation of the model (Heck et al., 2013).

The Eurobarometer 95.2 provides the same demographic variables as the Eurobarometer 92.3. Regarding the first level explanatory variables, information about the frequency of internet usage and internal political efficacy are missing. Instead, the survey contains three new interesting variables which can serve as proxies for the constructs in which we are interested. 1) One question probes into the extent to which interviewees engage with science and technology issues (do they talk about it with friends or family, do they watch documentaries about it… See appendix 1) which we aggregated into a cultural capital regarding science and technology scale. 2) Another question probes into the external self-perceived efficacy regarding science and technology (We have no option but to trust those governing science and technology), and 3) a last question asks about the internal self-perceived efficacy regarding science (Science is so complicated that I do not understand much about it). Lastly, although the variable "My voice counts in the EU" is present in the data, the values for the UK are missing. Hence, we drop this variable, since we already know that it is strongly correlated with "My voice counts in *My Country*".

For the country level variables, we only include GDP, HDI, and Gini index since based on the first analysis (on the Eurobarometer 92.3) these are perceived to be the most promising and insightful.

3) Analysis

In the result section, we focus primarily on the results of the model predicting the communication of an opinion on the question about how to ensure an ethical development of AI since its dependent variable (DV) ratio is the lowest and it presents the best example of the phenomenon we try to investigate, namely the unequal refrainment of giving an opinion on abstract questions. We will compare this model with three other models predicting communication of an opinion on three other AI governance-related questions. In the last subsection, we will present the results of the analyses on the Eurobarometer 95.2.

We test our hypotheses through a multilevel random intercept binary logistic model executed through R studio, running R 4.4.0, using the lme4 package (Bates et al., 2014). Several convergence issues occurred which were solved by using the bobyqa optimizer and, if necessary, restarting the estimation from the previous fit and increasing the max number of iterations (R documentation, 2022). For descriptive analyses, we have used SPSS. The problems experienced with estimation are probably due to a high DV ratio. When the DV ratio is high, the power to find significant predictors will be lower. Hence, parameters that are significant, are probably strong predictors (Buchanan, 2019). Besides, because there are only 28 countries included in our sample, the power to predict contextual-level effects is low.

Since multiple countries are included in the survey, relevant characteristics of the respondents will be nested on the country level. To avoid violating the assumption of independence of observations, we decided to use a multilevel model as is recommended (Field, 2018; Hox, 2010; Twisk, 2006).

4) Results

1) *The effect of abstractness*

Table 1 suggests that on more complex questions, i.e., more knowledge is required for a substantiated opinion, fewer people state an opinion. As already mentioned, we choose to discuss primarily the model predicting the communication of an opinion on the ethical development of AI statement.

Table 1: *Percentages of DK answers per AI government statement (weighted by W23)*

	DK	**Communicates opinion**
Do you think that you should be informed when a digital service or mobile application is using artificial intelligence?	7.0%	93.0%
Which statements below, if any, would you select to finish the statement: Artificial intelligence can be best used to	7.7%	92.3%
Which statements below, if any, would you select to finish the statement: You are concerned that the use of artificial intelligence could lead to	9.1%	90.9%
To ensure that Artificial Intelligence applications are developed in an ethical manner	11.9%	88.1%

2) *The effect of country-level variables on communicating an opinion*

As Figure 2 shows, there is variation between the member states of the EU in the percentage of the population that states an opinion, especially so on the statement we discuss.

