The Dutch effect: perceptions towards robots and AI stealing peoples' jobs

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ABSTRACT,

The widespread use of AI applications like ChatGPT and BERT has thrust artificial intelligence into the forefront of public debate around automation technologies and its impact on society as we know it today. Job insecurity is one of the most common associations with automation technologies, but do these perceptions differ between nations? This research investigates national perceptions towards robots and artificial intelligence stealing peoples' jobs, using data from the Eurobarometer survey 460. The goal was to confirm the "Dutch effect" apparent after reviewing the survey results: Dutch respondents, especially managers, tend to disagree with the idea, in stark contrast to the average European respondent. A partial proportional odds model revealed that the interaction effect of being a Dutch manager resulted in very significant coefficients with the odds of being in the highest category of 'totally disagree' increase by 84.1% ($p < 0.01$). Their European counterparts: the average manager reported only significant effects with the odds of being in a higher category than 'totally agree' increase by 28.1% ($p < 0.001$) and 'tend to agree' increase by 18.3% ($p < 0.01$). This confirms the Dutch effect and highlights national and socio-professional differences in perceived job insecurity. These findings benefit national and international policymakers and decision-makers, helping Dutch managers understand and address the differences in perceptions between their subordinates and European counterparts, thereby improving organizational effectiveness in implementing automation technologies.

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1. INTRODUCTION

Public attention towards automation technologies such as robots and artificial intelligence has intensified over the last couple of years. Artificial intelligence, as a technological advancement, has gained the attention of the world due to the emergence of applications such as ChatGPT and BERT. Technology that was once regarded as futuristic has now entered the present. Although the precise impact that the implementation of artificial intelligence will have is yet unknown, artificial intelligence and increased robotization will have a massive impact on the way we organize, view, and perform our work—if there are still human jobs left to be done. According to Makridakis (2017), "The expected changes being brought by AI technologies will be just as, or even more significant as those of the Industrial revolution and much harder to predict for two reasons. First, they will depend on the speed that AI technologies will succeed in automating non-repetitive mental tasks currently performed by humans and replacing them in the process, and secondly the extent of the accelerated process of technological change as intelligent computer programs will become available and capable of developing new programs on their own" (p. 53).

This unpredictable potential impact has fueled the debate around increased automatisation through the implementation of robots and artificial intelligence and its potential impact on society, with a focus on the labor market.

In 2017, the Eurobarometer survey 460: Attitudes towards the Impact of Digitalization and Automation on Daily Life was published at the request of the European Commission. When reviewing the survey, I observed an interesting phenomenon: Dutch respondents are split between disagree and agree to the statement;" Robots and artificial intelligence steal peoples' jobs." Whereas the totality of EU respondents agrees with 73.52%, a noteworthy difference. Digging deeper in this discrepancy, I looked at the different socio-professional categories: managers, white-collar workers, and manual workers. 28% of Dutch managers fall in the various levels of agreement compared to 61% of the European Union managers. 42% of Dutch white-collar workers agree compared to 73% of the EU white-collar workers. 52% of Dutch manual workers agree compared to 75% of the EU. Thus, national and socio-professional differences seem to be apparent. These initial findings sparked the research presented in this paper. Why are the Dutch less agreeable on this statement? Does this apparent Dutch effect stand at the national level and the individual-level within a multivariate analysis? Is the effect significant and to what degree?

There has been research on the various sentiments and perceptions on technologies such as robots and artificial intelligence at the national level. Research has been conducted on robot acceptance at work (RAW) in the form of a multilevel analysis of how robot acceptance at work varies between individual and national attributes in EU 27 (Turja & Oksanen, 2019), utilizing two other Eurobarometer surveys on the topic of public attitudes towards robots conducted in 2012 and 2014. Another study that utilized the 2012 data has been conducted by Dekker et al. (2017). This study revolved around the topic of economic self-interest and its interaction with fear of robots at work, covering 20 European countries. Another study on the national level, in this case with the focus on a single country-Bulgaria-has researched drivers and solutions to automation fears, with a focus on analyzing how Bulgarians perceive the automation of their job (Ivanov *et al.,* 2020). Research that explores the differences between Norway and The United Kingdom on the implications of robotics and artificial intelligence for employment and wider society has been conducted, exploring social actors and the role of institutions on shaping technological change (Lyod & Payne, 2023). Another study researching cross-country variation has been conducted by examining 37 OECD and EU countries. Leibrecht et al. (2023) state, "how the association between automation and unemployment rates depends on the organization of collective bargaining" (p. 272).

There has also been research on the individual-level with respect to robots and artificial intelligence. Research has been done on the challenges that human resource management leaders and departments face due to the intimate interaction between human workers and artificial intelligence, emphasizing the team level (Arslan *et al.,* 2022). How social influence interacts with perceptions towards assistive robots at work has been researched, with a focus on whether positive user experience of a familiar or unfamiliar colleague increased positive attitudes towards assistive robots (Latikka *et al.,* 2023). There has also been done research on blue-collar workers and their perceptions towards job security in human-robot collaboration, with a focus on varying levels of collaborative assistance. Kaur et al. (2023) state, "The overarching theme suggested by our study is that as-needed assistants have the potential to improve outlook on acceptability of robots in the workforce" (p. 191).

Research into these perceptions both on the national and individual level has not been done with respect to the Netherlands and its managers. Parallels with the existing literature can be drawn, and this research is an attempt to fill the gap within current academic literature.

1.1 Research objective & question

The objective of this research is to confirm the apparent Dutch effect by transitioning from a bivariate analysis of the survey results to a multivariate analysis through conducting a 'gologit2' data analysis on the survey data. Creating a partial proportional odds model with various variables to confirm and contextualize this effect, aiming for a statistically significant effect of being Dutch on disagreeing with the statement: "Robots and artificial intelligence steal peoples' jobs" (European Commission, 2017, p. 74). More specifically, this research investigates whether this effect is also statistically significant among the various socio-professional categories as assigned in the survey, with a special focus on the interaction effect of being a Dutch manager.

With respect to the research gap and the initial findings of the bivariate analysis, the following research question was formulated; "Is there a significant effect of being Dutch on the likelihood of disagreeing with the statement: 'Robots and artificial intelligence steal peoples' jobs,' and how does this effect manifest across the different socio-professional categories, with an emphasis on Dutch managers compared to the other EU respondents?"

