ARTIFICIAL INTELLIGENCE FOR GOVERNMENT USE

A quantitative study of the EU citizens' perspective

I. Abstract

As Artificial Intelligence (AI) is used more in the public sector, the topic becomes increasingly interesting for public administration research. However, what citizens think of AI implementation in the public sphere is largely unknown. This research aims to discover to what extend citizens support the use of AI in public policy areas as well as what influences their support. To answer the question, a quantitative analysis is conducted using data from the Eurobarometer 92.3 from 2019. National differences are investigated because AI governance is in the domain of EU member states. Additionally, drawing from previous research on e-government transformation, this research tests whether trust in government is an influential predictor for citizens to support AI use in public policy areas. The analysis from the data shows that EU citizens generally show support for AI use in this context. However, whether a member state addresses the issue of AI use in a national strategy does not contribute to citizen support. Though, if a person trusts the government a positive relation towards support for AI was found.

1. Introduction

Since the invention of the first computer in the past century we are now undeniably living in the age of technology. Information processing systems are found in every household. Data processing capacity has exponentially increased, and the internet has led to an endless amount of information being available in no time. Artificial Intelligence (AI) is a technology that even offers application for tasks where human intelligence was previously necessary. The journey started with AI systems learning how to play games like Go and ultimately beating the human world champion (Silver et al., 2016).

Today, applications go beyond playing games and towards practical implementations that can result in better and more efficient completion of tasks. An AI system in your car can analyse the traffic environment and operate as your driving assistant, your stockbroker can use AI to analyse all data about the stock market within seconds and make investment recommendations for you. However, this is only the beginning. The scope for AI employment includes communication through voice recognition, language processing, machine learning, and reasoning and planning based on the processing of large amounts of data (Samoili et al., 2020). The rapid development in AI technology can already be seen in the private sector but also the public sector has started recognising the transformational power of AI (Agarwal, 2018; Misuraca & van Noordt, 2020). In the public sphere AI systems can improve citizen communication and public engagement. Also, AI is used to analyse large amounts of data to inform policy making processes or decisions like granting social benefits. This is only a small selection of applications. Areas where AI systems are implemented keep growing (Misuraca & van Noordt, 2020).

Consequently, the application of AI tools in public institutions is of growing importance for public administration scholars. One stream of research focuses on challenges that emerge from using AI in a public context. Theoretical arguments include challenges to accountability and democratic legitimacy of AI. Additionally, questions about privacy concerns and fairness resulting from AI are researched (Busuioc, 2020; Lee, 2018; Pencheva et al., 2018; Zarsky, 2016). Most empirical studies are case studies aiming to explore and analyse instances where AI systems are already implemented. The focus lies mostly on implications that result from the novel technology (Pencheva et al., 2018; Ranerup & Henriksen, 2020; van Noordt & Misuraca, 2020). Even though, the research in this area of public administration is increasing much is still unknown. As the technology in question is relatively new, applications are still limited. There

is still a lack of theoretical frameworks for explaining the use of AI technologies in the public sector (Pencheva et al., 2018). Consequently, knowledge generated from the existing empirical studies is difficult to put in relation with each other. Furthermore, the role of citizens as a stakeholder in a democratically governed country has barely been included into current research. If so, research was limited to theoretical arguments for legitimacy, but only little empirical research was conducted in this area (Busuioc, 2020). Though, as the citizen is the ultimate source of democratic legitimacy empirical research on their support of AI is important for further development of AI use in the public sector.

This following research will contribute with a quantitative analysis to the existing body of knowledge. It addresses the gap in research that results from the prevalence of case studies. With a quantitative analysis, previous findings from case studies can be related to a bigger picture more easily. This can lead to an improved understanding of the matter. As citizens are crucial to achieve legitimacy for any democratically elected government their perceptions towards AI use in the public sector is important to consider. Previous research established an understanding how and where AI is implemented. Consequently, the next step is to include citizens as stakeholders into research. As there is still a lot of uncertainty, this is a valuable addition to the existing body of knowledge. Also, this paper might uncover factors that contribute to citizens perceptions that were previously unknown and inspire future research. Driven by these gaps in literature this research aims to answer the following research question:

> *To what extend do citizens of EU member states support the use of AI in public policy areas and what influences their support?*

The setting for all question is the European Union (EU) and the unit of analysis are individual citizens. The EU has addressed the issues resulting from the growing implementation of AI tool in its member states with various White Papers. However, regulation and implementation of AI is a competence of the individual member states (Brattberg et al., 2020; Misuraca & van Noordt, 2020). Not all 27 EU member states have published a national regulatory framework on AI (Brattberg et al., 2020). This difference in measures taken by member states leads to the first sub question, investigation national differences in support for AI:

> *SQ1: What are national differences in support of AI in the public sector by individual citizens?*

Lastly, the research aims to explore what influences citizen support of AI tools in the public sphere. The national governments have the competency to address AI implementation and need to regulate AI implementation in public policy areas. Hence, the citizen–government relationship is explored as a possible factor contributing to citizen support. The following sub question is formulated to guide the analysis:

SQ2: How can citizens' trust in government explain their support for AI use in public policy areas?

For public officials, this research is fundamental in deciding how and in which contexts AI tools can and should be implemented. Due to the novelty of AI and the resulting lack of regulatory frameworks the insights gained from public administration research can have a large impact on the formulation of regulations. This can help to increase the benefits AI tools offer in a variety of contexts while also trying to limit negative externalities that have already been identified by public administration scholars.

First, a literature review about relevant theories and concepts is presented. The section is split into the conceptualization of AI, and AI implementation in the public sector across EU member states followed by theory about trust and trust in government. Hypotheses to answering the research questions are established by connecting the theoretical concepts with their relevance to answer the research question. Then, the research design is presented as well as the operationalization of the relevant variables to establish a statistical model. Next, the results are analysed and discussed. Lastly, answers to the research questions are presented in a conclusion.

2. Relevant Theories and Concepts

To answer the research questions different concepts and theoretical background is relevant. First, a deeper understanding what AI is, and why it might be different to previously developed technologies is necessary. Additionally, an overview of how AI is used in the public sector is given. The risks and benefits of application in the public sector differ in some areas for public use, hence these arguments are presented. As the national government plays a major role in managing these challenges the role of the government as a stakeholder is presented. Also, resulting from the important position the government has as a regulator, the concept of trust and trust in government is introduced. Citizens' trust in the government can influence their view on how the government address AI use and ultimately affect their support for AI.