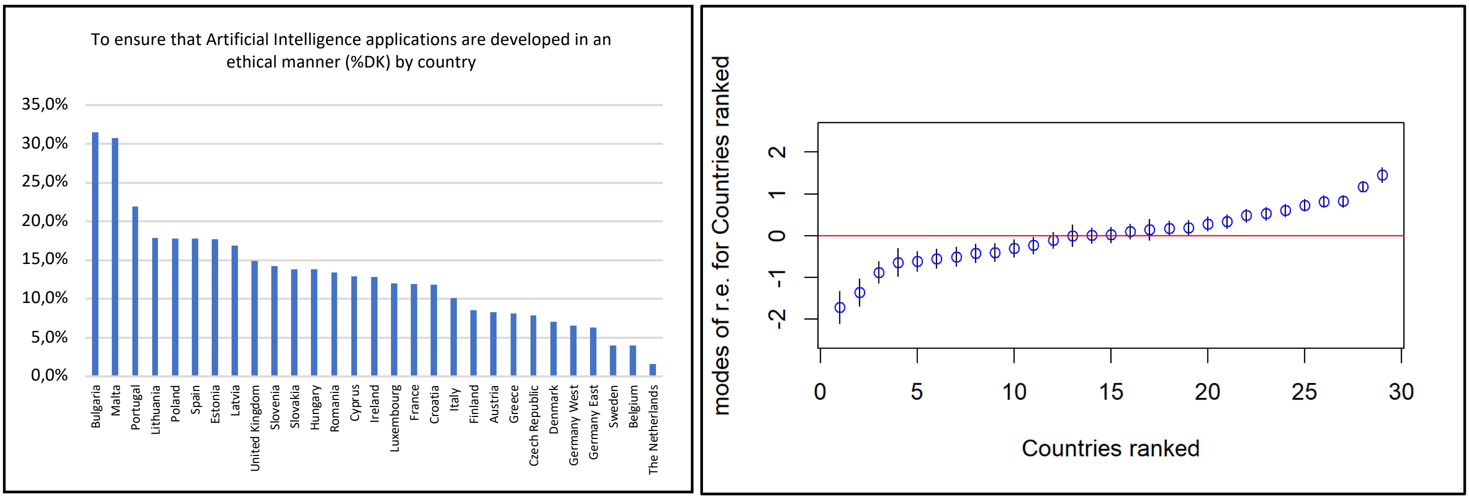

Figure 2: Percentage of the population answering DK per country (weighted by W1) at the left and a caterpillar plot (produced in R) showing the residuals at country level at the right (the blue lines indicate the 95% confidence intervals of the country level residuals).

A LRT between the model with fixed intercept and random intercepts indicates a significant increase of fit ($\chi^2(1) = 1183{,}2952$, $p < 0{,}001$). All three other models show significant variation across countries in communicating an opinion. The caterpillar plot (Figure 2) also points to a multilevel structure in our data. Hence, we are justified in constructing a multilevel model (Heck et al., 2013).

Model 1 (Table 2) shows the effect of Gini as the only predictor in the model since this is the variable where we are mainly interested in from our theoretical perspective. To test hypotheses 4.1 and 4.2, we will add other variables as well. However, since the sample size on country-level is not very large and the contextual level variables are moderately to strongly correlated (see Table 3, Appendix 1), we chose to control for the other relevant variables, listed in hypothesis 4.2, by each time only combining one variable with the Gini coefficient (hence leading to 5 models with two contextual level variables, see Tables 4-7, appendix 1) to maintain statistical power.

Including Gini as a predictor significantly increases the fit of the model ($\chi^2(1) = 7.2$, $p < 0.01$). The estimated coefficient is in the expected direction, countries with more inequality are related to populations that less often communicate an opinion. Adding other contextual predictors does decrease the effect size (see Table 7, appendix 1), but in general it remains a significant predictor (only when controlling for HDI, it becomes marginally significant: $z = 1.862$, $p = 0.063$ while HDI is highly significant in this model: $z = -4.035$, $p < 0.001$). Also adding GDP and the percentage of DK on the question about self-perceived digital literacy lead to a significantly better fitting model ($\chi^2(1) = 4.172$, $p < 0.05$ & $\chi^2(1) = 7.067$, $p < 0.01$ respectively). Adding media literacy and internet usage conversely does not increase the fit of our models. All these models explain a substantial proportion of the variance on country level (including Gini reduced the random variance on country level from 0.5 to 0.38, adding the other variables decreased the country level variance even further until 0.3572 when including media literacy and even 0.2783 when including percentage of population answering DK on self-perceived digital literacy, signifying that Gini and percentage of DK's together explain 44% of the unexplained country level variance in the null model).

The models predicting the communication of an opinion on the other questions generally suggest that inequality has a negative effect on the communication of opinions (see appendix Tables 4-6, although when we control for the other variables, Gini is often only marginally or not significant). Adding other variables does not increase the fit of the models for these statements.

Hence, these results suggest that contextual level variables do play a role in predicting the communication of opinions, especially on the question of how to make AI develop ethically. Inequality in particular seems to be detrimental to the communication of opinions, but also the percentage of DK's on self-perceived digital literacy, GDP per capita, and HDI seem to be important predictors.

3) The relationship between social position and stating an opinion

Figure 3 illustrates the relationship between occupation and stating DK. Except for some minor changes in order, the general picture remains the same across the different statements: the higher the social position of the occupation (for example professionals or managers compared to farmers and fishermen), the less often one states DK.

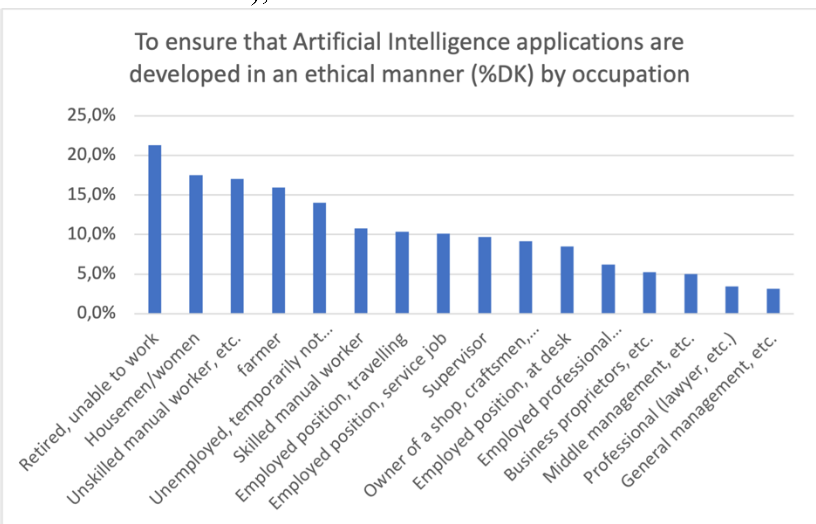

Figure 3: Percentage of citizens of the EU answering DK per occupation (weighted with W23)

