AI Suffrage:
A four-country survey on the acceptance of an automated voting system

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Abstract

Governments have begun to employ technological systems that use massive amounts of data and artificial intelligence (AI) in the domains of law enforcement, public health, or social welfare. In some areas, shifts in public opinion increasingly favor technology-aided public decision-making. This development presents an opportunity to explore novel approaches to how technology could be used to reinvigorate democratic governance and how the public perceives such changes. The study therefore posits a hypothetical AI voting system that mediates political decision-making between citizens and the state. We conducted a four-country online survey (N=6043) in Greece, Singapore, Switzerland, and the US to find out what factors affect the public's acceptance of such a system. The data show that Singaporeans are most likely and Greeks least likely to accept the system. Considerations of the technology's utility have a large effect on acceptance rates across cultures whereas attitudes towards political norms and political performance have partial effects.

1. Introduction

Although the topic of automated decision-making generates considerable discussion (e.g., [1], [2], [3], [4]), relatively little is known about how governments employ complex systems that make use of AI. Most scholars focus on how governments should regulate these technologies but not on how states themselves employ them. This is true despite the fact that numerous state administrations utilize automated decision-making in law enforcement, public health, or social welfare [5]. Freeman Engstrom, Ho, Sharkey, and Cuéllar [6] point out that almost half of US federal agencies have experimented with AI tools or, at a preliminary stage, with algorithmic decision-making. In Europe, the use of such systems is experimental too, and the domains of application remained largely unmapped until recently [7]. Various European governments employ algorithmic decision-making and at times AI to facilitate policing [8], [9] or to control access to social security systems [10], [11]. In China, the central government implements large-scale projects that combine big data and AI technology (e.g., facial recognition systems) to monitor the behavior of individuals [12], [13].

At the same time, polities around the world struggle with political legitimacy. For example, the percentage of people in Europe and the US who feel it is "essential to live in a democracy" has fallen from two thirds to under one third during the period from World War II to 2017 [14]. Additionally, the circulation of misinformation and fake news (e.g., [15]) puts a strain on civic and political cultures and causes discontent among sizable parts of the electorate with politicians, established political institutions, and their seeming inability to act in the interest of their constituents. In many places, this contributes to a sense of alienation, radicalization, and subversive populism [16]. This state of agitation gives rise to a loss of trust in political actors, which is essential to the proper working of democratic governance [17]. As Newton [18] points out, satisfaction with government and confidence in public institutions correlates significantly with generalized trust that provides an essential basis for all sorts of everyday activities. Degenerating trust in government thus implies harmful consequences for organized society as a whole.

Evidently, questions about how to upgrade government systems in ways that improve governance and restore trust in public institutions are critical. In this regard, a few eye-catching, antithetical shifts in public opinion have taken place. For example, the proportion of Americans who believe that experts should decide what is best for the country rather than the government increased from 32% from the World War II period to 49% in 2017 [14]. Public opinion surveys also find that, due to the COVID-19 pandemic, Europeans are more open to trust experts [19]. In a similar vein, 51% of Europeans would support reducing the number of national members of parliament and giving those seats to an algorithm; this percentage reaches 75% in China and 40% in the US [20]. These developments present an opportunity to explore whether the public accepts novel technological systems and, if so, how they could be used to improve trust in institutions and good governance.

Against this backdrop, we conducted a cross-national survey to probe the public's attitude towards a hypothetical AI system that exercises voting rights on behalf of citizens. The system we propose is unusual in at least two ways. First, it doubtlessly challenges widely held beliefs about the value of political participation and how it should be practiced in democracies. Second, the voting system likely attracts a host of well-known criticisms regarding discrimination, accountability, privacy, and human autonomy (e.g., [21], [22], [23], [24]), which are associated with algorithmic decision-making and AI in general. Critics might also argue that while AI and related technologies perform some tasks exceptionally well, they are not good at predicting social outcomes [25]. These observations are certainly appropriate. In the near future, however, advancements in data hygiene, predictive accuracy, and fairness might alleviate some of these criticisms, which might make an AI system more suitable for the purposes intended here. We also propose that if such a system was implemented in a transparent and accountable manner, it could be used to devise policy proposals and for long-term planning that fosters democratic inclusiveness and technocratic effectiveness (technocracy is a form of government that relies on technical systems and expert knowledge for decision-making rather than on the political affiliation or the skill of representatives) [26]. More importantly, previous research indicates that the perception of decision-making driven by algorithms and AI depends on application contexts (e.g., media, health, or judicial contexts) [27], [28]. The hypothetical scenario at hand thus allows us to explore attitudes and opinions of the public about automated decision-making in the context of politics, an area which so far has received relatively little attention.

The remainder of this study is structured as follows. Section 2 briefly outlines how we conceptualize the AI voting system. After that, Section 3 summarizes the theoretical assumptions and the conceptual model on which the survey is based. We then elaborate on the research method in Section 4 and eventually present the results, their discussion, and research limitations in Section 5. Section 6 concludes the study with a few final thoughts.

2. Conceptualizing an AI voting system

What if a computer guided political decision-making? This idea is not entirely new, even if it seems to spring from the current zeitgeist. As Lepore [29] shows, behavioral researchers tried to devise a machine that predicts public opinion and attitudes as early as the 1960s. Back then, the aim was to develop a computer model that simulates the behavioral processes of everyone in a given population. On this simulated reality, generated from representative samples and from the processing power of computers, the researchers envisioned to test ads for consumer goods. Marketing goods and services, however, was not their sole interest. On top of that, they tried to build a general model of society that would predict individual voting behavior and, at the same time, simulate political processes at an aggregate level. The scientists called this the "people machine" [29].

Opinion polls and electoral forecasts are commonplace today, but a complete simulation of voting publics never came about. However, today's advances in data collection technologies and AI might make the prediction and use of political preferences on a large scale more feasible. To capture this idea in a material way, we envisage a hypothetical AI voting system that collects vast amounts of data about voters. Data already available to administrative agencies and additional data voluntarily provided to the government by its citizens could be combined and used as inputs to the system that assesses the political preferences of every citizen. The insights generated by the system could inform political decision-making with the aim to improve political participation and representative government. Ultimately, this would result in two different types of voting systems, one representing a more radical departure from current voting practices than the other. Using the more radical type of system, constituents would no longer cast votes but would see themselves represented by the insights generated through the AI voting system. The second more moderate type would use the data-based recommendations of the AI system as a tool that supports political decision-making and runs alongside traditional voting systems.