2.1 Defining Artificial Intelligence

For the concept of AI, no commonly shared definition has been established. Though, existing definitions approach AI systems as software systems that are programmed by humans to achieve a specific goal. Contrasting regular IT systems, AI can behave like humans or fulfil tasks that previously required human intelligence (Samoili et al., 2020). Hence, this definition includes a multitude of technologies. AI can be used in a growing number of subdomains and applications. Shared features of AI include the ability to process environmental influences, processing of large amounts of data including its interpretation, and making decisions based on collected data. Ultimately, these attributes lead to the achievement of a specific goal previously defined by the programme creators (Misuraca & van Noordt, 2020; Samoili et al., 2020).

In more detail, AI systems can function as decision support systems through its great data processing capability and recommending the best course of action according to the previously defined goal (Araujo et al., 2020). Similar applications utilize the goal-oriented behaviour of AI to plan with goals like scheduling and optimization. Another area with huge potential is machine learning. In machine learning the AI is only given a specific goal and trained based on which the programme automatically learns how to achieve the given goal. With machine learning there is no specific programming necessary on specific ways to reach the goal (Samoili et al., 2020). Communication is another subdomain for AI application. Here, AI software is used to understand and process natural language in written and spoken form. Similarly, the domain of perception focuses on ways for AI to become aware of its environment through audio processing and computer vision (Rossi, 2019).

As broad as the possible uses of AI are also new challenges that emerge with the constantly improving technology. Any time AI is used to make decisions or inform a decision-making process questions about the accountability and fairness of the decision outcome arise (Busuioc, 2020; Rossi, 2019). Especially in the subdomain of machine learning AI is often referred to as a "black-box" because the specific algorithm that led to a decision outcome was established in the learning process and sometimes cannot be clearly identified by programmers (Busuioc, 2020; Misuraca & van Noordt, 2020; Rossi, 2019; Samoili et al., 2020). These novel characteristics of AI lead to ethical considerations of AI implementation and the task for the government to address these issues (Rossi, 2019).

2.2 AI in the Public Sector

The characteristics of AI lead to a variety of applications of the software, not only on the economic market. The government and government institutions can be a user of AI software to increase effectiveness and efficiency of public service delivery (Misuraca & van Noordt, 2020). Beside these traditional economic effects, the potential for AI contributing to societal benefits are being explored by governments, international organizations, and researchers (Ulnicane et al., 2021). Over 200 instances of AI systems being implemented in the member states of the European Union were identified. In the public sector most AI tools are used in the delivery of public services and citizen engagement, followed by systems used for predictive analysis and automated decision-making (Misuraca & van Noordt, 2020). For instance, chatbots integrate language processing abilities of AI and can be used in a government environment. These systems enable closer, and larger amounts of citizen contact with public administration around the clock (Henman, 2020). For example, an AI chatbot by the Latvian Register of Enterprises is available to citizens to respond to frequently asked questions (Misuraca & van Noordt, 2020).

AI systems that use predictive analysis can process large amounts of data and recognize patterns within the data that might not be obvious to a human administrator (Henman, 2020). An AI tool by the Flemish Agency for Child and Family is used to determine which childcare facility requires further inspection based on previously collected data (Misuraca & van Noordt, 2020). In automated decision making the analysed data is then used to inform decision made by public administrators. In Poland, AI is used for profiling citizens' eligibility for unemployment benefits. Based on individual data the systems groups applicants and indicated which unemployment benefits the applicant is eligible for (Misuraca & van Noordt, 2020). These are only a few examples where AI has already been implemented and the number of AI use in the public sector is likely to grow. Additionally, there are cases in the EU where AI is used to improve public safety, support law enforcement, improve traffic regulation and optimize internal management in public organizations. However, AI in the public sector is still novel and empirical evidence on the social implications AI use has is very limited (Misuraca & van Noordt, 2020).

In the public sector specific challenges arise for the implementation of AI due to its special characteristics. Public institutions have higher ethical standards to satisfy to be democratically legitimate. This is especially challenging, as many decisions in the public sphere require a

certain degree of discretion (Barth & Arnold, 1999; Filgueiras, 2021). To programme and train an AI system, a lot of data is necessary. Here the issue of privacy rights arises, as well as the possibility of bias in training data that can consequently be reinforced by the AI (Agarwal, 2018; Filgueiras, 2021; van Noordt & Misuraca, 2020).

Also, the way data is processed in the public context can be problematic. To achieve a legitimate outcome, accountability and transparency of the AI used is required. Regarding transparency, many AI systems are extremely complex, and its algorithms might not be fully understood by public administrators and citizens. This transparency challenge can lead to a lack of legitimacy of the institutions and lack of support by the citizens. Especially in the application of AI as a decision-making entity or decision support system the opacity that results from AI operating as a black box leads to challenges for AI implementation in the public sector (Busuioc, 2020; Filgueiras, 2021; Harrison & Luna-Reyes, 2020).

Similarly, accountability is required for a legitimate decision outcome. The question arises to what extend public administrators and public institutions can be held accountable if AI systems play a major role in the decision-making process. The position of programmers in this context needs to be reassessed (Filgueiras, 2021; van Noordt & Misuraca, 2020).

Public administration scholars have not only been researching the different challenges that emerge with AI in the public sector but have also identified possible solutions. Namely, there is a need for an appropriate governance structure that oversees the use of AI in public institutions. Furthermore, regulations are required that address the legitimacy threats. Also, closer cooperation between public administrators and AI system designers needs to be fostered. These can ensure better understanding of the system by the administrators. Additionally, the incorporation of the high ethical standards for public institutions needs to be overseen (Busuioc, 2020; Filgueiras, 2021; Harrison & Luna-Reyes, 2020). Adequate regulation is necessary to ensure data privacy of citizens. Good data governance structures should be established to create a safe and reliable way to handle citizen data (Filgueiras, 2021; Harrison & Luna-Reyes, 2020; van Noordt & Misuraca, 2020).

From the conceptualization of AI and AI in the public sector it becomes apparent that there are strong arguments to support AI implementation as well as against it. AI systems can contribute to economic goals by increasing the efficiency and effectiveness in reaching a specific goal (Misuraca & van Noordt, 2020). Also, the quality of an outcome can be improved though using AI. Such systems outperform humans in analysing large amounts of data or can contribute to more consistency in decision making. Additionally, with high quality training data bias in the

decision-making process can be combated (Filgueiras, 2021; Misuraca & van Noordt, 2020; Ranerup & Henriksen, 2020). On the contrary, important challenges that arise with the use of AI in the public sector were identified. Citizen data is required for using AI in this sector which leads to questions about data security and privacy rights (Agarwal, 2018). Furthermore, with AI it becomes unclear who is accountable for decisions made by AI or were influenced by AI. This is especially problematic as accountability is a main aspect for legitimacy of public institutions (Busuioc, 2020). Moreover, using AI decreases the transparency of public sector operations which also impacts legitimacy negatively (Harrison & Luna-Reyes, 2020).