In Table 2, model 2 presents the multilevel model with only the demographic variables included. Regarding model fit, based on the Likelihood Ratio Test (LRT), we see that model 2 fits the data significantly better than the null model ($\chi^2(29) = 1442.4$, $p < 0.001$). Turning to the fixed effects, we observe that all five variables are significant predictors of communicating an opinion. The model predicts that the reference group (i.e., male professionals who are between 25 and 34 years old, ended their education after being 20, and with almost never or never problems paying the bills) has a probability of 1.58 percent to refrain from communicating their opinion. Professionals, general management, and business proprietors most often communicate an opinion while farmers and fishermen least often communicate an opinion (6.9% of them state DK, holding the other variables constant at their most optimal level). Turning to education, we observe that all categories differ significantly from the reference category, albeit with smaller effect sizes. The variable representing economic capital has two significant differences compared to the reference group: people with difficulties paying the bills most of the time or people refusing to answer this question significantly more often refrain from communicating an opinion. People who have difficulties paying the bills sometimes, remarkably, significantly more often communicate an opinion, although the parameter is only marginally significant. Age also shows significant differences. People from 55 to 75 or more tend to refrain from communicating an opinion significantly more often (our model suggests that people aged between 45-54 also more often refrain from communicating an opinion, but the parameter is only marginally significant). Lastly, considering gender, women's odds of communicating an opinion are roughly 1,4 times as small as those of men.

While interpreting these effects, it is important to consider that we control for the other variables, while these variables are correlated (retired people are older, people with more education have fewer problems with paying the bills, and education is also related to age…). So, observing that these variables still lead to independent significant differences is quite remarkable.

The results for the models predicting the communication of an opinion on the other questions are roughly the same. First off, all models fit significantly better than the null model.

Second, in all these models, all predictors contain significant parameters. They also follow the same pattern (the higher the education, the more likely one is to communicate their opinion. The older respondents are, the less likely that they will communicate their opinion…). The only notable difference is that occupation is less predictive (see Table 8, Appendix 1).

4) Habitus as the mediator between social position and stating an opinion

Model 3 presents the estimated model with first level explanatory variables included. The LRT indicates a significantly better fitting model (χ^2 (20) = 1118.9, $p < 0.001$ compared to model 2). Also notable, the random effect variance of the random intercept has decreased from 0.474 in model 2 to 0.317 in this model. additionally, the pseudo-R^2 statistics also increased notably compared to model 2 (see Table 2).

All variables in model 3 contain significant parameters. The expected probability for the reference group to refrain from communicating an opinion (i.e., the same as in model 2 but now the reference group are also people who totally agree with the statement that they understand well what is going on in today's world, that use the internet every day or almost every day, who perceive themselves as upper class and who totally agree that their voice counts in EU and their country) is 0.86 percent compared to 1.58 percent in model 2.

In general, we observe a decrease in the effect sizes of the demographic variables. This is evidenced by the diminished differences between the probabilities of the reference group and the groups discerned in the categorical predictors. For example, being a farmer or fisherman was related to a 6.90 percent probability of not communicating an opinion compared to 1.58 percent for professionals in model 2, while in model 3 the probability has decreased to 2.79 percent compared to 0.86 percent for professionals. Several parameters became less significant compared to model 2 or even insignificant. For example, only the oldest age category is now related to significantly less often communicating an opinion. Also the parameter for people with difficulties paying the bills most of the time is not significant anymore. Remarkably, the parameter for people with difficulties paying the bills from time to time is now very significant. The decrease of the effect sizes and significance of the demographic variables, suggests that the explanatory variables explain part of the variation previously explained by the demographic variables, implying that they partly mediate the relationship between social space and communicating an opinion.

Internal political efficacy is clearly a significant predictor. The less people agree with this statement, the more often they refrain from communicating their opinion. For the predictor internet usage, we observe the same pattern. Concerning the predictor perceived social class, the only significant answer categories are those representing the difference between upper class and working class and None, refusal, other, or DK. They are related with a lower probability of communicating an opinion. The two variables operationalizing external political efficacy are highly correlated to each other (χ^2 (16) = 35601.340, $p < 0.001$; $\rho = 0.655$, $p < 0.001$). Hence, it is not surprising that we observe smaller effect sizes in both variables. Nevertheless, it is surprising that they both explain a unique significant proportion of the variation in the dependent variable. The effect of the 'my voice counts in the EU' seems to be stronger than that of the 'my voice counts in my country' variable. Lastly, we observe that the biggest effect sizes (but also SE's) are systematically those of the 'DK' category across all variables discussed above.

