Received: 14 November 2022 | Accepted: 13 December 2022

DOI: 10.1111/ijsw.12586

INTERNATIONAL JOURNAL OF SOCIAL WELFARE

ORIGINAL ARTICLE

The rise of artificial intelligence, the fall of human wellbeing?

Yong Zhao[1] | Da Yin[1] | Lili Wang[2] | Yihua Yu[3]

[1]School of Economics, Renmin University of China, Beijing, China

[2]Institute of International Economy, University of International Business and Economics, Beijing, China

[3]School of Applied Economics, Renmin University of China, Beijing, China

Correspondence
Yihua Yu, School of Applied Economics, Renmin University of China, Beijing, China.
Email: yihua.yu@ruc.edu.cn

Funding information
National Social Science Foundation of China, Grant/Award Number: 20BJY195

Abstract

Concerns exist regarding the impact on our lives of the rise of artificial intelligence (AI). Using a large dataset of 137 countries over the period 2005–2018 from multiple sources, we estimate the causal effect of AI on individual-level subjective wellbeing. Our identification strategy is inferred from the gravity framework and uses merely the variation in exogenous drivers of a country's AI development. We find a significant negative effect of AI on an individual's wellbeing, in terms of current levels or expectations of future wellbeing. The results are robust to alternative measures of AI, identification strategies, and sampling. Moreover, we find evidence of significant heterogeneity in the impact of AI on individual wellbeing. Further, this dampening effect on individual wellbeing resulting from the use of AI is more prominent among young people, men, high-income groups, high-skilled groups, and manufacturing workers.

KEYWORDS

artificial intelligence, subjective wellbeing, trade gravity model, world poll

INTRODUCTION

Rarely a day goes by without the rise of artificial intelligence (AI) being mentioned in the media, with debate on its potential implications. Over the past decade, AI diffusion has been rapid. For instance, the worldwide stock of operational industrial robots was 2,722,077 units in 2019 and this has been increasing at an annual average rate of 11% since 2014 (IFR, 2020). Today, AI technology manifesting as robotics, machine learning, neural networks, and intelligent user- interfaces, is increasingly ubiquitous.

The rapid rise of AI raises concerns about all aspects of our lives. On the one hand, AI has impressive application, with significant economic, social, and sustainability benefits in nearly every sector of society (Walsh et al., 2019). On the other hand, the rise of AI is accompanied by concerns that advances in AI will lead to massive 'technological unemployment' or job losses (Brynjolfsson & McAfee, 2014; Ford, 2015), income inequality (DeCanio, 2016; Michaels et al., 2014; P. Zhang, 2019), or privacy threats (Jin, 2018; Tucker, 2019). Notable individuals, such as the legendary scientist Stephen Hawking and Tesla founder Elon Musk, even hold an extremely pessimistic view regarding the potential dangers of AI.

The present study partly addresses these concerns by providing pioneering evidence on the nexus between AI

Abbreviations: AI, artificial intelligence; AR, Anderson Rubin; BACI, base pour l'analyse du commerce international; CEA, Council of Economic Advisers; COVID-19, Corona Virus Disease 2019; EM-DAT, Emergency Events Database; EIU, Economist Intelligence Unit; GDP, gross domestic product; GWP, Gallup World Poll; HS, harmonized system; IDC, International Data Corporation; IFR, International Federation of Robotics; ILO, International Labour Organization; ILOSTAT, International Labour Organization's central statistics; ISCO, International Standard classification of occupations; IV, instrumental variable; KP, Kleibergen Paap; OECD, Organization for Economic Co-operation and Development; OLS, ordinary least squares; SWB, subjective wellbeing; SOC, Standard Occupational Classification; US, United States; USD, United States dollar; WLS, weighted least-square regression; 2SLS, two-stage least squares.

and individual-level subjective wellbeing. The reason for choosing such a topic is mainly based on the following three considerations. First, as mentioned above, the use of AI, such as robots, intelligent driving, and face recognition, has been very popular in some countries, especially developed countries. Second, although the use of AI in some countries is relatively limited, it is highly likely that AI will play a more significant role given the pace and development of AI. Meanwhile, the fact that there are national differences in the use of AI makes cross-country comparisons possible. Third, individual welfare is not only related to external conditions, but also to individual decision-making and thinking mode, which reflects individual utility structure and decision-making logic. To discuss the impact of AI on welfare is essentially to discuss the impact of AI on individual decision-making and behaviour of residents. Specifically, we ask the following research questions: (i) Does AI improve an individual wellbeing? (ii) Which groups of people are most affected by AI? (iii) What channels through which AI affects individual wellbeing?

