



Artificial Intelligence Perceptions and Life Satisfaction

Tim Hinks¹

Accepted: 19 December 2023
© The Author(s) 2024

Abstract

The paper estimates whether there is any relationship between life satisfaction and people's perceptions towards artificial intelligence. Using data from 39 European countries collected in 2021, it is consistently found that people with negative perceptions report lower life satisfaction. This finding is robust across a number of robustness checks. This provides further evidence that people may fear some new technologies, in this case artificial intelligence, which adds weight to governments needing to establish moratoriums to openly discuss what the objectives of new science, technologies and innovations are and how best to manage and steer policy and regulation to achieve these objectives.

Keywords Life satisfaction · Artificial intelligence and automation · Fear

JEL Classification O33 · I31 · C21

1 Introduction

Every day there are new revelations about what new scientific, technological and innovative (STI) developments can and will do and what this means for the economic landscape. As with previous technological upheavals, much of the focus is on labour markets implications.¹ Large firms are already expecting to make large-scale redundancies or cease hiring for certain roles as tasks become increasingly automated.² Research into the impact robots have had on labour markets paints a bleak picture of falling employment, falling wages

¹ Autor and Dorn (2013) more recent citations here show that computerisation eroded wages and labour relocated to largely low-skill/pay service occupations with evidence of a hollowing out of the middle-skilled occupations.

² IBM announced recently it will cease hiring for approximately 8,000 roles that it thinks can now be performed by artificial intelligence. British Telecommunications (BT) expects to reduce its workforce by 40 per

✉ Tim Hinks
timothy.hinks@uwe.ac.uk

¹ Bristol Research in Economics (BRE), University of the West of England, Coldharbour Lane, Bristol BS16 1QY, UK

and increasing wage inequality (Acemoglu & Restrepo, 2020; Graetz & Michaels, 2018; Dauth et al., 2021; Aksoy et al., 2021; de Vries et al., 2020). As yet it is less clear whether the increased adoption of robots has had any positive job creation effects through raising productivity of firms who adopt this technology or through a process of creative destruction. Researchers have now begun to shift attention towards blockchain, Big Data and artificial intelligence (AI). At this stage there is no hard data on what new STI are being adopted or the speed of adoption. This has resulted in a variety of methods and data being used to capture the impact of STIs on labour markets, with a particular focus on AI. Acemoglu et al. (2022) analyse the impact of AI on the labour demanded by AI-using firms in the US using different labour skills taxonomies and online job vacancy data. They find evidence that these firms have reduced their demand for labour, while there is a degree of AI substituting for tasks which can result in new tasks emerging for employees. They find no aggregate effect on wages or employment at industry or occupation-level. Other work uses information on labour-saving patents and taxonomies of skills to predict likely impacts on labour demand through substitutability (Mann and Püttmann, 2023; Montobbio et al., 2021) and finds consistent evidence of new STIs substituting for tasks and sometime occupations.

In contrast to these footprint-type methods, Babina et al. (2020) and Alekseeva et al. (2021) study the direct association between AI adoption and employment at firm and industry-level. Both find that in the US, larger firms benefit more from adopting AI. Babina et al. (ibid.) also find that firms with elements of market power (e.g. higher mark-ups, greater R&D intensity) are more likely to invest in AI and that these firms have higher rates of growth. Regarding labour demand the authors conclude those local labour markets with higher educated workforces and higher wages experience higher rates of AI-skill hiring, which means, *ceteris paribus*, increased inequality in labour markets.

Some work has also attempted to understand the impact new STI is having and will have on labour itself, with a focus on those most at risk and who require new training/re-training to compete or complement with new STI (Jaimovich et al., 2021; Illanes et al., 2018; Caselman & Satariano, 2019). Again, this is presently in its infancy with it being unclear what the quantity and quality of occupations and jobs will look like in the coming years. Workers who have been impacted by recent automation do not report their lives to be universally better or worse off, instead the impact of automation varies. Matching data from the General Society Survey on quality of work with O*NET data on tasks and occupations most at risk from automation, Nazereno and Schiff (2021) find some evidence that aspects of quality of work, such as job stress, are negatively impacted by risk of automation while other aspects (e.g. job satisfaction), are not. Previous research analysing the relationship between humans and machines has also found a negative effects on workers' mental wellbeing through acting as a stressor (Robelski & Wischniewski, 2018; Körner et al., 2019; Szalma & Taylor, 2011). Gornay and Woodard (2020) find evidence that jobs most at risk from automation are associated with lower job satisfaction in both the US and Europe although workers perceptions of the subjective worth of their job mitigate this association. Gihleb et al. (2022) argue that increased robot penetration creates pressure and fear in US workers that has detrimental effects on workers' mental health but that there is no relationship between robot penetration and mental health, job satisfaction and life satisfaction in Germany.

cent (55,000 jobs) by 2030. Wendy's fast-food chain is training voice-recognition AI to staff its drive-through outlets. AI is already being used to generate news content (e.g. VentureBeat).

