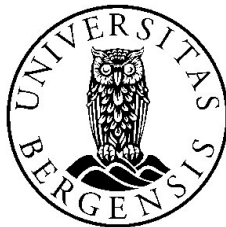


Responsiveness to a Digital Age:
Voting on Artificial Intelligence in the European
Parliament

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Master's thesis

Spring 2022

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Abstract

Artificial Intelligence is a growing technology that is likely to be central for economies and industries across the whole globe. The European Union wants to be at the forefront of the development and deployment of this technology. To lead the development of artificial intelligence is essential to keep up with superpowers like USA and China. The problem is that artificial intelligence can also harm people if not deployed and developed in a human-centric way that benefits the public. It is therefore essential to understand if the EU is responding to public preferences regarding the development of this technology.

This thesis investigates if the Members of the European Parliament are responding to the public opinion on Artificial Intelligence. The theoretical argument originates from the theory of responsiveness, which argues that policymakers move their policy preference along with public opinion. The thesis also tries to uncover what might condition responsiveness on this issue. This thesis uses a multilevel analysis method to test the argument. The analysis combines roll-call voting data from the European Parliament with public opinion survey data making it possible to examine effects on multiple levels.

The empirical analysis shows no discernible effects between MEPs and the issue of artificial intelligence. However, it also shows that the largest determining of the votes of the MEPs are their national parties. So, if the MEPs vote in line with their national parties, the responsiveness might be found on the party level. The party-level analysis shows that party size significantly affects the parties' votes, and smaller parties seem more responsive. By including a cross-level interaction between party size and public opinion on AI, the analysis finds a significant effect of the interaction. The interaction effect indicates responsiveness to public opinion on AI conditioned that the party is small enough.

Acknowledgments

Through my time in the European studies bachelor program and my study trip to Salzburg, I developed a deep interest and fascination for the European Union and the processes within this most interesting political union. My time as an exchange student in Austria has highlighted the importance of political, social, and financial cooperation across borders. My studies at the bachelor's level demonstrated just how important the European Union and its institutions are to developing a legislature that will enrich the lives of everyone within its sphere of influence. My interest in technology and technological development, which I inherited from my father, has made me curious about how the EU deals with technological advancements that move rapidly. The result of this is a master's thesis that tries to uncover whether the European Parliament responds to the public's views on technology when voting on issues.

Working on this thesis has been challenging work as well as highly educational. It has challenged me in many ways, and through writing this thesis, I have discovered new sides of myself, which I hope will help me develop even more. To have been able to investigate the political processes of the European Parliament have been fascinating. I am grateful to all my professors, lecturers, and seminar leaders who have helped me reach my goals. This thesis is the culmination of five years of study, and I feel like I have been able to accumulate into this master's thesis a lot of what I have learned through these years, both at the bachelor's and master's levels.

I am incredibly grateful to my supervisor, Raimondas Ibenskas, who have been very helpful in the process of writing my master's thesis. Thank you for all the good conversations and discussions that have made this thesis possible. Your patience, expertise, and input have been of great help to me in this process. I also want to thank my girlfriend, Ida Birkeland, who has been very patient with me during this time and supported me when I needed it. I also want to thank my parents for always being there and believing in me. Lastly, I want to thank my fellow students at Sofie Lindstrøms hus, who have made my time as a master's student much easier.

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Abbreviations

EU	European Union
MEP	Member of European Parliament
EP	European Parliament
EC	European Commission
AI	Artificial Intelligence
US	United States of America
Council	Council of the European Union
NP	National Party
ICC	Intraclass Correlation
SD	Standard Deviation
COD	Ordinary Legislative Procedures
INL	legislative Initial Procedures

1. Introduction

Access to the best AI technology could prove essential in determining who will be leading economies and who will fall behind. The problem with artificial intelligence is that it has some pretty significant downsides. Computers and robots making decisions without human input could be devastating if misused. This technology could be used in military applications to void responsibility and opaque decision-making and remove working-class jobs from the market. These are some of the potential risks that follow AI. To stop this and ensure the technology is used in a human-centric way that benefits the people. The EU and other large governing bodies need to implement ground rules for how this technology is developed and implemented. Undoubtedly, AI technology will change the world as we view it today. This technology can be as important as the invention of steam engines, computers, and the internet. It could be the dawn of a new technological revolution. For this to happen in a way that benefits the people, the policymakers need to listen to the people affected by the technology. The goal of this thesis will therefore be to see if the European Parliament is responding to the public opinion of the people in the EU and to try and understand what may impact the EP's responsiveness to AI.

This thesis will first examine the conceptualization of critical terms like democracy, the European Parliament, and responsiveness before moving on to the literature review. The literature review and the following chapter on theoretical explanations for responsiveness follow the three main factors: institutional factors, party characteristics, and issue characteristics. Lastly, the literature review brings up some literature on AI. The theory chapter summarizes some key points of the literature review into some hypotheses of results that can be expected from the analysis based on earlier literature. The thesis forms the empirical arguments starting with the data chapter. The data chapter presents the different roll-call votes included in the analysis, the variables, how they are coded to fit into the multilevel analysis, and lastly, some data limitations. After presenting the data, the thesis presents the methodical framework for the analysis, presenting simple logistic linear regression, multilevel, and multilevel logistic regression of two

and three levels. The method chapter also considers pitfalls associated with multilevel regression, like the multicollinearity issue. Applying the method to the data in the analysis shows some interesting discoveries, especially the relationship of party votes with the MEP votes indicating that party votes matter more than the individual votes. Indicating that a multilevel regression using party votes as the dependent variable could be interesting to the results. In the multilevel regression using party votes as the dependent variable, the results find that the size of parties matters and that a cross-level interaction between the party size and the public opinion on the AI variable has substantial and statistically significant results. The discussion chapter finds that the analysis can confirm H1, H2, H5, and H6, while it finds no support for H3 and H4. The concluding chapter discusses the research question and finds that even though it is difficult to determine if the MEPs are responsive to public opinion on AI based on the analysis, the results could indicate that they are. It also finds that MEPs largely vote in line with their parties, indicating that the party policy is likely to be important in determining responsiveness. The thesis also concludes that smaller parties are more likely to respond to AI issues than larger parties. Lastly, the conclusion chapter discusses some Impactions for future research and finds that larger datasets on roll-call votes and time-series data could benefit future research. The Inclusion of other potential influences on policy-making like interest groups could also be interesting to include in future results, as well as the difference in responsiveness between different EU institutions like the EC and EP.

1.2 Research question

(1) Are the MEPs of the European Parliament representing the public opinion of their respective member states? (2) Why do some MEPs pay more attention to the public opinion than others when they vote on issues relating to AI?

2. Literature review

This chapter Introduces the relevant literature on the responsiveness of AI. It will briefly summarize some relevant literature on democracy and the European Parliament. The chapter will

try to find what earlier research has discovered to be the main reasons for responsiveness in different political systems.

2.1 A crude conceptualization of democracy and its relationship to responsiveness

To understand responsiveness, there needs to be an understanding of how responsiveness works in relationship with democracy. In his 1971 book *Polyarchy* Robert A. Dahl list a set of conditions necessary for a democracy:

1. To formulate their preferences
2. To signify their preferences to their fellow citizens and the government by individual and collective action
3. To have their preferences weighed equally in the conduct of the government, that is, weighted with no discrimination because of the content or source of the preference (Dahl 1971, 2).

Then according to Dahl, having responsive representatives is a requisite for democracy. The political preferences of citizens need to be considered as political equals to the preferences of the representatives. In that way, responsiveness becomes a vital characteristic of a functioning democracy (Dahl 1971, 1). In his book “democracy” (2007), Charles Tilly divides definitions of democracy into four main categories: Constitutional, substantive, procedural, and process-oriented. To try and define democracy is a monumental task and would probably take a whole book to do it justice, so this chapter will only go over the different categories briefly (Tilly 2007, 7)

The constitutional definition is a broad classification of democracies based on a regime's laws, and constitutions define a country's political process. It is fruitful to define democracy based on this to compare regimes in extensive historical comparisons. However, this category of definitions lacks the human elements of democracy and focuses more on the broad strokes of democracy. On the other hand, the substantive approach focuses more on the human aspects of democracies. Does the regime promote welfare, freedom, security, and equality? Can we call it a democracy if not all these rights are adequately taken care of? These rights are essential for democracy, but it does not say anything about the institutional and lawful structures of a state

(Tilly 2007, 7). Procedural definitions focus on elections and a narrow range of governmental practices. A procedural definition works best for trying to describe an electoral democracy, often in transition, but fails to include elements of more longevity. On this point, the Process-oriented approaches have more promise. The most notable author of the Process-oriented approach is Dahl and his five process-oriented criteria for democracy: Effective participation, voting equality, enlightened understanding, control of the agenda, and inclusion of adults (Dahl 1998, 37-38). Dahls' definition of democracy as presented in both "Polyarchy" and "On Democracy" lends itself poorly to comparing democracies between countries. The criteria might have a conflict of interest between each other, and influential groups of association such as racist, sexist, or elitist groups could undermine the inclusiveness of the democratic regime and, as such, breaks with the rules laid forth by Dahl (Tilly 2007, 11).

Democracy as a concept is very complicated. The issue has a long history, creating confusion and disagreement about what the term "democracy" should and should not include (Dahl 1998, 3). One can argue that modern "democracy" is closer to a representative government rather than a democracy as understood by the Greeks and Romans. In the book, *Democracy, Accountability and Representation*, Adam Przeworski, Susan C. Stokes, and Bernard Manin argue that modern "democracy" is an elitist system, a rule by the few. It is a competitive oligarchy where others rule the people but replaces and select them through votes (Manin, et al. 1999, 4). The issue of a representative government is central to the issue of responsiveness and is central to Dahl's criteria for a working democracy. A combination of well-informed citizens and representatives acting on the best available information creates a system where more often than not the decisions will be the correct ones, a verdict reflected in the outcome of votes in an election (Manin, et al. 1999, 5).

Dahls' view on democracy emphasizes many points central to explaining responsiveness in representative democracies. Freedom of expression, organization, vote, and institutions for making government policies depend on votes and other expressions of preference (Dahl 1971, 3). For this thesis, "democracy" will be understood with a process-oriented approach in line with

Dahl's requirements for a functioning democracy from "Polyarchy" and "On Democracy" (see Dahl 1971 & Dahl 1998).

2.2 The European Parliament

The European Parliament was established as the Assembly of the European Coal and Steel union but adopted the name of the European Parliament in 1962. Although the EP was initially viewed as a less influential institution, it has become one of the most critical institutions in the EU through reforms. The EP influences policy creation in the EU in three main ways: legislative process, control, and supervision of the executive and budgetary processes. The primary role of the EP is to vote on new legislation, but the EP also suggests and participates in policy development with the EC. The EC promised in 2010 to give the EP ample attention and devotion to these requests. However, there is little evidence to show it has much impact. Just 18 such proposals were adopted in the 2009 to 2014 sessions (Nugent 2017, 201-203). The EP works closely with the EC and Council for the budgetary process. The EP has the right to propose modifications and amendments and vote on approval or rejection of the final budget with the Council (Nugent 2017, 205-206).

National Parties are involved in the EP in three ways. Firstly, most MEPs are members of a national party and are often obliged to or willingly follow their party's position or concerns. Secondly, MEPs are voted into the EP through their national party. The policies advocated by the voters are often domestic issues, with a trend of moving away from larger opposition parties to smaller opposition parties. Third, within the EP groups, which are larger groups of MEPs, there exist national party groups which can disrupt the EP groups. There is a lack of coordination among the EP groups, and the national parties are often free to adhere to their party guidelines rather than the EP group. The national parties in the EP often act on their priorities and loyalties. When there is a clash between EP groups and national parties, the national parties' preferences often take precedence (Nugent 2017, 217-218).

2.3 Conceptualization of responsiveness

In an article from “The oxford handbook of Political Representation in Liberal Democracies,” Zoe Lefkofridi conceptualizes the concept of congruence. In short, congruence is a concept that compares citizens' opinions with the opinions and actions of the political elite or those that make the policy to see whether representation works (Lefkofridi 2020, 1). The Lefkofridi article talks about congruence between citizens and elites, but congruence might not be feasible to measure with the data available on AI due to the differences in measurement and scales between the citizen data and the data on political elites in the European parliament, an alternative is to look at responsiveness rather than congruence

Both Congruence and responsiveness are schools of thought looking to untangle the relationship between policy preferences at the citizen level and policy decisions at the elite political level. However, they are two different approaches to this goal (Beyer and Hänni 2018, 14). Congruence is a static notion of overlapping interest between policymakers and the citizens. On the other hand, responsiveness suggests a more dynamic relationship where policy makers to a much larger degree respond to the citizens by enacting policies that align with their preferences. Daniela Beyer and Miriam Hänni suggest that the idea of responding elites present in responsiveness creates a causal element that is not present in the more static environment of congruence. Beyer and Hänni urge that despite this causal element in responsiveness, there have been many difficulties establishing causality in empirical research on responsiveness (Beyer and Hänni 2018, 16). Responsiveness often tackles cases of opinion and policy, while congruence focuses more on ideological position and policy output. Responsiveness is more suitable for research questions that compare citizens' opinions and elites' policy development (Lax and Phillips 2012, 149). For a thesis looking at specific policy outputs of the European Parliament, it would be challenging to use congruence because policy and ideology lack a standard measurement metric. Congruence might be more suited to understanding political systems where the majority opinion is more important, like the American political system where policies are expected to align with the majority opinion (Lax and Phillips 2012, 148). For political systems that rely more on the consensus model of decision making, comparing policy and opinions would

be more fruitful because they can more easily be compared to each other without having to rely on that the policy matches majority public opinion (Lax and Phillips 2012, 150). Responsiveness only relies on a positive correlation between opinion and policy (Lax and Phillips 2012, 148).

2.4 Responsiveness based on issue characteristics

Most of the initial work and findings on the responsiveness of politicians and leaders to public opinion focused on the United States. Most of these studies used time-series aggregated data on a state, national, or district level (Beyer and Hänni 2018, 29). Benjamin I. Page and Robert Y. Shapiro were some of the first to use this approach. Their study from 1983 shows that public opinion tends to precede policy changes which could point in the direction of responsiveness by American policymakers. When Policy preferences shift, congruent policy changes will likely follow, especially if the issues are prominent, sustained, and salient. Page and Shapiro also find that policy affects opinion a substantial number of times (Page and Shapiro 1983, 188-189). They also emphasize that even though it is tempting to conclude that there is responsiveness in American politics and that the citizens get what they want from the government, there are some caveats. Their results concern broad and salient issues, and the results may be different for more specific and detailed policies, some of these less salient issues might not change with opinion changes.

James A. Stimson, Michael B. Mackuen, and Robert S. Erikson find in their article that significant scale shifts in public opinion lead to large-scale shifts in government policy, but they find little evidence of opinion reacting to policy, unlike the Page and Shapiro article. The situation is more complex than the results indicate, and simple regression models struggle to include the subtleties of the relationship between opinions and policy. They emphasize that they do not have enough information to characterize the full relationship (Erikson, et al. 1995, 559). Stuart N. Soroka and Christopher Wlezien take this a step further by introducing the thermostatic representation model, which considers the preferred level of policy action. By looking at the difference between preferred and actual policy action, they can discover the preferred general policy level. By considering preferred policy action, the model becomes dynamic. It no longer

looks at just responsiveness as a one-dimensional exchange. It also considers that when the government is responsive to an issue, the relative demand for an opinion on that issue decreases (Soroka and Wlezien 2012, 1409-1410).

Following up on their research on the thermostatic model of preferences Soroka and Wlezien introduce the concept of absolute preferences. Absolute preferences look for the “ideal” position where the voter is satisfied with a policy. Soroka and Wlezien refer to Stimson's “zone of acquiescence,” which describes a range in which the voter would say that the policy is “just right (Stimson 1991). However, it is hard or even impossible for voters to say at what point they are satisfied with a policy. However, even though it is hard to uncover or document, Soroka and Wlezien argue that it can further explain the dynamics of responsiveness. To uncover and explain the absolute preferences of welfare spending, Soroka and Wlezien use the relation between economic measures and relative preferences (Soroka and Wlezien 2021, 167). They choose the issue of welfare spending in the United States because they claim through earlier research (Wlezien 1995; Wlezien 2004) that in some domains, there is little to no evidence of a thermostatic relationship between opinion and policy, but there is evidence of an effect in US welfare spending (Soroka and Wlezien 2021, 166). Soroka and Wlezien start by creating a prediction of the amount of welfare spending that would lead to the average respondent preferring spending «status quo,» or (2) on a scale where (1) is less and (3) is more spending (Soroka and Wlezien 2021, 174-175). This initial prediction shows that Democrats and Republicans provide more welfare than the public wants. It implies that the poorer demographics who should want more welfare are more represented than the rich, even though earlier research implies that politicians are more responsive to the rich. This assumption might not be true, pointing to another power dynamic (Soroka and Wlezien 2021, 176). By replacing the middling survey response (2) with the mean spending preference, the prediction of absolute preferences compared to actual welfare spending turns out a little differently. This second prediction is much closer to the actual spending value, meaning that governments spend about the right amount concerning the public's preferred spending (Soroka and Wlezien 2021, 177). To summarize, they find that absolute preferences for welfare are trending upwards and are in line with actual welfare spending. Although this study is quite narrow in both area and policy, they claim that

what they have suggested here can be applied outside the parameters of this study (Soroka and Wlezien 2021, 178).

2.5 Responsiveness based on Institutional factors

Responsiveness is not perfect, and some issues may move in the opposite direction of opinion changes. Although these cases are rare, they should not be dismissed outright. Even if public opinion results in policy changes, it might not result from the “will of the people.” Politicians, interest groups, and other actors might affect voters before the change of public opinion, which makes subsequent responsive policy changes a result of a manipulated public opinion (Page and Shapiro 1983, 189).

Using the thermostatic model, Soroka and Wlezien find that governments respond to changing public preferences, and the public reacts to policy change. A caveat to their findings on responsiveness is that political institutions condition it. They also find that federalism constrains public responsiveness and that the balance between the executive and legislative lessens responsiveness. They also find that the type of electoral system the country operates with matters. On this point, they find that governments with proportional representation systems are less responsive to changes in public opinion (Soroka and Wlezien 2012, 1425).

One of the first researchers to study responsiveness in Europe was Frank Brettschneider. In his article from 1996, he looked to establish whether the German federal legislature was congruent and responsive to public opinion (Brettschneider 1996, 292). Brettschneider finds that there are linkages between parliamentary actions and majority opinion as well as opinion changes in Germany. This applies to parliament, parties, and government. (Brettschneider 1996, 307). Responsiveness is understood in this article as policy leadership by the public. Policy leadership means that public opinion changed first, followed by parliamentary action and congruent policy. Brettschneider finds fourteen cases of public opinion preceding policy changes. In the cases

where parliamentary decisions lead to a congruent opinion change, it is not responsiveness but leadership by the politicians (Brettschneider 1996, 306-307).

For leadership by politicians, Brettschneider finds twenty-five cases of opinion change where politicians tried to counteract policy change or got negative feedback on their actions and did not adopt the public's opinion. Twelve cases of policy change showed a reciprocal relationship between these two groups where none of the groups were dominant. In forty-three cases, he could not establish the relationship's direction. Brettschneider argues that the direction of influence needs to be determined case-by-case (Brettschneider 1996, 307). Although he finds links between opinion and policy, he emphasizes that there is insufficient evidence of a causal relationship between policy affecting opinion or opinion affecting policy. Brettschneider offers some possible variables that might affect responsiveness, especially the political system under which the process operates. This is in line with Erikson, Mackuen, and Stimson's argument of responsiveness working differently between institutions (Erikson, et al. 1995). Is responsiveness different in parliamentary and presidential systems where parties do not matter as much, or can types of states or party systems play into how responsive governments are towards the citizens (Brettschneider 1996, 308)?

Stimson, Mackuen, and Erikson also state that politicians in the United States translate changes in public opinion into changes in policy. They also argue that this responsiveness differs between the different institutions. The Senate and the House of Representatives are equally good at responding to public opinion. However, the most critical form of representation for the Senate and the presidency comes from electoral changes. At the same time, the House of Representatives is equally responsive-without the evidence of personnel change (Erikson, et al. 1995, 560).

In their article about presidential and congressional responsiveness, Shapiro and Lawrence R. Jacobs follows this. They find that the White House is improving at responding to the public. However, as Shapiro and page pointed out, they also get more opportunities to manipulate and lead public opinion to fit their agenda. They point out how the Reagan administration used “pulse line” analysis to pinpoint the most effective presentation and language in speeches. This

form of analysis can manipulate public opinion to fit their preferred policies. However, it could also benefit the public by having the President use time and resources to monitor public policies. They could become more aware of the people's will, but it does not mean they will comply. They find that during election years, the responsiveness for presidential candidates and congress representatives rises. They also find that presidents and Congress leaders often leave public opinion to the side and follow their agenda in years between elections. The Vietnam war after Johnson's reelection, Reagan's support for "freedom fighters" in Nicaragua, and Clinton's invasion of Haiti are examples of decisions that went against public opinion in the years between elections (Jacobs and Shapiro 2000, 13).