1.2 Academic & practical relevance

As mentioned in the introduction, there is literature on the perceptions towards robots and artificial intelligence on job insecurity, both on the national and individual levels. However, literature on this topic with respect to the Netherlands and its various socio-professional categories is missing. This research can contribute to the broader research by examining and analyzing how these concepts interact within the Dutch sample size in comparison to the European Union average. The confirmation and contextualization of this Dutch effect through the partial proportional odds model enhances the understanding of national differences and their manifestations across the different socio-professional categories within the broader research on robots, artificial intelligence and their impact on perceived job insecurity.

The practical relevance of this research is of another nature. Increased automatization trough robotics and artificial intelligence will have a substantial impact on society, especially in the area of work. Within the law and regulations that businesses and organizations must adhere to, management and the board are most often in charge of deciding on the implementation of these technologies. Therefore, it is very significant to have an insight in the perceptions of these decision-makers and what may drive their stance.

This research has another dimension of interest due to the European single market, also known as the common or internal market. The aim is to ensure the four freedoms: free movement of goods, free movement of capital, freedom to establish and provide services, and free movement of labor (Mariniello *et al.*, 2015). Multinational organizations should be interested in understanding which countries are preferable for implementation of these technologies and to identify factors that may drive a more positive sentiment amongst the workforces. Dutch organizations will benefit from a deeper understanding of their Dutch employees' perceptions, while multinational Dutch organizations can critically assess to which extend they assumed homogeneity among their European or global workforce in comparison to Dutch employees. Dutch managers can reflect on the potential discrepancies between their own perceptions and those of their subordinates and consider how such differences may impact organizational effectiveness. Policy makers both on the European and national levels may also benefit from the insights of this research.

1.3 Thesis structure

Hereafter, the research paper will introduce the foundational literature and theory, followed by the methodology and descriptive statistics, thereafter the data analysis and results will be discussed, concluding with the discussion section.

2. LITERATURE REVIEW

In the following subsections literature will be discussed that forms the foundation on which this research has been build. Evaluating the insights and findings to contextualize them within the framework of this thesis, thereby creating an understanding of the current research.

2.1 Job insecurity

Academics have formulated numerous definitions of job insecurity, the following are a few of these definitions. Greenhalgh & Rosenblatt (1984) state, "powerlessness to maintain desired continuity in a threatened job situation" (p. 438). Heany, Israel, & House (1994) state, "an employee's perception of a potential threat to continuity in his or her current job" (p. 1431), and Rosenblatt & Ruvio (1996) state. "an overall concern about the future existence of the job" (p. 587). With these definitions in mind, sections 2.2 and 2.3 delve into the literature that interacts with job insecurity at both the national and individual levels.

2.2 National level & job insecurity

National differences on perceptions of job insecurity can be viewed along macroeconomic and institutional conditions (Dekker *et al*., 2017). Research on job insecurity has founded that perceived job insecurity is higher within an insecure macroeconomic climate. There are several key indicators to explain this phenomenon. The first key indicator is economic growth. It has been found that growth in GDP: gross domestic product, has a negative relationship with respect to the perception of job insecurity (e.g. Lübke & Erlinghagen, 2014). This is no surprise because a healthy and growing economy is associated with better economic opportunities in the area of employment. Therefore, a more optimistic sentiment is to be expected. Moreover, the second key indicator according to the literate is unemployment rate. Employees in countries that experience high unemployment rates are more insecure (e.g. Green, 2006; Chung & van Oorschot, 2011). This research on the general interaction between job insecurity and macroeconomic conditions can be used to indicate job insecurity that is related to increased robotization and the implementation of artificial intelligence in the area of work within the national context. This national context is very relevant to this research, as the aim is to confirm and contextualize a phenomenon of nationality, in this case the Dutch.

Institutional security seems to be a logical condition for people to adapt more easily to novel situations within the labor market. The available literature suggests that there are various arrangements of institutional protection for employees from market forces. According to Dekker, Salomons, & van der Waal (2017), "Three important sources of such protection are (a) the generosity of unemployment benefits, (b) the level of employment protection legislation (EPL) and (c) trade union density" (p. 543). This seems to be logical, as these three sources come together in the so-called 'social safety net'. In relation to this and source a, research has found that people in conditions with higher levels of public social expenditure note less-subjective job insecurity (Mau *et al.*, 2012). With respect to points b and c, laying off workers tends to be more difficult within a context of a high level of employment protection legislation and more powerful trade unions. Strong unions reduce total unemployment compared to systems with weak collective bargaining (Leibrecht *et* al., 2023). Moreover, this is also the case with higher trade union density (Sverke et al., 2006; Esser & Olsen, 2012; Dixon *et al*., 2013). The effect of employment protection legislation has been studied by Anderson and Pontusson (2007), who found that countries with higher levels of employment protection legislation have workers that experience lower levels of job insecurity. The data analysis will not include various variables discussed above, such as the generosity of unemployment benefits, the level of employment protection legislation, union strength and density due to the lack of such variables within the data set. Although it seems to be very likely that in the case of the Netherlands, these variables have significant impact. These findings on the effect of institutional security on job insecurity are attributed to differences in labor markets (e.g. Gallie, 2007) and institutional design of welfare states (e.g. Esping-Andersen, 2000). Again, this general interaction between job insecurity and institutional security can be used to explain job insecurity which is related to increased robotization and the implementation of artificial intelligence in the area of work within the national context. Although not part of the model, the effect of institutional security on job insecurity is highly relevant for the contextualization of the results from the analysis.

2.2.1 Hypothesis 1

Based on the research gap and the foundational literature above the following hypothesis was formulated: "There is a significant effect of being Dutch on the likelihood of disagreeing with the statement: 'Robots and artificial intelligence steal peoples' jobs.'"