Another aspect of this research that remains in its infancy is how people perceive the impact STI will have on them and others today and in the future. These perceptions and expectations of people with respect to new STI are an important area of research for several reasons. Firstly, these perceptions will determine how resistant or embracing workers will be to firms adopting STI (Bhargava et al., 2021). These perceptions may also determine which new training and skills are required for current and future workers. Thirdly, these perceptions will impact whether people want more or less regulation of new STI and people's preferences on other possible interventions (Busemeyer et al., 2023; Busemeyer & Sahn, 2021; Kurer & Hausermann, 2021). Fourthly, if people's perceptions of new STI are negative then this could well result in greater uncertainty, anxiety and fear both now and in the future.

One way in which researchers have analysed these relationships is through studying people's perceptions and experiences of working alongside new technologies and self-reported well-being. Cambre and Cook (1985) found employees working alongside and with computers reported greater levels of fear at work and greater fear about these new technologies on their lives. Aghion et al. (2016) were the first to model the expected impact of new technologies on subjective well-being through job turnover, job creation and job destruction rates. They found that higher job turnover increased well-being, after controlling for local unemployment rates, arguing that this signalled higher economic growth rates and higher chances of the unemployed finding a job. Job creation and destruction were associated with higher and lower well-being respectively. Schwabe and Castellacci (2020) find that increased robotic automation is associated with a greater fear of replacement amongst workers which causes a significant reduction in job satisfaction though only for non-degree holders. Recent work by Dekker et al. (2017) and Hinks (2021), analyse whether there is a direct association between people who are more fearful of robots with respect to future employment and current life satisfaction. Both papers find evidence of a negative relationship. Giuntella, et al. (2023) find evidence that German workers, particularly those in medium-skilled jobs, who are highly exposed to artificial intelligence suffer a relative decline in both life and job satisfaction and that these workers are more concerned about their job security and economic situation. This paper contributes to this small but growing empirical literature that focusses on how people perceive automation and AI and whether this is associated with self-reported life satisfaction.

We find evidence that holding negative perceptions towards automation and AI correlates with significantly lower life satisfaction. This result is robust to a number of model specifications including considering people's average perceptions towards other scientific and technological innovations. Some will argue that such findings are not important since these negative perceptions are misplaced. Some others will argue these perceptions do not matter since these changes are imminent so people will have to adapt as has happened in previous technological revolutions. Others will argue that the state and civil society should immediately try and limit the economic disruption caused by these new technologies. Many though will find some middle ground in which the fears of citizens form part of regional and national moratoriums on what new STI will mean and whether there is a need to steer how and where these new technologies are used in line with a framework of responsible innovation.³

³ The political economy of how these discussions are formed and the power of the different agents in these discussions is relatively under-researched at present, notably about the impact that country-specific

The remainder of the paper is structured as follows. Section 2 presents the data and variables used. Section 3 presents the results. These are discussed in Sect. 4 as are the limitations of the study. We end with a conclusion.

2 Data, Variables and Descriptive Statistics

We use data from Eurobarometer 95.2 survey conducted between April-May 2021, which was a follow-up survey to Eurobarometer 81.5 survey in June 2014 that focussed on how science and technology is perceived in Europe. This survey asks over 20 questions about people's views, perceptions and knowledge of science of technology. 38 countries were included in the survey including the 27 EU member states with the majority of countries interviewing approximately 1,000 individuals over the age of 15. A multi-stage, random probability sample design was used and in each country a number of sampling points was drawn with probability proportional to population size (for a total coverage of the country) and to population density. Due to the Covid-19 pandemic, interviews were conducted within countries either face-to-face, sometimes with a mix of face-to-face and computer assisted web interviews (CAWI) and sometimes using purely CAWI.

2.1 Dependent Variable

In keeping with other Eurobarometer surveys life satisfaction is captured by the question "On the whole, are you very satisfied=1, fairly satisfied=2, not very satisfied=3 or not at all satisfied=4 with the life you lead?". After recoding the answers so higher life satisfaction was given a higher value the average life satisfaction reported from our sample was 3.04 across all countries, indicating that on average people were fairly satisfied with the lives they lead Women represented just over 50 per cent of our sample and the average age was just over 47 years.