2.6 Responsiveness based on party system and party characteristics

In his 2012 study, Armen Hakhverdian looks at parties' responsiveness in the United Kingdom (UK) and collects previous literature points into three hypotheses (Hakhverdian 2012): The responsiveness, leadership, and counter movement hypothesis (Hakhverdian 2012, 1388).

"The responsiveness hypothesis" centers around general preference as one of the keystones of a democratic system (Dahl 1971). He identifies the mechanics by which the people can control the representatives and governments as "electoral turnover" and "rational anticipation." "Electoral turnover" means that the people influence representatives by voting the parties or representatives that best represent their values and preferences into government. Suppose the policies of an elected government drifts too far away from public opinion. In that case, the turnover will ensure that a new government will draw policy back closer to the preferred policy position of the people. "Rational anticipation" builds on the concept that governments develop policy to win elections. This creates an opening for the people to influence policy creation more directly. The idea is that parties' will shift their policy preferences closer to the preferences of public opinion to win the election. "Rational anticipation" can therefore be interpreted as the more direct form

of public opinion influencing policy. Both works together to ensure that government policies follow in the same direction as the public opinion (Hakhverdian 2012, 1389).

The “Democratic leadership” hypothesis builds on the idea that political parties, elites, and governments push back against public opinion to bring it closer to their policy position. This phenomenon reflects some of the ideas presented in earlier literature (Brettschneider 1996; Page and Shapiro 1983; Soroka and Wlezien 2012). The key idea of this hypothesis is that democratic leadership occurs when public opinion aligns with the government's policy preferences. Hakhverdian presents a quote from Theodore Roosevelt quoted in (Warren 1964): «I simply made up my mind what they [the people] ought to think, and then did my best to get them to think it» (Hakhverdian 2012, 1390). The main argument of the second hypothesis is that for political parties, elites, and representatives not to try and use state power to influence and maximize their electoral chances both in and out of office would be highly irrational. Therefore a shift in public opinion should be preceded by a shift in policy (Hakhverdian 2012, 1391).

The last hypothesis presented in the Hakhverdian article is the “counter-movement” hypothesis. This hypothesis bases itself on the idea of public rationality. If the government overshoots its policy targets, the public will act counter actively until the policy aligns with the public opinion (Hakhverdian 2012, 1391). This idea aligns with the thermostat theory from the Soroka and Wlezien article (Soroka and Wlezien 2012; Wlezien 1995). To adjust its public opinion, the people would need to possess valid and reliable knowledge of government action, which builds on the unequal representation theories presented (Soroka and Wlezien 2021). In this hypothesis, the media also plays a vital role in distributing this information. A biased media will lead to less valuable and reliable knowledge of government action, leading to a democratic leadership scenario where the government could influence the voters through the media (Hakhverdian 2012, 1391-1392).

The article finds strong support for the responsiveness hypothesis but not for the reverse effects of policy on opinion, which would entail a poor fit for the other hypotheses. However, they

found that this was dependent on the government in power. A popular government proved able to change the direction of public opinion to the preferred policy position. They also find that with unpopular governments, the public could move counter to the government action (Hakhverdian 2012, 1402). This indicates that responsiveness is conditional on several factors, like whether the public has enough valid information and what kind of governmental system the country operates in. The article finds it unlikely that there will be similar levels of responsiveness in electoral systems with multiple parties. The British Westminster system has an advantage because of its two-party structure. Electoral systems with multiple parties could end up with mixed policy signals which could cause confusing responsibility that would lessen the public's ability to counteract policy that moves against the public opinion (Hakhverdian 2012, 1403).

Contrary to Hakhverdian's findings, when studying the congruence of parties, Joris Boonen, Eva Falk Pedersen, and Marc Hooghe, as well as Mikko Mattila and Tapio Raunio, find that the number of parties and party systems do not matter for the party - opinion congruence (Boonen, et al. 2017; Mattila and Raunio 2006). Mattila and Raunio expected that party system characteristics would have an effect in line with the predictions made by Hakhverdian, but their analysis refutes this (Mattila and Raunio 2006, 446). Boonen, Hooghe, and Pedersen follow this by finding no support for the idea that complex party systems (that of multiple coalition parties) will lessen party-opinion congruence. They figure that an explanation for this might be that the complexity of a party system does not relate to voter-party ideology congruence (Boonen, et al. 2017, 325).

In their article looking at party responsiveness, James Adams et al. find that parties shift their ideological positions to public opinion when they find that opinion is shifting away from the party's ideological positions. They also find that election results do not play a part in shifting party ideology. This result entails parties responding to public opinion, but not necessarily opinion presented through past election results as discussed in other literature (Adams, et al. 2004, 608). The economic left-right ideology of parties surfaces as the most critical variable for explaining congruence in the literature on party congruence and responsiveness. Rory Costello, Jacques Thomassen, and Martin Rosema find that despite not being able to guarantee that public

policy preferences are represented in parliament, congruence is higher on the left-right dimension than on the cultural and European integration dimensions. They find that the public policy preferences are fulfilled if most cases in the European Parliament related to economic issues (Costello, et al. 2012, 1245-1246). Mattila and Raunio also find that the voters congregate more with parties on the economic left-right dimension and that there was a gap between voters and parties on the question of European integration (Mattila and Raunio 2006, 445). Parties are often more in favor of integration than the voters, and this finding is supported in the article by Costello, Thomassen, and Rosema (Costello, et al. 2012; Mattila and Raunio 2006). Mattila and Raunio also looked at the responsiveness of European parties, where they found that more centrist parties are less responsive than fringe parties. Opinion congruence was also higher in smaller parties which correlates to fringe parties that, in many cases, are smaller than the centrist parties respond more (Mattila and Raunio 2006, 445).

2.7 Theoretical explanations for responsiveness

John M. Carey raises the issues of institutions' effect on party unity. Generally, parties in presidential systems are viewed as more fractured than those in parliamentary systems. Federal systems that encourage party creation on the subnational level create conflict within parties at different levels. These assertions of institutions' effect on party stability are not universally accepted across the research field. Carey references an article by Figueiredo and Limongi from 2000 arguing that parties in centralized control systems could govern just as well as those in parliamentary systems that are often viewed as more stable (Carey 2007, 92). Simon Hix, in his article from 2004, looks more specifically at how the electoral institutions affect the legislative behaviors of MEPs in the European Parliament (Hix 2004, 194-195). The model Hix uses to analyze the relationship between electoral institutions and legislative behavior assume as a baseline that MEPs have the same goals as regular politicians and would therefore act similarly. MEPs might vote in a particular way to promote a specific topic, attract votes, or secure a specific parliamentary position. The way MEPs get elected is also essential to understand for why they vote a specific way; MEPs are affiliated to their parliamentary group and their national party. MEPs will likely vote more in line with their national parties because MEPs get elected at

the national level, not at the European level (Hix 2004, 203). This is important because it suggests that MEPs vote more in line with the national interest. If the MEPs respond to the citizens, their votes on policy would be in line with citizens' opinions on the national level.

In a study about the congruence of salient issues in Switzerland, Nathalie Giger and Zoe Lefkofridi find that salient issues are more congruent than none salient issues, and they argue that there is support for the claim that the salience of an issue matter to the congruence between parties and the public (Giger and Lefkofridi 2014, 299). They find support for this in the 1963 article by Warren E. Miller and Donald E. Stokes. When looking at congress voting on slave rights in the south, it finds that the issue is not salient and therefore would likely not gain notable votes and likewise will not lose any votes. Hence, they abstain from taking a firm stance on the issue (Miller and Stokes 1963, 55). More relevant to this thesis is the importance of policy salience for the congruence and responsiveness of parties. Giger and Lefkofridi cite an article by Lawrence Ezrow et al. that finds evidence for larger parties focusing more on broad ideological lines than specific salient policy issues. This is because larger centrist parties apply a catch-all system that has a higher congruence across a larger group of voters, but taking a strong stance on specific salient issues might alienate parts of their voter base (Ezrow, et al. 2010; Giger and Lefkofridi 2014, 290-291). Ezrow et al. also find that niche parties respond well to changes in their voter base's issue position while ignoring the general shifts in the mean voters' position (Ezrow, et al. 2010, 288). Niche parties are responsive to the salience of issues within their voter base and shift their party position according to this. Bonnie M. Meguid finds in her article from 2005 that niche parties' strategy of focusing on salient issues also affects the strategy of the larger catch-all parties. Meguid finds that the large parties might shift to a focus on salient issues if this focus by the niche parties offers enough of a treat to the large parties' legislative shares (Meguid 2005, 357). Adams et al. expect that the key to understanding European party dynamics may lie in party leaders, informational environments, or the perceived risks associated with changing policy direction (Adams, et al. 2004).

Mark N. Franklin and Christopher Wlezien argue in their 1997 article that responsiveness is only expected in policy areas with some degree of popular salience. Responsiveness will rely on

whether the policy area is salient or not (Franklin and Wlezien 1997, 347). Christopher Wratil argues that the high and stable salience of left-right issues makes these issues key to understanding the responsiveness of government actors. According to Wratil, the anticipation of the government actors will be to respond to these types of issues. He finds that there is more responsiveness from political actors on issues and legislation with high salience (Wratil 2017, 69). On the public's side of responsiveness, Franklin and Wlezien point out that for the public to be responsive to a policy, they need to collect and manage reasonably accurate information about policymakers and the legislation they are pushing. This is more likely to happen to a policy that the public finds essential and, therefore, salient (Franklin and Wlezien 1997, 349).

According to the 2014 article by Nicholas Clark, some scholars argue that the low public interest in EP elections results from EU issues being less salient than similar issues on the domestic level (Clark 2014, 350). The European public might not see issues on the EU level as relevant to their own life. This might lead to EU issues and legislation becoming less salient among the public and lessening the interest in EP elections. This means that interest in EP elections would be low because EU issues are not salient rather than EU issues being less salient because of low interest in EP (2014, 340). The salience of EU issues is not as stable as some of the literature suggests. Looking at statistics of European unification from Franklin and Wlezien, the salience was low in the 70s but increased throughout the 80s. However, they emphasize that it is unclear whether European policies are more or less salient than domestic policy (Franklin and Wlezien 1997, 352).

Regarding party responsiveness to issue salience, Tarik Abou-Chadi, Christoffer Green-Pedersen, and Peter B. Mortensen argue that larger parties have more incentives to move their policy positions based on changes to the public salience of different issues. Smaller parties often try to differentiate themselves from the larger parties and improve their limited vote share by focusing on more niche issues (Abou-Chadi, et al. 2020, 750). Although larger parties seem to be shifting more towards salient issues than smaller parties, the process of policy shifting is more complex because the median voter's position on salient issues might not be consistent with the broader ideological position of a party. The voters might view a party as ideologically

inconsistent if the party drifts too much on the ideological spectrum based on the salience of different policy issues. The parties must balance the possible electoral gains of moving their ideological position towards an issue when its salience increases (2020, 752-753).

2.8 Artificial Intelligence

Anneke Zuiderwijk, Yu-Che Chen, and Fadi Salem have written an article discussing the complications of AI in governance. Although this thesis will not delve into the technicalities of AI in governance, it is interesting because it may affect how MEPs view AI as a tool or hindrance in their governance. They define AI systems as a technological component that can process data and information in a way that entails intelligent behavior (Zuiderwijk, et al. 2021, 1). In a study on the effect of AI on skill demand in Chinese manufacturing from 2011 to 2017, Mengmeng Xie, Lin Ding, Yan Xia, Jianfeng Guo, Jiaofeng Pan, and Huijuan Wang found that AI adoption in manufacturing reduces the demand for low-skilled workers. Although this is a complicated case with many nuances, implementing AI will increase labor transfer between regions and improve firm-level labor skills in the long run (Xie, et al. 303-304). Although the results from this study are not black and white on whether AI is good or bad for low-skill workers, it indicates that this should be an essential issue for lower-educated workers. As noted in the article by Zuiderwijk, Chen, and Salem, most AI research is technical and lies in computer science. It is lacking a bit on the side of AI in Policy and governance. Where there is research, there is little consensus on how to handle the challenges associated with the emergence of AI in the political field (Zuiderwijk, et al. 2021, 2).

In February 2020, the European Commission (EC) published the “white paper on artificial intelligence, ” laying the groundwork for how the EU plans to deal with the emerging challenges of artificial intelligence. The white paper looks to set out policy options on how to enable scientific breakthroughs and preserve the technological leadership of the EU while ensuring that AI is for the good of all Europeans. AI affects many policy areas, including healthcare, agriculture, climate, security, and the military. AI technology will improve all these aspects of

our lives, but it is not without risks. The white paper mentions a few potential risks that AI might bring to our society: “Opaque decision-making, gender-based or other forms of discrimination, intrusion in our private lives or being used for criminal purposes” (Commission 2020, 2-3). The EC, together with the member states and industries, seeks to create a framework for policy to boost research, innovation, and investment while increasing the usage of AI in small to medium enterprises. They also try to lay the groundwork for future legislative and regulatory frameworks for using AI. Europe needs to embrace the development of AI and help develop and reinforce the industrial and technological capabilities of Europe to enable the EU to become leading within the area of AI and become a global hub for data. AI will enable the EU to deal with monumental societal changes like environmental issues, protection of citizens against crimes, and protection of our democracy, given that it is implemented ethically and sustainably that follows and respects our human rights (Commission 2020, 25).

Ronit Justo Hanani presents three explanatory factors for shaping AI legislation in the EU. The three explanatory factors are global economic competition, institutional structure in the EU, and preferences for domestic actions (Justo-Hanani 2022, 137). The article argues that all of the explanatory factors explain the process and outcome of AI legislation in the EU. That means there is no overarching factor, but the different factors play different roles in different parts of the legislation process. Hanani proposes that economic factors mostly play a role in the background of reform and timing. EU institutional factors affect the agenda-setting process of the EC, and most important for this thesis, the policy preferences of domestic actors had the most effect on the decisions made in the decision-making stage in the EP. Interest groups and powerful domestic industrial actors also play a prominent role in the preferences of these domestic actors. Hanani underlines that the regulations of AI are still undergoing, so any research on this subject will be preliminary (Justo-Hanani 2022, 154). This is especially true before implementing the “Artificial Intelligence Act” awaiting committee decision. This legislation will give a much clearer picture of the direction of AI legislation in the EU. According to the EC's legislative proposal, the “Artificial Intelligence Act” aims to create a universal framework for the development, marketing, and use of AI so that it conforms to EU values. This legislation will try to make it clear where different types of AI lands in accordance

to a three risk approach to make it easier to make more specified and targeted legislation on AI, as well as create a “single future-proof definition of AI” (Commission 2021). The White paper lays down some groundwork for the EU to have a risk-based approach to using AI. Hanani seems to think that it is difficult to say if the high-risk approach that the EU seems to have taken to AI so far will keep them relevant as the competition from the US and China increases. “The Artificial Intelligence Act” might clarify the path of AI legislation in the EU (Justo-Hanani 2022, 154).

3. Theory

The main objective of this thesis is to uncover whether the EP responds to public opinion on issues of AI. It is imperative to see if the literature supports the idea of responsiveness, the responsiveness of parties, and responsiveness in the EU. The first point of Dahl's definition of democracy is “Effective Participation” (Dahl 1998). Further in his 1971 book, he argues that public preferences need to be prioritized by the government (Dahl 1971). The public must be able to express their opinion, and the government must consider their preferences when governing. Multiple articles that look at the American political system find some responsiveness between policy makers and public opinion (Erikson, et al. 1995; Jacobs and Shapiro 2000; Page and Shapiro 1983; Soroka and Wlezien 2021). There are some caveats to these findings, and most scholars agree that responsiveness has a dependency on other variables. Through the research on the American political system, scholars find that both institutional and policy factors can affect if policy makers are responsive to an issue (Erikson, et al. 1995; Jacobs and Shapiro 2000; Page and Shapiro 1983; Soroka and Wlezien 2021).

When looking at responsiveness in Europe and, more specifically, Germany, Brettschneider finds a link between policy and opinion, but struggles to find sufficient evidence for a causal relationship. He also has a hard time establishing the influence's direction in many cases (Brettschneider 1996). Hakhverdian finds strong support for his responsiveness hypothesis in his study of responsiveness in Britain. He argues that because of the two-party structure, the British system lends itself much more to responsiveness than a multiparty electoral system. Confusion

related to mixed policy signals from a multiparty system might make it harder for the general public to counteract policy that moves against public opinion (Hakhverdian 2012). Based on these two articles on the state level, it seems that the vast multiparty structure of the European parliament would not have good responsiveness. Research on the party level tells a different story. Boonen, Pedersen, and Hooghe, as well as Mattila and Raunio, find that the number of parties and the party system present are not relevant for party-opinion congruence (Boonen, et al. 2017; Mattila and Raunio 2006). This also seems to be the case in the responsiveness of parties. Adams et al. find that parties shift their ideological positions toward public opinion when opinion shifts away from the parties' position. Costello, Thomassen, and Rosema also find responsiveness among parties in Europe but largely dependent on the economic left-right dimension (Adams, et al. 2004; Costello, et al. 2012). Matilla and Raunio also find that larger parties tend to be less responsive than their smaller counterparts (Mattila and Raunio 2006).

Hix argues in his 2004 article that MEPs largely vote more in line with national interests rather than the interests of the European voter base. Because the MEPs are voted in at the national level, they are expected to vote in line with national interests or in the interest of their national parties. Therefore, Hix expects responsiveness in the EP, but the MEPs will be responsive on national rather than European issues (Hix 2004). Costello, Thomassen, and Rosema also find a degree of responsiveness by the EP. However, they argue that this responsiveness largely depends on the economic left-right orientation of an issue. If an issue is sufficiently economical, the EP is expected to respond to public opinion (Costello, et al. 2012). The article by Xie et al. looks at the consequences of AI on the labor market and if AI will make low-skilled work obsolete. They conclude that it is not clear whether or not AI is positive or negative for low-skilled workers, but it puts AI into an economic sector, not only a technological one (Xie, et al. 2021). The white paper presented by the commission presents AI in both technological and economic sectors. The Commission is trying to develop a framework to advance AI as a technology and make it available to businesses, underling the potential for AI to be used both culturally and economically. This points to issues relating to AI being economical but not as cut dry because it affects multiple policy areas (Commission 2020). Hanni argues that legislation on AI depends on multiple factors; economic, institutional, and domestic. Looking at the arguments

from Hix and Costello, Thomassen, and Rosema, both economic and domestic factors could play a role in the EU's decision-making on this issue (Justo-Hanani 2022).

The null hypothesis (H0) here will be that the MEPs of the EP do not respond to public opinion. H0 is supported by the literature of Hakhverdian and Brettschneider, which argues that multiple parties could create an unfavorable environment for responsiveness. Most literature also finds caveats to the success of responsiveness which might make H0 a likely result. The first hypothesis predicts the existence of responsiveness:

H1: MEPs respond to public opinion on issues of AI

H1 is supported by the fact that most literature finds responsiveness to be occurring on some level. Although the electoral systems studied in the literature vary quite a bit, the assumptions made by Hakhverdian are contested by the articles studying responsiveness and congruence in parties. Whether this thesis finds support for H0 or H1 largely depends on other factors. Most of the literature that finds support for responsiveness also finds that it is dependent on multiple factors. This thesis has categorized these factors into three main categories, issue characteristics, institutional factors, and party characteristics.

The literature agrees that responsiveness is not a constant overarching rule of law that is equal in every scenario. If a researcher finds responsiveness in one study, that does not mean that every representative in every political system will be responsive to public opinion on all issues. The first category is issue characteristics, and not all issues are equal. Page and Shapiro argue that responsiveness or congruence from public opinion to policy output is likely if the issue is large enough, sustained, and salient (Page and Shapiro 1983). This thesis will focus mainly on the salience of an issue to see if issue characteristics influence the responsiveness of AI legislation. The size of an issue can primarily be related to its salience. It is expected that a significant issue will be salient, and a salient issue will be significant. As for the longevity or sustainability of an issue, this requires time-series data, which is impossible with the available data. Salience

surfaces in the literature as a significant reason for responsiveness. Therefore, uncovering if AI is a salient issue is essential to understand whether there is responsiveness in AI-related issues. Franklin and Wlezien argue that some level of popular salience is needed to expect any responsiveness. This view supported by other scholars such as Wratil, Abou-Chadi et al., and Giger and Lefkofridi (Abou-Chadi, et al. 2020; Franklin and Wlezien 1997; Giger and Lefkofridi 2014; Wratil 2017). Clark argues that the low salience of EU issues could be a reason for low turnout in EP elections (Clark 2014). Whether AI issues are salient or not could be an essential predictor of whether responsiveness is to be expected. Even though salience is an interesting metric, it is not the end-all for explaining why there is or is no responsiveness to an issue. Based on the literature, the second hypothesis predicts that AI is a salient issue and should therefore be responsive.

H2: AI is a salient issue and will lead to responsiveness on this issue.