2.3 Individual-level & job insecurity

Socio-professional categories relate to one's occupation and place in society, and therefore, one's individual-level economic position. According to research, men, full-time employed workers, the higher educated, and managers note lower levels of subjective job insecurity in comparison to their female, part-time workers, the lower educated, and nonmanager counterparts

(Green, 2009; Mau *et al*., 2012). This seems logical when you examine what these differences entail; the distinction between the abovementioned groups; they can be summed up as their different labor market position. According to Dekker et al. (2017), "Those in stronger labor market positions report lower levels of subjective job insecurity...their labor contracts are more secure and they are...better able to retain their jobs...when those in a strong labor market position become unemployed, they find a new job relatively easily" (p. 542). This is in line with the research on macroeconomic conditions; the perception or reality of a good economic position positively influences perceived job insecurity. This general interaction between individual-level economic position and job insecurity can be used to explain job insecurity in relation to both robots and artificial intelligence in the context of this study. These individual characteristics that influence perceived job insecurity are highly relevant for this research, as the variables of managers, and nonmanagers are part of the of the regression analysis. The literature on managers is especially relevant for this research due to the emphasis on the interaction effect of being a Dutch manager.

2.4 Individual-level & fear of robots

As described in 1921 for the first time, "Robots are machines that can navigate through and interact with the physical world of factories, warehouses, battlefields and offices" (Brynjolfsson & McAfee, 2014, p. 27). The fear of robots, sometimes coined as 'Robophobia,' describes negative associations and feelings, mostly fear, towards robots and its related technologies (Greatz & Michaels, 2018). Besides individual-level economic position, other individual-level variables are relevant for this research. For example, personal experience with robots; the fear of robots in the workplace decreases due to prior exposure to robots (e.g. Nomura *et al*., 2006; Bartneck *et al*., 2007). Also, perceived robot suitability to one's occupational field and openness are two factors positively associated with positive attitude towards assistive robots (Lakitta *et al*., 2023). Lastly, age and gender influence individuals' perception towards robots (e.g. Enz *et al*., 2011; Heerink, 2011). Specifically, female gender was associated negatively with perceived robot usefulness (Lakitta *et al*., 2023). According to Hinks (2020), "a fear of robots does significantly correlate with a lower life satisfaction" (p. 335). The various individual level characteristics above, such as experience with robots, age, gender, and life satisfaction are very relevant for this research to contextualize the apparent Dutch effect within a multivariate analysis. All these variables are present within the data set and will be discussed in the third section of this paper below.

2.4.1 Hypothesis 2

On the basis of the research gap and the foundational literature above, the following hypothesis was formulated: "There is a significant positive interaction effect of being a Dutch manager, in contrast to the European Union average manager, on the likelihood of disagreeing with the statement: 'Robots and artificial intelligence steal peoples' jobs.'"

3. METHODOLOGY AND DESCRIPTIVE STATISTICS

3.1 Data source

As mentioned within the introduction, this research utilizes data provided by the European Commission in the form of the Eurobarometer survey 460: Attitudes towards the Impact of Digitalization and Automation on Daily Life. This survey was carried out by TNS Political & Social network in the 28 Member States of the European Union between the 18th and 27th of March 2017. In total, 27,901 EU citizens from various social and demographic backgrounds were interviewed face-to-face, in their native language, at home. The following is the definition of a robot that was provided to the respondents by the conductor of the survey, "A robot is defined as a machine which can assist humans in everyday tasks without constant guidance or instruction, e.g. as a kind of co-worker helping on the factory floor or as a robot cleaner, or in activities which may be dangerous for humans, like search and rescue in disasters. Robots can come in many shapes or sizes and some may be of human appearance. Traditional kitchen appliances, such as a blender or a coffee maker, are not considered as robots" (European Commission, 2017, p. 120).

Hereafter follows the definition of artificial intelligence given by the conductor of the survey, "Artificial Intelligence (AI) is a term used to describe systems that, to some extent, can sense, perceive, think and act like humans and behave rationally. Artificial Intelligence is used, for instance, in driverless cars or drones, in our homes to adjust the heating automatically, in healthcare to improve medical diagnoses and in farming to apply pesticides only where they are absolutely necessary" (European Commission, 2017, p. 120).

3.2 Variables & descriptive statistics

This research paper revolves around question d12_6 of the Eurobarometer survey, where respondents' self-asses their level of agreement to the statement: "Robots and artificial intelligence steal peoples' jobs." This question of the survey is the dependent variable of this research paper. Responses are given within five categories of agreement: totally agree, tend to agree, tend to disagree, totally disagree, and don't know. Within this analysis the responses of don't know are coded as missing values. This variable is coded as ordinal. Table 1 below gives an overview of the frequencies, and percentages belonging to the various categories of agreement on the variable, with a median in the second category of agreement: tend to agree.

Table 1

ROBOTS/AI: STEAL JOBS	*Frequency*	*Percentage*	*Cum.*
Totally agree	7,808	35.98	35.98
Tend to agree	8,025	36.98	72.97
Tend to disagree	3,950	18.20	91.17
Totally disagree	1,193	5.50	96.67
Don't know	723	3.33	100.00
Total	21,699	100.00	

3.2.1 Control variables

The first of two control variables, also a demographic/descriptor variable, is d11. Respondents are asked the following question: "How old are you?" This is coded as a continuous variable ranging from 15 until 67 years old, because the Dutch age of retirement is at 67 years old. The variable of age as mentioned has been restricted to include the working population, 15 through 67. The central tendency and dispersion of the variable is the following: a mean of 44.60, a median of 46, and a standard deviation of 14.57.

The second of the two control variables, this is again a demographic/descriptor variable, is question d10 of the survey. Respondents are categorized by gender into two groups: women and men. The categorical binary dummy variable is coded with woman being 0, and men being 1. Table 2 below provides an overview of the frequencies, and percentages belonging to the categorical binary variable of 'Gender.'

Table 2

GENDER	*Frequency*	*Percentage*	*Cum.*
Women	11,931	54.98	54.98
Men	9,768	45.02	100.00
Total	21,699	100.00	

3.2.2 Independent variables

The first independent variable is a question of the survey, question 1. Respondents are asked: "What is your nationality? Please tell me the country(ies) that apply(ies)." Variable q1_10 are the respondents that answered the Netherlands. This is coded as a binary dummy variable with not mentioned as 0 and mentioned as 1. There are 831 respondents with Dutch nationality. This allows for the testing of the first hypothesis, which predicts that there is a significant effect of being Dutch on the likelihood of disagreeing with the abovementioned statement.