Citizen support of AI technologies is likely to depend on weighing these arguments. As both sides present strong arguments theoretical elaborations an empirical distribution of citizen support is relevant to research. Previous studies have shown a that there is generally a mixed attitude towards AI by citizens. However, these studies did not focus specifically on AI use in public policy areas and used other settings than citizens of all EU member states AI (Araujo et al., 2020; Zhang & Dafoe, 2019).

2.3 National Strategies for AI Governance

The EU has addressed the use of AI technology in the public sector and its risks and benefits in multiple reports and White Papers. However, implementation and regulation of AI lies within the domain of the individual member state. Since the beginning of 2017 member states have started to publish national strategies on AI (Brattberg et al., 2020). As of early 2020, 15 of the EU27 have published an AI strategy with similar documents still in progress in the other 12 member states (van Roy, 2020). The depth of the strategies varies among member states and there is no common European framework. Generally speaking, the AI strategies of northern European countries were assessed as very concrete whereas central and eastern European countries stayed vague in the strategy papers (Brattberg et al., 2020). Additionally, the government as a user of AI is usually not explicitly mentioned in the national strategies. The government is acting as a regulator and facilitator for AI implementation and research. A common focus in the strategies is on ethical implications of the novel technology. Moreover, the member states move away from solely focusing on economic opportunities but also highlight social implications that can result from AI tools (Brattberg et al., 2020; Misuraca & van Noordt, 2020; Ulnicane et al., 2021).

However, with a focus on the public sector different initiatives that are aligned with the national strategy can be identified. Most efforts can be seen in the areas of improving data quality and

accessibility. Similarly, AI pilot projects are launched that follow the "learning by doing" approach. Additional efforts include raising awareness for AI, training public administrators on AI, developing ethical frameworks, as well as funding different AI projects in the public sector (Misuraca & van Noordt, 2020). These efforts are evaluated as a good step towards addressing the risks of AI. Nevertheless, there is still room for improvement to increase transparency of AI systems and their use. As AI in the public sector operates with citizen data this transparency is necessary to trust the government and for support of the novel technology (Brattberg et al., 2020). Additionally, alignment of the different national strategies towards a common European framework of AI might be useful in the future. This can ensure coherence and common goals that can give guidance to countries with weaker national AI strategies (Brattberg et al., 2020).

2.4 Citizen Support across Countries

As elaborated the individual member states are an important stakeholder in AI advancement. Some countries have already addressed the various risks associated with AI in national strategies. By implementing such a strategy, a common national narrative is created, AI is put on the political agenda, and ways to harness the benefits of AI are established (Brattberg et al., 2020). Hence, a national AI strategy was identified as a policy measure that can influence citizen support for AI use in public policy areas. Next to facilitating AI research and implementation, many AI strategies also stress the ethical challenges that arise with broader use of AI technologies. Such an ethical framework, as well as having AI on the political agenda, shows that national governments address the associated risks (Brattberg et al., 2020; van Roy, 2020). Even though the national strategies that have been published at this point do not explicitly focus on the government as a user, the established ethical framework also applies to public sector use (Misuraca & van Noordt, 2020). When deciding whether to support AI for public sector use one must consider the different risks and benefits that might occur. As a citizen in a county where an AI strategy has been published, there are government guidelines in place that address the specific risks. On this basis the following hypothesis is put forward:

H1 Citizens of countries with a national AI strategy express more support for AI in public policy areas compared to citizens of countries without a national AI strategy.

The unit for testing this hypothesis is the individual citizen. The independent variable, whether the country of citizenship has a national AI strategy in place, is expected to be positively

associated with support for AI in public policy areas. The expected effect is grounded on the assumption that such an AI strategy addresses the risks associated with AI use in the public sphere. This can help citizens to be more aware of the risks and increase understanding for the issue of AI use. Consequently, in citizen assessment whether AI is supported, the benefits outweigh the risks which leads to greater support.

2.5 Trust and Trust in Government

As national governments are an important stakeholder in AI implementation and regulation, the concepts of trust and trust in government is introduced. The perception of trust in government is a way of understanding how government efforts are valued regarding AI (Rossi, 2019). The concept of trust is highly ambiguous, and its definition is subject for researchers from various fields ranging from psychology to political science (Bannister & Connolly, 2011). Trust and trusting behaviour originate from an interpersonal relation and can be defined as the belief that the other party will act in one's interest. In the presence of trust, one exposes oneself to situations even if the possibility of exploitation exists (Newton, 2012). When dealing with the concept of trust in government, the interpersonal trust relationship is aggregated on an organizational level. When one is trusting the government, there is less personal risk associated with trusting behaviour. The core for trust in government is the belief by an individual that the government is acting in a correct manner. Additionally, the assumption that the government will not engage in abusing its power is strongly related with trust (Bannister & Connolly, 2011; Cook & Gronke, 2005; Horsburgh et al., 2011). The trust in government can be expressed towards individual politicians, specific government agencies or the government body as a whole.

The presence of political trust is necessary for a stable democracy and an active political life. When citizens trust the government, they are more likely to comply with laws. This is of practical importance for the government when implementing new policies (Cook & Gronke, 2005; Newton, 2012). Due to the importance of trust in government, factors that determine trust have frequently been researched. Even though, there is no clear consensus on antecedents of trust three factors were identified. Firstly, personal characteristics of the individual one example being social-economic class can determine trust in government. Additionally, trust in public institutions grounded on integrity and professionalism is important. Lastly, trust in government can be shaped through previous positive experiences like good public service delivery (Bannister & Connolly, 2011).

2.6 Trust in Government and Support for AI

As AI implementation in the public sector is a relatively new phenomena its relationship with trust in government is still unknown. Nevertheless, general trust in government can include trust by citizens that the government manages the risks of AI in an appropriate manner (Brattberg et al., 2020). In previous research, this relationship was explored in the context of transformation towards e-government. Scholars have researched how trust in government affects the citizens' support for e-government transformation (Bannister & Connolly, 2011; Horsburgh et al., 2011; Pérez-Morote et al., 2020; van de Walle & Bouckaert, 2003). E-government refers to the digitalization of government including for example public service provision and government – citizen communication. AI systems are a new form of digitalization, therefore, referring to e-government literature is an informative starting point for research on AI implementation in the public sector. Pérez-Morote et al. found in their Europe-wide study a positive relationship between trust in government and the willingness to use e-government services. This implies that such services were supported and found useful (Pérez-Morote et al., 2020). An earlier study by Horsburgh et al. conducted in Australia and New Zealand, also found a correlation between trust in government and the support for government investment in e-government (Horsburgh et al., 2011).

Nevertheless, another stream in literature focused on the reversed relation were trust in e-government positively affects trust in government (Bannister & Connolly, 2011; van de Walle & Bouckaert, 2003). According to their argument and interpretation of empirical data, e-government increases the communication with the citizen and increases the efficiency and effectiveness of public service delivery. These improvements of the public sector led to increased trust in the government by citizens (Bannister & Connolly, 2011; Cook & Gronke, 2005).