In the models predicting the communication of an opinion on the other questions, we observe similar results. First, according to an LRT, each of the models which include first-level explanatory variables, fits significantly better than model 2 (χ^2 (20) = 1031.9, $p < 0.001$; χ^2 (20) = 913.1, $p < 0.001$; χ^2 (20) = 1034.7, $p < 0.001$ respectively for statement 1, 2 and 3). Also notable is that the second-level variance declines in all models compared to the demographics-only models. Most of the demographic variables became less significant or insignificant and concordantly their effect size diminished (see Tables 9-11, Appendix 1) while the introduced parameters are often very significant. Hence, our results support hypothesis 3.

5) The full model

In model 4 we present the social position-, habitus- and the contextual level variables. We adopt the same strategy as when testing the effect of the contextual level variables (starting with Gini and combining Gini with the other contextual level variables of interest).

Regarding the model fit, all models fit the data significantly better compared to model 3 (see Table 9, Appendix 1). Especially the unexplained country-level variance decreases substantially. Remarkably, the only variable that helps explain a significant proportion of the unexplained variance on top of Gini is the percentage of DK's on self-perceived digital literacy when we account for the demographic and individual level explanatory variables.

Regarding the predictors, we observe that the effect size of Gini decreases when we account for social position and habitus variables (the odds ratio per unit increase, decreases from 1.089 to 1.069). However, it remains a significant predictor ($z = 2.747$, $p < 0.01$). Also the effect of the other contextual level variables decreases when we account for the social position and habitus variables (see table 15, appendix 1). HDI and real GDP per capita are not significant predictors anymore. Only the percentage of DK's on self-perceived digital literacy is significant ($z = 2.133$, $p < 0.05$). Gini stays a significant predictor in all models, only in the model where we control for HDI, it becomes marginally significant ($z = 1.696$, $p = 0.090$).

Regarding the models predicting the communication of an opinion in the other statements, the contextual effects are less pronounced (see Appendix Tables 12-15). In the models predicting the communication of an opinion on statements 2 and 3, Gini is significant on its own, but often becomes marginally significant or insignificant when we add other contextual level variables. The other contextual level variables are not significant.