The second independent variable is the occupation of respondents, which is scaled into different categories. The categories relevant for this study are managers, other white-collars and manual workers. These categories are made up of various occupations. Managers are made up of the employed professional, general management, and middle management. Other white collars are made up of the employed position at desk, and the employed position while travelling. Manual workers are made up of the employed position service job, supervisor, skilled manual worker, and the unskilled manual worker. These are coded as qualification dummies with 0 being unmentioned and 1 being mentioned. Henceforth, there are three variables of socio-professional category: 'Manager', 'White-collar', and 'Manual worker'. This allows for the testing of the second hypothesis, which predicts that there is a significant positive interaction effect of being a Dutch manager on the likelihood of disagreeing with the abovementioned statement in contrast to the EU average manager. Table 3 below provides an overview of the frequencies, and percentages belonging to the categorical dummy variables of the three socio-professional categories: managers, white-collar workers and manual workers.

Table 3

MANAGER	*Frequency*	*Percentage*	*Cum.*
0	18,750	86.41	86.41
1	2,949	13.59	100.00
Total	21,699	100.00	
WHITE-COLLAR	Frequency	Percentage	Cum.
0	18,495	85.23	85.23
1	3,204	14.77	100.00
Total	21,699	100.00	
MANUAL WORKER	Frequency	Percentage	Cum.
0	16,484	75.97	75.97
1	5,215	24.03	100.00
Total	21,699	100.00	

The third independent variable is a question of the survey, question d12_1. Respondents are asked to self-asses their level of agreement to the statement, "Due to the use of robots and artificial intelligence, more jobs will disappear than new jobs will be created." Responses are given in five categories; totally agree, tend to agree, tend to disagree, totally disagree, and don't know. This is coded as an ordinal variable, don't know responses are coded as missing values. Table 4 below provides an overview of the frequencies and percentages belonging to the various categories of agreement for the variable, with a median in the category: tend to agree.

Table 4

ROBOTS/AI: JOBS NET LOSS	*Frequency*	*Percentage*	*Cum.*
Totally agree	8,307	38.28	38.28
Tend to agree	8,060	37.14	75.43
Tend to disagree	3,389	15.62	91.05
Totally disagree	897	4.13	95.18
Don't know	1,046	4.28	100.00
Total	21,699	100.00	

The fourth independent variable is a question of the survey, question d8. Respondents are asked: "Have you ever used or do you currently use a robot at home or at work." The variable qd8_2 captures the answers of yes, at work. Coded as a categorical binary dummy variable with not mentioned as 0, and yes, at work as 1. Table 5 below gives an overview of frequencies, and percentages belonging to the binary variable of 'Robot used at work'.

Table 5

ROBOTS USED: AT WORK	*Frequency*	*Percentage*	*Cum.*
Not mentioned	20,400	94.01	94.01
Yes, at work	1,299	5.99	100.00
Total	21,699	100.00	

The fifth variable is again a question of the survey, question d9. Respondents are asked the following question: "In the last 12 months, have you heard, read or seen anything about artificial intelligence?" The categorical binary dummy variable is coded as yes being 0 and no being 1. Table 6 below gives an overview of the frequencies, and percentages belonging to the variable of 'Read about AI'.

Table 6

READ ABOUT: AI	*Frequency*	*Percentage*	*Cum.*
Yes	10,635	49.01	49.01
No	10,766	49.62	98.63
Don't know	298	1.37	100.00
Total	21,699	100.00	

The sixth variable is a demographic/descriptor question of the survey, d70. Respondents are asked the following question: "On the whole, are you very satisfied, fairly satisfied, not very satisfied, or not at all satisfied with the life you lead?" This is coded as an ordinal variable scaled from one to four, with four being not at all satisfied. The fifth option of don't know are coded as missing values. Table 7 below gives an overview of the frequencies, and percentages belonging to the variable of 'Life satisfaction'. With a median in the category: fairly satisfied.

Table 7

LIFE SATISFACTION	*Frequency*	*Percentage*	*Cum.*

Very satisfied	5,265	24.26	24.26
Fairly satisfied	12,418	57.23	81.49
Not very satisfied	3,203	14.76	96.25
Not at all satisfied	700	3.23	99.84
Don't know	113	0.52	100.00
Total	21,699	100.00	

This variable is also a demographic/descriptor question of the survey, d63. Respondents are asked the following question: "Do you see yourself and your household belonging to…?" Self-assessing themselves into the following options: the working class of society, the lower middle class of society, the upper middle class of society, and the higher class of society. This is coded as an ordinal variable scaled numerically from one to four, with four being the upper class of society. The answers of other, none, refusal, and don't know are coded as missing values. Table 8 below gives an overview of the frequencies, and percentages belonging to the various categories of 'Social class'. With a median in the category: The middle class of society.

Table 8

SOCIAL CLASS: SELF-ASSESMENT	*Frequency*	*Percentage*	*Cum.*
Working class	5,545	25.55	25.55
Lower middle class	3,551	16.36	41.92
Middle class	10,092	46.51	88.43
Upper middle class	1,465	6.75	95.18
Higher class	149	0.69	95.87
Other	879	4.13	100.00
Total	21,699	100.00	

3.3 Analytical approach

The data analysis of this research has been conducted with the use of StataSE edition 18.5 statistical software (StataCorp, 2024). The dependent variable is ordinal, as stated in section 3.2 of this paper. The basic assumption of standard ordinal regression models is met; the dependent variable behaves in an ordinal fashion with each predictor (Harrell, 2015, p. 312). Therefore, an ordinal logistic regression model is suitable.

Traditional models like the 'ologit' command in StataSE rely on the proportional odds assumption: the relationship between the predictor variables and the log odds of being in a higher category versus all lower categories is constant across all category thresholds. This assumption was violated when conducting the analysis using the 'ologit' command. The 'gologit2' command in Stata allows for relaxation of this assumption, it can be configured to allow predictor variables to vary in their effect across categories. Thus a 'gologit2' model is used to conduct this analysis. William (2006) states, "gologit2 is a user-written program that estimates generalized ordered logit models for ordinal dependent variables" (p. 1). The Stata command 'gologit2' is the second version of the generalized ordinal logistic regression model. The first 'gologit" command was written by Vincent Kang Fu of the Utah Department of Sociology (Williams, 2006).