AI is only implemented in very limited number of cases, and citizens have either no or only little experiences with AI software in the government context. Consequently, the time-order suggests that trust in government precedes the trust in AI implementation in the public sector. Hence, in this research it will be explored whether trust in government can explain citizens belief in usefulness of AI in the public sector by testing the following hypothesis:

H2: A high level of citizens' trust in government is positively associated with support for AI in public policy areas.

The independent variable in H2 is citizens' trust in their national government. In the presence of trust a positive effect on the independent variable, support for AI in public policy areas, is expected. The unit of analysis are individual citizens of EU member states. The mechanism underlying this expected relationship is based on the finding that in the presence of trust less risk is associated with the use of AI in the public sector (Bannister & Connolly, 2011). Trusting the government implies that this trust is also given to the subdomain of government use and regulation of AI technology. Hence, an individual generally trusts that the national government manages the risks associated with AI adequately. As risks like privacy concerns and questions about accountability are addressed by government regulations, benefits of AI outweigh, and the novel technology is supported by an individual. On the contrary, if one does not trust the government, the risks of AI are prevalent, and an individual might choose not to support the use of AI in public policy areas.

3. Methodology

3.1 Research Design

To answer the research question, a quantitative research design was chosen. A secondary data analysis was conducted with data from the Eurobarometer 92.3. This research method was selected as the collection of primary data from different EU member states was not feasible for this research. Even though, this research design opens the possibility for working with a large, high quality data set, the disadvantage of reduced flexibility primary data collection has, needs to be considered (Dale et al., 2012). Also, the conceptual definitions underlying the questions in the survey experiment are not explicitly explained. Therefore, the concepts underlying this research are elaborated in the previous section. When reflecting on the analysis outcomes, the possible discrepancy in conceptualization is addressed. However, a strength of the secondary quantitative analysis is that it allows for generalization of the whole population which is highly valuable to answering the research question and was another reason for selecting this specific research design (Dale et al., 2012). Also, the questionnaire and information about the sampling methods for the Eurobarometer are publicly available which allows for in depth assessment of the survey data.

The Eurobarometer is a survey which is conducted biannually with citizens of the European Union by Kantar Public on behalf of the European Commission. The interviews were conducted face-to-face in November and December of 2019.The individuals, which are the unit

of analysis for the Eurobarometer, were selected by using stratified probability sampling (European Commission, 2020). Respondents were required to be a citizen of a European member state and demonstrate sufficient language skill of the national language to answer the questionnaire (Nissen, 2014). The data is publicly available through the GESIS Leibnitz Institute for Social Sciences, the data archive managing the Eurobarometer Data for the European Commission.

The survey data of 2019 was selected from the repeated cross-sectional study as the topic of AI was added to the standard Eurobarometer 92.3. Beside information on opinions about AI, the survey includes extensive data on personal characteristics and political opinions of citizens in all EU member states (European Commission, 2020). Previous criticism on the Eurobarometer includes vague formulation of questions included in the survey. Also, due to a lack of control questions in some instances it remains unclear whether respondents have sufficient background knowledge for answering the questions in a meaningful way. This can lead to difficulties in analysing responses (Nissen, 2014). For this paper these weak points of the survey are considered when analysing the results.

For conducting the secondary data analysis, first the distribution of the independent variable, citizen support of AI in public policy areas, were operationalised. In the analysis, descriptive statistics of the variable are presented and discussed. For answering the first sub question, the levels of citizen support for AI in public policy areas is presented for the different nationalities. This descriptive statistic is followed by a comparison of national means in the distribution among the independent variable. Lastly, to test H2 a regression analysis is conducted to test for the effect between trust in government and support for AI in public policy areas.

Because the dependent variable of this hypothesis is dichotomous, and the dependent variable is ordinal, as elaborated in the following operationalization, an ordinal logit regression is conducted. Ordinal logit regression is a form of ordered logic regression adjusted for these kinds of variables. Additionally, the robustness of the statistical model is tested by controlling for possible interaction effects. In the literature it has been indicated that personal characteristics influence trust in government (Bannister & Connolly, 2011). Similar personal characteristics were found to affect support for AI (Araujo et al., 2020). Hence, the influence of age, gender, and social class are included in an extended statistical model. As with any statistical analysis, causality is only derived from the theoretical underpinning in relation with the possible correlation found in the dataset

3.2 Operationalisation of Independent Variables

The first independent variable is whether the country of citizenship has a national AI strategy in place. To investigate the national differences, the data was divided by nationality. In the survey data the official political citizenship is not included. Instead, individuals were grouped by countries of residence not regarding whether the respondents have citizenship in the same country. For investigating the national differences in support of AI no explicit characteristics that come with citizenship are required. Membership in the national public, which is given through residing in a country, is sufficient to inform this research. As the scope for the analysis are the 27 member states of the European Union, the dataset was filtered for these. Additionally, as separate samples were drawn from East and West Germany, the country variable was recoded to include only one value for all of Germany. Lastly, the countries were divided by whether a national AI strategy has been published in November 2019, the time frame when the survey data was collected. This leads to the following groups presented in Table 1.

Table 1: National AI Strategies by Country by November 2019

Countries with a National AI Strategy	Countries without a National AI Strategy
Czech Republic	Austria
Denmark	Belgium
Estonia	Bulgaria
Finland	Croatia
France	Cyprus
Germany	Greece
Lithuania	Hungary
Luxembourg	Ireland
Malta	Italy
Netherlands	Latvia
Portugal	Poland
Slovakia	Romania
Sweden	Slovenia
	Spain

Countries ordered alphabetically; adapted from van Roy, 2020

Usually, approximately 1000 respondents were interviewed per country. In countries with a significantly small population, namely Cyprus, Malta, and Luxembourg, approximately 500 people were interviewed. Additionally, as two separate samples were originally drawn from Germany, the combined sample of East and West Germany includes 1540 cases. This led to a total 26372 cases included in the analysis.

For the independent variable *trust in government,* the corresponding variable from the Eurobarometer was operationalized. Respondents were asked whether they trust the national government. Possible answers were "tend to trust", "tend no tot trust", and "don't know". For the analysis the variable was recoded into the dummy variable *trust in government*. The value 0 was assigned to the response "tend not to trust", and the value 1 to the response "tend to trust". Cases who replied with "don't know" are excluded from the recoded variable. 14728 (59.2%) respondents expressed the tendency not to trust the government and 10149 (40.8%) people tend to trust the government. Excluded from the analysis were 1495 people, 5.7% of all respondents, as they replied "Don't know" to this question.