2.2 Variables of Interest

The first question of interest is the agreeableness of people with the statement "Artificial intelligence and automation will create more jobs than they will eliminate". There are five possible responses ranging from totally agree (=1) to totally disagree (=5). This question relates AI and automation directly to people's livelihoods and maybe interpreted as people themselves thinking they may be threatened by job losses through AI and automation. Some people may also have experienced or witnessed AI and automation in a workplace that

responses have on other countries e.g. high-income on middle and low income countries. Given the recent headlines of AI representing another potential existential crisis for humanity there are now stronger voices from within the AI-generating sector itself for all parties in countries (public, private and civil) to discuss and thrash-out regulatory frameworks to discuss what these new technologies mean presently and will likely mean in the future for citizens and society as a whole. One aspect of this that needs considerable attention is the current powers of the state in many countries which are more limited than previously in history due to the neo-liberal approach to global capitalism that has encouraged and produced economically and politically powerful conglomerates and institutions which prize the highest private return over wider societal objectives. An old narrative has formed pitching the innovation and growth creating private sector against the interfering, regulatory state but at the same time large tech companies have recently called for greater regulation of the sector.

resulted in job losses. Given this we would expect people who disagree with this statement to report lower life satisfaction.

The second question of interest asks “Do you think Artificial Intelligence will have a positive, a negative or no effect on our way of life in the next 20 years?” with responses ranging from very positive (= 1) to very negative (=4).⁴ This question likely captures a more general fear of AI amongst people regarding many different aspects of life including work. Since it is framed over a 20-year period though, it might reasonably be expected to not correlate with current life satisfaction because of a low discount rate (check this).

⁴ For this question the response “no effect” was originally recorded as 5. We recoded responses so that no effect was 3, “negative effect” was 4 and “very negative effect” was 5.

Table 1 Descriptive statistics for main variables of interest

	Frequency	Percentage
Panel A		
Artificial intelligence and automation will create more jobs than they will eliminate		
Totally Agree	2,933	8.49
Agree	7,520	21.76
Neither Agree or Disagree	10,132	29.32
Disagree	9,341	27.04
Totally Disagree	4,625	13.39
Do you think AI will have a positive, a negative or no effect on our way of life in the next 20 years?		
Very positive effect	6,482	18.76
Positive effect	15,862	45.91
No effect	1,062	3.07
Negative effect	7,807	22.6
Very negative effect	3,338	9.66
Panel B		
	Mean	Std Dev
Artificial intelligence and automation will create more jobs than they will eliminate (totally agree=1, totally disagree=5)		
	2.585	1.284
Do you think AI will have a positive, a negative or no effect on our way of life in the next 20 years? (very positive effect=1, very negative effect=5)		
Dummy variable=1 if disagree or totally disagree with the statement “Artificial intelligence and automation will create more jobs than they will eliminate”, = 0 otherwise	0.404	0.491
Dummy variable=1 if you think AI will have a fairly negative or very negative effect on our way of life in the next 20 years, =0 otherwise.	0.323	0.467
Sample Size	34,551	

The frequency of responses to the two questions are provided in Panel A of Table 1. Panel B provides average responses to the two questions with both means around the middle category. We also created dummy variables for both of the questions, where negative responses=1, otherwise=0. That 40.4 per cent of our sample disagree or strongly disagree that AI and automation will create more jobs than it destroys whilst 30.3 per cent agree or strongly agree that job creation will outstrip job destruction reflects the concerns people have with this technology. Far fewer people think negatively towards the impact AI will have on our future way of life (32.3 per cent) with the majority thinking there will be positive effects on our way of life (64.7 per cent).⁵

2.3 Control Variables

In line with the empirical happiness economics literature we control for age, age-squared, gender, education category, marital status, economic activity, religious group, household size and whether born abroad. There is no specific question about household income or earnings. Instead, we create 3 categories in response to whether people have found it difficult to pay household bills in the last month. To capture other material aspects of the person's or the household's life we include a subjective social class term. We also take advantage of questions unique to the survey that may mitigate the effect that views about new STI have on life satisfaction. We include a categorical variable that captures peoples scores on eleven yes/no science questions. Those who score more highly may hold new STI in a more positive light. Alternatively, it can be argued that being more informed about science can lead to people being more fearful. Familiarity with STI may also influence people's perceptions of STI, so we include a dummy variable for whether a family member(s) had ever worked in the research, science, technology and innovation development field.

3 Method and Results

We estimate the life satisfaction equations using ordinary least squares (OLS) regressions rather than ordered logit or ordered probit models since the estimated coefficients are more or less equivalent according to Ferrer-i-Carbonell and Frijters (2004). It is important to stress that these estimations cannot be interpreted as causal. Whilst people who feel more negative towards AI and automation are likely to report less life satisfaction it is also feasible that people's life satisfaction can cause them to have particular views about new technologies.⁶

⁵ A surprising result is that people who think there will be no effect comprise just 3.1 per cent of our sample. Frequently the neutral option in these questions has the highest proportion of respondents or near the highest proportion. To have the lowest proportion calls into question our recoding of this question if we were to use all responses in our empirical section. To overcome this is less of an issue if we use the dummy variable created instead.