Predictors		Null model			Model 1					Model 2					Model 3					Model 4				
		Estimate	SE	Probability	Estimate	SE	z	p value	Probability	Estimate	SE	z	p value	Probability	Estimate	SE	z	p value	Probability	Estimate	SE	z	p value	Probability
	Intercept	-1.953	0.135	12.42%	-1.954	0.119	-16.45	<0.001***	12.41%	-4.129	0.356	-11.59	<0.001***	1.58%	-4.753	0.370	-12.834	<0.001***	0.86%	-4.757	0.36913	-12.89	< 2e-16	0.85%
Contextual																								
	Gini				0.085	0.030	2.860	0.004**	1.089[1]											0.066	0.024	2.747	0.006**	1.069
Individual																								
Occupation	General management									0.193	0.471	0.408	0.683	1.91%[2]	0.242	0.478	0.506	0.613	1.09%	0.245	0.480	0.511	0.609	1.09%
	Business proprietors									0.578	0.379	1.526	0.127	2.79%	0.594	0.383	1.552	0.121	1.54%	0.599	0.386	1.553	0.120	1.54%
	Middle management									0.826	0.340	2.430	0.015*	3.55%	0.843	0.344	2.452	0.014*	1.96%	0.848	0.346	2.448	0.014*	1.97%
	Employed professional									0.745	0.357	2.086	0.037*	3.28%	0.759	0.362	2.097	0.036*	1.81%	0.761	0.364	2.092	0.036*	1.81%
	Student									1.266	0.352	3.599	<0.001***	5.40%	0.943	0.357	2.641	0.008**	2.17%	0.948	0.360	2.636	0.008**	2.17%
	Employed position at desk									1.130	0.333	3.393	<0.001***	4.75%	1.162	0.337	3.450	<0.001***	2.68%	1.167	0.340	3.438	<0.001***	2.69%
	Owner of a shop, craftsmen									0.987	0.348	2.832	0.005**	4.14%	1.023	0.352	2.903	0.004**	2.34%	1.026	0.355	2.891	0.004**	2.34%
	Supervisor									0.991	0.379	2.614	0.009**	4.16%	0.872	0.385	2.263	0.024*	2.02%	0.877	0.388	2.262	0.024*	2.02%
	Employed position, travelling									1.123	0.344	3.269	0.001**	4.72%	1.103	0.348	3.170	0.002**	2.53%	1.107	0.351	3.157	0.002**	2.53%
	Employed position, service job									1.126	0.334	3.370	<0.001***	4.73%	1.071	0.338	3.169	0.002**	2.45%	1.075	0.340	3.157	0.002**	2.45%
	Skilled manual worker									1.055	0.332	3.173	0.002**	4.42%	0.973	0.337	2.892	0.004**	2.23%	0.977	0.339	2.882	0.004**	2.23%
	Unemployed, temporarily not working									1.358	0.335	4.053	<0.001***	5.89%	1.084	0.339	3.193	0.001**	2.49%	1.089	0.342	3.183	0.001**	2.49%
	Farmer and fisherman									1.526	0.368	4.151	<0.001***	6.90%	1.204	0.375	3.213	0.001**	2.79%	1.207	0.377	3.200	0.001**	2.79%
	Unskilled manual worker									1.437	0.340	4.227	<0.001***	6.34%	1.213	0.344	3.522	<0.001***	2.82%	1.217	0.347	3.506	<0.001***	2.82%
	Responsible for ordinary shopping									1.329	0.336	3.956	<0.001***	5.73%	1.182	0.341	3.470	<0.001***	2.73%	1.186	0.343	3.457	<0.001***	2.74%
	Retired, unable to work									1.477	0.330	4.477	<0.001***	6.58%	1.253	0.334	3.751	<0.001***	2.93%	1.257	0.337	3.733	<0.001***	2.93%
Education	17-19									0.406	0.054	7.538	<0.001***	2.36%	0.219	0.056	3.890	<0.001***	1.06%	0.220	0.056	3.905	<0.001***	1.06%
	0-16									0.832	0.059	14.119	<0.001	3.57%	0.375	0.064	5.814	<0.001***	1.24%	0.375	0.064	5.814	<0.001***	1.23%
	DK and refusal									0.831	0.137	6.060	<0.001***	3.56%	0.521	0.145	3.582	<0.001***	1.43%	0.519	0.145	3.569	<0.001***	1.42%
Diff. paying the bills	from time to time									-0.086	0.047	-1.815	0.070.	1.46%	-0.253	0.050	-5.114	<0.001***	0.67%	-0.256	0.050	-5.172	<0.001***	0.66%
	most of the time									0.282	0.066	4.293	<0.001***	2.09%	-0.007	0.070	-0.106	0.916	0.85%	-0.011	0.070	-0.163	0.870	0.84%
	refusal									0.880	0.135	6.499	<0.001***	3.73%	0.396	0.145	2.737	0.006**	1.27%	0.394	0.145	2.719	0.007**	1.26%
Age	35-44									0.023	0.085	0.267	0.789	1.62%	0.002	0.087	0.017	0.986	0.86%	0.002	0.087	0.021	0.983	0.85%
	45-54									0.135	0.082	1.649	0.099.	1.81%	0.048	0.084	0.576	0.565	0.90%	0.049	0.084	0.578	0.563	0.89%
	55-64									0.286	0.081	3.548	<0.001***	2.10%	0.105	0.084	1.250	0.211	0.95%	0.105	0.084	1.251	0.211	0.95%
	65-74									0.401	0.094	4.251	<0.001***	2.35%	0.077	0.100	0.765	0.444	0.92%	0.077	0.100	0.768	0.442	0.92%
	75+									0.934	0.099	9.481	<0.001***	3.94%	0.416	0.108	3.868	<0.001***	1.29%	0.416	0.108	3.868	<0.001***	1.29%
	15-24									0.103	0.117	0.877	0.381	1.75%	0.088	0.121	0.730	0.465	0.93%	0.088	0.121	0.728	0.466	0.93%
Sex	Women									0.336	0.040	8.439	<0.001***	2.20%	0.287	0.041	6.950	<0.001***	1.14%	0.287	0.041	6.950	<0.001***	1.13%
Int. pol. Eff.	Tend to agree														0.237	0.061	3.896	<0.001***	1.08%	0.238	0.061	3.917	<0.001***	1.08%
	Tend to disagree														0.635	0.067	9.476	<0.001***	1.60%	0.637	0.067	9.516	<0.001***	1.60%
	Totally disagree														0.796	0.087	9.124	<0.001***	1.88%	0.799	0.087	9.159	<0.001***	1.87%
	DK														1.297	0.118	10.959	<0.001***	3.06%	1.301	0.118	10.996	<0.001***	3.06%
Internet usage	Less often than everyday														0.215	0.063	3.434	<0.001***	1.06%	0.215	0.063	3.435	<0.001***	1.05%
	Never														0.745	0.060	12.316	<0.001***	1.78%	0.744	0.060	12.312	<0.001***	1.78%
	No access														0.756	0.100	7.599	<0.001***	1.80%	0.757	0.100	7.603	<0.001***	1.80%
	DK														0.980	0.178	5.496	<0.001***	2.25%	0.980	0.178	5.497	<0.001***	2.24%
S-p class	Middle class														0.114	0.119	0.961	0.336	0.96%	0.115	0.119	0.968	0.333	0.95%
	Lower middle class														0.208	0.127	1.637	0.102	1.05%	0.208	0.127	1.641	0.101	1.05%
	Working class														0.506	0.123	4.107	<0.001***	1.41%	0.507	0.123	4.109	<0.001***	1.41%
	None, refusal, other or DK														1.053	0.145	7.289	<0.001***	2.41%	1.053	0.145	7.286	<0.001***	2.40%
External eff. EU	Tend to agree														0.066	0.089	0.740	0.460	0.91%	0.066	0.089	0.745	0.456	0.91%
	Tend to disagree														0.213	0.094	2.278	0.023*	1.06%	0.214	0.094	2.291	0.022*	1.05%
	Totally disagree														0.409	0.099	4.127	<0.001***	1.28%	0.410	0.099	4.137	<0.001***	1.28%
	DK														0.912	0.114	7.991	<0.001***	2.10%	0.911	0.114	7.983	<0.001***	2.09%
Ext. eff. country	Tend to agree														0.157	0.074	2.133	0.033*	1.00%	0.154	0.074	2.096	0.036*	0.99%
	Tend to disagree														0.139	0.083	1.670	0.095.	0.98%	0.134	0.083	1.607	0.108	0.97%
	Totally disagree														0.236	0.092	2.569	0.010*	1.08%	0.228	0.092	2.490	0.013*	1.07%
	DK														0.553	0.127	4.339	<0.001***	1.48%	0.549	0.127	4.312	<0.001***	1.47%
Model summaries																								
	Random effect Variance			0.5011					0.3842					0.4735					0.3167				0.2463	
	log-likelihood			-10392.4					-10388.8					-9671.2					-9111.8				-9108.4	
	Deviance			20784.8					20777.6					19342.4					18223.5				18216.8	
	-2LLR test'			NA					7.2[3]	**				1442.4	***				1118.9	***			6.7	**
	df			27380					27379					27351					27331				27330	
	AIC			20788.8					20783.6					19404.4					18325.5				18320.8	
	BIC			20805.3					20808.3					19659.2					18744.6				18748.1	
	n			27382					27382					27382					27382				27382	
	R^2 cs			NA					0.0003					0.0513					0.0893				0.0895	
	R^2 n			NA					0.0005					0.0965					0.1679				0.1683	