The primary issue with respect to the default 'gologit/'gologit2' model is that these models include possibly more parameters then necessary in comparison to the 'ologit' model. This is due to the fact that these methods free all variables from the abovementioned assumption. The 'autofit' feature of 'gologit2' allows for the relaxation of this assumption only for the variables that violate the proportional odds assumption, this is then referred to as a partial proportional odds model (Williams, 2006). Therefore the option of 'autofit' has been applied.

Within this analysis there are three cumulative thresholds or cut points for the ordinal categories ranging from 'totally agree' to 'totally disagree'. The first threshold examines the likelihood of being in a higher category than 'totally agree'. The second threshold examines the likelihood of being in a higher category than 'totally agree' and 'tend to agree'. The third threshold examines the likelihood of being in a higher category than 'totally agree', 'tend to agree', and 'tend to disagree'. This approach captures the possible varying effects across categories, providing a more nuanced understanding of the data, while enhancing the robustness of the findings (Williams, 2006).

4. DATA ANALYSIS AND RESULTS

The three tables below, Tables 9,10, and 11 present the results of the 'gologit2' partial proportional odds model regression analysis, conducted based on the methodology and descriptive statistics mentioned in section 3. Each table represents a cut point within the cumulative logit model. The first cumulative threshold, represented by Table 9, examines the variables influencing the likelihood of being in a higher category than 'totally agree'. The second cumulative threshold, represented by Table 10, examines the variables influencing the likelihood of being in a higher category than 'totally agree' and 'tend to agree'. Lastly, the third cumulative threshold, represented by Table 11, examines the variables influencing the likelihood of being in a higher category than 'totally agree', 'tend to agree', and 'tend to disagree'. Significant results will be reviewed, calculated, and compared with previous tables, to provide an overview of the changes between the cumulative thresholds.

Table 9

ROBOTS &AI: STEAL PEOPLES JOBS	*Coefficient*	*Std. Error*	*P>|z|*	*95% CI*
Totally agree				
Age	-.003	.001	0.041	-0.008 -0.003
Gender	.106	.029	**0.000 *** **	.048 .164
Being Dutch	.628	.139	**0.000 *** **	.356 .899
Manager	.248	.059	**0.000 *** **	.133 .364
Dutch-Manager	.610	.211	**0.004 ** **	.197 1.023
White-Collar	.157	.053	**0.003 ** **	.052 .261
Dutch White-Collar	.284	.202	0.161	-.113 .680
Manual worker	-.055	.038	0.145	-.129 .019
Dutch manual worker	.407	.214	0.057	-.013 .827

Jobs net loss	1.969	.031	**0.000** ***	1.909 2.030
Robots used at work	.221	.029	**0.000** ***	.103 .338
Read about AI	-.285	.031	**0.000** ***	-3.445 -.225
Life satisfaction	-.120	.026	**0.000** ***	-.224 -.098
Social class	.146	.016	**0.000** ***	.114 .179
_Cons	-2.469	.113	**0.000** ***	-5.029 -4.505

**** and **. Coefficients are statistically significant at 0.001 and 0.01 respectively*

4.1.1 Significant coefficients & odds ratios from Table 9: the likelihood of being in a higher category than 'totally agree'

The predictor variable of 'Being Dutch', for the cumulative threshold of being in a higher category than 'totally agree', has a statistically highly significant coefficient of 0.628 ($p < 0.001$). The odds ratio is calculated as: $e^{.628} = 1.874$, meaning that for each one-unit increase in the predictor variable, the odds of being in a higher category increase by 87.4%. The predictor variable of 'Manager' has a has a highly significant coefficient of .248 ($p < 0.001$). with an odds ratio of $e^{.248} = 1.281$, this means that for every one-unit increase in the variable, the odds of being in a higher category increase by 28.1%. The predictor variable of the interaction effect of 'Dutch-Manager' has a very significant coefficient of .610 ($p < 0.01$). The odds ratio is the following: $e^{.610} = 1.841$, meaning that for each one-unit increase of the predictor variable, the odds of being in a higher category increase by 84.1%. The predictor variable of 'White-Collar' has a very significant coefficient of .157 ($p < 0.01$). With an odds ratio of, $e^{.157} = 1.170$, meaning that for every one-unit increase in the variable, the odds of being in a higher category increase by 17%.

The following are other independent variables included in the analysis that might explain and contextualize perceptions towards robots and artificial intelligence stealing peoples' jobs within the first cumulative threshold. The variable of 'Gender', men, has a highly significant coefficient of .106 ($p < 0.001$). With the following odds ratio, $e^{.106} = 1.112$, this means that for every one-unit increase of the variable, the odds of being in a higher category increase by 11.2%. 'Job net loss' is the variable attached to survey question d12_1 in section 3.2.2. With a highly significant coefficient of 1.969 ($p < 0.001$), $e^{1.969} = 7.163$. For each one-unit increase in the variable, the odds of being in a higher category increase by 616.3%. 'Robots used at work' refers to question d8 in section 3.2.2 and has a highly significant coefficient of .221 ($p < 0.001$), $e^{.221} = 1.247$. Each one-unit increase in the variable increase the odds of being in a higher category by 24.7%. Not having 'Read about AI 'refers to question d9 in section 3.2.2, with a highly significant coefficient of -.285 ($p < 0.001$). $e^{-.285} = 0.752$, for every one-unit increase in the variable the odds of being in a higher category decrease by 24.8%. 'Life satisfaction' has a highly significant coefficient of -.120 ($p < 0.001$). Not at all being satisfied has an effect of $e^{-.120} = 0.887$, meaning that for every one-unit increase the odds of being in a higher category decrease by 11.3%. Concluding with the variable of 'Social class' which refers to question d70 of the survey. Being in the higher class of society has a highly significant coefficient of .146 ($p < 0.001$), $e^{.146} = 1.157$. This means that with every one-unit increase the odds of being in a higher category increase by 15.7%