Institutional factors are another category that emerges as an essential indicator of whether responsiveness occurs. Page and Shapiro argue that even though public opinion might affect policy change, the effects might be reversed, and the political actors might be affecting the public opinion (Page and Shapiro 1983). Stimson, Mackuen, and Erikson do not find evidence for this reversal of effects seen in the article by Page and Shapiro. The exact direction of responsiveness effects is contested, and the role of institutions in shaping public opinion could be hard to uncover (Erikson, et al. 1995). Soroka and Wlezien highlight the problem of public knowledge to the independence of public opinion. Suppose public knowledge is independent of interference from political institutions and actors. Then the public must possess valid and reliable knowledge of government actions (Soroka and Wlezien 2021). Free and non-biased media must be available so the government cannot use the media to influence voters (Hakhverdian 2012). Some of the literature also finds differences in responsiveness between institutions. Stimson, Mackuen, and Erikson find a difference between the senate, the house of representatives, and the presidency. It would be logical to assume that there would be a similar tendency between the institutions of the EU. However, since this thesis only covers the EP, it is not relevant as an explanatory variable (Erikson, et al. 1995).

Hakhverdian finds it unlikely to find similar levels of responsiveness in political systems that operate with multiple parties as he does when studying the British Westminster system (Hakhverdian 2012). Soroka and Wlezien also find that institutions matter for responsiveness, but they also find that responsiveness in federalism lessens responsiveness, which is in line with the arguments presented by Hakhverdian (Soroka and Wlezien 2012). In this regard, the American system is unique because it defines itself as a federalist state that operates with a party system. The EU, on the other hand, makes this even more complicated as the EP operates with a multi-party system. While it can hardly be defined as a federalist state, it inhabits many traits associated with federalism (Nugent 2017). Based on this, one should not expect an EU institution to be responsive to the public or for the public to have the knowledge and clarity to articulate their opinion in a way that makes it easy for representatives to respond.

The 2021 study from Soroka and Wlezien finds that both major US parties spend more on welfare than the public wants. This implies that the political elites respond most to the poorer demographic, who benefit the most from welfare. This contradicts what they found to be the case in earlier studies which argue that the political elites are more responsive toward the wealthier parts of the population (Soroka and Wlezien 2021). Multiple articles in the literature find economic variables to be important explanatory factors for the level of responsiveness that is to be expected. Costello, Thomassen, and Rosema find that the public policy preferences are more likely to be fulfilled if the issue relates to economic issues. A similar result is found by Matilla and Raunio, who argue that EU integration issues are much less salient than economic issues in the EP (Costello, et al. 2012; Mattila and Raunio 2006). Economic variables could therefore be argued to influence if there is an effect on whether responsiveness occurs or not. The hypothesis of the institutional factors will therefore be that the responsiveness of the EP will be dependent on institutional covariate variables, such as a trust in media, state, or the EU. The responsiveness is also expected to depend on the public's economic status and the country's general economic position.

H3: The responsiveness is expected to depend on whether there is trust in the media, state, and EU.

H4: The responsiveness is expected to depend on the public's economic and educational level position.

The last category is party characteristics. As Neil Nugent argued, domestic parties have much influence inside the EP (Nugent 2017), so party characteristics might have some explanatory value as to why responsiveness occurs or not. Hix argues that because MEPs are voted into the EP through their national parties, they are likely to vote in accordance with their national party. Hix assumes that representatives of the EP will behave similarly to regular politicians, and they might therefore want to promote topics that will ensure them more votes. That means that MEPs will try to focus their efforts on salient vote-grabbing issues and answer to their domestic parties (Hix 2004). The most prominent party characteristic affecting responsiveness in the literature is the idea that the size of a party affects its ability and willingness to chase and adapt its policy based on the saliency of an issue. Ezrow et al. find in their 2010 article that larger centrist catch-all parties might be congruent with a larger voter base across issues, but they are hesitant to respond to public opinion on specific issues. On the other hand, they find that smaller niche parties are more willing to be responsive to salient public opinion (Ezrow, et al. 2010; Giger and Lefkofridi 2014; Mattila and Raunio 2006).

The size of the party might not matter, as Meguid finds that larger parties might respond to shifts in niche parties' positions on an issue if they deem the issue as enough of a threat to their elected seats. Also, here the salience of an issue will play a role. If the issue is salient, the larger parties will likely feel more threatened by shifting niche parties (Meguid 2005). The issue of party size might be nulled out because if niche parties respond, larger parties follow suit. If the niche parties do not respond, the larger parties would not feel threatened and would, therefore, not be likely to respond. Based on the theories of party responsiveness, the last hypothesis will be:

H5: If AI is a salient issue, the national parties should influence the responsiveness of MEPs.

H6: Smaller parties will be more responsive than large parties

TABLE 3.1

Table of the presented hypothesis

Hypothesis	
<u>Hypothesis 1.</u>	MEPs respond to public opinion on issues of AI
<u>Hypothesis 2.</u>	AI is a salient issue and will lead to responsiveness on this issue.
<u>Hypothesis 3.</u>	The responsiveness is expected to depend on whether there is trust in the media, state, and EU.
<u>Hypothesis 4.</u>	The responsiveness is expected to depend on the public's economic and educational level position.
<u>Hypothesis 5.</u>	If AI is a salient issue, the national parties should influence the responsiveness of MEPs.

<u>Hypothesis 6.</u>	Smaller parties will be more responsive than large parties
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4. Data

This thesis uses multiple data sources to uncover the effect of the responsiveness of the MEPs on the public's views on AI regulation. There was needed data on both roll call votes on AI issues in the EP and the public view of AI. For the roll-call votes, this thesis uses votes picked out from the European Parliament Legislative Observatory, which provides detailed information on all the roll-call votes performed in the EP. The Legislative Observatory has good informational data, but it is difficult to extract large numbers of roll-call votes. Parltrack, on the other hand, provides large data dumps of both basic information of MEPs and MEP plenary roll-call votes (parltrack 2022a; parltrack 2022b). Parltrack is a free tool and database dedicated to making it easy to track law-making in the EP (EU 2011). This thesis uses two Eurobarometer datasets for the public survey data, Eurobarometer 87.1, and Eurobarometer 87.2 (Commission and Parliament 2017a; Commission and Parliament 2017b).

AI data are lacking for public surveys and roll-call votes in the EP. There is not that much legislation on AI in the EP, and especially for ordinary legislative procedures (COD), most of the roll-votes are either legislative initiative procedures (INL) or own-initiative procedures (INI). The EP has the most power in ordinary legislative procedures, where they and the Council have co-decision power. The EP has veto rights on these legislative proposals, which increases the EPs' power and bargaining influence. The EP is not looking to reject proposals but amend them for ordinary legislative procedures. Ordinary legislative procedures can potentially reach three reading procedures if the EP and the Council cannot agree. However, the EP and the Council often agree on the first reading. If the Council and EP cannot agree after the second reading, the proposal fails if there is an absolute majority against the EP (Nugent 2017, 203). The EC has an

almost exclusive right to initiate legislation. However, the EP can propose legislation to the EC by article 225 in the “Treaty on the Functioning of the European Union” (TFEU). However, the EC does not have an obligation to submit a proposal. In addition to promoting legislation to the EC, the EP can create non-legislative “initiative reports” to pressure the EC. The legislative powers of the EP are indirect. However, the Lisbon treaty strengthened its position by making it obligatory for the EC to give reasons for refusals on a case-to-case basis (Kotanidis 2020, 2). This is where legislative initiative procedures and own-initiative procedures come in. They are preliminary proposals on legislation voted on by the EP. Although they are not as important as the ordinary legislative procedures, they could give an insight into the placement of the EP on specific forms of legislation like the issue of AI. An ordinary legislative procedure on AI is coming up for the vote in the EP, called the Artificial Intelligence act (Commission 2021). See chapter 2.7 for more details. It has not been up for the vote in the EP, so this study cannot include it.

Because of the limited number of roll-call votes that inhibits the question of AI, the roll-call votes chosen for the analysis were the reports that were available in the “parltrack” dataset concerning AI issues. The website legislative observatory was used To find the roll-call votes. The legislative observatory is the EPs database for tracking EU-decision making processes. This database makes it easy to track amendments that concern different topics. Roll-call vote “2018/2088(INI)” aims to promote the development and deployment of AI and robotic technology in order for the EU to be at the forefront of this technology and in all the affected industries. Although it also implores that the development is done in a human-centered way. Its main objective is to ensure more development of AI technology and is therefore coded as such (Parliament 2019). Roll-call vote “2020/216(INI)” is aimed at making the management on AI stricter on criminal law issues, highlighting the risks and consequences widespread use of AI will have on the protection of fundamental human rights. The main objective of the vote is to ensure more regulation of AI technology and is therefore coded as such (Parliament 2021a). Roll-call vote “2020/2015(INI)” aims to improve the property rights of AI technologies to promote the development of AI in Europe. The EP wants to encourage the investment and development of these technologies by ensuring that there is legal certainty in the development process of AI. This

vote aims to ensure the development of AI technologies and is therefore coded as such (Parliament 2020b). Roll-call vote “2020/2017(INI)” aims to restrict the use of AI in education, audiovisual media, and culture so that fundamental rights, values, and freedoms are preserved. When deploying AI and related technologies, it is imperative to respect the ethical principles of privacy, personal data, cultural diversity, intellectual property rights, and freedom of expression. The main objective of this vote is to ensure more regulation of AI technology, which is therefore coded as such (Parliament 2021b). Roll-call vote “2020/2216 (INI)” aims to improve the use of AI for European consumers by calling for the commission to regulate AI technology to prevent unfair and abusive use of the systems. However, this technology is crucial to developing agriculture, industry, and the economy. To meet these demands, AI must be developed. Because of this, the vote is coded as aiming to develop AI further (Parliament 2021c). Roll-call vote “2020/2014(INL)” wants to strike a balance between encouraging the development of artificial intelligence and protecting citizens. The vote aims to ensure that high-risk AI systems are appropriately managed and that there is civil liability tied to the use and development of AI. Although the vote is trying to balance the development and management of AI technologies, the vote is mainly aiming to apply more regulations to the use of AI. It is therefore coded as such in the analysis (Parliament 2020a). Coding these roll-call votes is difficult because they are often both for and against the development of AI. Often, they want to develop the technology, but for it to be done in a human-centric and ethical way. The coding leans heavily on personal opinion of the solutions to determine how the votes will be coded. The collection of votes only includes final votes and not votes on amendments within the resolution process.

TABLE 4.1 TABLE OF ROLL-CALL VOTES INCLUDED IN THE DATA

Roll-Call Votes			
ID	Title	Year	Number of MEPs participating in the final vote
2018/2088 (INI) A8-0019/2019	“Comprehensive European industrial policy on artificial intelligence and	2019	671

	robotics”		
2020/2016 (INI) A9-0232/2021	“Artificial intelligence in criminal law and its use by the police and judicial authorities in criminal matters”	2021	687
2020/2015 (INI) A9-0176/2020	“Intellectual property rights for the development of artificial intelligence technologies”	2020	690
2020/2017 (INI) A9-0127/2021	“Artificial intelligence in education, culture and the audiovisual sector”	2021	696
2020/2216 (INI) A9-0149/2021	“Shaping the digital future of Europe: removing barriers to the functioning of the digital single market and improving the use of AI for European consumers”	2021	693
2020/2014(INL) A9-0178/2020	“Civil liability regime for artificial intelligence”	2020	691

There were problems in finding data on the subject for the public survey data. That AI is a pretty new technology might be the reason for this. Two datasets included variables on the use and trust of AI: The world risk poll (WEP) and the Eurobarometer 87.1. Based on the Eurobarometer having better questions for public opinion on AI and the WEP dataset missing data on The Czech Republic, the Eurobarometer was the better choice for the survey data in the analysis. This thesis has merged the Eurobarometer 87.1 with the 87.2 datasets to get variables on education, wealth, and trust in the media. Both datasets are from the same year and were produced by the Leibniz Institute for the social sciences. This hopefully eliminates some possible variances that differing collection methods could create and other outside factors that could affect the data.

This thesis has extracted the variables of interest from all the datasets (see Table 4.2) before aggregating the public survey data to the country level to merge them with the voting data. Merging the aggregated survey data with the EP roll-call votes creates a data set with three levels: country, party, and MEP. This makes it natural to perform a multi-level regression to see if the national parties influence the responsiveness of the EP, see section 5.

4.1 Variables

TABLE 4.2 TABLE OF THE VARIABLES USED IN THE ANALYSIS WITH THEIR ORIGINAL VALUES BEFORE AGGREGATION.

Original variable values						
Variables	Minimum Value	Mean	SD	Maximum value	Level	Units (N)
Dependent Variables						
Vote on AI	0 (NO)	0.3285	0.4697	1 (YES)	MEP	664
Party votes on AI	0	0.3292	0.1490	1	Party	211
Explanatory Variable						
Public opinion on AI	1	1.514	0.6809	4	Individual	17093
Control Variables						
Party Size	1	8.2839	7.3945	25	Party	211
Party Vote	0	0.3292	0.1490	1	Party	211
Trust in Media	0	0.3991	0.4897	1	Individual	24730
Education	1	5.9631	2.8196	9	Individual	24730
Wealth	1	2.4345	1.0973	5	individual	24730
Social inequality	1	1.776	0.7539	4	individual	17093

Left-Right	0	5.298	2.1897	10	individual	17093
Gender	0	0.4031	0.4906	1	MEP	664
National Party (The national parties included are the parties that have representatives in the EP that voted on the roll-call votes presented earlier)	NA	NA	NA	NA	Party	219
Country (Countries included are the member states of the European Union)	NA	NA	NA	NA	Country	27

The dependent variable of Vote is coded as a bivariate variable based on what the individual MEP voted in roll-call votes on issues related to AI. They could either vote for the promotion and development of AI “1” or stricter regulation of AI “0” those who abstained from voting got left out of the analysis because their intentions are complex to determine based on the votes. The vote variable is compiled from six votes on AI issues in the EP. The roll-call votes included in the variable were not all asking the same question. A “yes” vote in one roll-call vote could mean more development, while a “yes” vote in another might require stricter regulation. By manually going over each roll-call vote and shifting the direction of the vote, so it reflected either more or less development of AI, and the final variable reflects the intention to support the development of AI or implement stronger regulation of AI. When all the votes were adjusted so that the value of

“1” was in favor of more development of AI and “0” were in favor of stricter regulation, the roll-call votes were merged to create one dichotomous variable. The primary explanatory variable is public opinion on AI from the Eurobarometer dataset. This variable is “robots, and artificial intelligence are technologies that require careful management,” this variable is coded from 1-4, where four is “totally disagree,” and one is “totally agree.” To fit the views on the AI variable into the EP dataset, it needed to be aggregated from the individual level to the country level.

The control variables are chosen based on the literature and hypothesis of this thesis. The education, trust in media, wealth, social inequality, and left-right variables are aggregated to country-level from individual-level originating from the Eurobarometer datasets. The education variable was initially coded from 1-9, where one is the least amount of education and nine is the most amount of education. The trust in media variable was initially coded as a dummy variable from 0-1, where zero tends not to trust media, and one tends to trust media. Wealth was coded as 1-5, where one was part of the working class, and 5 was part of the wealthier class. When aggregated to the country level, the wealth variable indicates that country's general wealth level. It represents how the population feels about their wealth level rather than the country's actual wealth. The social inequality variable describes whether or not the respondents find social inequality important in their country. This variable was coded as 1-4, where one was social inequality was very important, and four social inequality was not important at all. The left-right variable describes where respondents placed themselves on the political left-right spectrum. This variable was coded initially as 1-10, where one was left, and ten were right. For this analysis, it is not interesting to see the spectrum of left to right only whether they lean towards the right or the left side of the political spectrum. Therefore, this variable was recoded into a dummy variable where zero is left and one is right. The recoding of this variable was done by taking the values 1-5 equals left, and 6-10 equals right. It was then coded as a dichotomous variable where 0=left and 1=right. On the party level, the first control variable is the size of the parties. This variable is coded from the number of members of each party participating in the roll-call votes. This creates a variable that describes approximately the number of MEPs of each party in the EP. This number is not exact as some MEPs might not have voted in any of the roll-call votes, or they have been left out of the data sorting due to missing values. As the total number of MEPs is 705

and the units of the vote variable is 664, some are missing (European-Parliament 2022). Despite these inaccuracies, it approximates the size of each national party in the EP. The Variable was recoded from accurate size numbers into a value of 1-6, where one is a small party, and six is a large party. The reason for recoding the variable is that it was not coded as the actual value of MEPs in the party, which means values were missing if there were no party with that number of MEPs. The variable was coded to values of 1-6 rather than a descriptive number series to make it better for the regression. The variable of gender is a control variable at the MEP level coded as a dummy variable of values 0 and 1. Based on the literature, it is not expected to influence the dependent variable. None of the literature mentions gender as a potential factor for responsiveness in general or to AI issues. The party vote variable is a continuous variable aggregated from the MEP vote-dependent variable. The aggregation was done by taking the mean value of the votes for each party, creating a new variable that describes the mean vote of the MEPs of each party. This variable can help us see if the MEPs vote following their party or if they vote independently. Suppose there is a significant effect on the party vote variable as well as the main explanatory variable. It could indicate that rather than the MEPs responding to public opinion. In that case, it could be that the national party is responding, and the MEPs follow their party.

TABLE 4.3 TABLE OF THE VARIABLES USED IN THE ANALYSIS WITH THEIR VALUES AFTER AGGREGATION.

Final variable code						
Variables	Minimum Value	Mean	SD	Maximum value	Level	Units (N)
Dependent Variables						
Vote on AI	0	0.3285	0.4697	1	MEP	664
Party vote on AI	0	0.3292	0.1490	0.6666	Party	211
Explanatory Variable						

Public opinion on AI	1.2340	1.53	0.1515	1.8193	Country	27
Control Variables						
Party Size	1	2.77	1.8184	6	Party	211
Party Vote	0	0.3292	0.1490	0.6666	Party	211
Trust in Media	0.1465	0.3902	0.0957	0.6296	Country	27
Education	4.4325	5.7194	0.7870	8.2850	Country	27
Wealth	1.8801	2.4536	0.2772	3.1333	Country	27
Social inequality	1.4761	1.7439	0.1924	2.1796	Country	27
Left-Right	0.1850	0.3622	0.0875	0.5123	Country	27
Gender	0	0.4031	0.4906	1	MEP	664
National Party	NA			NA	Party	219
Country	NA			NA	Country	27

4.2 Limitations of the data

The roll call votes data from the EP will be a little biased because the votes in the final roll call might not represent the actual opinion of some of the MEPs. They might have a more dynamic view of AI and oppose some parts of the legislation, but they largely favor “yes.” This creates a lack of variation in the dependent variable that was an issue, but there was no good way of resolving this. This lack of variation of the dependent variable means that the variable will be skewed towards passing the vote. The lack of variation makes it hard to draw any conclusive evidence from an analysis deploying these data because the results might not represent the MEPs' actual position on the issue. To mitigate these issues, the vote data needed to be manually adjusted, so the variable represented a vote for the development of AI or more restrictions on AI. Doing this makes the data more varied, not favoring one side as much as the untreated data.

Although it still might not represent each MEP's views on AI, it represents their voting preference based on the goal of each roll-call vote. When that is said, the responsiveness of a political institution can only truly be measured by the policy output of that institution. Even though the individual MEP might not agree with every point of the passed legislation, they still favor most of the points or vote in favor of what their party wants. When looking at responsiveness, the public will probably not be interested in the individual MEPs' position on points within a resolution but in what they vote on and what resolutions are passed. The analysis might be a bit unbalanced because of this, but the basis for the analysis still stands as it relates to responsiveness.

Most of the literature on responsiveness reviewed in this thesis uses time-series data and analysis to discover the effects of responsiveness. Questions of responsiveness lend themselves well to time-series data analysis because they want to see how policymakers respond to public opinion. The most logical way of doing that will be to see if there has been a change in public policy, leading to a shift in the position of policymakers on the same issue. The analysis of this thesis does not operate with time-series data because the data on artificial intelligence from a social science perspective is limited. Also, the votes on AI issues in the EP are recent, ranging from 2019 - to 2021.

FIGURE 4.1 FIGURE PRESENTING THE OPTIMAL RESEARCH DESIGN FOR UNDERSTANDING RESPONSIVENESS



It is a problem for the analysis because, without time data, it is difficult to see the changes in public opinion or the change in policy output. The position of the two might be constant. Without the variable of time and the changes in public opinion or policy output, there is no good way of

establishing a causal link between public opinion and policy output. It is possible to find a correlation between the two, but it cannot tell if one caused the other. For this thesis, the goal is not to establish a causal link between public opinion and policy output but to see if there is a correlation between the two. There is an aspect of time in the data in this analysis, as the public opinion survey was performed before the policy output data was voted on. This mitigates some problems with missing the time-series element, although it still cannot pinpoint the shift of opinion and policy. The problem of time is a direct result of there being too little data on the issue of AI. Suppose there was to be performed analysis that can discover a causal link between public opinion on AI and policy output on AI issues. In that case, it needs to incorporate a time-series element. The analysis of this thesis can at most indicate if there is responsiveness from MEPs on public opinion on AI issues and what elements might be affecting that correlation. Measuring MEPs' responsiveness to AI issues by having a public opinion time-series dataset and testing it against several roll-call votes is probably the best way of uncovering causal responsiveness to AI issues.