3.3 Operationalization of Dependent Variable

To measure trust of citizens to use AI in public policy areas a question were respondents had to state beneficial uses of AI was used. First, participants were introduced to the concept of AI with the following definition:

"Artificial Intelligence are computer programmes that make predictions, recommendations or decisions. Contrary to traditional computer programmes, these take into account the results from their previous predictions, recommendations or decisions. Examples include face recognition, voice assistants, music or book recommendation or credit worthiness assessments."
(European Commission, 2020)

Then, respondents were asked to choose two areas where AI has the greatest benefits. Suggested was AI use to improve medical services, to improve traffic and air quality, to monitor pollution, to improve productivity and safety in the workspace, or to improve safety of society. It was also possible to choose all or none of the above. To operationalize AI in public policy areas, the aspects medical services, traffic and air quality, monitoring of pollution, and safety of society were identified. With such broad categories, the division between the public and private sphere is not clearly distinguishable. In approaches like new public

governance or public private partnerships multiple stakeholders are engaged and can vary per instance. For this research, the selection of these areas as public policy areas was derived from AI Watch's report on AI in Public Service (Misuraca & van Noordt, 2020).

Next, the ordinal variable *support for AI in public policy areas* was created with values ranging from 0 to 4. To do so, each area selected by a respondent was assigned with the value 1. The amount of policy areas selected were added in the next step. In the Eurobarometer it was only possible for respondents to select two out of all suggested policy areas. Consequently, the variable cannot have the value 3. However, the value 4 was assigned if a responded chose "all of the above" as this indicated support for all 4 public policy areas suggested in the survey. In total, 26372 answers were included, with the mean of support for AI in public policy areas being 1.3 (scale 0-4) with a standard deviation of 0.89. In Table 2 the distribution is presented. 4902 respondents (18.6%) expressed no support for AI in public policy areas. Support for AI in only a specific public policy area was selected by 9533 people (36.1 %), 11089 (42.0%) interviewees support AI in multiple areas. Lastly, 848 (3.2%) individuals support AI use in all indicated public policy areas.

Table 2: Descriptive Statistics for all relevant Variables (N=26372)

Variable	N	%	Min	Max	Mean	St. D.
Trust in Government	24877		0	1	0.41	0.49
No (0)	14728	59.2%				
Yes (1)	10149	40.8%				
Support for AI in…	26372		0	4	1.33	0.89
…No public policy area	4902	18.6%				
…Only a specific public policy area	9533	36.1%				
…Multiple public policy areas	11089	42.0%				
…All public policy areas	848	3.2%				

4. Results

4.1 Support for AI use in Public Policy Areas by Country

First, the correlation between the independent dichotomous and dependent ordinal variable are analysed using a point biserial correlation. This measure of association indicates the strength of association specifically for a dichotomous variable and an ordinal variable on a scale between -1 and 1. Values close to $+/-1$ indicate a strong relationship whereas values close to 0 indicate no relationship between the variables (Khamis, 2008). The $r_{pb} = 0.03$ with a significance of $p = 0.00$ indicates no relationship between the two variables. Nevertheless, the mean for the variable *Support for AI in public policy areas* was compared between the two groups.

For respondents living in a country without a national AI strategy the average support for AI in public policy areas was at 1.31 on a scale from 0 to 4. This mean lies slightly above the value for supporting AI in one specific policy area. For countries with a national AI strategy the mean for the same variable is at 1.36. Even though, this mean is slightly above the mean for countries with no AI strategy the difference is only 0.05 percent points on a 5-point scale. To investigate this small difference further, means of all countries for the variable support for AI in public policy areas are compared, see Figure 1. Green pillars represent countries who have published a national AI strategy, red ones for countries without one.
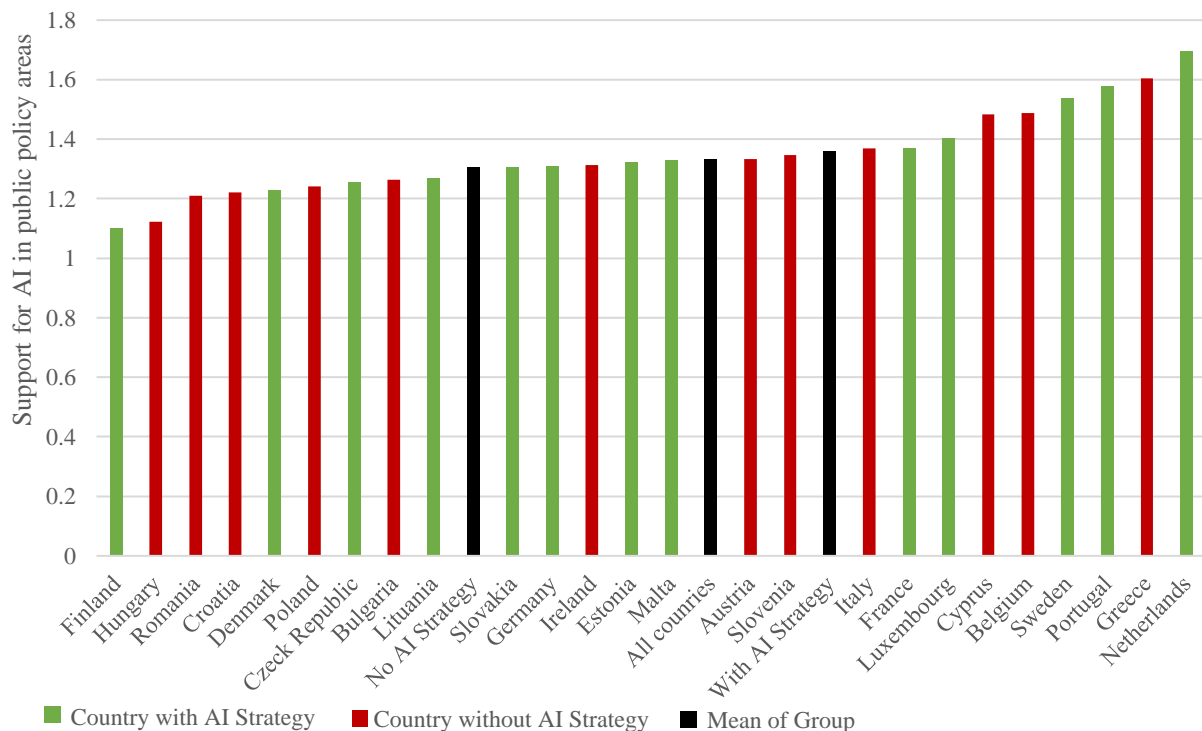

Figure 1: Support for AI use in Public Policy Areas by Country Mean

Looking at the means in the country distribution there is no clear division of trends between countries with or without a national AI strategy. For example, Finland, the country with the lowest mean of 1.1 for support of AI in public policy areas, and the Netherlands, the country with the highest mean of 1.69 have both published a national AI strategy.