To this end, we retrieve and merge a large-scale panel dataset from multiple sources. One is the Gallup Organisation, which surveys citizens in at least 160 countries and interviews about 1000 residents aged 15 years and older per country/year. The second major source is Thompson Reuters' Web of Science database from which we retrieve the annual number of AI-related publications for each country by a keyword search. Last, as a proxy for an alternative measure of AI development, we use the less-explored database of the International Federation of Robotics (IFR), which constructs sectoral and country-level data of industrial robots. They consolidate information on sales of industrial robots from almost every supplier worldwide (Barbieri et al., 2019).

Our empirical design seeks to overcome the following identification challenge: AI development could be related to third variables (e.g., labour union power or COVID-19 pandemic) that are omitted in the model and these could be factors affecting wellbeing. There may also be a reverse causality between AI development and wellbeing. To solve the endogeneity problem, following and expanding on Feyrer (2009) and Blanchard and Olney (2017), we construct our instruments using six different but complementary identification strategies. These are inferred from the gravity of trade model, and use only merely the variation in exogenous drivers of a country's AI development. These may be trading partners' robot instalments, a natural disaster, or bilateral geographical and cultural connections. By teasing out the endogenous variables that influence a country's development of AI, we can identify the causal impact of AI on individual-level subjective wellbeing. Using this trade gravity-based instrumental variable (IV) strategy, we estimated the relationship between AI and individual wellbeing, and found evidence that rising AI tends to reduce people's wellbeing in general. AI not only significantly reduces the current wellbeing level, but also the expectations of future wellbeing.

To bolster confidence in our results, several robustness checks are conducted. First, we use aggregated nation-level data to avoid the problem of uneven distribution of surveyed respondents, thereby excluding the influence of large economies. Second, we use long-differencing and rolling-window regression techniques to eliminate the short-term fluctuation in sample estimation, and establish the long-term relationship between AI and individual wellbeing. Third, we use different subsamples and add additional control variables to analyse the impact of AI. Finally, we adjust the weight of the surveyed sample to better reflect the demographics of a country. The results remained robust.

We also discuss the mechanisms through which AI affects individual wellbeing by investigating whether the impacts of AI on wellbeing vary across different subgroups. We find that individual characteristics are important in shaping the effect of AI on individual wellbeing. The dampening effect of the use of AI on individual wellbeing is more prominent for young people, men, high-income groups, high-skilled groups, and manufacturing workers. This result, to some extent, shows that employment and income are important channels for AI to influence individual wellbeing.

This study makes two important contributes to the wellbeing literature. Firstly, we provide the first direct causal estimate of the influence of AI on subjective wellbeing at the individual level, which is an important outcome, unexplored in prior work. With the developments of AI technology through machine learning and neural networks, an extensive body of ongoing research on AI both theoretically and empirically address important outcomes as follows: economic growth (Aghion et al., 2017; Athey, 2019), productivity growth (Graetz & Michaels, 2018), employment (Acemoglu & Restrepo, 2020; Autor & Salomons, 2017; Benzell et al., 2015; Bessen et al., 2019), innovation (Klinger et al., 2018; Rock, 2019), income inequality (Guerreiro et al., 2022; Korinek & Stiglitz, 2021; Sachs, 2019), and trade (Artuc et al., 2020; Goldfarb & Trefler, 2018). However, these studies are more concerned with the impact of AI on aggregated economic variables; no prior work directly examines individual-level outcomes, such as individual wellbeing.