Another issue with the data used for the analysis in this thesis is the sample size and importance of the roll-call votes used to code the dependent variable. Because of the limited amounts of votes on AI issues, the dependent variable is compiled from only six unique roll-call votes. A larger sample of roll-call votes could have given more variety and significance to the dependent variable. As noted earlier in this chapter, none of the roll-call votes used in this analysis are CODs, meaning they have little true significance for EU policy on AI technology and can at best indicate the views held by the MEPs on AI. The roll-call vote of the “artificial intelligence act” would give the analysis more significance. The votes of MEPs could change based on the importance of the legislation presented. Legislation with more impact might have a more distributed vote, although it might suffer the same effect as the votes used in this analysis. By the time the legislation reaches the EPs' final vote, it has been modified to a point where it pleases most MEPs. The survey data variables are aggregated to the country level to combine with the voting data. This makes the number of observations that can affect the statistical significance of the models. It also decreases the number of potential control variables, as too many variables with a small number of observations might make the models overfit.

5. Methodology

This thesis uses quantitative analysis to try and answer the research question of whether the EP's MEPs respond to public opinion on AI-related issues. The primary method I will be using is the logistic regression model using the variable of EP votes as a dichotomous dependent variable. The thesis will use multi-level logistic regression analysis to see if there are differences between the different levels of parties and countries. The choice of the method comes from what the chosen as the research question. The research question asks if the MEPs represent the public opinion, which implies the use of several levels of data. Because the question asks for an effect of public opinion on the MEPs' decisions, it is natural to use the decisions of MEPs as the dependent variable. As the votes of the MEPs are coded with values of zero and one, it is a dichotomous variable. It is more beneficial to use logistic regression, given that the research question asks for explanations for why MEPs respond (or do not respond) to public opinion. The analysis needs to incorporate multiple variables in a multiple regression rather than a bivariate regression.

5.1 Logistic Regression

Logistic regression is the most popular model for linking dichotomous variables with one or more independent variables. Logistic regression is helpful because, unlike ordinary linear regression, it can handle dependent variables with residuals without normal distribution, and with a dichotomous variable with values zero and one it is unlikely that the residual would have a normal distribution. The formula for a logistic regression model is this (Finch, et al. 2019, 116):

EQUATION 5.1

linear regression with the dichotomous dependent variable

$$\ln\left(\frac{p(\gamma = 1)}{1 - p(\gamma = 1)}\right) = \beta_0 + \beta_{1x} + \varepsilon$$

The right side of this formula is the same as in a regular linear model, with the slope and intercept of the independent variable. On the other hand, the left side makes this model a logistic regression. Within the parentheses are the odds that the dependent variable will take the value of one. For this analysis, that would be yes to more development of AI. This is the logistic link function or the natural log of the odds that an MEP voted for more development of AI. A positive slope would indicate that the larger the value of x , the greater the chance of the targeted outcome. The second parameter of the intercept indicates the chance of the targeted outcome to occur when x equals zero. The estimates of the regression models are the slope of the relationship between the dependent and independent variables, so if the MEPs respond to public opinion, the estimated coefficient is expected to be positive (Finch, et al. 2019, 117).

The analysis of this thesis will present both a bivariate logistic regression and a multiple logistic regression. The main difference between bivariate and multiple regression is that in multiple regression, the coefficient of each added variable displays the relationship between the dependent variable and each variable, holding constant the value of the coefficient of the other variables in the model. That means that the other variables control every coefficient value, giving the model a better explanation value. Because the variables in the model will not always be comparable due to different values, a multiple regression will use standardized regression coefficients to compare the effects of the different values of the independent variables on the dependent variable (Finch, et al. 2019, 7-8; Grønmo 2017, 336). The value of R^2 can also be used on multiple regression models to explain how much of the variance in the dependent variable can be explained by the independent variables combined. While the coefficients of the regression explain the effect each of the variables has on the dependent variable the R^2 can indicate the explanation value of the model (Grønmo 2017, 337).

5.2 Multilevel logistic regression

A multilevel regression is a model that accounts for units on two or more levels. Multilevel regression analysis looks at the relationship between the different levels. The effects being studied could, in a multilevel regression, be more nuanced than looking at the same relationship

in a regression that only incorporates one level. Often when performing a multilevel regression, the goal is to understand the relationship between variables on different levels. Even though there is found a relationship between variables on one level, the relationship might be conditional on what country the respondent is from or differences in socioeconomic contexts between countries (Grønmo 2017, 409). Émile Durkheim's study on suicide in 1897 is a classic example of a multilevel study. In his study, Durkheim finds that Suicide is also conditional on factors between countries and differences between the individual victims of suicide. Using a multilevel study, Durkheim can give a more nuanced view of suicide as a societal problem, not only an individual problem related to mental illness or other individual-level factors (Durkheim 2002, 263).

In a simple regression model, the assumption of independent errors is violated if there is a dataset with several levels. Ignoring a multilevel data structure can lead to false positives. It is reasonable to assume that when working with data on individual parliament members, parliament members of the same political group or political party will vote similarly. Their votes correlate more with the other members of their party than the other members of their parliament. This could be because they have the same leader, ideological background, and party policy. Using a regular linear regression will cause problems estimating the standard error for the model parameters due to the intra-party correlation. This will lead to the model having errors of statistical inference, which can lead to p-values being lower than they should be and the null hypothesis being discarded. Another problem with ignoring a multilevel data structure is that it might end up missing out on explanatory variables on different levels that might have explanatory value for the dependent variable. By not including variables on multiple levels, the researcher might not be presenting a false representation of the dependent variable (Finch, et al. 2019, 29). Looking at the example from Durkheim's study of suicide, if he did not include variables on several levels, he might have missed out on the explanatory factors between countries (Durkheim 2002). Including variables on multiple levels gives the models greater complexity that may lead to a better understanding of the phenomenon. It is simple to add variables on different levels when working with a quantitative model (Finch, et al. 2019, 29).

The first step when thinking of performing a multilevel analysis like a multilevel regression is to establish if there is an interclass correlation in the data. Interclass correlation measures the proportion of variation of the dependent variable between the groups and the total variation present in the model. Interclass correlation is measured on a scale from zero to one, where zero is no variation between individuals within the groups, and one means that a more significant share of the outcome measure is associated with the individuals belonging to a group. The interclass correlation can be measured using this formula (Finch, et al. 2019, 24):

EQUATION 5.2

Process of determining interclass correlation

$$\rho_I = \frac{\tau^2}{\tau^2 + \sigma^2}$$

σ^2 = Population variation within groups

τ^2 = Population variation between groups

It is possible to see if there is enough variation between the groups to justify using a multilevel model. The results of an ICC test fall into the categories 0,5>=, 0,5-0,75, 0,75-0,90, and 0,90<, indicating poor, moderate, reasonable, and excellent reliability for the model (Koo and Li 2016).

Moving on from the Interclass correlation, a multilevel model is quite like a linear regression model on one level, with some notable differences. A multilevel model is interested in not only the general mean value for y when x=0 for all individuals in the population but also the differences in the mean between the different groups included in the model. Multilevel models include a general or average intercept that is constant across all the groups in the model represented by “ γ_{00} ”. It also includes a random effect that varies between the groups in the model, represented by “ U_{0j} ”. The multilevel model is interested in finding the deviation between the fixed and random effects. The multilevel analysis begins by creating a null model or a model with no predictors. A null model does not provide any information on the effect of independent variables on the dependent variable. Although it has no explanatory value, it is not useless. The null model is used to build the model and is used as a baseline for comparison to the subsequent models. It is used to calculate if there is an interclass correlation in the data presented. The formula for the null model is (Finch, et al. 2019):

EQUATION 5.3

A null model for multilevel regression

$$y_{ij} = \gamma_{00} + U_{0j} + \varepsilon_{ij}$$

Adding a single predictor variable gives us the model:

EQUATION 5.4

A null model for multilevel regression with a single predictor variable

$$y_{ij} = \gamma_{00} + U_{0j} + \gamma_{10}x_{ij} + \varepsilon_{ij}$$

γ_{10} is a measure of the impact of the independent variable on the dependent variable, or the impact of the dependent variable with one unit change in x (independent variable). The formula presented here is for a multilevel linear model with two levels. Due to the levels of the dataset, the models needed in the analysis need to be a three-level multilevel regression. Introducing individual random and fixed functions to all three levels will provide individual scores from the resident country of the MEPs and the national party of the MEPs. As the dependent variable is on the MEP level and the primary explanatory variable is on the national level, the model needs to include at least these two levels. Based on the literature and theory, there is also reason to expect that national parties might play a role in the responsiveness of MEPs; the analysis will therefore need to account for all three levels in the models. The formula for a three-level multilevel regression is (Finch, et al. 2019, 39-40):

EQUATION 5.5

Model for multilevel regression with three levels

$$y_{ijk} = \delta_{000+} V_{00k} + U_{0jk} + (\delta_{100} + V_{10k} + U_{1jk}) + x_{ijk} + \varepsilon_{ijk}$$

The dependent variable in the formulas presented here is for a regular linear multilevel regression. To get a multilevel logistic regression, the model needs to change the dependent variable into a dichotomous one.

EQUATION 5.6

Model for multilevel regression with three levels and a dichotomous dependent variable

$$\ln\left(\frac{p(\gamma = 1)}{1 - p(\gamma = 1)}\right)_{ijk} = \delta_{000+} V_{00k} + U_{0jk} + (\delta_{100} + V_{10k} + U_{1jk}) + x_{ijk} + \varepsilon_{ijk}$$

The analysis is looking to use a multilevel logistic regression model on a dichotomous dependent variable. The process of performing a multilevel regression starts by creating a null model that only includes the dependent variable of MEP votes on AI issues in the EP, allowing a random intercept. This assumes that the likelihood of MEPs voting yes to the development of AI is constant among parties and countries. From the null model, we can use the variance and standard deviation of the random effects to calculate the interclass correlation to see if there is a difference between and within the parties and countries in the model. This is the first step of the multilevel method (Finch, et al. 2019).

The next step is introducing the primary explanatory variable to the model to see if the public opinion on AI influences the MEPs' votes. We can use the AIC and BIC values presented by the “Multilevel Generalized Linear Model” in R to see if the explanation value is better from the empty null model to the model, including one explanatory variable. (Finch, et al. 2019, 136). AIC and BIC are measured for the close fit of the model and are not significant tests. They measure unexplained variation with a penalty for model complexity. A lower score of AIC and BIC will indicate a better fit for the data. An additional test of model fit is the R squared. This test displays the shared variety of the model and is the pearsons r test squared. R squared is measured on a scale of 0-1 and is a more direct measurement of the share of the dependent variable that the independent variables can explain. This can be used to measure how robust the model is (Grønmo 2017, 336-337).

To explore the reasons for an effect or a lack of effect, we need to add more variables to the model to see if the results are conditional on other variables. At this stage, it is good to add variables to the model to see what variables might have an effect, starting with adding variables on one level. Because of restraints on the number of variables in the model caused by the number of observations, it can be useful to see what seems to have an effect and then remove the variables that are not significant or have very low estimates. This is a way of trying to make the model a better fit and make the overall model more accurate. At this stage, we can also begin adding variables on different levels to see if the effect we are looking for can be explained on

variables on different levels. This first model only displays the random intercept and the fixed effects used in regular linear regression (Finch, et al. 2019, 134). The critical thing to look for at this stage is to see if the model including more variables has any more explanation value than the null model and the model with only the primary explanatory variable. To do this, we can deploy the same tests as previously mentioned. AIC and BIC tests are good for seeing if the explanation value has increased by adding more variables to the model. If the AIC and BIC have gone down, the model fit goes up. In that case, AIC and BIC also inhabit a penalty for model complexity which means that even though the model explanation value has increased by adding more variables, so has the complexity of the model (Finch, et al. 2019, 139). By deploying a penalty for model complexity, we can get a clearer idea if making the model more complex has improved the model. To see if the variables in the model get more explanation value for the model, the R squared output is a good measure. Adding multiple variables also introduces the problem of multicollinearity that should be checked. See 5.3 for a more in-depth description of the multicollinearity effect. The R squared output explains the amount of variance the variables can explain in the model. If the R squared output is 0,10, then ten percent of the variance can be explained by the variables included in the model. This measures how much explanatory value the variables have, which reflects how good the model's explanatory value is (Grønmo 2017, 336).

The next step in a multilevel regression would be to add random coefficients to the model to check if the coefficients of the variable differ across the groups. By letting the impact of the effect of the independent variables on the dependent variable vary across the effects of the other variables in the model. When introducing the concept of random effects, one was used for the intercept ($1 \mid \text{National Parties}$), then to introduce level one slopes randomly across the other levels, one variable replaces the intercept of one: ($\text{Public View AI} \mid \text{National Parties}$). Doing this allows the variable of public view on AI to be random across the National Parties. Introducing the random coefficient, the model gets less variation from the differences in the random intercept and the coefficient across levels from the variable used as the random coefficient. It is also possible to introduce multiple random coefficients by adding another variable into the model ($\text{Public View AI} + \text{Gender} \mid \text{National Parties}$). This will let the slopes of both public views on AI and Gender be random across the National Parties (Finch, et al. 2019, 50-52). Changing a model

from a random intercept model to a random coefficient model might change the effect or the variable significance. If there is a significant effect, this can be interpreted as group differences in the relationship of the independent variables to the dependent variable. As for the earlier versions of the models, we can check if the explanation value of the model goes up by looking at the AIC and BIC values.

In one-level regression models, it is possible to introduce interactions between variables to see if the effect of one variable is conditional on another. This is also possible to do in multilevel regression models. When working with models that include more than one level, it is possible to have interactions between variables in the same level and between different levels called cross-level interactions. Cross-level interactions are the impact of a variable on one level on the dependent variable if the effect is dependent on the variable's value on another level. To test for cross-level interactions, the level one variable needs to be multiplied by the level two variable, making a new variable dependent on the value of both variables simultaneously. Suppose the cross-level interaction variable is significant and positive. In that case, it means that when the level two variable's value increases, the relationship between the level one variable and the dependent variable becomes stronger. When the interaction effect is negative, the relationship between the level one variable and the dependent variable becomes weaker. Both variables fitted in the cross-level interaction do not need to be significant for the interaction effect to be significant. Interaction between the variables can affect the model even if one of the variables has no effect by itself (Finch, et al. 2019, 49-50).

So, to recap the multilevel regression modeling process. First, we test the dependent variables and the levels to see if any difference exists between the levels included in the dataset. This will tell us if there is a reason to proceed with the multilevel model, creating models for a three-level multiple regression and the extra levels. Creating a model for all levels can show if some are redundant. There is a risk that the interesting levels do not have as much variance between them as expected. This will make the explanation value of the random effects minimal. After looking at the variance between the levels, more variables need to be added to see if there might be some more explanation value tied to other variables. Moving on, we test the different models to see

what configuration fits the model the best, including variables on different levels. The models must also be fitted for cross-level interaction effects and random coefficients to check for different kinds of effects. Making the models more complicated and checking for different kinds of effects should improve the models, but it also comes with overfitting problems. A model becomes too complex because it has too many explanatory variables or complex terms like interaction effects, random coefficients, or non-linear terms (Babyak 2004, 411). Checking the fit between the models is essential, and the AIC and BIC values are a good way of doing this, although these values are more general for the models and struggle to provide details of the model fit. In nested level models like multilevel regression, the chi-square test can help us understand whether the model fit differs significantly. The advantage of the maximum likelihood estimation of the chi-squared is that it tests the differences between random and fixed effects in the model (Finch, et al. 2019, 57). Checking for both AIC and BIC as well as the chi-square should give a good view of model fit in the analysis.

5.3 Checking for multicollinearity

Multicollinearity can be a problem in empirical analysis, and it refers to an issue where multiple independent variables of the model are too similar. There are two types of Multicollinearities, complete or perfect multicollinearity or partial multicollinearity. The perfect multicollinearity is often not what worries researchers. This type of multicollinearity appears if the variables overlap entirely and prevent any form of coefficients in the model. This type of multicollinearity is rare in the social sciences, and it rarely appears unless the sample size of the dataset is tiny or there is a simple error in the preparation of the data or model specifications. The second form of multicollinearity is what researchers commonly refer to when discussing problems with this phenomenon. Partial multicollinearity refers to an issue where multiple independent variables correlate at some level. Almost all randomly chosen variables will have some level of correlation. Partial multicollinearity is a matter of degree, and they often have a linear relationship that does not correlate completely. Partial multicollinearity does not affect the coefficient estimates or give false conclusions about a model, but it can give some doubt to the conclusions made from a model. Stephen Voss argues that most researchers poorly understand

multicollinearity, and taking it too seriously and trying to fix the issue might hurt the analysis more than it helps (Voss 2005, 759-760). It is an excellent test to check for potential problems with the conclusions drawn from the analysis. There are several ways of calculating Multicollinearity, but the one used in this analysis is the VIF value. The VIF values should be as small as possible, indicating a low correlation among the variables. Lower VIF values than five should indicate an acceptable amount of multicollinearity (Hair, et al. 2014, 221).

When introducing interaction effects in a regression model, there often surfaces problems of multicollinearity. Centering of predictors is a way of fixing multicollinearity and creating a more straightforward interpretation of interaction effects. To center the predictors, one must subtract the mean value of each value in the variable. These centered versions of the variables can be included in the model to help alleviate the problem created by the interaction effect. Centered values can help understand if significant effects created by the interaction effects are actual or caused by multicollinearity (Finch, et al. 2019, 55).

5.4 Saliency

AI saliency is measured using a similar method to Wratil's paper on opinion-policy linkage in the EU. We can plot the missing values of all the variables to see what issues are most salient among the subjects that participated in the survey. By extracting the variables' missing values on the same level, we can see what variables are essential to the public. Although this method is not foolproof, other factors could play into why some issues have more missing values than others. Although the findings in the Wratil article indicate that there should be a connection between the number of participants who answered a question and how important or salient that issue is to them (Wratil 2019, 203).

6. Analysis

In this chapter, I conduct an analysis to try and answer the research question and the hypothesis. The primary method used in the analysis is the multilevel logistic regression to see if the public

opinion on the management of AI technology affects the votes in the EP and what factors might influence this effect.

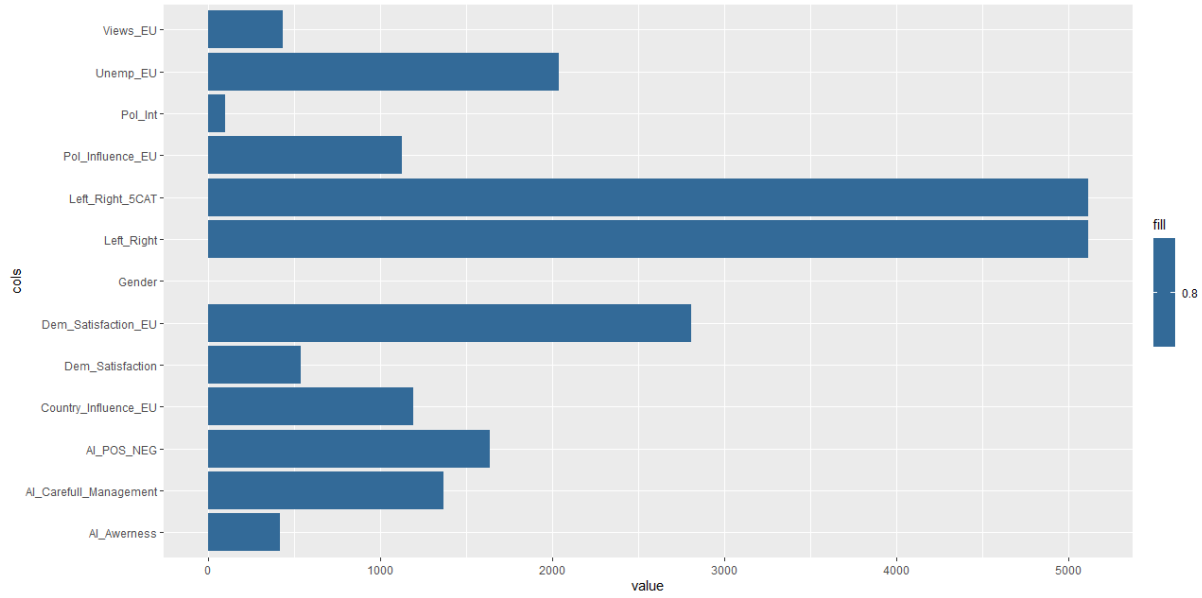
6.1 Saliency of AI

Figure 6.1 shows the distribution of missing values across country-level variables. The dependent variable, management of AI, does not have the most missing values, but it does not have the least either. It makes sense that the gender variable has no missing values as it is descriptive of the respondent and does not ask for an opinion. The primary explanatory variable seems to be moderately salient, but it is also interesting to look at the variable of AI awareness. That this variable has so few missing values might indicate that the topic of AI might be fascinating to many respondents. However, they might only have a modest opinion on how to tackle the issues related to the use of AI. This makes sense as AI is a highly technical subject, and some of the populous might not understand enough about it to have a clear opinion about managing it. Taking these results into account, AI seems to be salient. Even though some of the populous might not understand or have a clear opinion on the use of AI, policymakers should still expect to see the issue as salient because many of the respondents follow the development of AI-related issues.