The mean as a statistical measure is very sensitive to extreme values. Hence, the distribution of support for AI in public policy areas is also compared between countries without and with a national AI strategy. The results are presented in Table 3. For countries with an AI strategy 18.1% of respondents do not support the use of AI tools in the public sphere, compared to 19% of respondents who live in a country with no national AI strategy. For support of AI in one specific public area the difference is between 38.1% of respondents in countries with an AI strategy and 34% in countries without an AI strategy. For support of AI in multiple public policy areas the difference between the groups is the largest. 44.7% of people support AI use in the public sphere in a country with a national AI strategy compared to 39.6% in a country without such a strategy. However, the support for AI in all public policy areas is slightly larger in countries with no AI strategy than in countries with a national AI strategy. In general, the distribution among the dependent variable is fairly equal. Only in the medium range including support for AI in a specific public policy area and multiple public policy areas a slightly more supportive attitude in countries with a national AI strategy is found.

Table 3: Support of AI in public policy Areas by Country with/without AI Strategy (N=26372)

	No public policy area	Only a specific public policy area	Multiple public policy areas	All public policy areas	Total
Countries with no AI Strategy	2607 (19.0%)	5231 (38.1%)	5430 (39.6%)	455 (3.3%)	13723 (100%)
Countries With an AI Strategy	2295 (18.1%)	4302 (34.0%)	5659 (44.7%)	393 (3.1%)	12649 (100%)
Total	4902 (18.6%)	9533 (36.1%)	11089 (42.0)	848 (3.2%)	26372 (100%)

Resulting from these finding, H1 *Citizens of countries with an AI strategy express more support for AI in public policy areas* cannot be confirmed. The measure of association shows no correlation between the variables. Additionally, the difference seen in a mean comparison between countries with and without a national AI strategy is extremely small. Also, when comparing the means of each country, no trend could be found that citizens in a country with a national AI strategy are more supportive of its use in the public sphere. When looking at the cross table, there is not a clear direction that citizens of countries with an AI strategy have a stronger support. Even though, more respondents expressed support in multiple public policy areas, slightly more people from countries with no AI strategy support the technology in all public policy areas. These findings are not strong enough to support the previously stated hypothesis. However, as some small differences could be found, and it would be interesting for future research to explore the national differences more elaborately. Potentially, third variables that interact with the relationship can be identified.

4.2 Trust in Government and Support for AI

To test the second hypothesis the ordinal logic regression Model 1 was created that analysed the relationship between trust in government and support for AI in public policy areas. In the Model 1, all logged odds for the dependent variable are statistically significant as presented in table 4. The largest value of the independent variable serves as the reference category in the model. Even though, the model is statistically significant, and the null hypothesis can be rejected, the Nagelkerke Pseudo R^2 of 0.002 indicated that only a very small amount of variation in support for AI can be explained by trust in government. The Nagelkerke Pseudo R^2 is a contingence coefficient that can be interpreted similarly as a Pearson's R^2 in linear regression analysis and has been adjusted for explaining variation in ordered logit regression (Menard, 2014).

In Model 2, the additional predictors age, gender, and social class were added to test the robustness of Model 1. The effect of trust in government on support for AI in Model 2 is not significant anymore for the category of support for AI in one specific public policy area. Though, the influence for all other values of the dependent variable remain statistically significant in Model 2, which shows that Model 1 is robust for these parts of the relationship. Additional variables that show a significant effect on support for AI in public policies areas were identified. As seen in Table 4 younger people as well as men are more likely to support

AI in public policy areas. Individuals who identify themselves as belonging to either the lower working class, or the lower middle class of society are less likely to support AI in public policy areas.

Table 4: Ordinal Logistic Regression Models for Trust in Government & Level of Support for AI in public policy areas

	Model 1		Model 2	
	Logged Odds	St. E.	Logged Odds	St. E.
Support for AI in…				
(All public policy areas = ref)				
…No public policy area	-1.61***	0.02	-1.75***	0.17
…Only a specific public policy area	0.87***	0.02	-0.17	0.16
…Multiple public policy areas	3.35***	0.04	3.31***	0.17
Trust				
No trust in government	0.15***	0.02	-0.12***	0.03
Trust in government	0	.	0	.
Age			0.21***	0.46
15-24years			0.20***	0.03
25-39 years			0.17***	0.03
40-54 years			0	.
55 years and older				
Social Class				
Lower working class			-0.56**	0.17
Lower middle class			-0.36*	0.17
Middle class			-0.16	0.16
Higher class			0	.
Gender				
Male			0.13***	0.02
Female			0	.
Nagelkerke R^2	0.002		0.018	