Table 2: *Results of the multilevel binary logistic regression-analyses predicting refrainment from communicating an opinion*.

[1] Since the contextual level variables are on a continuous scale, the increase per unit is not linear. Hence, instead, we opted to mention the odds ratio per unit increase.

[2]Since all individual level predictors are on a categorical scale, these percentages represent the predicted percentage that refrains from communicating an opinion, other predictors held at their reference category (which is the category related to the smallest chance of refraining from communicating an opinion).

[3] the likelihood ratio test results, result from the comparison between the previous model and the concerned model, except in model 2 (since it is not nested in model 1) which is compared to the null model.

[4]Significance: *** p<0.001, ** p<0.01, * p<0.05, . p<0.1 (marginally significant), rest is not significant

6) *Replication of results using more recent data*

To strengthen the argument for our model, and to test whether it remains relevant over time while the field of AI is rapidly changing and public awareness is rising, we decided to do an extra analysis on the Eurobarometer 95.2 from 2021. The result we try to predict in this dataset is answering DK on the questions “The following is a list of areas where new technologies are currently being developed. For each of these, do you think it will have a positive, a negative, or no effect on our way of life in the next 20 years?: Artificial intelligence” and “The following are some statements that people have made about science or technology. For each statement, please indicate to what extent you agree or disagree: Artificial intelligence and automation will create more jobs than they will eliminate”.

In the analysis of responses to these questions, a multilevel structure is evident, as indicated by the improved quality of fit for the multilevel model compared to the single-level logistic regression model (see Tables 1 & 2, Appendix 2). Despite this, there is no clear evidence that the country-level variables considered—Human Development Index (HDI), Gross Domestic Product (GDP), and Gini coefficient—are important predictors of communication of an opinion at the country level (see Tables 3-10, Appendix 2). Specifically, the Gini coefficient shows no significant impact, while HDI is highly significant according to the Wald Z-Test, and GDP is marginally significant. However, the Likelihood Ratio Test (LRT) does not show significance for either HDI or GDP. When all country-level variables were included in a single model, the LRT again indicated no significant effects. Multicollinearity tests revealed strong correlations among the country-level variables, particularly between GDP and HDI (see Table 11, Appendix 2).

Adding demographic variables to the null model does significantly improve the model fit for both statements (We will for the rest of this section first mention the result for the model predicting DK on the statement about AI’s influence on our way of life and second the model that predicts DK on the statement about AI's influence on the job market: $\chi^2(30) = 663.71$, $p < 0.0001$; $\chi^2(30) = 344.17$, $p < 0.0001$). A similar pattern as in the previous analysis emerges, with lower education, higher age, and being a woman significantly predicting the likelihood of stating DK on these statements. Regarding the economic dimension, we see less evidence of a significant correlation. Occupation appears slightly less predictive in these statements compared to the original analysis, though the overall pattern remains similar (see Tables 12 & 13, Appendix 2).