To test whether and under what conditions the public would support the use of an AI voting system, we presented survey respondents with the following vignette: "Imagine the following situation. The government in your country implements a new voting system driven by artificial intelligence (AI). This new system gathers various digital data about you to find out about your opinions, ideas, and political preferences. Based on the information available on all citizens, policy proposals would be developed and those proposals that represent the majority of people would be put into law. This would therefore mean that the AI voting system votes on your behalf instead of you actively casting a vote." After reading this description, the respondents were asked to answer the survey questions.

3. Theoretical development

The survey is based on four key assumptions (see Figure 1 for a visual summary). First, based on the technology acceptance model (TAM) [30], we expect that perceived usefulness and perceived ease of use explain potential users' acceptance of the AI voting system. Second, we assume that socio-demographic factors such as age, gender, and income affect the propensity to accept the system. Third, we assume that aspects of political support occupy an important role. Fourth, we anticipate that general trust in technology across different situations interacts with the acceptance of the system. The following paragraphs provide a more detailed overview of these assumptions and Table 1 presents a summary of the variables, measurements, and hypotheses.

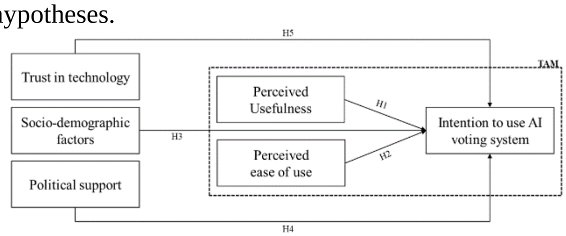

Figure 1. Conceptual model to be tested.

3.1 Technology acceptance model

In information systems research, one of the ongoing issues is to identify factors that cause people to accept and make use of technological systems developed and implemented by others. Because of its relatively straightforward underlying assumptions, TAM is one of the most widely employed models to do so. Based on theory from psychology [31], TAM uses perceived usefulness (PU) and perceived ease of use (PEOU) to predict the intention of potential users to make use of a technological innovation. Davis [30] defines PU as the extent to which people believe that an application will help them perform better. A system high in PU is thus one for which a user believes in the existence of a positive use-performance relationship. In addition, this relationship is theorized to be influenced by PEOU. Venkatesh and Davis [32] define PEOU as "the degree to which a person believes that using a particular system would be free of effort". Thus, according to TAM, a technological system that is perceived to be useful and easy to use is likely to be accepted by users.

Based on TAM theory, we consider three scenarios that result in a positive use-performance relationship. The AI voting system will be seen as useful (1) if it renders politics more transparent, (2) if it leads to better policies than traditional policy-making processes, (3) and if it advances direct democracy (that is, if voters are able to directly decide on policy initiatives instead of relying on elected representatives). Regarding PU, we therefore derive a first set of hypotheses:

- **H1.1**: Acceptance is higher among respondents who believe that the AI voting system creates more transparency.
- **H1.2**: Acceptance is higher among respondents who believe that the AI voting system leads to better policies.
- **H1.3**: Acceptance is higher among respondents who believe the AI voting system advances direct democracy.

With respect to PEOU, we posit the following. If respondents believe that their interaction with the system would be clear and understandable and if they trust that the system would work as promised, they perceive that using the system is free of effort. Based on these premises, we establish a second set of hypotheses:

- **H2.1**: Acceptance is higher among respondents who believe that their interaction with the AI voting system would be clear and understandable.
- **H2.2**: Acceptance is higher among respondents who believe that the AI voting system would work properly.

The above assumptions establish a baseline for the inquiry into the acceptance of the AI voting system. However, we expand beyond this core structure to explore an additional range of potential contextual influences (i.e., socio-demographic factors, political support, and trust in technology). Previous research (e.g., [33]) shows that such modifications are frequent and well accommodated by TAM.

3.2 Socio-demographic factors

Findings about how age and gender affect technology acceptance usually do not lead to firm conclusions. However, previous research indicates that older people are more susceptible to computer anxiety [34] and that increasing age negatively affects acceptance [35]. We therefore assume that younger respondents are more likely to accept the system. Regarding gender, Venkatesh, Morris, Davis, and Davis [36] found that technology acceptance of younger men is strongly affected by PU, whereas the acceptance of older women is more strongly influenced by PEOU. Even if evidence about the effect of gender is inconclusive and gender likely interacts with age, we assume on an exploratory basis that acceptance is higher among men:

- **H3.1**: Acceptance is higher among younger respondents.
- **H3.2**: Acceptance is higher among male respondents.

Compared to age and gender, the importance of education and income on an individual's technology acceptance is well documented (e.g., [37]). Previous research shows that education is negatively related to computer anxiety and positively related to technology acceptance in general [38]. We therefore assume that acceptance is higher among individuals with more education. In parallel, Rogers [39] maintains that technological innovations tend to spread in society through groups that have higher socio-economic status. These groups, the argument goes, possess a more favorable attitude towards decisions to accept new technologies and, more importantly, usually have higher incomes. We thus assume that acceptance is higher for respondents with larger incomes:

- **H3.3**: Acceptance is higher among respondents with more education.
- **H3.4**: Acceptance is higher among respondents with more income.

Whether the surrounding geography of a respondent's place of residence influences technology acceptance is unclear. Research that studies the "digital divide" between metropolitan and non-metropolitan areas concludes that while geographical location does affect the use of information technology, status indicators such as education or income are better predictors [40]. Nonetheless, we assume that respondents who reside in urban areas are more likely to accept the AI voting system. We thus derive the following hypothesis:

- **H3.5**: Acceptance is higher among respondents who live in urban areas.

3.3 Political support

The survey considers differences in political cultures with the aim to compare the distinct contexts of the countries in the sample. As Straub, Keil, and Brenner [41] show, there is reason to believe that cultural differences affect technology acceptance. To operationalize what we call political culture, we rely on Thomassen and van Ham's [42] framework of political support. In this framework, political support is defined as an attitude by which individuals situate themselves, either favorably or unfavorably, vis-á-vis the political community, the political regime, and the political authorities. Conceptually, political support encompasses normative judgments and attitudes about the rightful exercise of political power, e.g., preferences for a democratic political system, but also considerations of short-term utility, e.g., the satisfaction with the performance of the current government [43].