*$p<0.1$; **$p<0.05$; ***$p<0.01$ (two-tailed test); N = 26372*

For easier interpretation, the cumulative logged odds of Model 1 were transformed into the category probability[1]. As in Figure 2 presented, the probability of citizen who trust the government to not support AI is 17% compared to the probability of 28% citizens who do not trust the government. For Support of AI in a specific public policy area the probability is 46% for people who do not trust the government and 54% for people who do trust the government. The likelihood to support AI in multiple public policy areas is 24% for people who do not trust the government and 26% for people who do. In the last category, full support of AI in public policy areas, the probability to be in that category is 2% for citizens who do not trust the government compared to 3% for people who do trust the government. In this comparison, one can see that only for the category "No support for AI use in public policy areas" the probability for people who do not trust the government is higher. In all other categories, that include different levels of support for AI in public policy areas, the probability for citizens who trust the government is higher. The total probabilities for the dependent variable of Model 2 can be found in Figure 3 for comparison.
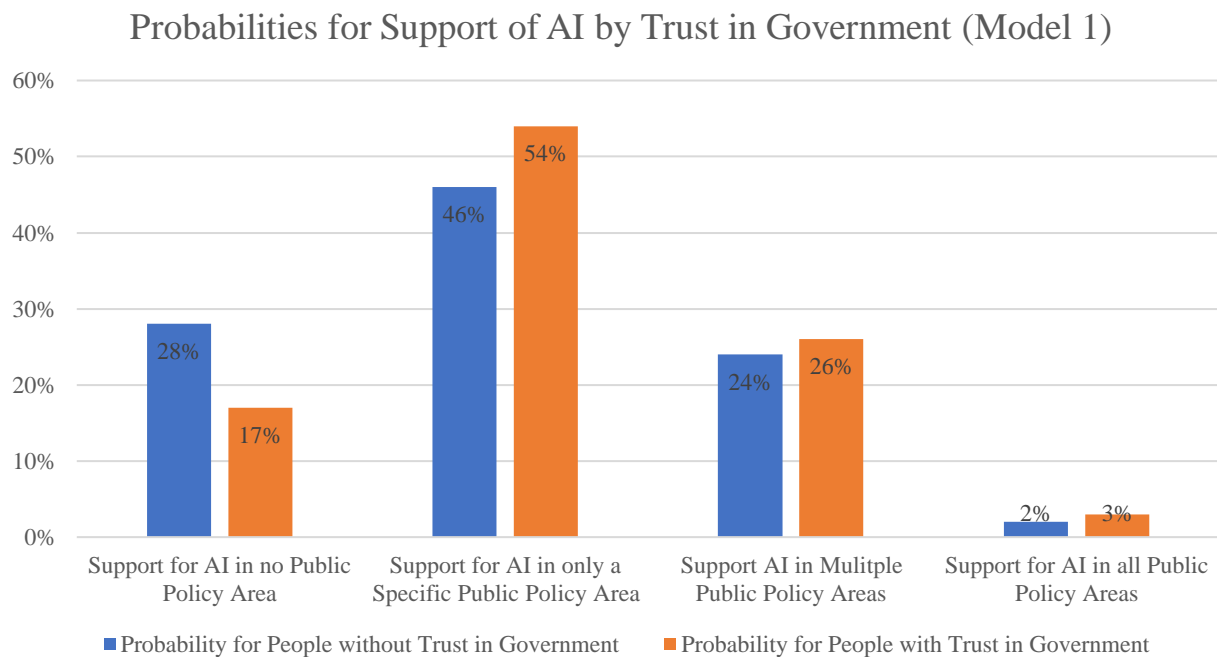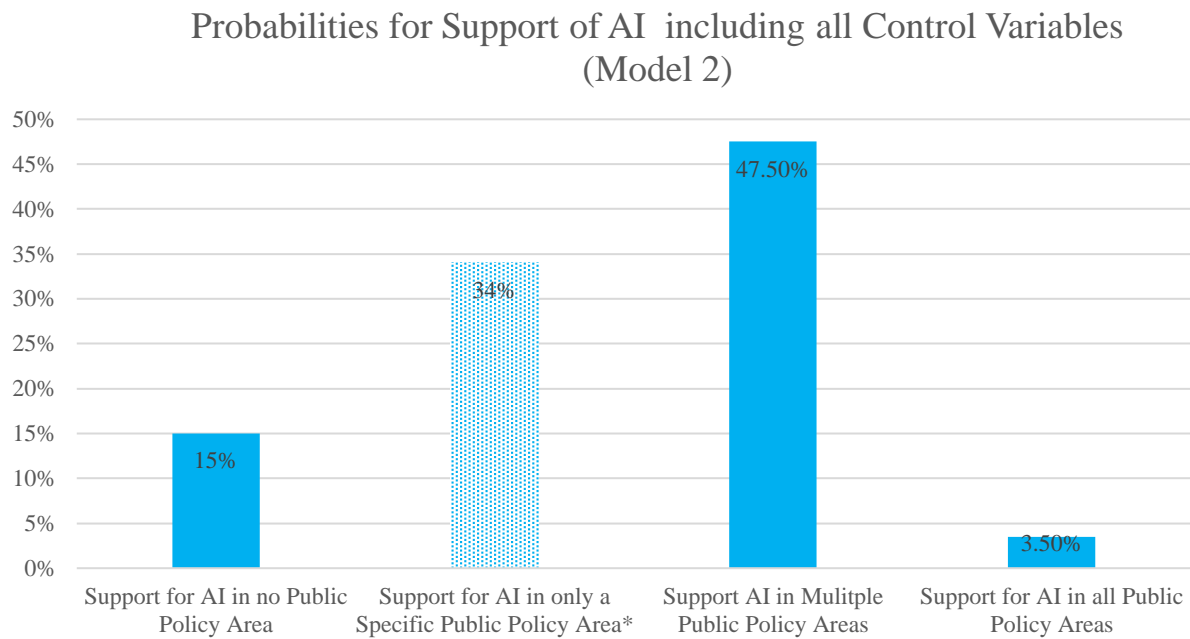

Figure 2: Ordinal Logit Regression Probabilities for Level of Support by Trust in Government

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[1] Transformation was done as follows: $1/(1+\text{cum logit}^2)$

Probabilities for Support of AI including all Control Variables
(Model 2)

Statistically not significant

Figure 3: Ordinal Logit Regression Probabilities for Level of Support including all control variables

On this basis hypothesis 2 *Citizens' trust in government is positively associated with support for AI in public policy areas* can be confirmed. However, due to the low explanatory power of the model indicated by the pseudo R^2, there are further variables expected to influence a person's support for the use of AI technology in public policy areas. Further exploration is outside the scope of this research but needs to be taken into consideration for future research.

Drawing from this analysis of the data the first hypothesis was rejected. Even though national differences in support for AI use in public policy areas were found, having a national AI strategy did not contribute to explaining these differences. The second hypothesis was supported by the data. People who have general trust in government are more likely to support AI use in the public sphere. However, this independent variable only explains a very small amount of variation in the data.

5. Discussion

5.1 Interpretation of Research Results

First, in researching the national differences in support for AI in public policy areas by citizens, it was found that national differences in support levels exist. However, having a national AI strategy does not contribute to explaining the different levels of support, based on this data. Even though, the national AI strategy does not explain different levels of support, the results contribute to answering the first sub question of the research, what are national differences in support for AI by citizens. The general level of support for AI in public policy areas lies between one or multiple public policy areas in the model across all EU countries. This shows that benefits of AI are seen by citizens but there are still hesitations about implementing the new technology across a wide variety of public policy areas. Previous research has also shown that citizens are receptive towards the benefits of AI use within a generally pessimistic public perception towards the new technology (Araujo et al., 2020). As displayed in Figure 1 the EU country with the highest level of support was the Netherlands, followed by Greece and Portugal. The lowest level of support was expressed by citizens of Finland.

However, as the first hypothesis was rejected, this research does not indicate how the national differences can be explained. In the theoretical underpinning multiple risks and benefits associated with AI use in the public sector were identified (Busuioc, 2020; Filgueiras, 2021; Harrison & Luna-Reyes, 2020). Especially for AI use in the government context the national government has been stressed by researchers in the area as an important stakeholder for addressing the risks (Busuioc, 2020; Misuraca & van Noordt, 2020). Apart from the structural causes for different levels of support, previous research has identified multiple individual level factors that contribute to a person's attitude towards AI. Online self-efficacy and domain specific knowledge are positively associated with support for AI (Araujo et al., 2020). Potentially, there are already national differences in the prevalence of these individual characteristics which ultimately lead to different national levels of support for AI. For instance, looking at the country with the highest level of support, the Netherlands has also a high level of technology adaption and internet use (Araujo et al., 2020). Also, in previous research about country-level factors on support for AI the influence of techno-socio environment was tested. Though, the results show that factors like GDP, innovation and government effectiveness do not explain varying levels of support for AI in European countries (Vu & Lim, 2021). Another possible, structural explanation for the national differences could be the countries' techno-

administrative traditions. In public administration research, it has been extensively discussed how a country's administrative history and tradition influences current transformations of public administration (Meyer-Sahling & Yesilkagit, 2011). Traditional differences are mainly identified between eastern and western Europe. A similar trend can be seen in the national differences of this research but for more reliable results, it needs to be the focus of future research.