⁶ There are many examples in the well-being and life satisfaction literature of research overcoming issues of causality by using panel data (Böckerman & Ilmakunnas, 2009; Marcus, 2013). Being restricted to a cross-sectional data set means to test for causality we would need an instrument that predicted views towards AI and automation but did not directly correlate with life satisfaction. Typically, such instruments capture local effects that would cause the persons views or actions and only through this mechanism would impact life satisfaction.

Table 2 Life satisfaction and perceptions of science, technology and innovation

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	LS	LS	LS	LS	LS	LS
Disagree with the statement “Artificial intelligence and automation will create more jobs than they will eliminate”=1, 0 otherwise	-0.074** (0.030)		-0.047* (0.027)	-0.069*** (0.015)	-0.071*** (0.015)	-0.051*** (0.012)
AI will have a negative effect on our way of life in the next 20 years=1, 0 otherwise.		-0.126*** (0.026)	-0.114*** (0.023)	-0.093*** (0.021)	-0.080*** (0.020)	-0.058*** (0.016)
Country Dummies	no	no	no	yes	yes	yes
Science and Technology	no	no	no	no	yes	yes
Demographic and Socio-economic controls	no	no	no	no	no	yes
Constant	3.052*** (0.044)	3.062*** (0.041)	3.077*** (0.045)	3.092*** (0.013)	2.898*** (0.033)	3.483*** (0.050)
Observations	34,551	34,551	34,551	34,551	34,551	34,551
R-squared	0.003	0.007	0.008	0.125	0.131	0.242

Notes: Reference groups are males, married, manual employee, Catholic, single person household, never or almost never unable to pay a bill at the end of a month and not born abroad. Robust standard errors in parentheses. Clustered at country level *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We choose to use dummy variables that capture negative views of AI in our two variables of interest for ease of interpretation of any correlation with life satisfaction.⁷ In Table 2 we initially regress life satisfaction onto the dummy for AI and automation having a positive effect on net-job creation. Those who disagree with this statement report 7.4% point loss in life satisfaction. In model 2 we control for the dummy on AI impact on way of life in the next 20-years. Those who views AI negatively report a 12.6% point loss in life satisfaction. When both variables are included (model 3) the size of our AI and automation dummy declines significantly and is significant only at the 10 per cent level.⁸ The estimated coefficient on the AI impact on way of life dummy falls insignificantly and remains significant at the 1 per cent level. This indicates a degree of overlap between the two variables but that they are both directly correlated with life satisfaction.

When country fixed effects are included our variables of interest remain negatively and significantly correlated with life satisfaction. When additional variables capturing scientific knowledge and family employment links to science and technology are controlled for in model 5 there is no impact on our main findings. Finally in model 6 we control for demographic and economic factors which, from previous work, we would expect to correlate with life satisfaction. The inclusion of these controls reduces the size of both the estimated

⁷ When we instead use numeric responses to the questions or control for each response category our main results do not change. When controlling for each categorical response, the estimated coefficients monotonically increase in size with those having the most negative views on AI reporting significantly lower life satisfaction relative to people with the most positive views. These results are available upon request.

⁸ The chi-squared statistic is 22.51.

Table 3 Life satisfaction and perceptions of AI and automation by different country groupings

Variables	(1)	(2)	(3)
	LS	LS	LS
Disagree with the statement “Artificial intelligence and automation will create more jobs than they will eliminate”=1, 0 otherwise	-0.061*** (0.017)	-0.050** (0.017)	-0.029 (0.020)
AI will have a negative effect on our way of life in the next 20 years=1, 0 otherwise.	-0.078*** (0.015)	-0.063** (0.023)	0.020 (0.053)
Constant	3.340*** (0.060)	3.338*** (0.079)	3.749*** (0.129)
Observations	18,100	10,573	5,642
R-squared	0.236	0.206	0.203
Number of Countries	21	11	7

Notes: Reference groups are males, no education, married, manual employee, Catholic, single person household, never or almost never unable to pay a bill at the end of a month. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

coefficients on our variables of interest, but they remain negative and significant at the 1 per cent level.⁹

The estimated coefficients on the controls are in line with the life satisfaction literature. Life satisfaction is U-shaped in age. People living in larger households report higher life satisfaction. People who have difficulty paying monthly bills are significantly less satisfied with life compared to people who have no difficulty. The self-employed report higher life satisfaction compared to manual workers and people who are unemployed report significantly lower life satisfaction. People who are born abroad report lower life satisfaction and people in a higher social class are more satisfied with life. Religious group also matters for life satisfaction with Protestants reporting higher life satisfaction than Catholics while Orthodox Christians and agnostics report lower satisfaction.¹⁰

Though we control for country-level effects by including country dummy variables these fail to consider broader regional factors that are exclusive to groups of countries. In the literature on life satisfaction, for example, there is evidence that people in ex-communist countries still report lower life satisfaction compared to people living in Western European countries (e.g. Guriev & Zhuravskaya, 2009; Guriev & Melnikov, 2017) with possible explanations being poorer institutional quality (Nikolova & Sanfey, 2016) and corruption (Djankov et al. 2016; Amini and Douarin, 2020). In line with this reasoning, we split our sample into three distinct geo-political groups that capture historical differences, Western European countries, ex-communist countries and Balkan countries. Results in Table 3 indicate that for Western and Ex-communist countries the negative views people have towards AI is associated with lower life satisfaction. This association is not apparent in the Balkans countries.