In line with the framework [44], the survey measures political support at three levels: regime principles, regime performance, and regime institutions. At the level of regime principle, the survey asks respondents whether they support governance by experts and whether voting is important to them. We hypothesize that acceptance is higher among those who support the rule by experts because, like technocratic decision-making, the AI voting system would advance decision-making based on specialized knowledge and performance rather than political affiliation or parliamentary skill. We also propound that the acceptance is higher among those respondents to whom voting is less important. This assumption is based on the view that those who value casting votes as an effective means of political participation might be unwilling to replace it with something that profoundly challenges established political decision-making processes. As a result, we arrive at the following hypotheses:

- **H4.1**: Acceptance is higher among respondents who believe that experts should decide what is best.
- **H4.2**: Acceptance is higher among respondents to whom voting is less important.

At the level of regime performance, the survey asks respondents whether they view the political system of their country as just and fair. In addition, respondents are asked to rate their satisfaction with the functioning of the political system in their country. On both counts, we expect that the acceptance of the system is higher for those who are less satisfied with regime performance. We assume so because low levels of satisfaction presumably generate little motivation to preserve the status quo and leaves individuals open to change. The corresponding hypotheses are:

- **H4.3**: Acceptance is higher among respondents who believe the political system of their country is characterized by low levels of justice and fairness.
- **H4.4**: Acceptance is higher among respondents who exhibit low levels of satisfaction with the functioning of the political system in their country.

At the level of political institutions, the survey queries respondents about their level of confidence in the national government and about how effective and competent they perceive politicians to be. Here, we assume that low confidence in government and politicians results in higher acceptance of the AI voting system. I.e., if respondents believe that political actors are untrustworthy or incompetent, they might perceive AI voting as a remedy that counteracts self-serving and ill-informed behavior. As a result, we posit the following hypotheses:

- **H4.5**: Acceptance is higher among respondents who have little confidence in the national government.
- **H4.6**: Acceptance is higher among respondents who believe that politicians are ineffective and incompetent.

Finally, the survey asks respondents about their own political efficacy [45]. Strictly speaking, the framework put forth by van Ham and Thomassen [44] does not mention self-reported political efficacy. However, from a conceptual point of view, including it aligns with the framework's overall goal which seeks to assess individuals' political attitudes towards regimes. We therefore add self-reported political efficacy and hypothesize that respondents who feel insecure about

Table 1. Variables, measurements, and hypotheses

Variable	Measurement	Hypothesis
Perceived usefulness		
Creates more transparency	1 = strongly disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = strongly agree	H1.1
Leads to better policies	1 = strongly disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = strongly agree	H1.2
Advances direct democracy	1 = strongly disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = strongly agree	H1.3
Perceived ease of use		
Clear & understandable	1 = strongly disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = strongly agree	H2.1
Would work properly	1 = strongly disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = strongly agree	H2.2
Socio-demographic factors		
Age	In years	H3.1
Gender	1 = female; 2 = male	H3.2
Education	0 = no formal education, 1 = low; 2 = medium; 3 = high	H3.3
Monthly income	1 = ≤ 210; 2 = ≤ 410; 3 = ≤ 830; 4 = ≤ 1700; 5 = ≤ 2500; 6 = ≤ 3300; 7 = ≤ 5000; 8 = ≤ 6600; 9 = ≤ 8300; 10 = ≤ 9900; 11 = ≤ 12000; 12 = > 12000	H3.4
Rural or urban residence	1 = rural; 2 = city	H3.5
Political support		
Experts decide what is best	1 = very good; 2 = fairly good; 3 = unsure; 4 = fairly bad; 5 = very bad	H4.1
Importance of voting	1 = not at all important; 2 = slightly important; 3 = neutral; 4 = important; 5 = very important	H4.2
Political system is just & fair	1 = strongly disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = strongly agree	H4.3
Satisfaction with performance	1 = not satisfied at all; 2; 3; 4; 5; 6; 7; 8; 9; 10 = completely satisfied	H4.4
Confidence in government	1 = a great deal; 2 = quite a lot; 3 = neither; 4 = not very much; 5 = none	H4.5
Effectiveness of politicians	1 = very ineffective; 2 = somewhat ineffective; 3 = neutral; 4 = somewhat effective; 5 = very effective	H4.6
Political self-efficacy	1 = strongly disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = strongly agree	H4.7
Trust in technology		
Technology works as promised	1 = strongly disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = strongly agree	H5.1
More reliable than human counterpart	1 = strongly disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = strongly agree	H5.2

evaluating political issues are more likely to accept the system. We do so based on the assumption that politically diffident individuals might willingly offload some of the mental effort required to participate in politics onto the AI voting system. This allows us to formulate the following hypothesis:

- **H4.7**: Acceptance is higher among respondents with low levels of self-reported political efficacy.

3.4 Trust in technology

Modifications to TAM include the addition of trust as an independent variable to improve its predictive power [46]. In general, trust is crucial to almost any type of social interaction in which uncertainty exists or undesirable outcomes might result [47]. Similar to trust in people, information systems research construes trust as the belief that a technology has the attributes necessary to perform as expected [48]. McKnight, Carter, Thatcher, and Clay [49] are more specific and provide definitions for a set of different kinds of trust. From among these definitions, we are specifically interested in what they call the propensity to trust in general technology. This conception of trust captures the tendency to be willing to rely on technology independent from situational influences or the specific technology in question. Based on this understanding, the survey asks respondents whether they trust that technology generally works the way it is promised to and if they believe that technology is generally more reliable than its human counterparts. For both questions, we assume that acceptance is higher for individuals with more general trust in technology:

- **H5.1**: Acceptance is higher among respondents who believe that technology is generally reliable.
- **H5.2**: Acceptance is higher among respondents who believe that technology is more reliable than its human counterpart.