Regarding trust in government as an influential factor for support of AI, hypothesis 2 was confirmed by the data. Consequently, the answer to the second sub question, how citizens' trust in government can explain their support for AI use in public policy areas, is that trust in government does contribute to explaining citizen support in AI in public policy areas. If an individual expresses support towards their government, they are more likely to express higher levels of support towards AI use in the public sector. This finding leads to the conclusion that the national government is an important stakeholder in managing the risks associated with AI use. However, looking at citizen support and referring to the first sub question, a national AI strategy is not a policy instrument with an immediate effect. At this point one must keep in mind that a strategy paper does not yet define any concrete policies. Though, by fostering general trust in government, this trust also applies to the subdomain of AI in public policy areas. As research in e-government transformation has already shown, this trust in government is crucial for implementing new technologies (Cook & Gronke, 2005; Newton, 2012). Also, this parallel of findings from this research focused on AI and previous studies on e-government transformation are an important addition to the existing body of knowledge. E-government refers to the digitalization of government services in general (Pérez-Morote et al., 2020). AI is a new development for digitalization that holds a great amount of transformational power. However, as AI for government use is a relatively new phenomena research is limited in this subfield. Being able to draw back on the more extensive research on e-government is a great starting point for future research and understanding the implications of AI in the public sphere.

This research was motivated by providing more generalizable results in the area of AI use in the public sphere as most existing research are case studies. With this research, a generalizable European overview of support for AI in public policy areas is added to the existing body of knowledge. With this contribution findings from past and future case studies in the field can be related to a bigger picture more easily. Additionally, the role of citizens as a stakeholder was included in empirical research and gave insight in citizens perception of AI use in the

public sphere. This is relevant for public administrators and governments when implementing AI tools in public policy areas as citizens are their ultimate source of democratic legitimacy.

5.2 Methodological Shortcomings and Implications for Future Research

Multiple methodological shortcomings need to be considered that can affect the result of this paper. Firstly, respondents were introduced to the concept of AI as part of the survey experiment. However, it remains unclear whether the individuals understood what AI technology actually is, what risks and benefits are associated with it, and what role governments can play in implementing and regulating AI. Previous research has already identified the lack of control questions in the Eurobarometer as a methodological weak point (Nissen, 2014). Also resulting from the secondary data analysis as a research design, compromises were made regarding the dependent variable that could have affected the results. In the questionnaire it was only possible to select two out of the five policy areas suggested where AI would be most useful (European Commission, 2020). This could have led to a misrepresentation to the level of support an individual has for AI use in public policy areas.

For testing hypothesis 1 a control question on whether the respondents are aware of the presence of a national AI strategy would contribute positively to the research. In order to influence the level of support an individual has for AI use in public policy areas, one has to be aware of the strategy or even how the strategy addresses risks associated with AI. However, this factor could not be included based on the dataset available for the secondary data analysis. Regarding the national AI strategy, national differences in the strategy were also not taken into consideration. Logically deriving from the theoretical framework, citizens are expected to support AI more, as a national AI strategy addresses and potentially manages the risks. However, each national strategy outlines different approaches for AI use. There are differences in quality and effectiveness that were not accounted for in this research (Brattberg et al., 2020). Moreover, the public sector as an area for AI implementation, which is the focus of the research, is not explicitly mentioned in any of the national AI strategies. This leads to the question how well particular risks for the public sector like the transparency and accountability challenge can effectively be addressed (Busuioc, 2020). For the second hypothesis a significant effect of trust in government on support for AI in public policy areas could be seen. However, the statistical model is very poor in explaining the variation in the data. Less than 1% of variation in the data

can be explained with the independent variable trust in government. Drawing from this research it remains unclear what stronger influences are on support for AI use in public policy areas

For future research a more elaborate model, potentially in form of a multilevel analysis could shed light on this. Building on this paper and the previous literature review such a model should include individual level factors additional to trust in government and structural factors based on national differences. Ideally, primary data is collected for example in form of a survey experiment. In the design, one needs to consider that public knowledge on AI, especially AI implementation in public services is still likely to be very limited. As mentioned in the previous section, control questions in the survey can account for that factor.

6. Conclusion

Conducting a secondary data analysis with the Eurobarometer 92.3 from 2019 it can be said that a majority of EU citizens support the use of AI technology in public policy areas. However, most people only support AI use in specific public policy areas and not the implementation of the new technology across multiple areas in the public sphere. Additionally, the research indicated that the level of support by citizens varies. This moderate level of support was found in all EU member states. However, slight differences in support were found in populations of the different member states. This indicates that the country of residence can influences the level of support for AI use in the public sphere. However, whether a country has a national AI strategy or not does not contribute to explaining the national differences. A factor that does have an influence on the level of support is trust in government. If an individual expresses trust towards the national government, they are more likely to support the use of AI in public policy areas. Nevertheless, trust in government is a poor predictor for support of AI. Factors that have a stronger influence on a citizen's position regarding this topic remain unknown. These results answer the overall research question of this paper, to what extend citizens of EU member states support the use of AI in public policy areas and what influences their support.

By conducting secondary data analysis, it was possible to examine EU wide data, establishing a general overview about perceptions of AI use in the public sector. AI use in the public sphere was not the focus of the Eurobarometer 92.3, which led to multiple methodological shortcomings. Nevertheless, through investigating national differences in support and possible influences on citizens' perception valuable insights are gained. For public administrators and policy makers it is crucial to understand the citizens' opinions. AI technology offers the

possibility to improve effectiveness and efficiency of governments. However, these benefits can only be yielded if citizens, as the ultimate source of democratic legitimacy, support implementation of the novel technology. In the public sector action needs to be taken to achieve state of the art policy making and public service delivery in the age of digitalization and vast technological advancements. However, support by citizens for AI implementation still depends on specific policy areas. Drawing from this research, governments could for example try to foster general trust by citizens in the institution. For future research, it would be interesting to further investigate predictors for citizen support of AI implementation in the public sphere. Only when the predictors are known, action can be taken to accommodate citizens. Also, further investigation in the national differences should be on the agenda for future research. From national comparison best practices in implementing AI for government use can be identified. Similar policies that might be identified as effective in managing the risks associated with AI technology could help inform the policy making in other countries.

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