Another problem is that because the populous only have a moderate interest in how AI should be managed, it is hard to tell how vocal they would be on the subject. The saliency issue is subjective as there is no clear point where an issue becomes salient. However, based on the low number of missing values of the AI awareness variable and the moderate number of the dependent variable, it is safe to assume that AI issues are salient.

FIGURE 6.1

Table representing the share of missing values across variables



6.2 Simple linear logistic regression

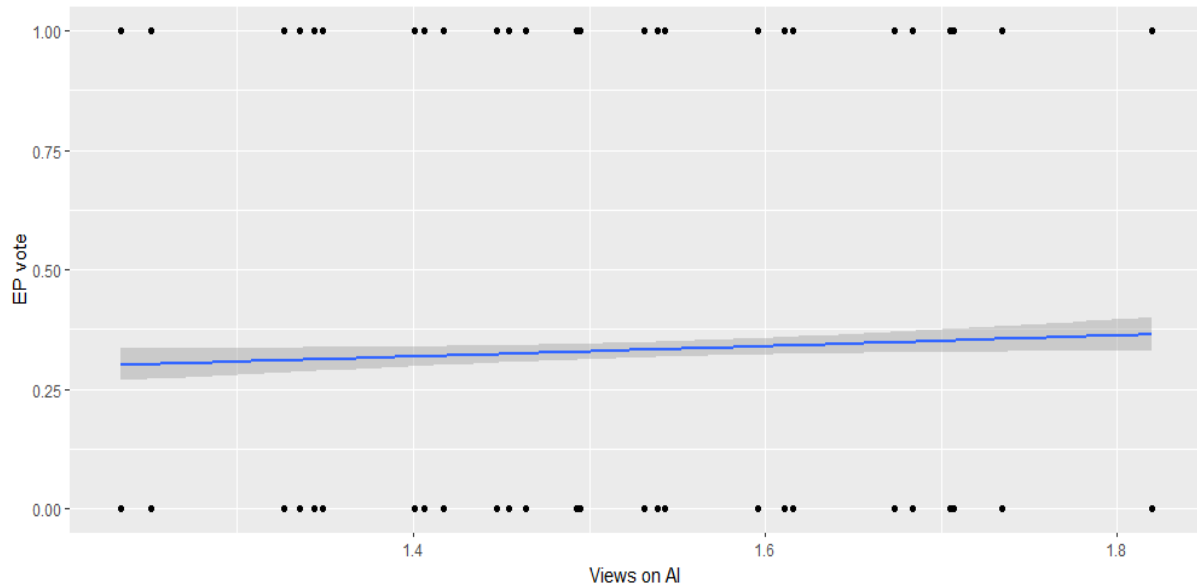
For the analysis, starting with a binomial linear regression is good to see if there is any relationship between the dependent variable and the primary explanatory variable. Because the two variables are on different levels, there is no explanatory value related to the regression in the first model in table 6.1. The R squared value is very low for this reason, and the regular linear regression tends to put out much higher significance levels when the variables are on different levels. The coefficient effect of the regression is high, which can point to a relationship, although the significance level cannot be trusted. Figure 6.2 shows the votes on the public views on the AI variable, and the distribution is pretty good, which is a good sign when adopting the data to a better model.

TABLE 6.1 REGRESSION TABLES, BINOMIAL LINEAR REGRESSION, AND MULTIVARIATE LINEAR REGRESSION

<i>Predictors</i>	<i>Vote</i>			<i>Vote</i>		
	<i>Odds Ratios</i>	<i>std. Error</i>	<i>p</i>	<i>Odds Ratios</i>	<i>std. Error</i>	<i>p</i>
Intercept	0.23 ***	0.09	<0.001	0.27 ***	0.10	0.001
AI	1.64 *	0.39	0.040	1.58	0.39	0.064
Gender				0.84 *	0.06	0.019
Observations		3402			3262	
R ² Tjur		0.001			0.003	

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

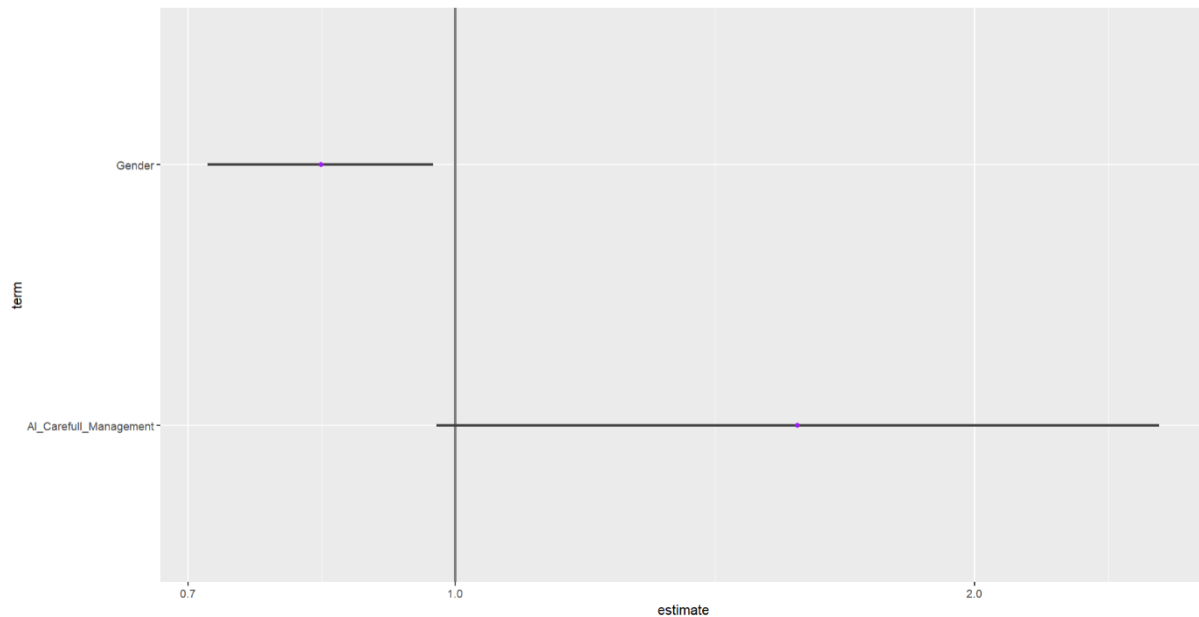
FIGURE 6.2 DISTRIBUTION OF VOTES ACROSS THE VIEWS ON AI IN A BINOMIAL LINEAR REGRESSION



The second regression in table 6.1 shows the same regression, but one independent variable is added on the same level as the dependent variable. The relationship between the dependent and primary explanatory variables is proven to be unstable by including the gender variable. The coefficient plot in figure 6.3 shows how significant the standard errors are in the explanatory

variable. This is because the relationship between variables on different levels cannot be trusted unless you use a multilevel regression that accounts for differences between the levels.

FIGURE 6.3 LINEAR REGRESSION COEFFICIENT PLOT



6.3 Multilevel logistic regression

The linear regression model analysis showed why we could not trust the results if the variables were on different levels. Because the dependent and explanatory variables are on different levels, a multilevel regression needs to be used. The variance between and within the levels or the inter-class correlation (ICC) needs to be considered to proceed with a multilevel regression. To do this, we start by creating a null model, which is a model which has no explanatory values. Looking at the plots in Figures 6.4 and 6.5, there seems to be quite a lot of dispersion in the votes across national parties and countries. The ICC Between countries is 0%. The ICC between national parties is 5%, and between national parties and countries, the ICC is also 5%. Adding three levels to the regression does not increase the explanatory value of the model. An ICC on 0% is not enough to defend including it in the analysis. Using only national parties in the analysis makes the model less complicated than using three levels. The difference between models' levels only explains that 5% of the dataset is not great for defending using multilevel regression. However, it is still enough to defend using this method. To fit a model using variables on different levels, using a multilevel model is a necessity.

TABLE 6.2 NULL MODELS ON THREE LEVELS

Null Models									
<i>Predictors</i>	<i>Country/Parties</i>			<i>Parties</i>			<i>Country</i>		
	<i>Odds Ratios</i>	<i>CI</i>	<i>p</i>	<i>Odds Ratios</i>	<i>CI</i>	<i>p</i>	<i>Odds Ratios</i>	<i>CI</i>	<i>p</i>
(Intercept)	0.47 ***	0.42 – 0.52	<0.001	0.47 ***	0.42 – 0.52	<0.001	0.50 ***	0.46 – 0.55	<0.001
Random Effects									
σ^2		3.29			3.29			3.29	
τ_{00}	0.18	National_Party:Country		0.19	National_Party		0.01	Country	
ICC		0.00	Country						
N		0.05			0.05			0.00	
	219	National_Party		219	National_Party		27	Country	
		27	Country						
Observations		3402			3402			3402	
Marginal R ² / Conditional R ²		0.000 / 0.053			0.000 / 0.054			0.000 / 0.003	
AIC		4255.287			4252.463			4331.579	

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

FIGURE 6.4 PLOT SHOWING THE DISPERSION OF VOTES ACROSS THE NATIONAL PARTIES

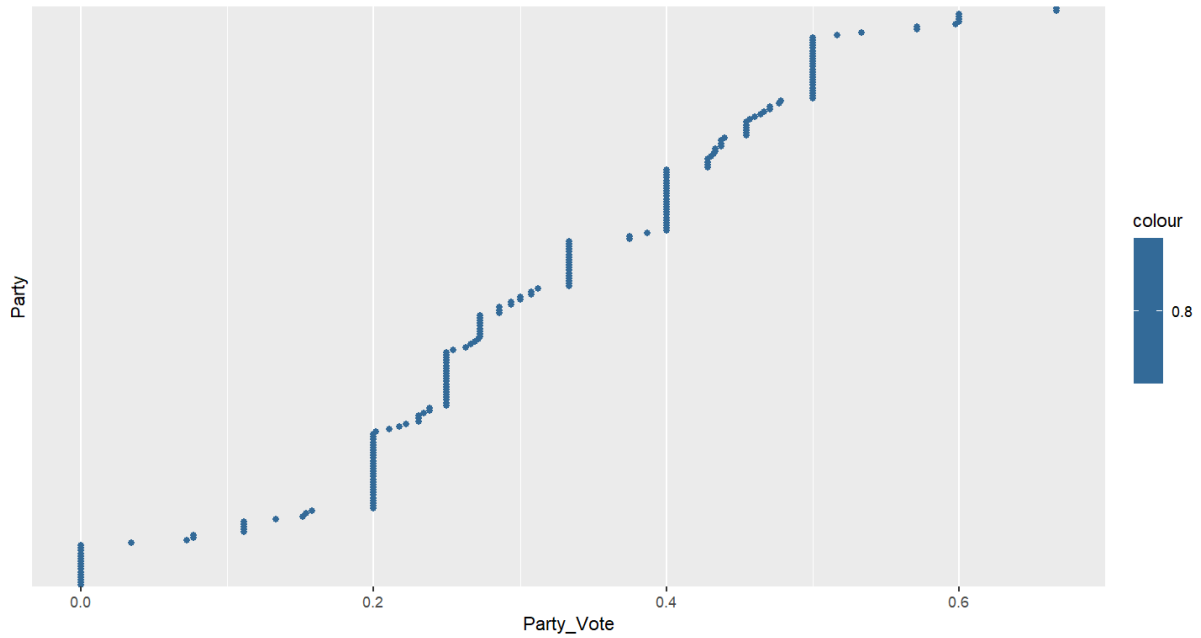
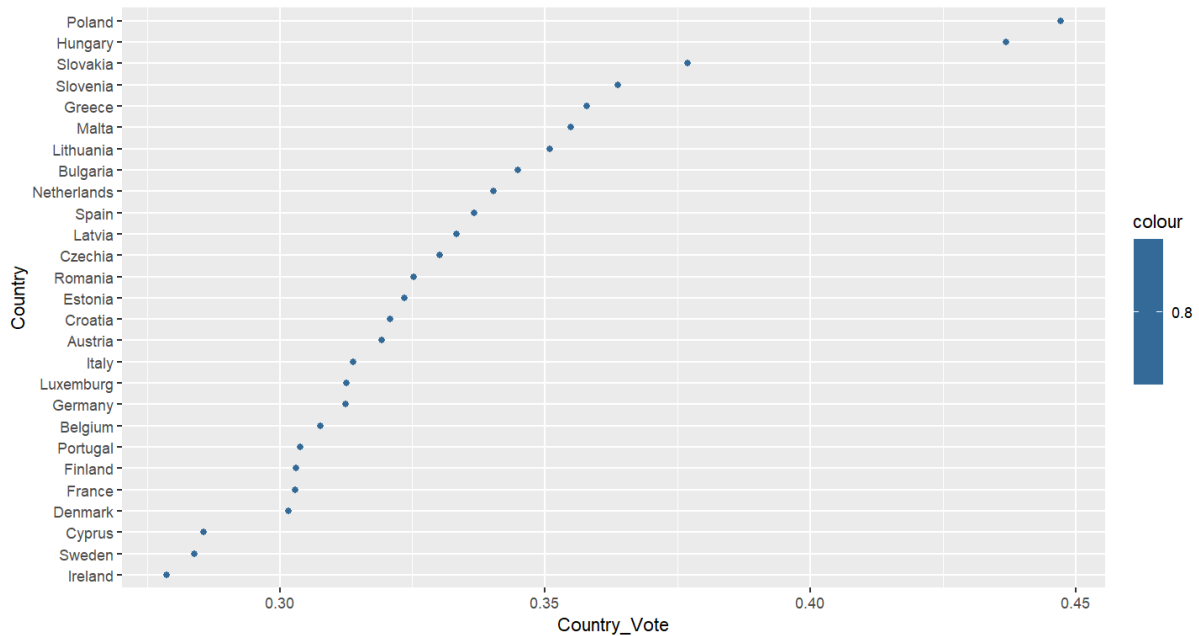


FIGURE 6.5 PLOT SHOWING THE DISPERSION OF VOTES ACROSS COUNTRIES IN THE EU



6.3.1 Adding an explanatory variable

Even though the explanation value of the random intercepts might have little explanation value overall in the models, the addition of the country level makes the models almost unusable. Table 6.2 shows a regression table for the model fitted with two and three levels and adding the primary explanatory variable. The first thing this table shows us is that having the country variable and the national party variable destroys the model because the ICC between countries is so small that it makes the explanatory value of the model nonexistent. As seen in table 6.5 is, the BIC and AIC values of the two-level model lower than the three-level model, which means that there is a better fit in that model. The R squared value is also non-existing, meaning that the variables in the model have no real explanatory value. The primary explanatory variable of views on AI management also has no statistically significant effect on the dependent variable. It is likely not to influence the MEP votes in the EP.

TABLE 6.3 MULTILEVEL LOGISTIC REGRESSION WITH BOTH TWO AND THREE LEVELS

<i>Predictors</i>	<i>Vote</i>				<i>Vote</i>			
	<i>Log-Odds</i>	<i>std. Error</i>	<i>CI</i>	<i>p</i>	<i>Log-Odds</i>	<i>std. Error</i>	<i>CI</i>	<i>p</i>
Intercept	-1.76 ***	0.52	-2.76 – -0.75	0.001	-1.74 ***	0.51	-2.75 – -0.74	0.001
AI	0.65	0.34	-0.01 – 1.31	0.052	0.65	0.34	-0.01 – 1.30	0.053
Random Effects								
σ^2	3.29				3.29			
τ_{00}	0.18 National_Party				0.18 National_Party:Country 0.00 Country			
ICC	0.05							
N	219 National_Party				219 National_Party 27 Country			
Observations	3402				3402			
Marginal R ² / Conditional R ²	0.003 / 0.056				0.003 / NA			

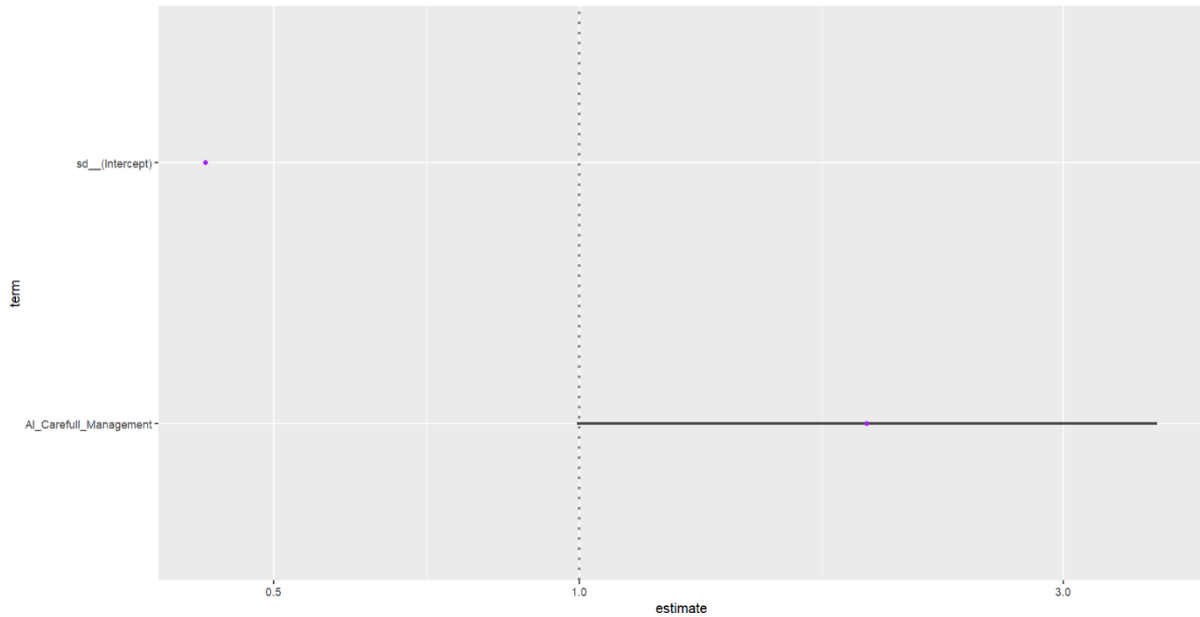
* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

TABLE 6.4 ANOVA MODEL, OF THE MODELS IN TABLE 6.3

<i>npar</i>	<i>AIC</i>	<i>BIC</i>	<i>logLik</i>	<i>deviance</i>	<i>Chisq</i>	<i>Df</i>	<i>Pr..Chisq.</i>
3	4250.69	4269.09	-2122.35	4244.69	NA	NA	NA
4	4253.57	4278.10	-2122.78	4245.57	0	1	1

The Standard error interval of the AI Management variable is large, meaning that adding control variables to the model might lessen the error interval of the variable. The AI variable is also close to significance by 0.003 points. If adding more variables makes the error interval go down, it might make the effect of AI on the votes statistically significant. Figure 6.6 show the coefficient plot of the bivariate multilevel model.

FIGURE 6.6 COEFFICIENT PLOT OF THE MULTILEVEL BIVARIATE MODEL



6.3.2 Adding country-level control variables

Based on table 6.3, the country level on the model has no real value, and the R squared, therefore, has no value. This shows that the random effects of the model are non-existent, as seen in figure 6.7 and table 6.5. The addition of more control variables on the same level as the primary explanatory variable did not lessen the error interval. None of the variables in the model presented in table 6.5 are statistically significant or very close to being statistically significant. Variables on the country level do not seem to affect the MEPs' votes on AI issues. Table 6.6 compares the models from tables 6.3 and 6.5. The AIC and BIC values are lower in the model with only the primary explanatory variable. Table 6.6 also shows that the differences between the models are not significant. The model in table 6.5 has a better R squared value, which is expected with more variables added. The model's overall fit and explanation value go down by adding the control variables. This is reflected in the coefficient plot in figure 6.7, which show sizeable standard error intervals across almost all the variables. There is little use in bringing these country-level variables into the analysis as they have such a low significance.