Table 10

ROBOTS &AI: STEAL PEOPLES JOBS	*Coefficient*	*Std. Error*	*P>|z|*	*95% CI*
Tend to agree				
Age	-.005	.001	**0.000** ***	-.008 -.003
Gender	.106	.029	**0.000** ***	.048 .164
Being Dutch	.754	.124	**0.000** ****	.510 .998
Manager	.168	.060	**0.005** **	.051 .284
Dutch-Manager	.610	.211	**0.004** **	.197 1.023
White-Collar	-.003	.060	0.962	-.121 .115
Dutch White-Collar	.284	.202	0.161	-.113 .680
Manual worker	-.055	.038	0.145	-.129 .019
Dutch manual worker	.407	.214	0.057	-.013 .827
Jobs net loss	1.956	.032	**0.000** ***	1.894 2.018
Robots used at work	.221	.060	**0.000** ***	.103 .338
Read about AI	-.285	.031	**0.000** ***	-.345 -.225
Life satisfaction	-.161	.032	**0.000** ****	-.224 -.098
Social class	.146	.016	**0.000** ***	.114 .179
_Cons	-4.767	.134	**0.000** ***	-5.028 -4.505

**** and **. Coefficients are statistically significant at 0.001 and 0.01 respectively*

4.1.2 Significant coefficients & odds ratios from Table 10: the likelihood of being in a higher category than 'tend to agree'

The predictor variable of 'Being Dutch', for the cumulative threshold of being in a higher category than 'totally agree' and 'tend to agree', has a statistically highly significant coefficient of .754 ($p < 0.001$), with an odds ratio of $e^{.754} = 2.126$, this means that for each one-unit increase of the variable the odds of being in a higher category increase by 112.6%, a substantial increase of 25.2 percentage points in comparison to Table 9. The predictor variable of 'Manager' has a very significant coefficient of .168

(p <0.01). The odds ratio is calculated as $e^{.168} = 1.183$, this means that for each one-unit increase in the variable, the odds of being in a higher category increase by 18.3%. The predictor variable of the interaction effect of being a 'Dutch-Manager' has a very significant coefficient of .610 (p < 0.01), with and odds ratio of $e^{.610} = 1.841$, this means that for each one-unit increase of the predictor variable the odds of occurring increase by 84.1%.

Again, reviewing the results of the other independent variables included in the analysis that might explain and contextualize perceptions towards robots and artificial intelligence stealing peoples' jobs. The variable of 'Age' has a highly significant coefficient of -.005 (p < 0.001), $e^{-.005} = 0.995$, this means that for every on-unit increase of the variable, the odds of being in a higher category decrease by 0.5%. The variable of 'Gender', men, has a highly significant coefficient of .106 (p < 0.001). With the following odds ratio, $e^{.106} = 1.112$, this means that for every one-unit increase of the variable, the odds of occurring increase by 11.2%. No change in comparison to Table 9. The variable of 'Job net loss' has a highly significant coefficient of 1.956 (p < 0.001), $e^{1.956} = 7.073$. For each one-unit increase in the variable the odds of being in a higher category increase by 607.3%. This is a slight decrease in comparison to Table 9, with 9 percentage points. 'Robots used at work' has a highly significant coefficient of .221 (p < 0.001), $e^{.221} = 1.247$. Each one-unit increase in the variable increase the odds of being in a higher category by 4.7%, this is as strong of an effect in comparison to the previous table. Not having 'Read about AI' refers to question d9 in section 3.2.2, with a highly significant coefficient of -.285 (p < 0.001), $e^{-.285} = 0.752$, for every one-unit increase in the variable the odds of being in a higher category decrease by 24.8%. As strong of an effect compared to the previous table. 'Life satisfaction' refers to the variable of question d63 in section 3.2.2 and has a highly significant coefficient of -.161 (p < 0.001). Not at all being satisfied has an effect of $e^{-.161} = 0.851$, this means that for every one-unit increase the odds of being in a higher category decrease by 14.9%, a change of 3.6 percentage points compared to Table 9. Concluding with the variable of 'Social class' which refers to question d70 of the survey. Being in the higher class of society has a highly significant coefficient of .146 (p < 0.001), $e^{.146} = 1.157$. This means that with every one-unit increase the odds of being in a higher category increase by 15.7%. No change in comparison to the previous table.

Table 11

ROBOTS &AI: STEAL PEOPLES JOBS	*Coefficient*	*Std. Error*	*P>|z|*	*95% CI*
Tend to disagree				
Age	.001	.002	.0592	-.003 .006
Gender	.106	.029	**0.000** ***	.048 .164
Being Dutch	.097	.159	0.541	-.214 .409
Manager	-.082	.095	0.386	-.267 .103
Dutch-Manager	.610	.211	**0.004** **	.197 1.023
White-Collar	-.176	.103	0.090	-.378 .027
Dutch White-Collar	.284	.202	0.161	-.113 .680
Manual worker	-.055	.038	0.145	-.129 .019
Dutch manual worker	.407	.213	0.057	-.013 .827
Jobs net loss	1.777	.045	**0.000** ***	1.689 1.865
Robots used at work	.221	.060	**0.000** ***	.103 .339
Read about AI	-.285	.031	**0.000** ***	-.345 -.225
Life satisfaction	-.302	.054	**0.000** ***	-.408 -.196
Social class	.146	.016	**0.000** ***	.114 .179
_Cons	-6.624	.212	**0.000** ***	-7.040 -6.209

**** and **. Coefficients are statistically significant at 0.001 and 0.01 respectively*

4.1.3 Significant coefficients & odds ratios from Table 11: the likelihood of being in a higher category than 'tend to disagree'

The predictor variable of the interaction effect of being a 'Dutch-Manager' for the cumulative threshold of being in a higher category than 'totally agree', 'tend to agree', and 'tend to disagree', has a statistically very significant coefficient of .610 (p < 0.01), with an odds ratio of $e^{.610} = 1.841$, this means that for each one unit increase of the predictor variable the odds of being in a higher category increase by 84.1%.