4. Method

To collect the data, an online survey was conducted in Greece (GR), Singapore (SG), Switzerland (CH), and the United States (US). These countries were chosen based on three selection criteria: (1) form of government, (2) political trust, and (3) technological affinity. Greece, Switzerland, and the US are all full democracies with relatively similar forms of government. In contrast, Singapore is the only semi-democratic country. Political trust, measured as confidence in parliament, is low in Greece (14.2%) and the US (14.8%), middling in Switzerland (54.4%), and high in Singapore (75.5%) [50]. To measure technological affinity, the percentage of the population that frequently uses the Internet was used as a rough proxy. Here, Greece ranks low (70%) [51], Switzerland (85.7%) [52] and the US (83%) [53] rank in the middle, and Singapore ranks highest (93%) [54]. As illustrated in Table 2 (see Appendix), the countries vary on several of the selection criteria. A juxtaposition along these criteria is expected to enable comparability and the observance of differences that provide hints at generalizable inferences across countries.

The questionnaire was developed based on the research presented in this paper and was self-administered by respondents. The respondents were recruited by a market research firm based in Germany using a non-probability river sampling method, i.e., by inviting them to follow links posted on the web. The links were placed on a variety of apps and mobile websites geared towards different activities and interests, e.g., shopping (e.g., Amazon), social networking and picture sharing (e.g., Instagram), gaming (e.g., DesignHome), and messaging (e.g., Line). Respondents could earn rewards for their participation such as access to premium content, extra features, vouchers, or small cash prizes. Before answering the questionnaire, respondents went through a suitability screening which collected their age, gender, and level of education. The screening process also served as a security measure that prevented bots from participating in the survey. The final sample only includes respondents that completed every survey question. Incomplete responses were removed from the sample. In addition, respondents who straight-lined answers or substantially deviated from the median response time were excluded from the statistical analysis and all further use. Such answers are typically of insufficient quality due to fraud, fake answers, or excessive satisficing [55]. Overall, this led to a sample size of 6043 (1612 in GR, 1705 in SG, 1094 in CH, and 1632 in the US). The socio-demographic characteristics of the sample are presented in Table 3 and 4 in the Appendix. The total breakoff rates were at 39% in Switzerland, 29% in Greece, 40% in Singapore, and 38% in the US.

Because the analysis is based on an online river sample, the results of this survey resemble the Internet-connected population of each country. That is, the respondents in our sample are slightly younger than the general population and, because of the online nature of the survey, they likely show more of a natural liking for technology. However, even if the estimates for the distributions of respondents' characteristics are vulnerable to a certain degree of bias, the ranks and relations between categories in non-probability online surveys hold when compared to simple random sampling [55]. To improve the representativeness of the sample, country-specific age (18-65) and gender quotas were created based on the most recent census data from the Barro Lee data set [56]. Once these quotas were met, the data was weighed to corrected for minor under- and overrepresentation of population subgroups.

Eventually, we analyzed the data using multivariate ordered logistic regression in R to estimate the proportional odds coefficients. The dependent variable of interest was the acceptance of the AI voting system, measured with the following statement: "In general, I would support the use of the AI voting system." Respondents could choose from the following answer options: "strongly disagree, disagree, neither agree nor disagree, agree, strongly agree". The next section presents the results of this analysis and starts out by introducing the distribution of characteristics regarding the acceptance of the AI voting system. After that, the effects of the independent variables on the dependent variable are elaborated on. The hypothesized assumptions of TAM are examined first, followed sequentially by the effects of socio-demographic factors, political support, and trust in technology.

5. Results

The results demonstrate that acceptance is highest among Singaporeans (39% acceptance vs. 34% nonacceptance). Singaporeans are also most likely to perceive the AI voting system as useful and easy to use. The Swiss express support for and opposition to the system in equal measure (37% acceptance vs. 37% nonacceptance). In contrast, a sizeable part of the American sample rejects the system (37% acceptance vs. 45% nonacceptance). Greek respondents adopt the most hesitant attitudes and express the lowest acceptance rate and the highest nonacceptance rate (25% acceptance vs. 50% nonacceptance). In addition, relatively large portions of respondents (between 18% and 27%) are undecided. Figure 2 offers a summary of these distributions. To follow up on these insights and to test the hypotheses developed above, the following section presents the results of the ordered logistic regression analysis.

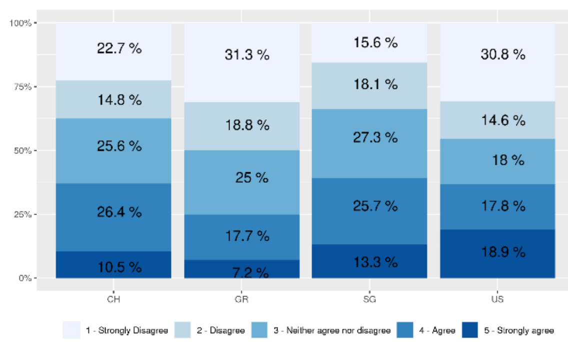

Figure 2. Acceptance of the AI voting system by country.

5.1 Effects on acceptance

We estimated the odds ratios (OR), summarized in Figure 3, to test our hypotheses. OR quantify the strength of the association between two variables. An OR greater than 1 denotes a positive association between the variables in question. An OR equal to 1 means that there is no association and an OR smaller than 1 stands for a negative association (for a detailed explanation of OR see [57]).

Our hypotheses based on TAM predict that PU and PEOU positively affect acceptance. H1.2, H1.3, and H2.2 can be squarely accepted because the results are significant and positive. For example, the results for H1.2 are highly significant (p<.01), and the OR are positive across countries (Switzerland, OR=1.7; Greece, OR=2; Singapore, OR=1.6; US, OR=1.8). For H1.2, the odds to accept the system are thus 1-2 higher for respondents who believe that AI voting system produces better policies than for respondents who do not share