Secondly, this study is also related to existing research by explaining cross-country (or state) differences in wellbeing. Several studies find significant differences in wellbeing from different countries/states (Frijters et al., 2020; Nikolova & Graham, 2015; Veenhoven, 2012), and provide explanations from different angles, such as (neighbouring) income (Noy & Sin, 2021; Reyes-García et al., 2016; Sacks et al., 2012), corruption and governance quality (Helliwell et al., 2018; Li & An, 2020), economic freedom (Graafland & Compen, 2015; Spruk & Kešeljević, 2016), migration (Nikolova & Graham, 2015), environment and air pollution (Zhang et al., 2017), weather condition (Frijters et al., 2020), and cultural participation (Ateca-Amestoy et al., 2016; Grossi et al., 2012). We supplement these studies by highlighting the importance of AI. In fact, as an emerging technology, the adoption of AI varies greatly not only from country to country, but also over time within a country. As such, we believe accounting for the differences in AI development can better explain variations in cross-country wellbeing. Furthermore, compared with previous cross-country studies, our research sample is diverse (137 countries) and across a long span (2005–2018). This increases the generalisability of our findings.

The rest of the paper is organised as follows: Possible mechanisms through which AI can affect individual wellbeing are discussed in Section 2, followed by data description in Section 3. The empirical strategy is outlined in Section 4, and empirical findings are shown in Section 5. Section 6 tests potential channels through which AI can affect individual wellbeing. The last section concludes and highlights directions for future research.

WHAT CONNECTS AI TO WELLBEING?

There are several possible mechanisms through which AI can affect individual wellbeing either positively or negatively, as discussed in the following subsections.

Income

Income is one of the most important factors impacting individual wellbeing changes. As a new technology, AI can boost economic growth by enhancing capital accumulation, innovation, and productivity (Cockburn et al., 2018; Graetz & Michaels, 2018; Jäger et al., 2015), thereby leading to changes in individuals' income and wellbeing. For example, IDC (2020) forecasts that global revenue from the AI market will surpass USD 300 billion by 2024, rising from USD 156 billion in 2020. According to a McKinsey report by Bughin et al. (2018), AI will add USD 13 trillion to the global economy by 2030, boosting gross domestic product (GDP) by 16%. Using a panel data set of industries of 17 countries during 1993–2007, Graetz and Michaels (2018) empirically find that more robot use is related to increased wage and labour productivity. Specifically, increased robot use contributes to productivity growth by around 0.36 percentage points a year on average; this effect is comparable with that of other general-purpose technologies, such as the steam engine in the nineteenth century.

In terms of the nexus between income and wellbeing, individuals might not necessarily become happier when their incomes rise, as inferred by the Easterlin paradox. However, this does not mean that income does not have a positive welfare effect (D'Ambrosio et al., 2020). On the one hand, the relationship between income and wellbeing can be affected by a myriad of factors. When income changes, some other factors are also changing, for instance, the rising expectations for consumption and financial gains. These factors may reduce personal satisfaction with life (Easterlin, 2011). On the other hand, there may be other factors that affect the relationship between income and welfare. For instance, Ahuvia and Friedman (1998) state that, when the living standard is relatively low, the increase of income will bring about the increase of welfare, but when the living standard is high, the welfare impact of income growth may be no longer significant. However, it should be mentioned that, while the use of AI increases overall income, the income gap is also increasing, which implies that the rising income does not necessarily improve personal quality of life. There is empirical evidence that AI promotes overall income growth, the impact is heterogeneous across different groups. In other words, AI has made some individuals better off, and some worse off (Goyal & Aneja, 2020; Korinek & Stiglitz, 2021; Zhou & Tyers, 2019). Furthermore, the increase in the income gap will inevitably cause additional tension and anxiety for low-income groups, which will increase overall social tension, and is not conducive for improving wellbeing or happiness.

Employment

Employment is another important mechanism through which AI affects an individual's wellbeing, but the empirical results are mixed. For an excellent survey for this topic, readers may refer to Abrardi et al. (2019). Acemoglu and Restrepo (2020) calculate that one additional robot per 1000 workers lowers the employment-population ratio in the US by 0.2 percentage points. Dauth et al. (2018) find that the use of industrial robots reduces employment in the manufacturing sector, but they stress that industrial robots have increased employment of the service sector. Overall, the influence of robots on the labour market is not obvious. Similar views are held by Bessen (2018) and Blanas et al. (2019).

Furthermore, some scholars discuss the impact of AI on different types of workers (by skill, income, and education level). For instance, Graetz and Michaels (2018) suggest that, although the use of robots does not significantly affect overall employment, it reduces the employment share of low-skilled workers. The CEA (2016) and Arntz et al. (2016) hold similar views. They find that when workers' income and education levels are high, the risk of their jobs being replaced by automated machines is much lower. Therefore, from the perspective of employment mechanisms—depending heavily on the nature of the individual's work and characteristics—the adoption of AI may either ameliorate or deteriorate quality of life.