Including explanatory variables (see Tables 14 & 15, Appendix 2) also significantly enhances model fit according to the LRT ($\chi^2(19) = 644.19$, $p < 0.0001$; $\chi^2(19) = 691.5$, $p < 0.0001$). The Wald Z-test highlights the significance of variables operationalizing cultural capital regarding science and technology, as well as internal efficacy regarding science (which is reverse coded: the more one disagrees, the higher the self-perceived internal efficacy regarding science). While all these first level explanatory variables have at least one significant value, external efficacy concerning science and technology appears to be the least predictive in the model.

In the full models, only HDI was included due to multicollinearity among contextual variables, and since HDI appeared to be the most promising contextual level variable. Nevertheless, results in Tables 16 and 17 suggest that HDI is not a significant predictor since its inclusion does not improve model fit ($\chi^2(1) = 1.8769$, $p > 0.05$; $\chi^2(1) = 1.4316$, $p > 0.05$).

Overall, the findings consistently show that stating DK in explanatory variables is one of the strongest predictors for stating DK when asked about opinions on AI.

5) Discussion

In general, our analyses support the proposed theory. In both the Eurobarometer 92.3 (2019) and the Eurobarometer 95.2 (2021), we observe that individuals in lower social positions are more likely to state DK on questions concerning AI, its governance, and its impact. While there is a clear effect of occupation in the 2019 survey, this is less evident in the 2021 survey. Notably: age, education, and gender emerge as strong predictors among the demographic variables.

Our analyses also support the mediation of the relationship between demographic variables and communicating an opinion about AI by relevant variables of the habitus. In both surveys, including first-level explanatory variables decreases the effect size of the demographic variables.

Both the 2019 and 2021 surveys provide evidence for the effect of perceived social class, consistent with prior studies (Kraus et al., 2015; Laurison, 2015). Both surveys also support the relationship between external political efficacy and the communication of an opinion, aligning with previous research findings (Beaumont, 2011; Kraus et al., 2015; Laurison, 2012). The same pattern holds for internal efficacy regarding politics in the 2019 survey and regarding science in the 2021 survey.

Additionally, among variables not comparable across the two surveys, internet usage is also a significant predictor of communicating an opinion about AI governance. Cultural capital is an important predictor in the 2021 survey while external efficacy regarding science is not very predictive, except for stating DK on this question. Generally, stating DK on the explanatory level variable is strongly related to abstaining from communicating an opinion about AI.

Lastly, evidence from the 2019 survey indicates the detrimental effect of inequality in a country on the communication of an opinion about AI. HDI, welfare, and the percentage of DKs on self-perceived digital literacy also seem to influence whether a population has opinions in this survey. However, when accounting for demographic variables and proxies for our habitus concept, only the percentage of DKs on self-perceived digital literacy remained significant (though its interpretation is challenging) and only for statement 4 of the 2019 survey. For the 2021 survey, we do not observe convincing evidence for the effect of the selected country-level variables. Therefore, we conclude that we cannot convincingly confirm hypotheses 4.1 and 4.2.

Furthermore, we cannot conclude that the differences in effects between surveys are caused by the evolution in time, as the questions we try to predict differ as well. Nevertheless, the analysis of the more recent survey strengthens the robustness of our findings, suggesting that they are generalizable over time and across questions about AI.

These findings are disturbing since they point to a double disadvantage for people in a low social position. They are in the worst position to reap the benefits of AI and most likely to feel its pernicious consequences. Indeed, research suggests that AI deepens social inequality by being most beneficial to the privileged and most threatening to the disadvantaged and vulnerable (Balaram et al., 2018; Bircan & Korkmaz, 2021; Brayne & Christin, 2021; Bughin et al., 2018; Gebru, 2019; Korinek & Stiglitz, 2019; O'Neil, 2016). At the same time, people in low social positions are less likely to gain the competence necessary to read these questions and position themselves in the landscape concerning the governance of AI. This makes it more likely that injustices because of AI are maintained because there is no political counterforce that defies it.

1) The survey and epistemic injustice

The concept of functional differentiation is a defining trait of modern societies, as noted by most founding fathers of sociology. Functional differentiation brings along many benefits, foremost efficiency and effectiveness in the functioning of these specialized domains. Nevertheless, functional differentiation comes with a cost, namely a gap in understanding these domains. Because of the complexity, it becomes increasingly difficult to be knowledgeable about all the important domains and processes taking place in society.