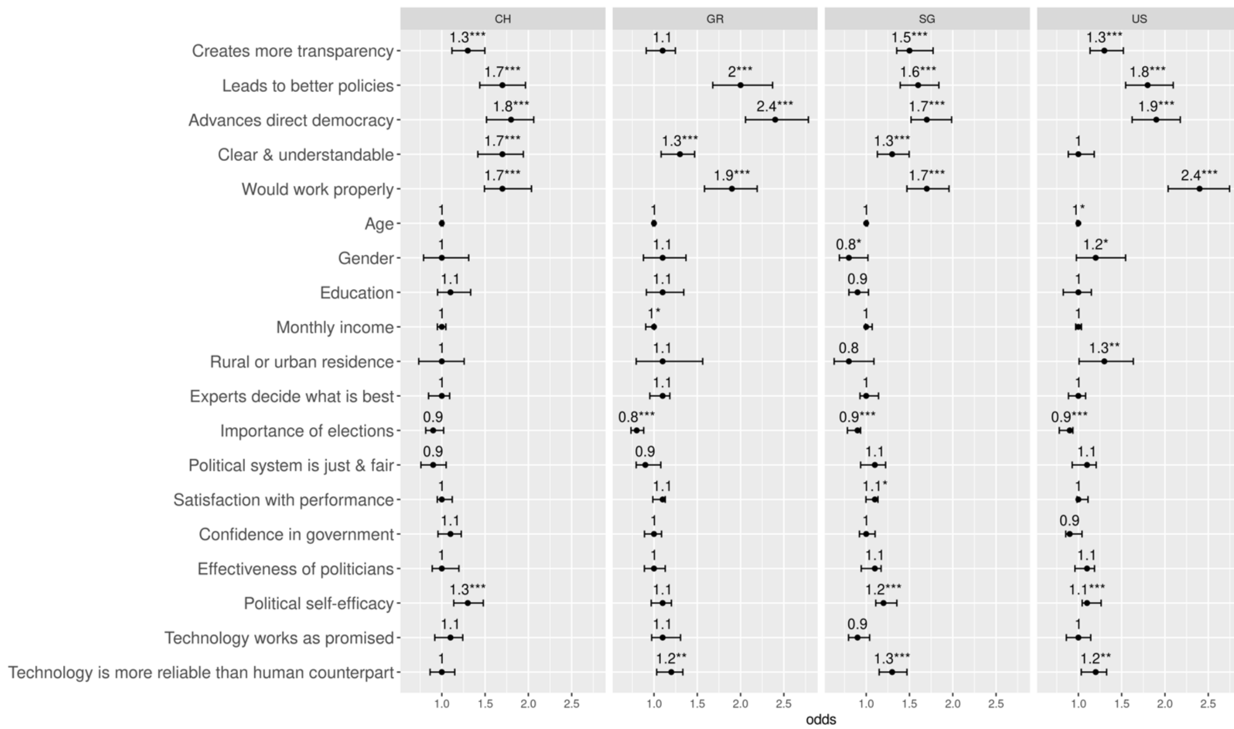

Figure 3. Proportional odds logistic regression: effects on the acceptance of the AI system. *p<.10, **p<.05, ***p<.01

this view. On a similar basis, H1.1 and H2.1 hold for all countries except for Greece and the US correspondingly; no significant effect is measurable for both cases. Overall, however, the analysis provides reasonable evidence to support the hypothesized TAM assumptions.

The analysis further shows that socio-demographic factors are relatively weak predictors, if significant effects occur at all. Contrary to H3.1, age exerts no significant influence on the likelihood to accept. In a similar fashion, education (H3.3) and income (H3.4) do not affect acceptance. Gender produces a small effect in Singapore and the US, albeit in opposite directions, but not in Switzerland and Greece. Accordingly, Singaporeans are marginally more likely to accept the system if they are female (OR=0.8) whereas Americans are more likely to accept if they are male (OR=1.2). The rural urban distinction has no significant impact bar in the US. American city dwellers are somewhat more likely to accept the system than respondents living in rural areas (OR=1.3).

The effects of political support are disparate. At the level of regime principles, we find some evidence in support of H4.2, which states that respondents to whom voting is important are less likely to accept the system. This holds true for Greece (OR=0.8), Singapore (OR=0.9), and the US (OR=0.9), all of which show small but highly significant effects. In Switzerland, the effect is negative as well (OR=0.9) but not significant. H4.1 concerning the fondness of technocratic decision-making by experts produces no significant effects across all countries. At the level of regime performance, the perceived fairness (H4.3) and the perceived satisfaction with the functioning of the political system (H4.4) produce no effects as well, except for a minimal impact of the latter in Singapore (OR=1.1, p<.10). The analysis establishes no significant effects at the level of regime institutions which concerns confidence in government (H4.5) and the perceived effectiveness of politicians (H4.6). However, self-reported political efficacy (H4.7) has a modest but highly significant effect on the acceptance of the system. Respondents in Switzerland (OR=1.3), Singapore (OR=1.2), and the US (OR=1.1) who are politically insecure are more likely to support the use of system. This relation is positive in Greece too (OR=1.1); however, it is not significant.

Finally, we find no support for H5.1 due to the negligible size and the statistical insignificance of the effect. Yet, there is evidence in support of H5.2. The hypothesis states that respondents who believe that technology is more reliable than its human counterpart are more likely to accept the system. This holds for Greece (OR=1.2), Singapore (OR=1.3), and the US (OR=1.2) but not for Switzerland (OR=1).

5.2 Discussion

In this paper, we introduced and tested a hypothesized model of AI voting acceptance. According to our knowledge, this is the first study to examine the effects of differences in people's attitudes towards governments and political actors on the acceptance of decision-making driven by AI technologies. First, we evaluated the effect of TAM on acceptance and found that the two base variables of PU and PEOU are good predictors across Greece, Singapore, Switzerland, and the US. The reliability of TAM across country-specific contexts is a first notable finding. It contributes to the strand of research that investigates TAM's predictive power across cultures [41]. Because of its reliability, TAM also provided a useful starting point from which to extend the analysis to political support, trust in technology, and socio-demographics. Overall, we find that normative judgements about the importance of voting and people's self-assessed political efficacy affect acceptance. Thus, political culture appears to be at least a contributing factor in the perceived desirability of automated decision-making in public institutions. We discuss the limits of this finding and point out unresolved questions.

If we consider the criteria based on which the countries in our sample were selected (i.e., forms of government, political trust, and technological affinity), political trust provides an explanation for acceptance rates. For example, political trust as well as acceptance rates are high in Singapore whereas political trust and acceptance rates are low in Greece. This positive association between political trust and acceptance also holds for Switzerland. But the US does not fit into this pattern. More importantly, however, this heuristic way of reasoning finds limited support in our quantitative analysis. Out of the seven variables that measure political culture, two (i.e., the perceived importance of voting and political self-efficacy) are associated with acceptance rates.