Lastly, looking at the results of the independent variables included in the analysis that might explain and contextualize perceptions towards robots and artificial intelligence stealing peoples' jobs within the third threshold. The variable of 'Gender', men, has a highly significant coefficient of .106 (p < 0.001). With the following odds ratio, $e^{.106} = 1.112$, this means that for every one-unit increase of the variable, the odds of occurring increase by 11.2%. No change in comparison to Tables 9 and 10. The variable of 'Job net loss' has a highly significant coefficient of 1.777 (p < 0.001), $e^{1.777} = 5.916$. For each one-unit increase in the variable the odds of being in a higher category increase by 491.6%. This is a substantial decrease in comparison to Table 10 of 115.7 percentage points and 124.7 percentage points when compared to Table 9. 'Robots used at work' has a highly significant coefficient of .221(p < 0.001), $e^{.221} = 1.247$. Each one-unit increase in the variable increase the odds of being in a higher category by 24.7%, this is again as strong of an effect in comparison to the previous tables. Not having 'Read about AI' refers to question d9 in section 3.2.2 and has a highly significant coefficient of -.285 (p < 0.001). $e^{-.285} = 0.752$, for every one-unit increase in the variable the odds of being in a higher category decrease by 24.8%. Again, as strong of an effect in comparison to the previous tables. 'Life satisfaction' refers to the variable of question d63 in section 3.2.2 and has a highly significant coefficient of -.302 (p < 0.001). Not at all being satisfied has an effect of $e^{-.302} = 0.739$, meaning that for every one-unit

increase the odds of being in a higher category decrease by 26.1%, a significant change of 11.2 percentage points when compared to Table 10 and a change of 14.8 percentage points in comparison to Table 9. Concluding with the variable of 'Social class', which refers to question d70 of the survey. Being in the higher class of society has a highly significant coefficient of .146 ($p < 0.001$), $e^{.146} = 1.157$. This means that with every one-unit increase the odds of being in a higher category increase by 15.7%. No change in comparison to both of the previous tables.

5. DISCUSSION

The objective of this research paper is to confirm and contextualize the existence of a Dutch effect within the Eurobarometer survey 460: Attitudes towards the Impact of Digitalization and Automation on Daily Life, emphasizing the interaction effect of being a Dutch manager. This was done by reviewing current literature and analyzing the data set provided by the European Commission through a 'gologt2' regression analysis. Researching the following question: "Is there a significant effect of being Dutch on the likelihood of disagreeing with the statement: 'Robots and artificial intelligence steal peoples' jobs,' and how does this effect manifest across the different socio-professional categories, with an emphasis on Dutch managers compared to the other EU respondents?" Two hypotheses were formulated, H1: "There is a significant effect of being Dutch on the likelihood of disagreeing with the statement: 'Robots and artificial intelligence steal peoples' jobs.'" And the second hypothesis, H2: "There is a significant positive interaction effect of being a Dutch manager, in contrast to the European Union average manager, on the likelihood of disagreeing with the statement: 'Robots and artificial intelligence steal peoples' jobs.'"

5.1 Conclusion

The first hypothesis has been confirmed within the model based on the data set. Having the Netherlands mentioned as nationality; in other words, being Dutch has a highly significant effect both in the first cumulative threshold and the second. With regards to the first cut point the odds of being in a higher category increase by 87.4%, the second cut point the odds of being in a higher category increase by 112.6%, a 25.2 percentage point increase between the two thresholds. Thus, being Dutch is a significant predictor variable for the first level of disagreement to the statement: "Robots and artificial intelligence steal people's jobs."

This is in line with the foundational literature discussed in section 2.2 national differences and job insecurity, as countries with higher levels of employment protection legislation have workers that experience lower levels of job insecurity (Anderson & Pontusson, 2007). The Netherlands scored 2.88 which is around the average of 2.53 (Dekker *et al*., 2017). Workers in countries with high unemployment rates are more insecure (e.g. Green, 2006; Chung & van Oorschot, 2011). As of January 2024, the Netherlands had an unemployment rate of 3.6 compared to the EU average of 6.0 (Eurostat, 2024). This significantly lower employment rate in the Netherlands is likely to be part of the puzzle of the positive Dutch perception and would be in line with the research discussed within the literature review. In relation to the GDP growth there is also a case to make that the GDP itself has an effect on perceived job insecurity. The GDP per capita, adjusted for price differences of the Netherlands was 45,000.00 Euros in 2022 compared to the EU average o 35,200.00 Euros (CBS, 2024). The Netherlands within that list ranks as the fourth richest country in the Union. The assumption is that the Dutch effect found in the survey is not a coincidental snapshot, therefore the different years than 2017 with respect to the abovementioned Dutch statistics are justified within this research.

The second hypothesis has also been confirmed within the model based on the data set. The interaction effect of 'Dutch Manager' has a very significant coefficient through all three cumulative thresholds represented by Tables 9,10, and 11 in section 4. The odds of being in a higher category than 'totally agree' increase by 84.1% ($p < 0.01$). The odds of being in a higher category than 'totally agree' and 'tend to agree' increase again by 84.1% ($p < 0.01$). Lastly the odds of being in a higher category than 'totally agree', 'tend to agree', and 'tend to disagree' increase by 84.1% ($p < 0.01$). However, the average European Union 'Manager' has only significant effects on the first two cut points by respectively 28.1% ($p < 0.001$) and 18.3% ($p < 0.01$). The contrast within the second hypothesis to the EU average managers has also been confirmed, as the effect is both less strong and does not sustain significance into the last threshold; 'totally disagree'. Furthermore, the variable of 'White-Collar' reports a significant effect only on the first cut point with 17% ($p < 0.05$) This was to be expected from the foundational literature on individual conditions and job insecurity. Managers' report lower levels of job insecurity than their non managing counterparts (Green, 2009; Mau *et al*., 2012). In addition, according to Dekker et al. (2017), "white-collar employees (such as office clerks), also feel threatened by the introduction of digital technologies such as robotics" (p. 551).