An alternative and arguably less ad hoc method for capturing between country differences is to use multi-level modelling. In the literature it is suggested that multilevel modelling is appropriate when intraclass correlations (ICC) exceed 0.05 (Hayes, 2006) with ICC values exceeding 0.15 considered large (Hox, 2010). When we run an intercept only multi-

⁹ We ran a stepwise regression for model 6 to test whether all our variables were valuable in predicting life satisfaction. This revealed that the education dummies added nothing significant to the model and were dropped from model 6 and all subsequent models.

¹⁰ The full set of results for all the models in the paper are available upon request but are not include here for reasons of space.

Table 4 Life satisfaction and perceptions of new STI (multi-level models)

Variables	(1)	(4)	(7)	(10)	(13)
	LS	LS	LS	LS	LS
Disagree with the statement “Artificial intelligence and automation will create more jobs than they will eliminate”=1, 0 otherwise	-0.050*** (0.007)	-0.051*** (0.007)	-0.051*** (0.007)	-0.053*** (0.007)	- 0.053*** (0.007)
AI will have a negative effect on our way of life in the next 20 years=1, 0 otherwise.	-0.059*** (0.007)	-0.059*** (0.007)	-0.059*** (0.007)	-0.058*** (0.008)	- 0.058*** (0.008)
Ln GDP per capita		0.107*** (0.028)			0.150*** (0.050)
Ut Rate			-0.007 (0.006)		0.004 (0.007)
AI Govt Read				0.007*** (0.002)	-0.001 (0.004)
Constant	3.466*** (0.050)	2.365*** (0.291)	3.518*** (0.068)	3.015*** (0.150)	1.963*** (0.393)
Observations	34,551	34,551	34,551	32,816	32,816
Number of groups	39	39	39	37	37

Notes: Reference groups are males, married, manual employee, Catholic, single person household, never or almost never unable to pay a bill at the end of a month. Model 1 excludes Cyprus-TCC and Models 5 and 6 exclude Cyprus-TCC and Kosovo because no information was available for government AI readiness. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

level model the ICC meant that 11.4 per cent of the total variation in individual LS was due to country-level variation. We report the multi-level estimates in Table 4. In models 2–4 we include separate country-level variables for log of gross domestic product (GDP) per capita and the unemployment rate. In keeping with previous research, we expect the former to be positively related to life satisfaction and the latter to be negatively related. In model 5 we include country measures from the 2021 Government AI Readiness Index. It is expected that greater readiness mitigates views towards AI.

We see from all the model specifications that our two variables of interest are still negatively related to life satisfaction. Regarding our country-level controls only log GDP per capita has the expected sign and is significant.

4 Discussion & Limitations

It is apparent from the above results that people’s views towards AI appear to correlate with current life satisfaction. These findings are consistent with the literature on how people’s views on new technologies relate to life satisfaction and to job satisfaction (Dekker et al., 2017; Schwabe & Castellacci, 2020; Hinks, 2021; Giuntella et al., 2023). That people’s views about AI specifically can mean a decline in life satisfaction is a new finding in the literature. It suggests that, as with many new technologies, there is uncertainty about what it will mean for jobs with people possibly fearing technological unemployment but also people fearing the impact on their lives more broadly.

As stated previously a potential issue with research into life satisfaction is that of simultaneity. It is possible that people with lower life satisfaction scores are more likely to hold negative views about many different aspects of life including the impact of new STIs. In

order to capture these underlying attitudes towards new STIs we estimate a life satisfaction equation including relative measures of our two variables of interest. We do so by dividing the score for each of our statements of interest by the average score across a number of different but related statements regarding science and technology and with regard to specific new technologies.

The relative term for views regarding AI and automation having a net positive effect on employment was calculated by dividing the score to this question by the average score across eight other statements about science including whether people agreed that “thanks to scientific and technological advances, the Earth’s natural resources will be inexhaustible”, and “thanks to science and technology, there will be more opportunities for future generations”.¹¹

The relative term for AI impacting negatively on our way of life in the next 20 years, was calculated by dividing the score of to this question (1=very positive effect, 5=very negative effect) by the average score across 9 identical questions but with respect to other new technologies. These were solar energy, wind energy, information and communication technology, brain and cognitive enhancement, vaccines and combatting infectious diseases, biotechnology and genetic engineering, space exploration, nanotechnology and nuclear energy for energy production.