A similar picture emerges for trust in technology. Again, if we compare technological affinity (another criterion based on which we selected the countries in our sample) and acceptance rates, the two roughly match. I.e., Singapore has high acceptance rates and high technological affinity and, conversely, Greece shows low acceptance rates and low technological affinity. This association holds for the US and Switzerland too. But, as pointed out above, this pattern is based on a rough and ready heuristic. Taking the results of the logistic regression analysis into account, we see that one out of two relevant variables associates trust in technology with acceptance rates. We thus find tentative support for theory that proposes a positive relationship between trust and technology use (e.g., [48], [49]).

Finally, our results on age and gender variables do not lead to fixed conclusions. As shown by others (e.g., [36]) the relationship between age, gender, and technology use is quite complex and escapes straightforward explanations. Our data shows no association between age and acceptance rates. In comparison, gender appears to have a slight influence on acceptance in Singapore (women are more like to accept) and the US (men are more likely to accept). In addition, the data shows that income, education, and rural-urban differences are not associated with acceptance. This is surprising because such correlations are relatively well documented in theory (e.g., [39]) as well as in empirical work (e.g.,[40]).

Taking everything into account, this study presents two main findings. First, usefulness and user-friendliness are good predictors of AI voting acceptance across cultures. Second, trust in technology and specific aspects of political culture likely contribute to technology acceptance. To better understand the implications of these findings, questions about the antecedents of trust in technology and of political culture seem to require more scrutiny. This study cannot answer such questions, but we believe that this is a promising avenue for further investigation. For example, research on digital inequality [58] illustrates that socioeconomic status affects technology related skills and access. Thus, positing socioeconomic factors such as income and education as antecedents to self-assessed political efficacy or the perceived importance of voting might further refine our ability to explain the acceptance of AI voting.

5.3 Limitations

The sample analyzed in this study was collected by means of a non-probability sampling mechanism, which is susceptible to topical self-selection bias and economic self-selection bias [59]. Quotas based on age and gender were implemented and the survey results were weighted to correct for inequalities in the probability of selection and to reduce possible sources of biases. However, the survey does not cover parts of the population without access to the Internet. I.e., survey results apply first and foremost to the Internet-connected population of each country and inferences to the general population level should be treated with caution. In addition, the vignette on which we base respondents' answers is hypothetical. The wording of the vignette and the overall speculative nature of the phenomenon under study might skew the evaluative tendencies of respondents. While this issue cannot be completely avoided, previous research shows that respondents do treat hypothetical items like meaningful opinions that correlate with personality dispositions [60].

6. Conclusion

AI voting is a contentious topic. In our final tally, the idea finds support in just one out of four countries;

in another, the public is undecided, and the publics of two countries reject it. Looking beyond this bottom-line total, however, we can see that if an AI voting system provided demonstrable practical benefits to voters, the general tenor of attitudes could become more favorable. A proof of concept, including the corroboration of its technical feasibility, would likely dispel some of the ambivalence regarding AI voting.

7. References

[1] S. Barocas and A. D. Selbst, "Big Data's Disparate Impact," *California Law Review*, vol. 104, no. 3, pp. 671–732, 2016.

[2] D. Boyd and K. Crawford, "Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon," *Information, Communication & Society*, vol. 15, no. 5, pp. 662–679, Jun. 2012.

[3] F. Pasquale, *The Black box society: the secret algorithms that control money and information*. Cambridge, Massachusetts: Harvard University Press, 2016.

[4] F. Johns, "Governance by Data," *Annu. Rev. Law. Soc. Sci.*, vol. 17, no. 1, p. annurev-lawsocsci-120920-085138, Oct. 2021.

[5] B. Lepri, J. Staiano, D. Sangokoya, E. Letouzé, and N. Oliver, "The Tyranny of Data? The Bright and Dark Sides of Data-Driven Decision-Making for Social Good," in *Transparent Data Mining for Big and Small Data*, vol. 32, T. Cerquitelli, D. Quercia, and F. Pasquale, Eds. Cham: Springer International Publishing, 2017, pp. 3–24.

[6] D. Freeman Engstrom, D. E. Ho, C. M. Sharkey, and M.-F. Cuéllar, "Government by Algortihm: Artificial intelligence in Federal Administrative Agencies," Administrative Conference of the United States, 2020.

[7] F. Chiusi, "Automating Society Report 2020," AlgorithmWatch, Oct. 2020. Accessed: May 11, 2020. [Online]. Available: https://automatingsociety.algorithmwatch.org/

[8] D. Gerstner, "Predictive Policing in the Context of Residential Burglary: An Empirical Illustration on the Basis of a Pilot Project in Baden-Württemberg, Germany," *European Journal for Security Research*, vol. 3, no. 2, 2018.

[9] M. Oswald, J. Grace, S. Urwin, and G. C. Barnes, "Algorithmic risk assessment policing models: lessons from the Durham HART model and 'Experimental' proportionality," *Information & Communications Technology Law*, vol. 27, no. 2, 2018.

[10] I. Braun, "High-Risk Citizens," *AlgorithmWatch*, 2018. https://algorithmwatch.org/en/story/high-risk-citizens/ (accessed Feb. 12, 2019).

[11] J. Niklas, K. Sztandar-Sztanderska, and K. Szymielewicz, "Profiling the Unemployed in Poland: Social and Political Implications of Algorithmic Decision Making," Panoptykon Foundation, Warsaw, 2015. Accessed: Feb. 12, 2019. [Online]. Available: https://panoptykon.org/sites/default/files/leadimage-biblioteka/panoptykon_profiling_report_final.pdf

[12] R. Creemers, "China's Social Credit System: An Evolving Practice of Control," *SSRN Electronic Journal*, 2018, doi: 10.2139/ssrn.3175792.

[13] X. Xu, "To Repress or to Co-opt? Authoritarian Control in the Age of Digital Surveillance," *American Journal of Political Science*, Apr. 2020.

[14] P. Khanna, *Technocracy in America: rise of the info state*, First Edition. CreateSpace, 2017.

[15] World Health Organization, "Immunizing the public against misinformation," Aug. 25, 2020. https://www.who.int/news-room/feature-stories/detail/immunizing-the-public-against-misinformation (accessed May 12, 2021).