Consumption

Although existing studies tend to discuss the impact of AI from the supply side, the demand side (e.g., consumers' consumption patterns and habits) perspective cannot be ignored. In fact, the impact of AI on the demand side may be one of the most direct channels through which AI influences the consumer's wellbeing. The advancements in AI are evident in a variety of applications in individuals' daily lives. For example, YouTube analyses billions of records to suggest videos a person might like based on previous reactions and choices, Google Map uses AI to help drivers and passengers plan the fastest route and predict overall travel times, while Siri and Alexa can help people to search for information, schedule appointments, and create to-do lists.

Meanwhile, the use of AI is expected to bring about changes not only in the convenience and mode of consumption, but also in the level of consumption. For example, based on international sales data from eBay, Brynjolfsson et al. (2019) empirically examine the impact of machine translation systems on cross-country sales, and find that introducing machine translation raises export quantity by 17.5%. In addition, the effect of increased exports is found to be larger for differentiated and cheaper products, as well as listings with more words in the title, and less experienced buyers.

Privacy

Regarding privacy, personal privacy concerns have escalated with the widespread use of AI technology due to its ability to cost effectively collect, store, and utilise personal information. If the emergence of increasingly sophisticated AI systems has exacerbated privacy concerns, the development of AI technology could be detrimental to individuals' wellbeing. Specifically, AI adoption poses threats to personal privacy, at least from the following three aspects:

First, the use of AI increases the amount of information that may be leaked. In other words, not only can AI learn current personal information about consumers, but it can also apply AI algorithms to infer other—sometimes sensitive—information, based on past attitudes and behaviours. For instance, a person's keyboard-typing style could be used to identify his or her emotional status, shopping behaviour may be used to determine sexual orientation and health status, and Facebook or Twitter activity logs may be used to judge political beliefs. This information is often considered to necessitate special protection. Wang and Kosinski (2018) find that the 'gaydar' of machine intelligence is far superior to that of humans, as the former can correctly 'distinguish between gay and heterosexual men in 81% of cases, and in 71% of cases for women'.

Second, AI increases the possibility of data persistence, data repurposing, hence the risk of privacy breaches. Personal information, once created, is stored for a long time owing to low storage costs, which implies that, at the moment of information creation, consumers do not know how or even whether their personal data could be used in the future (Tucker, 2019).

Third, the use of AI facilitates irresponsible data collection, storage, and utilisation, or data-related crime, due to low costs and poor policing. In the AI era, it is often difficult to trace high-risk data misuse for consumers, which incentivises sellers to consider only their own interests and over-collect buyer information, without consideration of harm to buyers. In fact, sellers are also motivated to commit to consumer-friendly data usage policies ex ante and renege them ex post, as it is difficult to punish the seller for misrepresented data policies (Jin, 2018).

Demographic factors

In addition to the above variables, individual factors such as age and gender can also affect the level of individual wellbeing. As far as the impact of age on individual wellbeing is concerned, existing studies have not reached a consistent conclusion. Some studies suggest that as individuals' physical functioning, income, and health status decline with age, the effect of age on individual wellbeing is inevitably negative (Lacey et al., 2006). However, some studies have also found that changes in individual wellbeing are actually stable and possibly even increasing that will accompany aging (Biermann et al., 2022; Cheng et al., 2017). Except for these studies, others have found a U-shaped relationship between age and individual wellbeing, with individual wellbeing decreasing and then increasing with age, with the turning point often occurring between ages 40–50 (Blanchflower, 2021; Blanchflower & Oswald, 2008).

In terms of gender, there are also contrasting findings in the existing literature. Some studies have found that men have a higher welfare level (Batz & Tay, 2018), while some studies believe that women have more advantages in individual welfare (Graham & Chattopadhyay, 2013; Senik, 2017), and some studies even believe that there is no significant difference between male and female (Zuckerman et al., 2017).

As for the role of marriage, ample studies have examined the relationship between marital status and individual wellbeing, and found that married groups have relatively higher levels of mental status and wellbeing compared to the unmarried counterpart, while adults who are widowed, divorced, or never married suffer more from relatively negative wellbeing effects (Chapman & Guven, 2016; Soulsby & Bennett, 2015; Wilson & Oswald, 2005, among others).