Table 5 shows that when included by themselves the two relative terms continue to show a negative association with life satisfaction, but the size of the coefficient on the relative term for AI and way of life has fallen indicating that some of the negative effect in previous models is capturing a general negative effect towards the other new technologies listed. In the final model the relative AI and way of life term is insignificant. This indicates a degree of collinearity between the two relative terms and that people with a higher relatively negative view on AI and automation on net employment growth report lower life satisfaction.

To illustrate the robustness of this result to heterogeneity across the countries, we tested whether our result from Model 1, Table 5 was masking a specific country effect by removing one country at a time. The estimated coefficient on the relative AI and automation variable

Table 5 Life satisfaction and relative measures of views on AI and automation

Variables	(1)	(2)	(3)
	LS	LS	LS
Relative value: Artificial intelligence and automation will create more jobs than they will eliminate	-0.082*** (0.020)		- 0.074*** (0.019)
Relative value: AI will have a negative effect on our way of life in the next 20 years		-0.020** (0.009)	-0.006 (0.009)
Constant	3.511*** (0.053)	3.504*** (0.056)	3.569*** (0.057)
Observations	33,321	31,546	30,906
R-squared	0.242	0.235	0.238

Notes: Reference groups are males, married, manual employee, Catholic, single person household, never or almost never unable to pay a bill at the end of a month. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

¹¹ There were two additional statements that people were asked to give views on: “Science and technology make our lives easier, healthier and more comfortable” and “Science and technology make our lives healthier”, but these had very poor response rates resulted in 20,000 observations being lost in both cases. As a result we excluded information from the these responses. The responses to 4 of the 8 questions used were negatively framed. We recoded these so they were positively framed.

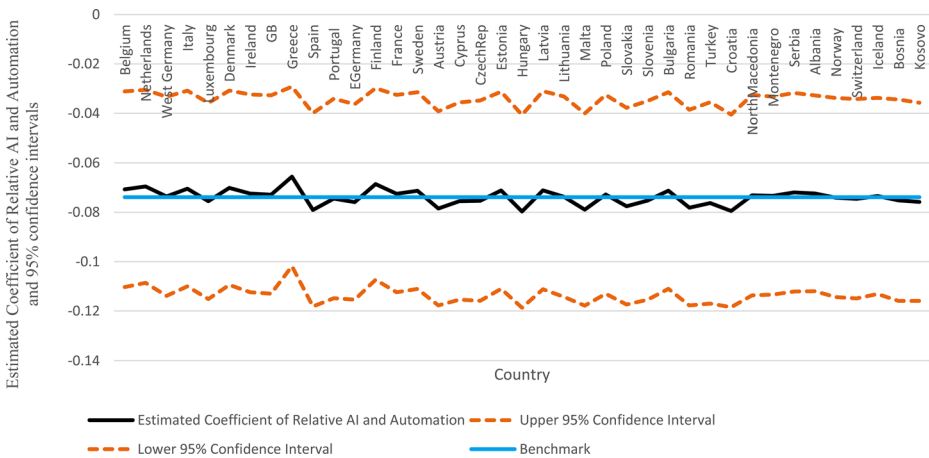


Fig. 1 Estimated coefficient of relative AI and automation on life satisfaction

and confidence intervals are presented in Fig. 1. This illustrates that there is little discernible country-specific effect.

4.1 Limitations

We are unable to formally test whether people’s views about AI and automation cause life satisfaction to decline. For this, instruments for predicting people’s views on such technologies are necessary which do not directly correlate with life satisfaction. Measures of regional or postcode level accessibility to broader technologies (e.g. internet, broadband speed), levels of e-participation and of spending on software by businesses and households may be a starting point here.

A second issue is that while we are implicitly arguing that views on AI and automation with respect to future employment and way of life are correlated with life satisfaction through fear, we do not control for fear. Fear is known as a basic emotion in psychology. Through an evolutionary lens, fear can trigger humans to feel threatened. Some people will have more triggers for being threatened than others, meaning in our model we could be capturing people’s general fear rather than a specific fear of AI and automation. It is also possible that some people are technophobes or technophiles and that our findings are in part capturing these elements as well.

Thirdly we cannot consider whether people have been directly impacted by automation in their lives. Research indicates that people in jobs that are more exposed to automation may suffer a decline in aspects of their mental health (Robelski & Wischniewski, 2018; Körner et al., 2019; Szalma & Taylor, 2011) but that automation may also improve lives by reducing the monotonous tasks people undertake (Gorny and Woodard, 2020).