[16] A. Reckwitz, *Society of singularities*. Cambridge: Polity, 2020.

[17] Y. Algan, S. Guriev, E. Papaioannou, and E. Passari, "The European Trust Crisis and the Rise of Populism," *Brookings Papers on Economic Activity*, vol. 2017, no. 2, pp. 309–400, 2017.

[18] K. Newton, "Social and Political Trust in Established Democracies," in *Critical Citizens*, P. Norris, Ed. Oxford University Press, 1999.

[19] Eurobarometer, "Public opinion monitoring at a glance in the era of COVID-19," European Parliament, Mar. 2020. Accessed: Aug. 13, 2020. [Online]. Available: https://www.europarl.europa.eu/at-your-service/files/be-heard/eurobarometer/2020/covid19/en-public-opinion-in-the-time-of-COVID19-20032020.pdf

[20] O. Jonsson *et al.*, "European Tech Insights," IE Center for the Governance of Change, Madrid, 2021. [Online]. Available: https://docs.ie.edu/cgc/IE-CGC-European-Tech-Insights-2021-%28Part-II%29.pdf

[21] R. Binns, "Algorithmic Accountability and Public Reason," *Philos. Technol.*, vol. 31, no. 4, pp. 543–556, Dec. 2018, doi: 10.1007/s13347-017-0263-5.

[22] O. H. Gandy, *The panoptic sort: a political economy of personal information*. Boulder, Colo: Westview, 1993.

[23] M. Hildebrandt and K. O'Hara, *Life and the Law in the Era of Data-Driven Agency*. Edward Elgar Publishing, 2020. doi: 10.4337/9781788972000.

[24] D. J. Solove, "Privacy and Power: Computer Databases Metaphors for Information Privacy," *Stanford Law Review*, vol. 53, no. 6, 2001.

[25] A. Narayanan, "How to recognize AI snake oil," presented at the Arthur Miller lectures on science and ethics, Massachusetts Institute of Technology, 2019.

[26] M. Meckel, "Das wäre die digitale Demokratie. Wo die Politik versagt, könnten bald Algorithmen das Sagen haben.," *Neue Zürcher Zeitung*, p. 40, Jun. 03, 2020.

[27] T. Araujo, N. Helberger, S. Kruikemeier, and C. H. de Vreese, "In AI we trust? Perceptions about automated decision-making by artificial intelligence," *AI & Soc*, Jan. 2020, doi: 10.1007/s00146-019-00931-w.

[28] R. Binns, M. Van Kleek, M. Veale, U. Lyngs, J. Zhao, and N. Shadbolt, "'It's Reducing a Human Being to a Percentage': Perceptions of Justice in Algorithmic Decisions," in *Proceedings of the 2018 CHI*

Conference on Human Factors in Computing Systems - CHI '18, Montreal QC, Canada, 2018, pp. 1–14.
[29] J. Lepore, *If then: how the Simulmatics Corporation invented the future*, First edition. New York, N.Y: Liveright Publishing Corporation, a division of W. W. Norton & Company, 2020.
[30] F. D. Davis, "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS Quarterly*, vol. 13, no. 3, pp. 319–340, 1989.
[31] M. Fishbein and I. Ajzen, *Belief, attitude, intention, and behavior: an introduction to theory and research*. California: Addison-Wesley, 1975.
[32] V. Venkatesh and F. D. Davis, "A model of the antecedents of perceived ease of use: development and test," *Decision Sciences*, vol. 27, no. 3, pp. 451–481, 1996.
[33] N. Marangunić and A. Granić, "Technology acceptance model: a literature review from 1986 to 2013," *Univ Access Inf Soc*, vol. 14, no. 1, pp. 81–95, Mar. 2015, doi: 10.1007/s10209-014-0348-1.
[34] M. Igbaria, "End-user computing effectiveness: A structural equation model," *Omega*, vol. 18, no. 6, pp. 637–652, 1990, doi: 10.1016/0305-0483(90)90055-E.
[35] J. E. Chung, N. Park, H. Wang, J. Fulk, and M. McLaughlin, "Age differences in perceptions of online community participation among non-users: An extension of the Technology Acceptance Model," *Computers in Human Behavior*, vol. 26, no. 6, pp. 1674–1684, 2010, doi: 10.1016/j.chb.2010.06.016.
[36] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User Acceptance of Information Technology: Toward a Unified View," *MIS Quarterly*, vol. 27, no. 3, p. 425, 2003, doi: 10.2307/30036540.
[37] H. Sun and P. Zhang, "The role of moderating factors in user technology acceptance," *International Journal of Human-Computer Studies*, vol. 64, no. 2, pp. 53–78, Feb. 2006, doi: 10.1016/j.ijhcs.2005.04.013.
[38] A. Burton-Jones and G. S. Hubona, "The mediation of external variables in the technology acceptance model," *Information & Management*, vol. 43, no. 6, pp. 706–717, Sep. 2006.
[39] E. M. Rogers, *Diffusion of innovations*, 5th ed. New York: Free Press, 2003.
[40] D. B. Hindman, "The Rural-Urban Digital Divide," *Journalism & Mass Communication Quarterly*, vol. 77, no. 3, pp. 549–560, Sep. 2000.
[41] D. Straub, M. Keil, and W. Brenner, "Testing the technology acceptance model across cultures: a three country study," *Information & Management*, vol. 33, no. 1, pp. 1–11, 1997.
[42] J. Thomassen and C. van Ham, "A legitimacy crisis of representative democracy?," in *The myth and realit of legitimacy crisis*, 1st edition., vol. 1, C. van Ham, J. Thomassen, K. Aarts, and R. Andeweg, Eds. Oxford University Press, 2017, pp. 3–16.
[43] D. Easton, *A systems analysis of political life*. New York, NY: Wiley, 1965.
[44] C. van Ham and J. Thomassen, "The myth of legitimacy decline," in *Myth and reality of the legitimacy crisis*, 1st edition., C. van Ham, J. Thomassen, K. Aarts, and R. Andeweg, Eds. Oxford University Press, 2017, pp. 17–34.
[45] P. Rössler, *Skalenhandbuch Kommunikationswissenschaft*, 1. Auflage. Wiesbaden: VS Verlag für Sozialwissenschaften, 2011.
[46] P. A. Pavlou and D. Gefen, "Building Effective Online Marketplaces with Institution-Based Trust," *Information Systems Research*, vol. 15, no. 1, pp. 37–59, Mar. 2004, doi: 10.1287/isre.1040.0015.
[47] N. Luhmann, *Trust and power*, English edition. Malden, MA: Polity, 2017.
[48] R. C. Mayer, J. H. Davis, and F. D. Schoorman, "An integrative model of organizational trust," *The Academy of Management Review*, vol. 20, no. 3, 1995.
[49] D. H. McKnight, M. Carter, J. B. Thatcher, and P. F. Clay, "Trust in a specific technology: An investigation of its components and measures," *ACM Trans. Manage. Inf. Syst.*, vol. 2, no. 2, pp. 1–25, Jun. 2011.
[50] World Values Survey, "World Values Survey Online Analysis," 2020.
[51] Statista, "Internet usage frequency among individuals in Greece in 2018," 2018. https://www.statista.com/statistics/379049/internet-usage-at-home-greece/
[52] Bundesamt für Statistik, "Internetnutzung," 2019. https://www.bfs.admin.ch/bfs/de/home/statistiken/kultur-medien-informationsgesellschaft-sport.assetdetail.11068657.html
[53] Statista, "Internet usage frequency of adults in the United States as of January 2018," 2018. https://www.statista.com/statistics/495078/us-adult-internet-usage-frequency/
[54] Statista, "Frequency of personal internet usage in Singapore as of January 2018," 2018. https://www.statista.com/statistics/803857/frequency-of-personal-internet-usage-singapore/
[55] M. Callegaro, K. Lozar Manfreda, and V. Vehovar, *Web survey methodology*. Los Angeles: SAGE, 2015.
[56] R. J. Barro and J.-W. Lee, "Barro-Lee Educational Attainment Dataset," 2018. www.barrolee.com
[57] M. Szumilas, "Explaining odds ratios," *J Can Acad Child Adolesc Psychiatry*, vol. 19, no. 3, pp. 227–229, 2010.
[58] E. Hargittai, A. M. Piper, and M. R. Morris, "From internet access to internet skills: digital inequality among older adults," *Univ Access Inf Soc*, vol. 18, no. 4, pp. 881–890, Nov. 2019.
[59] V. Lehdonvirta, A. Oksanen, P. Räsänen, and G. Blank, "Social Media, Web, and Panel Surveys: Using Non-Probability Samples in Social and Policy Research," *Policy & Internet*, vol. 13, no. 1, pp. 134–155, Mar. 2021, doi: 10.1002/poi3.238.
[60] G. F. Bishop, R. W. Oldendick, A. J. Tuchfarber, and S. E. Bennett, "Pseudo-Opinions on Public Affairs," *The Public Opinion Quarterly*, vol. 44, no. 2, pp. 198–209, 1980.