TABLE 6.5 MULTILEVEL LOGISTIC REGRESSION WITH MULTIPLE CONTROL VARIABLES ON THE COUNTRY LEVEL

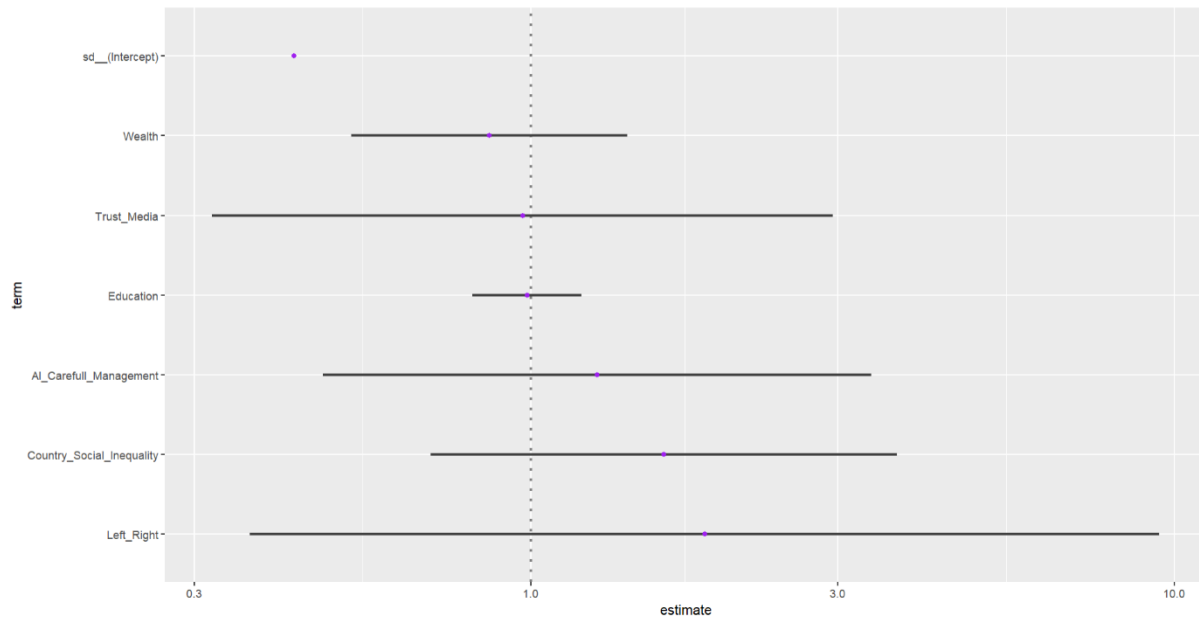
<i>Predictors</i>	<i>Vote</i>			
	<i>Log-Odds</i>	<i>std. Error</i>	<i>CI</i>	<i>p</i>
Intercept	-1.72	0.95	-3.59 – 0.15	0.071
AI	0.24	0.50	-0.75 – 1.22	0.637
Trust Media	-0.02	0.10	-0.21 – 0.18	0.880
Education	-0.03	0.57	-1.14 – 1.08	0.957
Social Inequality	0.48	0.43	-0.36 – 1.31	0.264
Left Right	0.62	0.83	-1.01 – 2.25	0.455
Wealth	-0.15	0.25	-0.64 – 0.34	0.551
Random Effects				
σ^2			3.29	
τ_{00} National_Party			0.18	
ICC			0.05	
N _{National_Party}			219	
Observations			3402	
Marginal R ² / Conditional R ²			0.006 / 0.059	

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

TABLE 6.6 ANOVA MODEL, OF THE MODELS IN TABLE 6.3 AND 6.5

<i>npar</i>	<i>AIC</i>	<i>BIC</i>	<i>logLik</i>	<i>deviance</i>	<i>Chisq</i>	<i>Df</i>	<i>Pr..Chisq.</i>
3	4250.69	4269.09	-2122.35	4244.69	NA	NA	NA
8	4257.31	4306.37	-2120.66	4241.31	3.38	5	0.64

FIGURE 6.7 COEFFICIENT PLOT OF THE MODEL WITH MULTIPLE CONTROL VARIABLES ON THE COUNTRY LEVEL



6.3.3 Adding party-level control variables

After establishing that the control variables on the country level have no explanatory value, the analysis brings in control variables from the MEP and Party levels. Based on the higher explanatory value of the party level, these variables are expected to have more significance than the country variables. The primary explanatory variable of AI still has no significant effect on the votes from the MEPs. There were also no significant effects from the party size and gender variables. The effects of these variables were also minimal when introducing the party vote variable. The party vote variable was very significant on a 0,1% level, the effect between party votes and the votes of the MEPs was substantial, and the effect of the party vote variable on the dependent variable can be seen in figure 6.9. This indicates that MEPs vote in line with their parties. This could mean that individual-level votes do not matter as much as the votes of the national parties. By including the party vote, the random effects of the model disappear entirely due to too small a variance. Therefore, the R squared of the whole model comes out as missing in table 6.7. On the other hand, the R squared of the fixed effects goes up by quite a bit. This reflects the problem that the model has with very low ICC. Although there are no random effects

in the model, both AIC and BIC values are lower in table 6.7 than in table 6.5 if we look at the anova model comparing the two. This indicates that the model in table 6.7 has a better fit than the model in table 6.5.

TABLE 6.7 MULTILEVEL LOGISTIC REGRESSION WITH ADDITIONAL CONTROL VARIABLES ON THE PARTY LEVEL

<i>Predictors</i>	<i>Vote</i>			
	<i>Log-Odds</i>	<i>std. Error</i>	<i>CI</i>	<i>p</i>
Intercept	-2.49 ***	0.61	-3.70 – -1.29	<0.001
AI	-0.09	0.37	-0.81 – 0.64	0.812
Gender	-0.06	0.08	-0.22 – 0.11	0.493
Party_Vote	5.03 ***	0.32	4.41 – 5.65	<0.001
Party Size	0.00	0.02	-0.05 – 0.05	0.962
Social Inequality	0.21	0.33	-0.44 – 0.86	0.526
Left Right	-0.10	0.56	-1.19 – 0.99	0.855
Wealth	-0.06	0.17	-0.39 – 0.28	0.740
Random Effects				
σ^2			3.29	
τ_{00} National_Party			0.00	
N _{National_Party}			202	
Observations			3138	
Marginal R ² / Conditional R ²			0.135 / NA	

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

The chi-squared value in the anova model of table 6.7 shows that the difference between the models in tables 6.5 and 6.7 is significant. This means that the model in table 6.8 has a better fit for data and that the difference is significant. A test for multicollinearity was performed to see if the party vote variable's strong and significant effect is not affected by the other variables included in the model. Figure 6.10 shows that none of the variables included in the model correlate to the degree that would affect the results.

TABLE 6.8 ANOVA MODEL COMPARING TABLES 6.5 AND 6.7

<i>npar</i>	<i>AIC</i>	<i>BIC</i>	<i>logLik</i>	<i>deviance</i>	<i>Chisq</i>	<i>Df</i>	<i>Pr..Chisq.</i>
8	3913.18	3961.59	-1948.59	3897.18	NA	NA	NA
9	3690.79	3745.25	-1836.39	3672.79	224.39	1	0.00

Figure 6.8 shows the effect of the variables in a coefficient plot, showing just how much larger the effect of party votes is than the rest of the variables. To understand the models a bit better and to see if the main explanatory variable might have more significance, the model in table 6.9 introduces a random coefficient of the variable.

FIGURE 6.8 COEFFICIENT PLOT OF THE MODEL WITH MULTIPLE CONTROL VARIABLES ON THE PARTY LEVEL

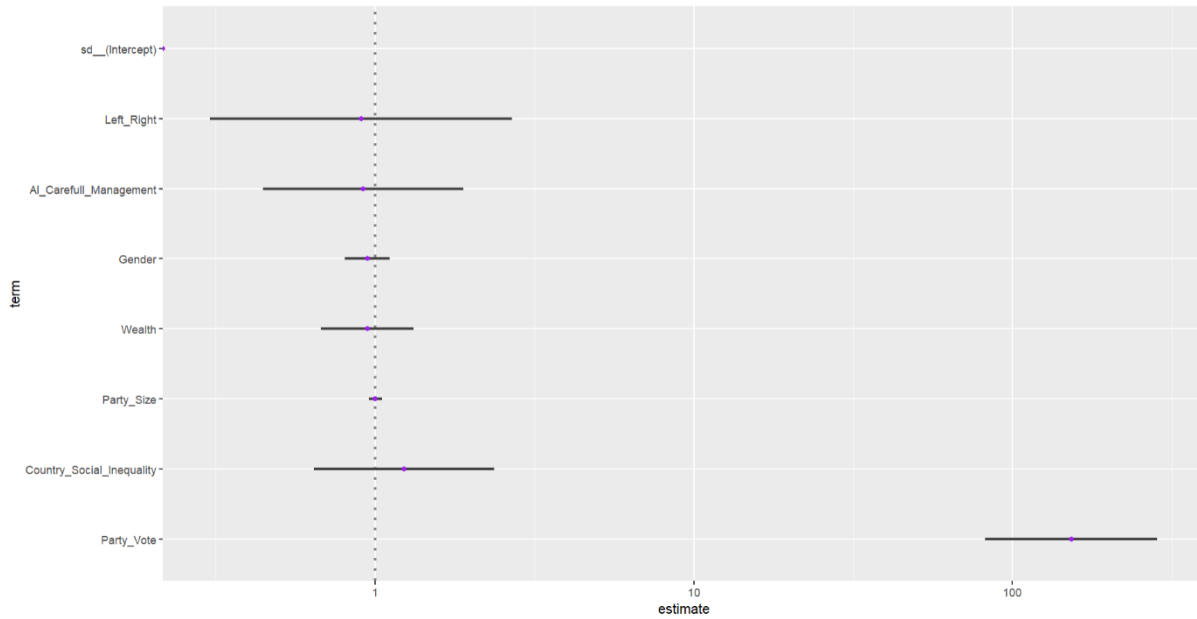


FIGURE 6.9 THE EFFECT OF THE PARTY VOTE VARIABLE ON THE DEPENDENT VARIABLE

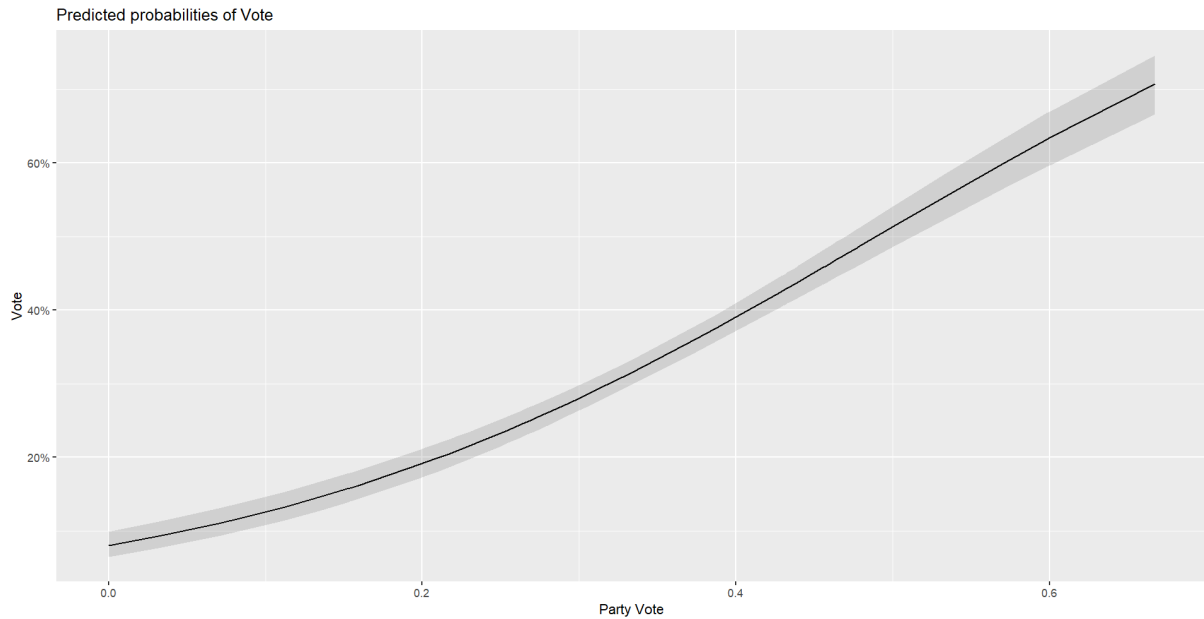
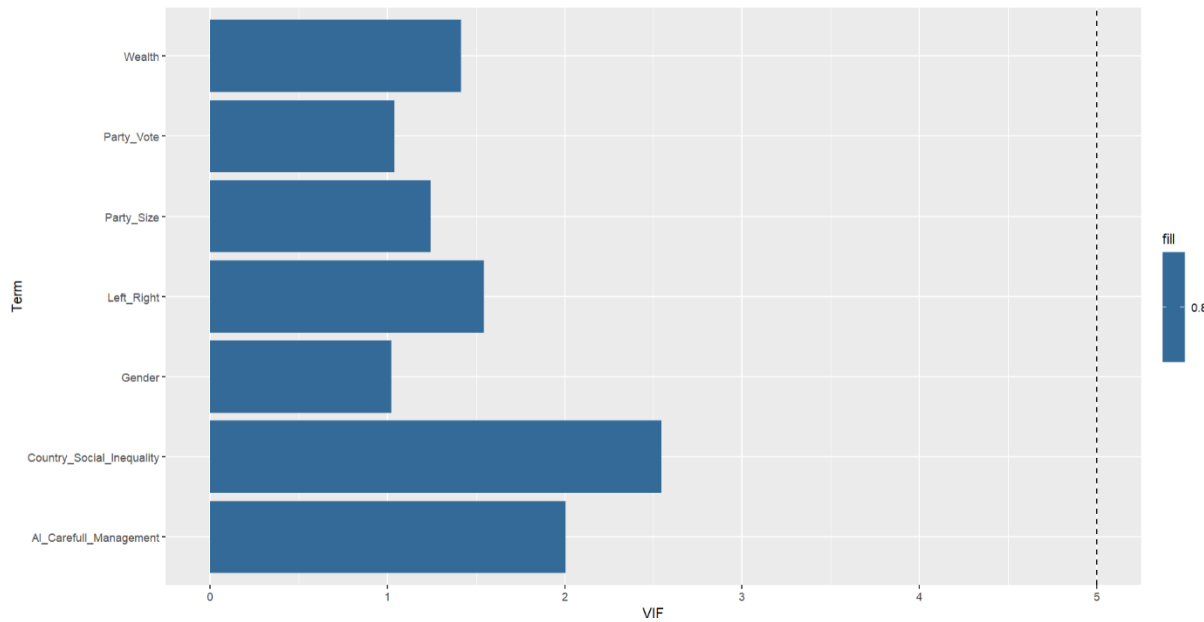


FIGURE 6.10 MULTICOLLINEARITY EFFECTS BETWEEN VARIABLES IN TABLE 6.8



6.3.4 Introduce a random coefficient

The random effects of the model do not change by adding the main explanatory variable as a random coefficient. The random effects of the model are still nonexistent, which can be seen in the missing R squared value for the whole model as well as the values for the random effects

remain the same. As for the fixed effects, the main explanatory variable of public opinion on AI management stays insignificant, and the party vote variable is still very significant with a very large effect of 5.01.

TABLE 6.9 MULTILEVEL LOGISTIC REGRESSION WITH A RANDOM COEFFICIENT

<i>Predictors</i>	<i>Vote</i>			
	<i>Log-Odds</i>	<i>std. Error</i>	<i>CI</i>	<i>p</i>
Intercept	-2.61 ***	0.40	-3.39 – -1.84	<0.001
AI	0.11	0.25	-0.38 – 0.60	0.668
Party_Vote	5.01 ***	0.29	4.43 – 5.58	<0.001
Random Effects				
σ^2			3.29	
τ_{00} National_Party			0.00	
τ_{11} National_Party.AI_Carefull_Management			0.00	
ρ_{01} National_Party			-1.00	
N National_Party			219	
Observations			3402	
Marginal R^2 / Conditional R^2			0.138 / NA	

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

The anova model of the models in tables 6.7 and 6.9 shows that the values of AIC and BIC go up slightly from table 6.7 to table 6.9, suggesting that adding a random coefficient to the model did not improve the fit for the model. The Chi-squared value shows that the difference between the models is insignificant. Introducing this complexity into the model does not improve the model.

TABLE 6.10 ANOVA MODEL COMPARING TABLES 6.7 AND 6.9

<i>npar</i>	<i>AIC</i>	<i>BIC</i>	<i>logLik</i>	<i>deviance</i>	<i>Chisq</i>	<i>Df</i>	<i>Pr..Chisq.</i>
6	3685.20	3721.51	-1836.60	3673.20	NA	NA	NA
7	3687.64	3730.00	-1836.82	3673.64	0	1	1

6.3.5 Introduce cross-level interaction effect

To see if the effect of the variables of AI and party vote are dependent on each other, they are given a cross-level interaction in the model of table 6.11. The results from table 6.11 show that the interaction does not have a significant effect, but it raises the effect of the party vote variable. However, it becomes less significant, although still within the margins of statistical significance. Reviewing the anova model for tables 6.9 and 6.11 shows that the model's fit does not improve with the added complexity of including a cross-level interaction. The AIC and BIC values are lower in table 6.9, and there is also no significant improvement in model fit. The model in table 6.11 also suffers from the lack of random effects caused by the inclusion of the party vote variable. The added complexity of cross-level interaction and random coefficient does not improve the model.

TABLE 6.11 MULTILEVEL LOGISTIC REGRESSION WITH A CROSS-LEVEL INTERACTION

<i>Predictors</i>	<i>Vote</i>			
	<i>Log-Odds</i>	<i>std. Error</i>	<i>CI</i>	<i>p</i>
Intercept	-3.47 **	1.25	-5.91 – -1.03	0.005
AI	0.67	0.82	-0.93 – 2.27	0.413
Party_Vote	7.50 *	3.24	1.15 – 13.86	0.021
AI*Party_Vote	-1.62	2.12	-5.78 – 2.54	0.445
Random Effects				
σ^2			3.29	
τ_{00} National_Party			0.00	
τ_{11} National_Party.AI_Carefull_Management			0.00	
ρ_{01} National_Party				
N National_Party			202	
Observations			3138	
Marginal R^2 / Conditional R^2			0.135 / NA	

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

TABLE 6.12 ANOVA MODEL COMPARING TABLES 6.9 AND 6.11

<i>npar</i>	<i>AIC</i>	<i>BIC</i>	<i>logLik</i>	<i>deviance</i>	<i>Chisq</i>	<i>Df</i>	<i>Pr..Chisq.</i>
6	3685.70	3722.01	-1836.85	3673.70	NA	NA	NA
7	3687.12	3729.48	-1836.56	3673.12	0.58	1	0.45

The analysis shows that the parties' voting pattern is probably the most important cause for MEP votes. This leads to the question, if MEPs follow the voting pattern, there might be responsiveness from Parties as a group rather than the MEPs individually, and the responsiveness might be explained by variables that had no effect when looking at MEPs individually. So, for

the next part of the analysis, rather than looking at individual MEPs as the dependent variable in a multilevel logistic regression, the analysis will look at a regular multilevel regression using party votes as the dependent variable.

6.4 Multilevel regression using party votes as the dependent variable

As explained earlier in the analysis, the dominance of the party vote variable indicated that MEPs largely voted with their party. Therefore, responsiveness could be expected from party votes rather than individual MEP votes. The dependent variable is on the party level, and the primary explanatory variable is on the country level. The multilevel model will therefore include these two levels. As with the first model, there is a need to figure out the variance between and within the country level. The null model presented in table 6.13 has an ICC of 8%, meaning there is more variance in this model than in the logistic regression model presented earlier. Looking at table 6.16, the difference between the countries in the model is statistically significant in the >0,1 percentile. The R squared is also larger for the null model using party votes as the dependent variable. There is more merit to this model compared to the logistic regression model.

TABLE 6.13 NULL MODEL WITH PARTY VOTE AS THE DEPENDENT VARIABLE

<i>Party Vote</i>				
<i>Predictors</i>	<i>Estimates std. Error</i>		<i>CI</i>	<i>p</i>
Intercept	0.33 ***	0.01	0.31 – 0.35	<0.001
Random Effects				
σ^2			0.02	
τ_{00} Country			0.00	
ICC			0.08	
N _{Country}			27	
Observations			3649	
Marginal R ² / Conditional R ²			0.000 / 0.075	

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

TABLE 6.14 ANOVA MODEL, THE NULL MODEL WITH AND WITHOUT COUNTRIES AS A FACTOR

<i>Res.Df</i>	<i>RSS</i>	<i>Df</i>	<i>Sum.of.Sq</i>	<i>F</i>	<i>Pr.F.</i>
3137	62.28	NA	NA	NA	NA
3111	56.09	26	6.19	13.21	0.00

6.4.1 Adding an explanatory variable

Adding the explanatory variable does not seem to be any difference in the effect of the primary explanatory variable on the votes in the EP versus the logistic regression model. Looking at the anova model, the difference between the null model and the model, including one explanatory variable, is not large, looking at the AIC and BIC values. However, the difference is significant at the 2% level. The R squared is not much better than the empty model, only a tiny improvement, but that is to be expected when adding explanatory value to the model.