5 Conclusion and Future Research

This paper analyses the views people have about AI and automation through the lens of life satisfaction. We find robust evidence to support the view that people who hold negative views towards these technologies report lower life satisfaction. When we consider general fear of new technologies this impacts our results but people who view AI and automation as having an overall negative effect on jobs still report lower life satisfaction. Whilst previous research has focussed on the impact computers and robots have on job and life satisfaction this is the first part to highlight a negative relationship between AI and life satisfaction.

This finding confirms a widely held view that citizens in Europe are concerned about the impact AI and other forms of automation will have on future employment chances. These concerns may well be based on personal experiences or observations of what is happening in local and national labour markets and across labour markets more widely. For this reason there is a need for much greater public debate about what automation and AI will mean for future employment and opportunities in order to allay the apparent fears of this new technology. This cannot simply involve discussion between Big-Tech firms and government but requires the participation of other parties to better understand what these technologies will mean for the quality and the quantity of jobs that will likely be both destroyed and created.

5.1 Future Research

The paper calls for more research into how new technologies are being accommodated into firms, whether this integration is a collaborative process with current employees, what current employees feel about these new technologies and whether there is evidence that productivity increases associated with these technologies has meant anything for employee pay. This research will feed into the wider question as to what exposure to increased automation means for worker wellbeing and for overall wellbeing. A more systematic approach is also needed to test whether general fear, fear towards new technologies and fear differences between new technologies that someone is exposed to, are all associated with lower life satisfaction. An initial small sample study by Khasawneh (2018) finds 16 factors that comprise an overall fear of technology, while Nimrod (2018) follows a similar method to find that techno-stress amongst older people results in lower reported life satisfaction. Arguably such research should be used in cross-country surveys to help better capture whether specific technologies are associated with greater fear, stress and anxiety than others.¹²

Acknowledgements Not applicable.

Funding Not applicable.

Declarations

Conflict of Interest The authors have no conflicts of interest to declare that are relevant to the content of this article.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License,

¹² Cugurullo and Acheampong (2023) have begun to address this question with regard to people's fears of autonomous cars.

which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

- Acemoglu, D., and Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6), 2188–2244.
- Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022). AI and jobs: Evidence from online vacancies, NBER working Paper Series Working Paper 28257.
- Aghion, P., Akcigit, U., Deaton, A., & Roulet, A. (2016). Creative destruction and subjective well-being. *American Economic Review*, 106(12), 3869–3897.
- Aksoy, C. G., Özcan, B., & Philipp, J. (2021). Robots and the gender pay gap in Europe. *European Economic Review*, 134, 103693.
- Alekseeva, L., Azar, J., Giné, M., Samila, S., & Taska, B. (2021). The demand for AI skills in the labor market. *Labour Economics* 71.
- Amini, C., & Douarin, E. (2020). Corruption and life satisfaction in transition: Is corruption a social norm in Eastern Europe? *Social Indicators Research*, 151, 723–766.
- Autor, D., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, 103(5), 1553–1597.
- Babina, T., Fedyk, A., Xi He, A., & Hodson, J. (2020). *Artificial intelligence, firm growth, and industry concentration*. Unpublished manuscript, Columbia University.
- Bhargava, A., Bester, M., & Bolton, L. (2021). Employees' perceptions of the Implementation of Robotics, Artificial Intelligence, and automation (RAIA) on job satisfaction, Job Security and Employability. *Journal of Technology in Behavioral Science*, 6, 106–113.
- Böckerman, P., & Ilmakunnas, P. (2009). Unemployment and self-assessed health: Evidence from panel data. *Health Economics*, 18(2), 161–179.
- Busemeyer, M. R., & Sahm, A. H. J. (2021). Social Investment, Redistribution or Basic Income? Exploring the Association between automation risk and Welfare State attitudes in Europe. *Journal of Social Policy*, 1–20.
- Busemeyer, M. R., MGandenberger, M., Knotz, C., & Tober, T. (2023). Preferred policy responses to technological change: Survey evidence from OECD countries. *Socio-Economic Review*, 21(1), 593–615.
- Cambre, M. A., & Cook, D. L. (1985). Computer anxiety: Definition, measurement, and correlates. *Journal of Educational Computing Research*, 1(1), 37–54.
- Casselman, B., & Satariano, A. (2019). Amazon's Latest Experiment: Retraining Its Work Force. NY Times. <https://www.nytimes.com/2019/07/11/technology/amazon-workers-retraining-automation.html>.
- Cugurullo, F., & Acheampong, R. A. (2023). *Fear of AI: An inquiry into the adoption of autonomous cars in spite of fear, and a theoretical framework for the study of artificial intelligence technology acceptance* (pp. 1–16). AI & SOCIETY.
- Dauth, W., Findeisen, S., Suedekum, J., & Woessner, N. (2021). The adjustment of labor markets to robots. *Journal of the European Economic Association*, 19(6), 3104–3153.
- De Vries, G. J., Gentile, E., Miroudot, S., & Wacker, K. M. (2020). The rise of robots and the fall of routine jobs. *Labour Economics*, 66, 101885.
- Dekker, F., Salomons, A., & van der Waal, J. (2017). Fear of robots at work: The role of economic self-interest. *Socio-Economic Review*, 15(3), 539–562.
- Djankov, S., Nikolova, E., & Zilinsky, J. (2016). The happiness gap in Eastern Europe. *Journal of Comparative Economics*, 44(1), 108–124.
- Ferrer-i-Carbonell, A., & Frijters, P. (2004). How important is methodology for the estimates of the determinants of happiness? *The Economic Journal*, 114(497), 641–659.
- Gihleb, R., Giuntella, O., Stella, L., & Wang, T. (2022). Industrial robots, workers' safety, and health. *Labour Economics*, 78, 102205.
- Giuntella, O., König, J., & Stella, L. (2023). Artificial Intelligence and Workers' Well-Being. IZA Discussion Paper IZA DP No. 16485.