Appendix

Table 2. A comparison of the criteria for the selection of the sample countries

	Greece	Singapore	Switzerland	USA
Form of government	Parliamentary republic	Anocracy	Direct democracy	Presidential republic
Political trust	14.2%	75.5%	54.4%	14.8%
Technological affinity	70.0%	93.0%	85.7%	83.0%

Table 3. Sample characteristics (part 1 of 2)

	Percent	Mean	SD	n
Greece				1612
Age		38.38	11.16	
Male	50.4			812
Female	49.6			800
Level of education				
No formal education	0.6			9
Low	2.5			40
Medium	45.0			725
High	51.9			838
Household income per month				
≤ € 210	5.3			85
≤ € 410	6.9			111
≤ € 830	19.1			308
≤ € 1700	28.8			465
≤ € 2500	15.1			243
≤ € 3300	5.1			82
≤ € 5000	2.4			38
≤ € 6600	0.3			5
≤ € 8300	0.6			9
≤ € 9900	0.2			3
≤ € 12000	1.3			21
> € 12000	2.4			39
Prefer not to say	12.6			203
Residence status				
Rural	13.2			213
Urban	86.8			1399
Singapore				1705
Age		38.30	11.93	
Male	51.8			884
Female	48.2			821
Level of education				
No formal education	2.8			47
Low	15.8			270
Medium	26.4			450
High	55.0			938
Household income per month				
≤ € 210	3.8			64
≤ € 410	2.5			42
≤ € 830	3.6			61
≤ € 1700	8.4			144
≤ € 2500	9.2			157
≤ € 3300	8.6			147
≤ € 5000	15.2			260
≤ € 6600	14.1			241
≤ € 8300	8.7			148
≤ € 9900	6.4			109
≤ € 12000	4.2			71
> € 12000	6.1			104
Prefer not to say	9.2			157
Residence status				
Rural	15.95			272
Urban	84.05			1433

Table 4. Sample characteristics (part 2 of 2)

	Percent	Mean	SD	n
Switzerland				1094
Age		39.01	12.76	
Male	52.5			574
Female	47.5			520
Level of education				
No formal education	3.0			33
Low	12.7			139
Medium	37.3			408
High	47.0			514
Household income per month				
≤ € 210	2.1			23
≤ € 410	2.2			24
≤ € 830	3.3			36
≤ € 1700	6.2			68
≤ € 2500	6.3			69
≤ € 3300	6.9			76
≤ € 5000	14.5			159
≤ € 6600	12.5			137
≤ € 8300	11.2			122
≤ € 9900	10.1			111
≤ € 12000	6.4			70
> € 12000	5.2			57
Prefer not to say	13.0			142
Residence status				
Rural	35.4			387
Urban	64.6			707
United States				1632
Age		39.64	12.67	
Male	48.8			796
Female	51.2			836
Level of education				
No formal education	1.7			28
Low	6.6			107
Medium	35.9			586
High	55.8			911
Household income per month				
≤ € 210	5.3			86
≤ € 410	2.9			47
≤ € 830	6.7			109
≤ € 1700	11.5			188
≤ € 2500	10.2			166
≤ € 3300	7.0			115
≤ € 5000	8.6			140
≤ € 6600	6.1			99
≤ € 8300	5.8			94
≤ € 9900	4.8			78
≤ € 12000	6.7			110
> € 12000	18.0			293
Prefer not to say	6.6			107
Residence status				
Rural	32.0			523
Urban	68.0			1109