TABLE 6.15 MULTILEVEL REGRESSION WITH ONE EXPLANATORY VARIABLE

<i>Party Vote</i>				
<i>Predictors</i>	<i>Estimates</i>	<i>std. Error</i>	<i>CI</i>	<i>p</i>
Intercept	0.18 *	0.08	0.03 – 0.33	0.021
AI	0.10	0.05	-0.00 – 0.20	0.054
Random Effects				
σ^2			0.02	
τ_{00} Country			0.00	
ICC			0.07	
N _{Country}			27	
Observations			3649	
Marginal R ² / Conditional R ²			0.010 / 0.078	

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

TABLE 6.16 ANOVA MODEL COMPARING TABLES 6.13 AND 6.15

<i>npar</i>	<i>AIC</i>	<i>BIC</i>	<i>logLik</i>	<i>deviance</i>	<i>Chisq</i>	<i>Df</i>	<i>Pr..Chisq.</i>
3	-3635.28	-3617.12	1820.64	-3641.28	NA	NA	NA
4	-3638.37	-3614.17	1823.19	-3646.37	5.09	1	0.02

6.4.2 Adding control variables on multiple levels

Adding control variables to the model has not notably changed the primary explanatory variable's significance. The other country variables do not have any significance to them either. The most exciting thing coming from this model is the statistical significance of the party size variable. This indicates that there could be a relationship between what the parties vote and how large the parties are. This effect is minimal at 0,01, but it is very significant. For the model, the R squared value for both fixed and random effects have gone from 0.078 to 0.098. For the fixed

effects, the R squared value went from 0.010 to 0.029. This means that the variables' explanatory value has increased both for the fixed effects and the whole model. Looking at the anova model in table 6.18, the model fit has not improved from table 6.15 based on the AIC and BIC values. However, there is a significant difference between the two models based on the chi-squared between the models. Figure 6.11 shows that there are not any problems of multicollinearity between the variables in table 6.17.

TABLE 6.17 MULTILEVEL MODEL WITH MULTIPLE INDEPENDENT VARIABLES

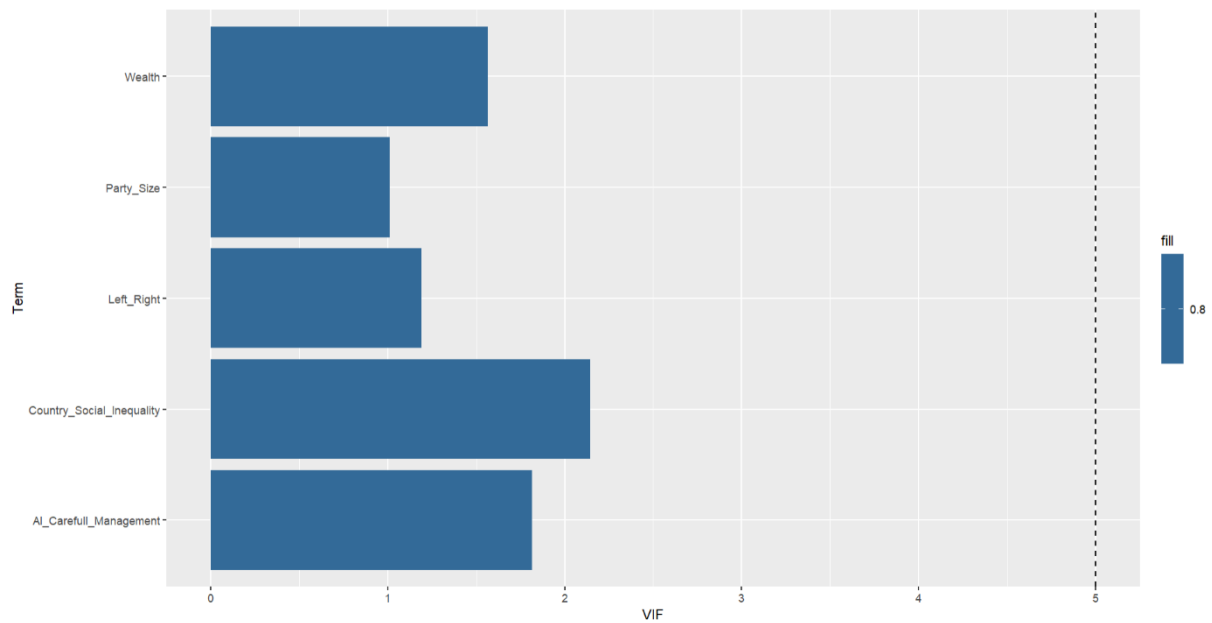
<i>Party Vote</i>				
<i>Predictors</i>	<i>Estimates</i>	<i>std. Error</i>	<i>CI</i>	<i>p</i>
Intercept	0.16	0.13	-0.09 – 0.41	0.203
AI	0.07	0.07	-0.07 – 0.21	0.315
Party_Size	0.01 ***	0.00	0.01 – 0.01	<0.001
Social Inequality	0.02	0.07	-0.12 – 0.15	0.813
Left Right	0.15	0.11	-0.06 – 0.36	0.171
Wealth	-0.02	0.04	-0.09 – 0.05	0.658
Random Effects				
σ^2			0.02	
τ_{00} Country			0.00	
ICC			0.07	
N Country			27	
Observations			3649	
Marginal R ² / Conditional R ²			0.029 / 0.098	

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

TABLE 6.18 ANOVA MODEL COMPARING TABLES 6.15 AND 6.17

<i>npar</i>	<i>AIC</i>	<i>BIC</i>	<i>logLik</i>	<i>deviance</i>	<i>Chisq</i>	<i>Df</i>	<i>Pr.Chisq.</i>
4	-3638.37	-3614.17	1823.19	-3646.37	NA	NA	NA
8	-3666.22	-3617.81	1841.11	-3682.22	35.85	4	0.00

FIGURE 6.11 MULTICOLLINEARITY BETWEEN VARIABLES FROM TABLE 6.17



6.4.3 Introducing a random coefficient

The model was also tested to see if there is more effect of the random effects when introducing the primary explanatory variable as a random coefficient. Introducing a random coefficient has not made any of the variables more significant, and the effects have not changed notably either. The random-effects between countries seem to have more effect when introducing the random coefficient. In table 6.19, the effects between countries have a value of 0.03, whereas, in table 6.17, the value was zero. The R squared values of the model in table 6.19 were slightly less than in 6.17 but almost the same, meaning that the explanatory value of the variables did not improve by adding a random coefficient. Looking at the anova model, the AIC and BIC values did not improve from table 6.17 to 6.19. However, the chi-squared value shows a statistically significant difference between the models. The model in table 6.19 is not much better than in table 6.17, but overall, the difference between the models is notable.

TABLE 6.19 MULTILEVEL MODEL WITH A RANDOM COEFFICIENT

<i>Predictors</i>	<i>Party Vote</i>			
	<i>Estimates</i>	<i>std. Error</i>	<i>CI</i>	<i>p</i>
Intercept	0.17	0.12	-0.07 – 0.41	0.161
AI	0.04	0.06	-0.08 – 0.17	0.497
Party_Size	0.01 ***	0.00	0.01 – 0.01	<0.001
Social Inequality	0.04	0.06	-0.07 – 0.15	0.516
Left Right	0.12	0.10	-0.07 – 0.31	0.206
Wealth	-0.01	0.03	-0.07 – 0.04	0.620
Random Effects				
σ^2			0.02	
τ_{00} Country			0.03	
τ_{11} Country.AI_Carefull_Management			0.02	
ρ_{01} Country			-0.99	
ICC			0.07	
N Country			27	
Observations			3649	
Marginal R ² / Conditional R ²			0.024 / 0.095	

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

TABLE 6.20 ANOVA MODEL COMPARING TABLES 6.17 AND 6.19

<i>npar</i>	<i>AIC</i>	<i>BIC</i>	<i>logLik</i>	<i>deviance</i>	<i>Chisq</i>	<i>Df</i>	<i>Pr..Chisq.</i>
10	-3828.48	-3766.45	1924.24	-3848.48	NA	NA	NA
12	-3846.85	-3772.43	1935.43	-3870.85	22.38	2	0.00

6.4.4 Introducing cross-level interaction effect

Introducing a cross-level interaction between public opinion on AI management and party size yields the most exciting results of the analysis. The cross-level interaction effect between the AI and party size variables is significant on a <0,01% level, with an effect of -0,11. Introducing the interaction effect into the variable also makes the AI variable significant on a <0,01% level, which means that the effect of 0,22 on the dependent variable is statistically significant. The party size variable, which is also statistically significant, went from an effect of 0,01 in table 6.19 to an effect of 0,18 in table 6.21. The interaction between the primary explanatory variable and the party size variable is substantial, indicating that the parties' responsiveness in the EP depends mainly on their size. The model also improves quite a bit from earlier models. The ICC of the model in table 6.21 goes up from 7% to 9%. The R squared values also go up on the fixed effects from 0,024 to 0,034. For the whole model, it goes up from 0,095 to 0,118. This means that the variables in the latest model have quite a bit more explanatory value than they had in the earlier models, as indicated by the rise in significance. The chi-square value indicates a significant difference between the model in table 6.19 to the model in table 6.21. The AIC and BIC values are a better fit for the model in 6.19. However, as noted in section 5.2, the chi-squared value is more reliable when comparing multilevel models because it considers both fixed and random effects.

TABLE 6.21 MULTILEVEL MODEL WITH CROSS-LEVEL INTERACTION EFFECTS BETWEEN AI AND PARTY SIZE

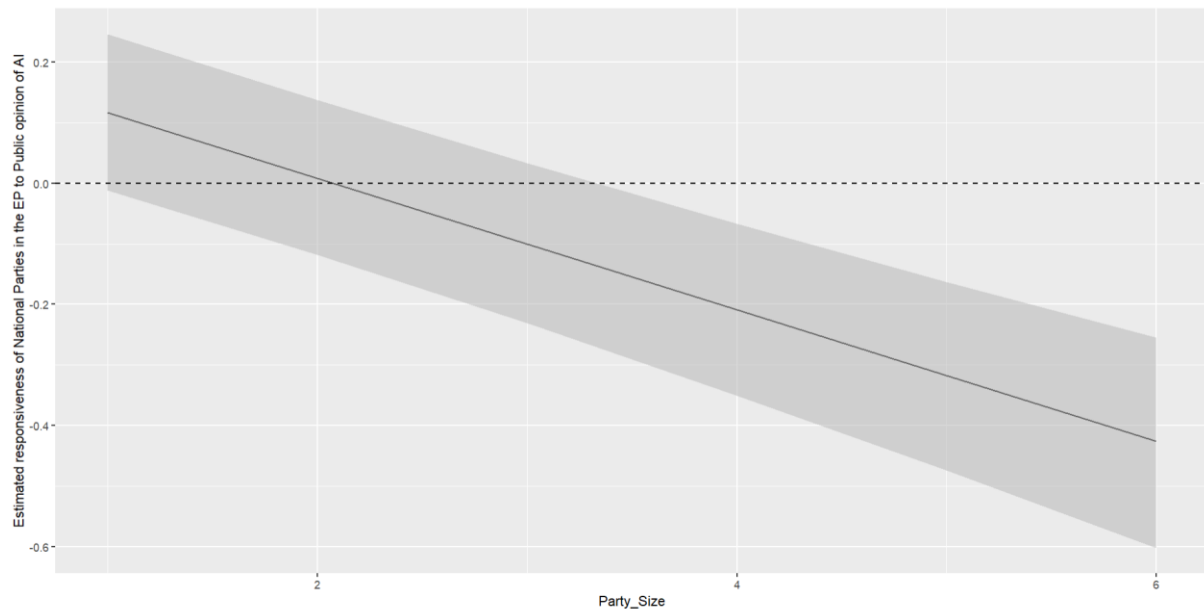
<i>Party Vote</i>				
<i>Predictors</i>	<i>Estimates</i>	<i>std. Error</i>	<i>CI</i>	<i>p</i>
Intercept	-0.19	0.14	-0.46 – 0.08	0.174
AI	0.22 **	0.07	0.09 – 0.36	0.001
Party_Size	0.18 ***	0.02	0.13 – 0.22	<0.001
Social Inequality	0.07	0.06	-0.04 – 0.19	0.220
Left Right	0.17	0.10	-0.03 – 0.37	0.098
Wealth	-0.01	0.03	-0.08 – 0.05	0.660
AI*Party size	-0.11 ***	0.01	-0.14 – -0.08	<0.001
Random Effects				
σ^2			0.02	
τ_{00} Country			0.02	
τ_{11} Country.AI_Carefull_Management			0.01	
ρ_{01} Country			-0.99	
ICC			0.09	
N _{Country}			27	
Observations			3649	
Marginal R ² / Conditional R ²			0.034 / 0.118	
* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$				

TABLE 6.22 ANOVA MODEL COMPARING TABLES 6.19 AND 6.21

<i>npar</i>	<i>AIC</i>	<i>BIC</i>	<i>logLik</i>	<i>deviance</i>	<i>Chisq</i>	<i>Df</i>	<i>Pr.Chisq.</i>
10	-3828.48	-3766.45	1924.24	-3848.48	NA	NA	NA
11	-3883.81	-3815.59	1952.91	-3905.81	57.33	1	0.00

Figure 6.12 shows the interaction effect between the party size and public opinion on AI. Given that this effect is significant, it can indicate that the smaller the party, the more responsive the parties are towards public opinion on AI. The larger the party, the less responsive toward public opinion on AI.

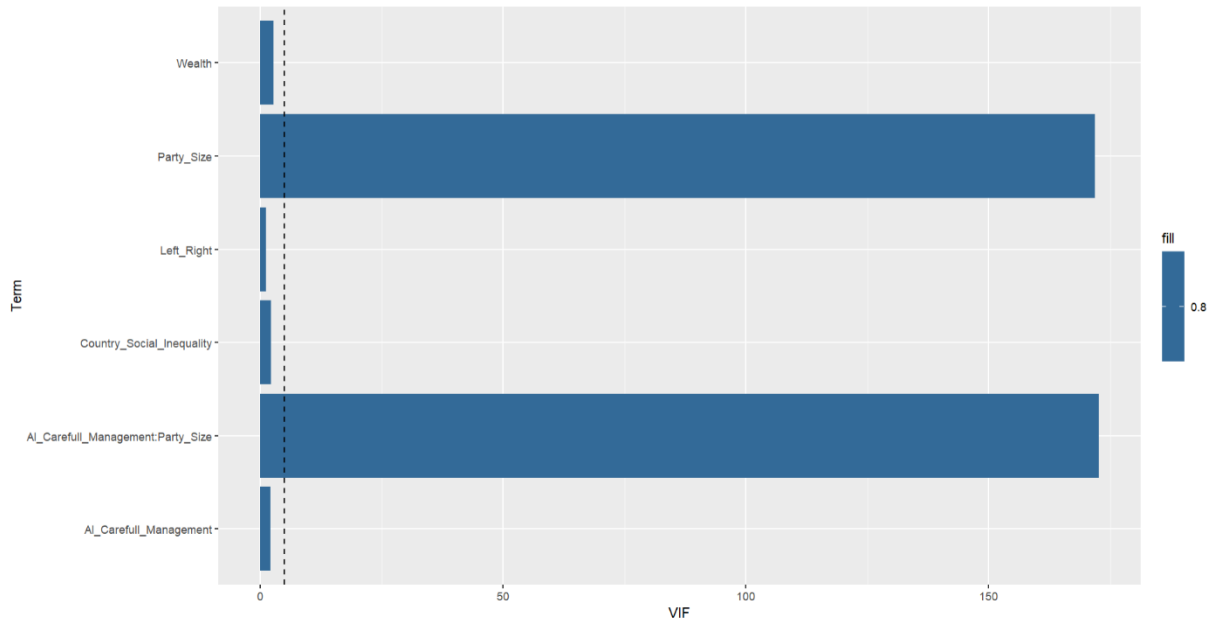
FIGURE 6.12 THE PLOTTED EFFECTS OF PARTY SIZE ON THE ESTIMATED RESPONSIVENESS OF PARTIES ON PUBLIC OPINION OF AI



6.4.5 Centering predictors

Looking at the plotted multicollinearity in table 6.21, the regression results can result from extreme multicollinearity. Therefore there is a reason for centering the predictors on seeing if the results still stand.

FIGURE 6.13 MULTICOLLINEARITY EFFECT OF THE REGRESSION IN TABLE 6.21



The model using centered predictors is much more modest than the model in table 6.1. Both the primary explanatory variable and the party size variable have reverted to the values of table 6.19. The primary explanatory variable of public opinion on AI management is no longer statistically significant, and the party size variable is still significant, but the effect has reverted to 0,01. Interestingly, the interaction effect between the two variables remains statistically significant after centering the variables while also retaining the effect of -0.11. The effect plotted in figure 6.12 therefore stands, suggesting that the national parties in the EP respond to the public opinion on AI, given that the party is small enough. Looking at figure 6.14, the multicollinearity effect displayed in figure 6.13 has gone down substantially, which gives a lot more confidence to the results displayed in table 6.23. The R squared values and the ICC of the model in table 6.23 is the same as in table 6.21.

TABLE 6.23 MULTILEVEL MODEL WITH CROSS-LEVEL INTERACTION AND CENTERED PREDICTORS

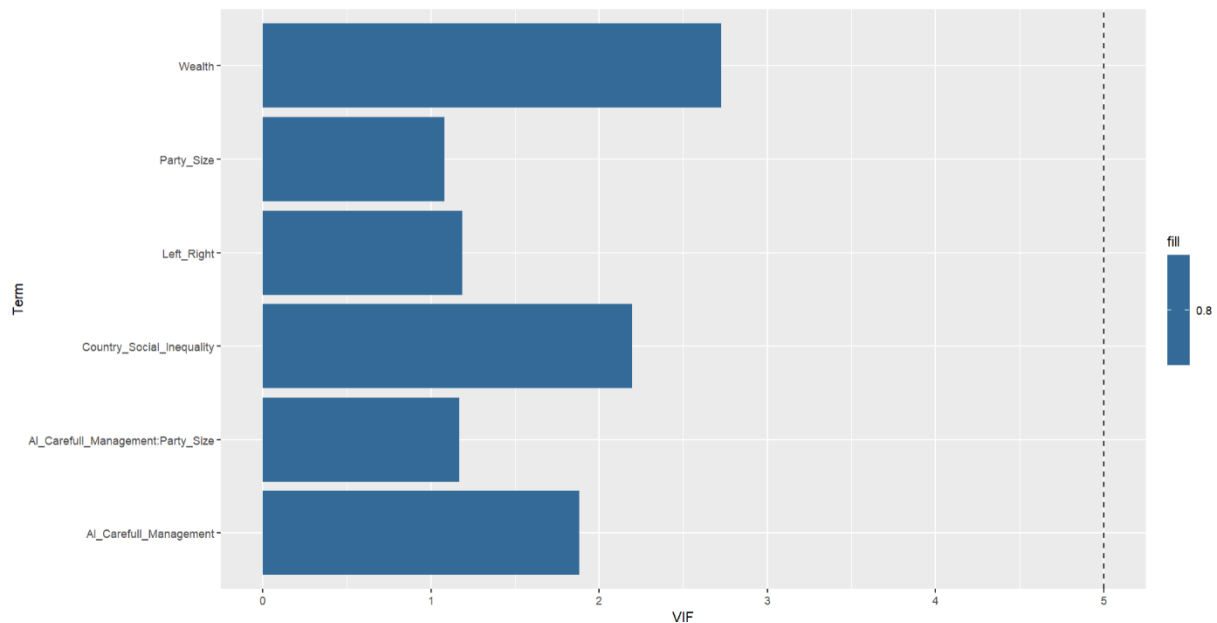
<i>Predictors</i>	<i>Party Vote</i>			
	<i>Estimates</i>	<i>std. Error</i>	<i>CI</i>	<i>p</i>
Intercept	0.21 *	0.11	0.00 – 0.42	0.045
AI	-0.07	0.07	-0.20 – 0.06	0.292
Party_Size	0.01 ***	0.00	0.01 – 0.02	<0.001
Social Inequality	0.07	0.06	-0.04 – 0.19	0.220
Left Right	0.17	0.10	-0.03 – 0.37	0.098
Wealth	-0.01	0.03	-0.08 – 0.05	0.660
AI*Party size	-0.11 ***	0.01	-0.14 – -0.08	<0.001
Random Effects				
σ^2			0.02	
τ_{00} Country			0.00	
τ_{11} Country.AI_Carefull_Management			0.01	
ρ_{01} Country			0.94	
ICC			0.09	
N Country			27	
Observations			3649	
Marginal R ² / Conditional R ²			0.034 / 0.118	

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

TABLE 6.24 ANOVA MODEL COMPARING TABLES 6.21 AND 6.23

<i>npar</i>	<i>AIC</i>	<i>BIC</i>	<i>logLik</i>	<i>deviance</i>	<i>Chisq</i>	<i>Df</i>	<i>Pr.Chisq.</i>
11	-3883.81	-3815.59	1952.91	-3905.81	NA	NA	NA
11	-3883.81	-3815.59	1952.91	-3905.81	0	0	NA

FIGURE 6.14 MULTICOLLINEARITY EFFECT OF THE REGRESSION IN TABLE 6.23



7. Discussion

The analysis supports some parts of the theory on responsiveness and fails to find any connection to other parts of the theory. The theory chapter presented the three main categories of factors for responsiveness to occur: Issue characteristics, Institutional factors, and party characteristics. All of these seem by the theory to influence responsiveness, although the different researchers have looked at responsiveness in different political systems and countries. Different factors might influence responsiveness based on where the research is taking place, although most of the research reviewed in this thesis finds some form of responsiveness. The researchers do not necessarily agree on what facilitates responsiveness. Should it always be the case that policymakers respond to the public, or are the effect of responsiveness dependent on outside factors?