An ethical governance of AI implies that we follow *la volonté générale* in developing the AI-ecosystem. As Shoshana Zuboff argues, the digital future belongs to the public (Zuboff, 2019). Surveys are an excellent tool to listen to the public's opinion, but only if we consider the precondition for effective communication which is that the required competence is equally distributed across social space. If surveys do not meet this precondition, this might be an expression of hermeneutical injustice (Fricker, 2007). Hermeneutical injustice occurs when people experience unfair obstacles in communication (Medina, 2017). For example, the scholastic barrier in surveys. At the same time, the limited answer options available to the participant result in *testimonial injustice,* i.e., the phenomenon that some messages are not taken seriously (Fricker, 2013). Only the provided answer options are deemed relevant. The resulting *epistemic injustice* entails a danger to the development of AI since some people's interests are not taken into account (Fricker, 2013). We understand inequality in opinion as an expression of epistemic injustice.

Based on the discussion above, we argue that overcoming epistemic injustice implies asking questions that are meaningful for everyone, and not just for the few who are acquainted with the field. The question of whether more governance regulation is necessary, or whether the market can regulate itself to ethically develop the field is perhaps interesting for people actively engaged in the field or following it closely. However, for the general public, it is probably a question about which a large proportion is not actively thinking and does not have a strong opinion. Hence, asking such questions using a survey might not be very elucidating.

Conversely, asking questions that are not universally understood can lead to manipulation and legitimization of policies that are in the interest of only a few. This epistemic injustice is possible because it is obscured through the *cult of the person* (Bourdieu, 1984). This is an ideology that idealizes the capacities of humans, claiming that certain competencies: to produce political opinions, to understand and enjoy art, to study anything you want, and to act rationally (for example to handle your money 'rationally') are universal (Bourdieu, 1984). However, they are only universal on paper (Bourdieu, 1984). In reality, these competencies are often generally low among the public and distributed unequally ((Delli Carpini, 2000; Fraile, 2011, 2014; Laurison, 2016; Vandebroeck, 2004) for political competence, (Bourdieu, 2000a) for 'rational' economic behaviour (Bourdieu & Passeron, 1979), and for equal opportunities in school). The cult of the person conceals inequality in political opinions by claiming that everyone can form political opinions.

However, in practice, as shown in our analysis, in the case of complex and abstract questions for which knowledge of the field is necessary, higher social positions will select themselves, and lower social positions are more likely to exclude themselves, resulting in a picture of public opinion that is disproportionately that of the privileged instead of being representative as desired.

Therefore, we argue that researchers engaging in public opinion research about AI should pay attention to inequality in public opinion, which represents a major threat to the validity of surveys and is an expression of epistemic injustice. Inequality in opinion should be assessed during preliminary studies. If identified, researchers should consider interventions ranging from rephrasing questions for broader inclusivity, to offering educational resources that enhance understanding of AI. Alternatively, employing a research methodology that allows for richer communication from the participants' side, such as more qualitative approaches like focus groups, may prove beneficial in addressing these concerns.

2) *Limitations and future directions*

The first limitation is that the power to detect significant contextual level predictors is small. This could explain why we cannot confidently confirm hypothesis 4.2. We recommend researchers to study the effect of other contextual-level variables on the communication of opinions and deem it important to base the selection of these variables on theory.

A second limitation is the fact that no people under 15 are sampled. While research on public opinion about AI consistently indicates that age is a significant variable, the perceptions and opinions of children and teenagers are underrepresented.

A third limitation and interesting associated future direction is that the rapid and far-reaching developments in the field of AI might alter our findings if the survey would have taken place in 2024. Hence, we argue that a longitudinal design is important in order to track the changes in public opinion about AI during its vibrant evolution.

Lastly, this study is limited by the suboptimal operationalization of certain concepts. For example the concept of social position: the Eurobarometer 92.3 dataset includes variables measuring level of education, economic situation and occupation but these do not capture the nuances our theoretical framework demands. For instance, economic status is crudely indicated by the ability to pay one's bills, whereas a more detailed income scale or a nuanced subjective measure would be preferable. Future research could adopt a more qualitative approach to understand better what drives people to communicate or abstain from communicating an opinion.

Conclusion

We applied Bourdieu's theoretical work in a new context, namely public opinion research about AI. This resulted in a theoretical framework that predicts and explains inequality in communication of opinions about AI, for which we found empirical support by doing a multilevel logistic regression analysis on the Eurobarometer 92.3 (2019) and the Eurobarometer 95.2 (2021). The results suggest that this inequality in public opinion about AI governance is related to one's social position. Older, less affluent and educated people are more likely to refrain from communicating an opinion. We also found support for the mediating role of the habitus (especially *self-perceived social class, external political efficacy, internal political and scientific efficacy, and relevant cultural capital regarding science and technology)* in explaining this relationship. *Lastly, we do not find consistent results regarding the effect of the selected contextual level variables across the two surveys. Our findings suggest inequality in communicating an opinion is widely present when studying public opinion about AI.* Our findings imply that research on public opinion about AI should be more attentive to the implications of their study's design on inequality of opinion and epistemic injustice.

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