Besides the two hypotheses, the data analysis has also confirmed the previous written literature on job insecurity with regards to the other independent, and or control variables, giving context to the research question and the subsequent analysis. The predictor variable of totally disagreeing with 'Job net loss' as a result of robots and artificial intelligence has the strongest coefficient within the model. With the odds of being in a higher category increase by respectively 616.3, 607.3, and 491.6 percent ($p < 0.001$). The variable of 'Robots used at work' has a highly significant effect across all thresholds with the odds of being in a higher category increase by 24.7% ($p < 0.001$). This is in line with literature that has found that previous personal exposure towards robots decreases the fear of robots in the workplace (e.g. Nomura *et al*., 2006; Bartneck *et al*., 2007). In addition, not having heard, seen or 'Read about AI' in the last 12 months has a highly significant effect through all cut points with the odds of being in a higher category decrease by 24.8% ($p < 0.001$). 'Gender,' men, has a highly significant effect through all cumulative thresholds with the odds of being in a higher category increase by 11.2% ($p < 0.001$). This is again in line with gender influencing how people perceive robots (e.g. Enz *et al*., 2011; Heerink, 2011; Lakitta *et al*.,2023). The effect of not at all being satisfied with your life increases through the thresholds by respectively 3.6 and 11.2 percent ($p < 0.001$) this is in accordance with research as Hinks (2020) state, "a fear of robots does significantly correlate with a lower life satisfaction" (p. 335).

Within the scope of this research paper and the therefore created partial proportional odds model one can conclude that yes, there is a significant effect of being Dutch on the likelihood of disagreeing with the statement: "Robots and artificial intelligence steal peoples' jobs." With the variable being significant until 'tend to disagree'. This effect as an interaction effect with the various socio-professional categories only manifested among the Dutch managers, being significant at even the third cumulative threshold of 'totally disagree' whereas the average European Union manager only reports significance up until 'tend to disagree'. Therefore, the average Dutch manager is more likely to disagree than the average EU manager and Dutch respondent within the context of the model.

5.2 Implications

5.2.1 Theoretical

This research is in accordance with the previous literature addressed within this research. With respect to the variables analyzed in the "gologit2' model no diversion from existing research has been found. This thesis builds on the previous research conducted using the 2012 and 2014 Eurobarometer surveys due to the inclusion of artificial intelligence that was part of the 2017 survey. Insights such as the highly significant negative effect of not having heard, read or seen anything about artificial intelligence in the last 12 months adds to the broader findings that previous experience with and exposure to robots reduces the fear of robots in the workplace (e.g. Nomura *et al*., 2006; Bartneck *et al*., 2007). Furthermore, the strongest predictor variable within the model; perceptions towards job net loss due to the implementation of robots and artificial intelligence contextualizes a key sentiment towards job insecurity in relation to these technologies.

A further addition to the broader research is the contextualization of the tendency to disagree among the Dutch sample size, with a special emphasis on its managers. This was done by incorporating variables understood to indicate national and individual differences towards job insecurity according to the literature. Together with other research into specific countries or groups of countries the effect of national differences and its interaction with job insecurity can be understood better in the context of increased robotization and the implementation of artificial intelligence within society, and especially in the realm of work.

5.2.2 Practical

The research conducted in this thesis can be helpful for policy and decision makers from both Dutch and international organizations, due to the insights gained by the multivariate analysis on the Eurobarometer survey data. The decision-makers of Dutch organizations and international organizations active in the Netherlands can benefit from the insights of this research, due to having a better understanding to what level and how strong their Dutch employees disagree with robots and artificial intelligence stealing peoples' jobs. The distinction between the various socio-professional categories allows for a more nuanced perspective on this general Dutch effect of disagreement. Dutch and other organizations that employ workers from within the European Union need to be aware of the differences between the various groups, in order to avoid misjudgment on assumed homogeneity.

Dutch Managers can benefit from reflecting on their own perceptions in comparison to their subordinates, recognizing whether they have generalized their own stance onto the rest of the employees at their respective organizations. This understanding within the context of the analysis can aid organizational effectiveness, by managing the current sentiment among the workforce when artificial intelligence within most organizations is more idea and less practice, yet still impactful due to the job insecurity that already comes with it, as well as managing future implementation of artificial intelligence within the workplace. Dutch policymakers can keep this Dutch effect in mind when they create national policies and when they negotiate on new European policy with respect to increased robotization and implementation of artificial intelligence within the wider European society, and the realm of work within the European single market. Therefore, international and other European policy makers can keep this phenomenon in mind when they are creating and negotiating with the Dutch on international and European policy.

5.3 Limitations

The major limitation of this bachelor's thesis is the period in which the survey was conducted: March of 2017. Although close enough in time to be relevant for today's world, a recent survey would give more topical insights on the current sentiment on the impact of digitalization and automation on daily life. The questions and demographic/descriptor variables used in this research were formulated and chosen by a secondary party, commissioned by the European Commission. Due to the secondary nature of the data, this research was limited by the provided data. Associations and relationships between previous research and between the previous literature and this research ought to be interpreted as observational and not implying causation. The relative newness of artificial intelligence technologies impacting our daily, and especially work life, has meant that there is limited literature on these technologies in this context, therefore further research is imperative.

5.4 Future research

There ought to be an increase in research on artificial intelligence and its current and potential impact on society. Further research into national differences and perceptions towards automation technologies is necessary to provide policy makers and decision-makers within European and national organizations with the information on which effective, and ethical decisions can be made. Research like this thesis on each country within the EU would add significant value to the proper and effective implementation of these technologies within the single market.

National differences aside, within any society, there is a form of socio-economic/professional hierarchy that will have an effect to which degree someone will be impacted by these changes, that increased robotization and the implementation of current and future artificial intelligence will bring. Therefore, further research into individual fears and drivers with regards to artificial intelligence within the workplace is necessary to fill in the gaps that national differences cannot explain. Transnational research on the industry level within the common market, especially industries prone to automation would be insightful, as those findings are not captured by national and individual differences.

It would be very useful and informative if the soon-to-be newly formed European Commission will commission a new Eurobarometer survey on the impact of digitalization and automation on daily life, allowing researchers to follow up on the 2017 survey data. Together with the 2012 and 2014 survey data, trends and relationships can be observed to establish a clearer understanding of the impact of these technologies over time. Due to the fast pace of the developments within the realm of AI, it would be wise to increase the frequency of these surveys to capture the valuable information necessary for informed and proper policy. As the European Union sets standards to which all participants involved with the single market need to adhere to (Mariniello *et al.*, 2015), there is a unique opportunity to develop automation and AI policies which considers human welfare as the priority.

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