The central hypothesis of this thesis is H1: MEPs respond to public opinion on issues of AI, and the corresponding null hypothesis is that there is no responsiveness from MEPs in the EP. This

first hypothesis is critical because if there is no effect between public policy and the policy output of the EP, then there will also be no conditioning factors for this effect. The analysis is a bit unsure of H1 as the public opinion of the AI variable does not seem to carry any significant effect on the dependent variable. In both the logistic and regular multilevel models, the public opinion on the AI variable affects the dependent variable. This suggests a rejection of H1 in favor of the null hypothesis. However, when introducing interaction effects in the model using party votes as the dependent variable, there surfaces a significant effect. This suggests that there might be some responsiveness from MEPs in the EP, although this effect is very dependent on other variables.

H2 states that if AI is salient, there is expected to be responsiveness, the null hypothesis for H2 is that AI is not salient and should therefore not be responsive. This hypothesis is supported by Franklin and Wlezien, Wratil, Abou-Chadi, et al., and Giger and Lefkofridi, who states that for policymakers to be responsive to an issue, the issue needs to have a certain level of salience. Based on figure 6.1, AI is not the most salient of the variables that were included. The primary explanatory variable is somewhat salient compared to the other variables but not enough to be conclusively salient. Although the variable of AI awareness has one of the lowest values in the table, this indicates that AI is an issue that is followed by a large majority of the public. Having specific opinions on how AI should be handled from a political viewpoint demands knowledge of what AI is and how it works. This might explain why the AI awareness variable is more salient than the primary explanatory variable, as it is more technical. Based on these two variables, issues of AI seem to be salient, although it is hard to tell if the perceived salience translates to political pressure. That AI should be salient is in line with the literature. It is a broad technology field that will impact lives directly and indirectly. For there to be responsiveness from the EP parliament on public opinion, there should be saliency, according to the literature. The analysis sees AI as a salient issue, and it is a prerequisite for any significant effects found in the analysis. Finding an effect of public opinion on votes in the EP confirms H2, even though this effect is dependent on other variables.

H3 and H4 relate to possible institutional factors for responsiveness. The literature highlights trust in media, the state, and the EU, as well as economic and educational levels as essential factors that should be related to responsiveness. The analysis does not find that the institutional factors matter for the responsiveness of MEPs or parties in the EP. None of the institutional variables were statistically significant in any of the models presented in the analysis. This is contrary to the literature that argues that various institutional factors should play a role in determining whether there is any responsiveness. Most of the studies examined in the literature review looked at responsiveness within countries and not the EP. It could be that the institutional factors on the country level do not matter as much when examining relations in the EP. That these institutional factors might play a more prominent role in determining responsiveness than the analysis has shown cannot be dismissed entirely. A more extensive selection of votes would give more variance in the different levels included in the analysis. This could make the effects of variables measured on the country level more significant in the model. However, as the analysis stand, there is no support for the expectation that trust in the media, state, and EU have any effect on the votes roll-call votes of the EP. There is also no evidence that these variables affect the responsiveness of the EP on the public opinion on AI. For the economic and educational levels of the countries, the analysis also finds no evidence that this affects the roll-call votes of the EP. There are also no significant effects of these variables influencing the responsiveness from the EP on the public opinion on AI. H3 and H4 can be dismissed with no supportive findings.

For the last and most interesting part of the analysis, this thesis finds that the most crucial factor for determining what MEPs in the EP vote are their national party's votes. The effect of party votes on MEPs was substantial in addition to being very significant. The correlation between these two variables drowned out the other variables' effects. This finding led to the analysis to include the model using party votes as the dependent variable and the model using MEP votes as the dependent variable. If the votes of the individual MEPs can largely be explained by what party they belong to, the responsive effects to the public opinion might be found in the party rather than the individual MEPs. This sentiment is reflected by Nugent and Hix, who find that the national parties have a considerable influence over the individual MEPs. Since the MEPs are voted into the EP through their national parties, they would likely vote in line with the parties.

This finding is supported by the analysis presented in this thesis. Hakverdian and Soroka, and Wlezien have thought it unlikely that a multiparty system would have any significant responsiveness. The analysis in this thesis contradicts these findings, suggesting that national parties have much influence over the voting of individual MEPs. The analysis supports the idea that MEPs will act similarly to national politicians, focusing on salient vote-grabbing issues that will get them reelected. Assuming that their main goal is to be re-elected, Hix finds that MEPs will follow their party, giving them the highest chance of reelection. Costello et al. argue that voters do not vote with their party on EU and European integration issues. Suppose AI issues were to fall into these categories. In that case, responsiveness should not be expected, which is supported by Costello, Thomassen and Rosema, Adams et al., and Mattila and Raunio. The white paper on artificial intelligence shows that AI is a broad issue affecting many parts of general living, politics, and economics (Commission 2020). AI can hardly be called an EU issue or an issue of European integration, responsiveness to AI issues should not be affected by this, and the analysis also supports this. It can still be argued that responsiveness from members of a national parliament might have more substantial effects than what is found in the analysis of the EP. If the effects of responsiveness on AI issues are different between the national and European parliaments would be a subject for later research.

Although the importance of party effects on EP votes is interesting, the most important findings for the research questions are the interaction effect between public opinion on AI and the size of parties. The analysis indicates that the responsiveness to AI's public opinion depends on the party's size. Although the centering of the variables removes the significance of the public opinion on the AI variable, the interaction effect between the two variables remains statistically significant. This still indicates that when accounting for both variables, there is statistically significant responsiveness from the EP on public opinion if The Party is small enough. Based on figure 6.12, the responsiveness decreases based on the size of the party. The larger the party, the more negative the effect becomes, indicating that the larger parties are less responsive than, the smaller parties. This supports the arguments of Ezrow et al. and Mattila and Raunio, which indicate that more prominent and centrist parties tend to be less responsive than smaller and fringe parties. Smaller parties have less to lose by shifting their policy preferences towards newer

and more salient issues. Larger parties might fear losing their traditional voter base by shifting their policy position toward newer salient issues.

Meguid argues that the size of the parties will not matter because larger parties will shift their policy if the issue is salient enough. It might be that AI is not salient enough for the larger parties to shift their policy position, but as demonstrated earlier in the analysis, AI seems to be a salient issue. H6 expects smaller national parties to be more responsive than larger parties, which is confirmed by the analysis. In conclusion, H3 and H4 cannot be confirmed by the analysis. The analysis confirms H1, H2, H5, and H6. Based on the analysis, there seems to be some responsiveness to AI, which is a salient issue. National parties also seem to influence the votes and responsiveness of MEPs in the EP quite heavily. There are indications that national parties are also affected by the size of the parties and that the smaller parties are more responsive than larger parties.

8. Conclusion

The thesis aimed to try and uncover if the Members of the European Parliament are responding to public opinion on artificial intelligence. This is important because artificial intelligence will impact the lives of millions of people, industries, and economies in Europe and the rest of the world. Artificial intelligence will undoubtedly benefit many people and industries. However, it is also a volatile technology that could result in significant damage if it is not used to benefit the people. Because of this, the opinion of the people matters. To ensure that the technology is used to their benefit, the European Parliament should respond to their opinion on the issue. Based on this, the research questions answered in this thesis are as follows:

(1) Are the MEPs of the European Parliament representing the public opinion of their respective member states? (2) Why do some MEPs pay more attention to the public opinion than others when they vote on issues relating to AI?

The argument of this thesis was built on what the literature deemed the main explanatory factors for responsiveness. The main factors in the literature were the issue characteristics, institutional factors, and party characteristics. The main element of issue characteristics was whether the issue in question was salient. This came up quite a lot in the literature and as a foundational factor for responsiveness. If an issue were not salient, policymakers would not care about it. The second factor was institutional factors, including all different country characteristics, like party system, media, wealth, and education. The last factor was party characteristics because MEPs are voted in on the national level through their national party. Because of this, some literature argued that MEPs would follow their party's policy position. This also includes the argument that smaller parties are more responsive than larger parties due to their fear of alienating their traditional voter base by shifting policy positions towards newer, more salient issues. All these variables were tested for in the analysis, and party characteristics emerged as the most essential factor in explaining the EP's voting patterns.

The empirical analysis showed that AI was a salient issue compared to other variables on the country level, giving the analysis a basis to build upon as this factor was repeated in the literature as important. The analysis did not find any evidence that the institutional factors affect the responsiveness to AI issues. For the votes of individual MEPs, the variance between countries also seemed to have little effect, although this improved when switching to party votes. The essential variable for MEP votes was party votes, which indicates that what MEPs vote in the EP is primarily based on their party's policy position. This is supported by less explanatory value in the variance between countries than between national parties. Introducing the multilevel regression model with party votes showed that eliminating parties from the equation makes the variance in countries much more prominent. This model finds that the size of the national party is significant to the party votes, although the effect is minimal. Creating an interaction effect between public opinion on AI and party size reveals a significant effect, indicating that the smaller the party is, the more effect it has on the responsiveness of the parties represented in the EP.

The analysis's main finding is that the significant effect of the interaction effect might indicate that parties in the EP are responsive to public opinion on AI, given that the party is small enough. So, to answer the research question (1), it is difficult to determine if the MEPs are responsive to public opinion on AI, but the analysis indicates that they are. (2) As much of the literature has indicated, the effect is dependent on other factors. Firstly, the national party of which the MEP is a member seems to be critical to what they vote in the EP, and secondly, the effect seems to be dependent on the size of the parties. The smaller parties seem to be more responsive than the larger parties.

8.1 Impactions on future research

One of the main problems with the analysis of this thesis was the lack of roll-call voting data because AI is a new issue for the world's policymakers, and as a result, there are not as many votes relating to the issue. For further research on the subject, machine learning could be used to compensate for the little data there is on the subject. Because of the little data on AI roll-call votes and limited amounts of the datasets, including the question of AI, there is no good way of creating a time-series data analysis on the subject. As discussed in the data section of the thesis, a time-series data analysis would probably be the best method to establish causation between MEP votes and public opinion on AI. Future research should try and deploy this method to establish causation on the subject. The analysis of this thesis indicates a relationship but cannot establish any causation.

Extending the analysis to look at other potential influences on AI policy could also be an exciting way forward in future research. AI is a technology that has applications in a wide variety of industries, like agriculture, healthcare, climate, security, and the military, so there are bound to be many interest groups looking to influence policymakers on the issue. The difference between interest group influence and public influence could be an exciting continuation of the study. It could also be quite interesting to look at the different institutions of the EU. Do the EC and EP have similar priorities when it comes to the development of legislation on AI? Since the EC does not answer directly to voters, and the EP does, it could be that the EC listens less to the public

opinion on AI issues than the EP does. AI is a crucial technology that must be handled with great care, so finding out exactly who and what impacts the decision-making on the issue will be significant. Studying the development and implementation of AI and other similar technologies will be essential to understanding how AI can benefit people.

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Appendix A

TABLE A: ALL PARTIES AND COUNTRIES WHICH IS INCLUDED IN THE ANALYSIS.

National Parties	Countries
Die Grünen - Die Grüne Alternative	Austria
Freiheitliche Partei Österreichs	Austria
NEOS – Das Neue Österreich	Austria
Österreichische Volkspartei	Austria
Sozialdemokratische Partei Österreichs	Austria
Centre Démocrate Humaniste	Belgium
Christen-Democratisch & Vlaams	Belgium
Christlich Soziale Partei	Belgium
Ecologistes Confédérés pour l'Organisation de Luttes Originales	Belgium
Groen	Belgium
Mouvement Réformateur	Belgium
Nieuw-Vlaamse Alliantie	Belgium
Open Vlaamse Liberalen en Democraten	Belgium
Parti du Travail de Belgique	Belgium
Parti réformateur libéral/Front démocratique des francophones	Belgium
Parti Socialiste	Belgium
Vlaams Belang	Belgium
Bulgarian Socialist Party	Bulgaria
Citizens for European Development of Bulgaria	Bulgaria
Democrats for Strong Bulgaria	Bulgaria
Movement for Rights and Freedoms	Bulgaria
Union of Democratic Forces	Bulgaria
VMRO	Bulgaria

Hrast – Pokret za uspješnu Hrvatsku	Croatia
Hrvatska demokratska zajednica	Croatia
Istarski demokratski sabor - Dieta democratica istriana	Croatia
Socijaldemokratska partija Hrvatske	Croatia
Živi Zid	Croatia
Democratic Party	Cyprus
Democratic Rally	Cyprus
Dimocraticos Synagermos	Cyprus
Movement for Social Democracy EDEK	Cyprus
Progressive Party of Working People - Left - New Forces	Cyprus
ANO 2011	Czechia
Komunistická strana Cech a Moravy	Czechia
Krestanská a demokratická unie - Československá strana lidová	Czechia
Obcanská demokratická strana	Czechia
PIRÁTI	Czechia
Svoboda a přímá demokracie	Czechia
TOP 09 a Starostové	Czechia
Dansk Folkeparti	Denmark
Det Konservative Folkeparti	Denmark
Det Radikale Venstre	Denmark
Enhedslisten	Denmark
Socialdemokratiet	Denmark
Socialistisk Folkeparti	Denmark
Venstre, Danmarks Liberale Parti	Denmark
Eesti Keskerakond	Estonia
Eesti Konservatiivne Rahvaerakond	Estonia
Eesti Reformierakond	Estonia
Isamaa	Estonia
Sotsiaaldemokraatlik Erakond	Estonia
Kansallinen Kokoomus	Finland
Perussuomalaiset	Finland

Suomen Keskusta	Finland
Suomen Sosialidemokraattinen Puolue/Finlands Socialdemokratiska Parti	Finland
Svenska folkpartiet	Finland
Vasemmistoliitto	Finland
Vihreä liitto	Finland
Vihreät	Finland
Alliance Écologiste Indépendante	France
Europe Écologie	France
Front national	France
Indépendant	France
La France Insoumise	France
La République en marche	France
Les centristes	France
Les Républicains	France
Liste "Alliance des Outre-Mers"	France
Liste Renaissance	France
Mouvement Démocrate	France
Nouvelle Donne	France
Parti socialiste	France
Partitu di a Nazione Corsa	France
Place publique	France
Rassemblement national	France
Rassemblement pour la République	France
Union pour la démocratie française	France
Union pour un Mouvement Populaire	France
Union pour un Mouvement Populaire - Parti Radical	France
Alternative für Deutschland	Germany
Bündnis 90/Die Grünen	Germany
Christlich-Soziale Union in Bayern e.V.	Germany
Christlich Demokratische Union Deutschlands	Germany
DIE LINKE.	Germany

Die PARTEI	Germany
Familien-Partei Deutschlands	Germany
Freie Demokratische Partei	Germany
Freie Wähler	Germany
Ökologisch-Demokratische Partei	Germany
Partei Mensch Umwelt Tierschutz	Germany
Piratenpartei Deutschland	Germany
Sozialdemokratische Partei Deutschlands	Germany
Volt	Germany
Coalition of the Radical Left	Greece
Communist Party of Greece	Greece
Elliniki Lusi-Greek Solution	Greece
Nea Demokratia	Greece
Panhellenic Socialist Movement - Olive Tree	Greece
Popular Association – Golden Dawn	Greece
Synaspismos tis Aristeras ton Kinimaton kai tis Oikologias	Greece
Demokratikus Koalíció	Hungary
Fidesz-Magyar Polgári Szövetség	Hungary
Fidesz-Magyar Polgári Szövetség-Keresztény Demokrata Néppárt	Hungary
Fidesz-Magyar Polgári Szövetség-Kereszténydemokrata Néppárt	Hungary
Jobbik Magyarországért Mozgalom	Hungary
Magyar Szocialista Párt	Hungary
Momentum	Hungary
Fianna Fáil Party	Ireland
Fine Gael Party	Ireland
Green Party	Ireland
Independent	Ireland
Independents for change	Ireland
Sinn Féin	Ireland
Alleanza nazionale	Italy
Forza Italia	Italy

Fratelli d'Italia	Italy
Il Popolo della Libertà	Italy
La Margherita	Italy
Lega	Italy
Lega Nord	Italy
Movimento 5 Stelle	Italy
Partito Democratico	Italy
Südtiroler Volkspartei	Italy
Unione dei Democratici cristiani e dei Democratici di Centro	Italy
Unione di Centro	Italy
"Saskana" socialdemokratiska partija	Latvia
Attistibai/Par!	Latvia
Gods kalpot Rigai	Latvia
Nacionala apvieniba "Visu Latvijai!"-"Tevzemei un Brivibai/LNNK"	Latvia
Pilsoniska Savieniba	Latvia
Politisko organizaciju savieniba "Par cilveka tiesibam vienota Latvija"	Latvia
Tevzemei un Brivibai/LNNK	Latvia
Darbo partija	Lithuania
Independent	Lithuania
Lietuvos lenku rinkimu akcija	Lithuania
Lietuvos Respublikos liberalu sajudis	Lithuania
Lietuvos socialdemokratu partija	Lithuania
Lietuvos valstieciu ir žaliuju sajunga	Lithuania
Tevynes sajunga-Lietuvos krikščionys demokratai	Lithuania
Déi Gréng - Les Verts	Luxemburg
Parti chrétien social luxembourgeois	Luxemburg
Parti démocratique	Luxemburg
Parti ouvrier socialiste luxembourgeois	Luxemburg
Partit Laburista	Malta
Partit Nazzjonalista	Malta
Christen Democratisch Appèl	Netherlands

ChristenUnie - Staatkundig Gereformeerde Parti	Netherlands
Democraten 66	Netherlands
Forum voor Democratie	Netherlands
GO Realisme & Daadkracht	Netherlands
GroenLinks	Netherlands
JA21	Netherlands
Partij van de Arbeid	Netherlands
Partij voor de Dieren	Netherlands
Partij voor de Vrijheid	Netherlands
Socialistische Partij	Netherlands
Staatkundig Gereformeerde Partij	Netherlands
Volkspartij voor Vrijheid en Democratie	Netherlands
Bezpartyjna	Poland
Bezpartyjny	Poland
Independent	Poland
Platforma Obywatelska	Poland
Polskie Stronnictwo Ludowe	Poland
Prawo i Sprawiedliwosc	Poland
Samoobrona RP	Poland
Sojusz Lewicy Demokratycznej	Poland
Sojusz Lewicy Demokratycznej - Unia Pracy	Poland
Solidarna Polska Zbigniewa Ziobro	Poland
Wiosna	Poland
Bloco de Esquerda	Portugal
Partido Comunista Português	Portugal
Partido Popular	Portugal
Partido Social Democrata	Portugal
Partido Socialista	Portugal
Pessoas-Animais-Natureza	Portugal
Partidul Conservator	Romania
Partidul Democrat	Romania

Partidul Democrat-Liberal	Romania
Partidul Libertate, Unitate & Solidaritate	Romania
Partidul Mișcarea Populară	Romania
Partidul National Liberal	Romania
Partidul Social Democrat	Romania
PRO Romania	Romania
Uniunea Democrată Maghiară din România	Romania
Uniunea Salvați România	Romania
Independent	Slovakia
Kotleba – Ludová strana Naše Slovensko	Slovakia
Kresťanskodemokratické hnutie	Slovakia
Obyčajní ľudia a nezávislé osobnosti	Slovakia
Progresívne Slovensko	Slovakia
Sloboda a Solidarita	Slovakia
Slovenská demokratická a kresťanská únia - Demokratická strana	Slovakia
Smer	Slovakia
SMER-Sociálna demokracia	Slovakia
SPOLU – občianska demokracia	Slovakia
Lista Marjana Šarca	Slovenia
Nova Slovenija	Slovenia
Slovenska demokratska stranka	Slovenia
Slovenska ljudska stranka	Slovenia
Socialni demokrati	Slovenia
Ciudadanos – Partido de la Ciudadanía	Spain
EH BILDU	Spain
Esquerra Republicana de Catalunya	Spain
Iniciativa per Catalunya Verds	Spain
Izquierda Unida	Spain
Junts per Catalunya - Lliures per Europa	Spain
Partido Nacionalista Vasco	Spain
Partido Popular	Spain

Partido Socialista Obrero Español	Spain
Partit dels Socialistes de Catalunya	Spain
PODEMOS	Spain
Unión, Progreso y Democracia	Spain
VOX	Spain
Arbetarepartiet- Socialdemokraterna	Sweden
Centerpartiet	Sweden
Kristdemokraterna	Sweden
Liberalerna	Sweden
Miljöpartiet de gröna	Sweden
Moderaterna	Sweden
Sverigedemokraterna	Sweden
Vänsterpartiet	Sweden