- Gornay, P.A., and Woodard, R.C. 2020. Don't Fear the Robots: Automatability and Job Satisfaction, MPRA Paper No. 103424.
- Graetz, G., & Michaels, G. (2018). Robots at work. *The Review of Economics and Statistics*, 100(5), 753–768.
- Guriev, S., & Melnikov, N. (2017). Happiness convergence in transition countries. EBRD working paper no. 204.
- Guriev, S., & Zhuravskaya, E. (2009). Un)happiness in transition. *The Journal of Economic Perspectives*, 23(2), 143–168.
- Hayes, A. F. (2006). A primer on Multilevel modeling. *Human Communication Research*, 32(4), 385–410.
- Hinks, T. (2021). Fear of robots and life satisfaction. *International Journal of Social Robotics*. <https://doi.org/10.1007/s12369-020-00640-1>.
- Hox, J. J. (2010). *Quantitative Methodology Series. Multilevel analysis: Techniques and applications* (2nd ed.). Routledge/Taylor and Francis Group.
- <http://www.nber.org/papers/w28257>.
- Illanes, P., Lund, S., Mourshed, M., Rutherford, S., & Tyreman, M. (2018). *Retraining and reskilling workers in the age of automation*. McKinsey Global Institute.
- Jaimovich, N., Saporta-Eksten, I., Siu, H., & Yedid-Levi, Y. (2021). The macroeconomics of automation: Data, theory, and policy analysis. *Journal of Monetary Economics*, 122, 1–16.
- Khasawneh, O. Y., & Technophobia (2018). : Examining its hidden factors and defining it. *Technology in Society*, 54: 93–100.
- Körner, U., Müller-Thur, K., Lunau, T., Dragano, N., Angerer, P., & Buchner, A. (2019). Perceived stress in human–machine interaction in modern manufacturing environments—results of a qualitative interview study. *Stress and Health*, 35, 187–199.
- Kurer, T., & Hausermann, S. (2021). Automation and Social Policy: Which Policies do At-risk Workers Supporters? Welfare priorities Working Paper Series, 2.
- Mann, K., & Püttmann, L. (2023). Benign effects of automation: New evidence from patent texts. *The Review of Economics and Statistics*, 105(3), 562–579.
- Marcus, J. (2013). The effect of unemployment on the mental health of spouses—evidence from plant closures in Germany. *Journal of Health Economics*, 32(3), 546–558.
- Montobbio, F., Staccioli, J., Virgillito, M. E., & Vivarelli, M. (2021). Labour-saving automation and occupational exposure: A text-similarity measure, LEM Working Paper Series, No. 2021/43, Scuola Superiore Sant'Anna, Laboratory of Economics and Management (LEM), Pisa.
- Nazereno, L., & Schiff, D. F. (2021). The impact of automation and artificial intelligence on worker well-being. *Technology in Society*, 67, 101679.
- Nikolova, E., & Sanfey, P. (2016). How much should we trust life satisfaction data? Evidence from the life in Transition Survey. *Journal of Comparative Economics*, 44(3), 720–731.
- Nimrod, G. (2018). Technostress: Measuring a new threat to well-being in later life. *Aging & Mental Health*, 22(8), 1086–1093.
- Robelski, S., & Wischniewski, S. (2018). Human-machine interaction and health at work: A scoping review. *International Journal of Human Factors and Ergonomics*, 5(2), 93–110.
- Schwabe, H., & Castellacci, F. (2020). Automation, workers' skills and job satisfaction. *PLoS ONE*, 15, e0242929.
- Szalma, J. L., & Taylor, G. S. (2011). Individual differences in response to automation: The five factor model of personality. *Journal of Experimental Psychology: Applied*, 17(2), 71–96.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.