Turning to education, the early view holds that education helps people to accomplish their goals, which contributes to the improvement of individual's subjective wellbeing level. Nevertheless, some recent studies show that high education level raises individual aspirations, which increases the difficulty of accomplishing a set goal, thereby reducing individual welfare level further (Chevalier & Feinstein, 2006; Ruiu & Ruiu, 2019).

Finally, some studies have also examined the impact of urban-rural differences on the level of individual wellbeing. Urban and rural areas are significantly different in terms of income, environment, and social security, which leads to spatial differences in the wellbeing of residents. On the one hand, some scholars argue that urbanization brings higher incomes and ameliorated living conditions, yielding higher levels of wellbeing for those living in cities (Easterlin et al., 2011; Veenhoven & Berg, 2013). On the other hand, urban residents face higher living costs, more serious pollutions, traffic congestion, crime and inequality, which in turn reduces to some extent the level of welfare of those living in cities (Glaeser et al., 2016).

DATA

Subjective wellbeing

The dependent variable we use is subjective wellbeing. The data are retrieved from the Gallup World Poll (GWP), which has tracked important issues worldwide since 2005. Some examples are food access, employment, and wellbeing. This is done by continually surveying respondents randomly selected and nationally representative in at least 160 countries. In a typical GWP in each year, around 1000 people aged 15 years and older in each country are contacted via telephone or in-person interviews for participation in the survey. There are exceptions: in some countries, Gallup collected oversamples in multiple times in major cities or areas of special interest, for instance, Gallup conducted four rounds of survey in Germany in 2012 (resulting in a total sample of 13, 269, the maximum number of interviewees in the whole sample over 2005–2018), four rounds in India and Iran, three rounds in China, two rounds in Russia; while rare, in some countries, the sample size is between 500 and 1000, for instance, the sample size is 513 in 2008 for Latvia (the minimum number of interviewees). Readers may refer to http://www.gallup.com for further methodological details.

The GWP includes a wide collection of questions about respondents' wellbeing on the Cantril ladder of life (Cantril, 1965). To measure subjective wellbeing, we first use the responses to the GWP survey asking respondents to evaluate their lives on a 0–10 scale. The English wording of this question is about the respondent's view on his or her 'feeling about life now', stated as follows:

> Wellbeing (current): '*Please imagine a ladder with steps numbered from 0 at the bottom to 10 at the top. Suppose we say that the top of the ladder represents the best possible life for you, and the bottom of the ladder represents the worst possible life for you. On which step of the ladder would you say you personally feel you stand at this time, assuming that the higher the step the better you feel about your life, and the lower the step the worse you feel about it? Which step comes closest to the way you feel?*'

In this study, we also use an alternative measurement of subjective wellbeing or view on life by asking the respondent's view on his or her 'feeling about life in the future', expressed as follows:

> Wellbeing (future): '*Please imagine a ladder with steps numbered from 0 at the bottom to 10 at the top. Suppose we say that the top of the ladder represents the best possible life for you, and the bottom of the ladder represents the worst possible life for you. Just your best guess, on which step do you think you will stand on in the future, say about five years from now?*'

We restrict the sample to 137 countries over 2005–2018 for which values on the wellbeing variable and key covariates are available, so that we have 1249 country-year observations and a total of 1,466,109 observations eventually. The countries used in this study are listed in Table A1.

Figure 1 shows the distribution histograms of current subjective wellbeing and respondents' expectation of future wellbeing. Some distinct patterns are summarised as follows: In general, most people seem satisfied Diener and Diener (1996). Nearly 23.33% of respondents rate their present lives with a score of 5; 36.38% of respondents are classified as 'thriving', scoring 7 or higher on the wellbeing scale; and only 16.99% of respondents are classified as 'suffering' (that is, scoring 3 or lower). In line with Veenhoven (2012), the cross-country comparisons of wellbeing rating are helpful as they show substantial evidence of heterogeneity across countries. For instance, in terms of current wellbeing in 2018 (Figure 2), the lowest scores on wellbeing are recorded in Yemen (2.98), Rwanda (3.50), Botswana (3.52), Tanzania (3.56), and India (3.88), while the highest are in OECD countries such as Finland (7.91), Denmark (7.71), Norway (7.61), Switzerland (7.57), and the Netherlands (7.52).

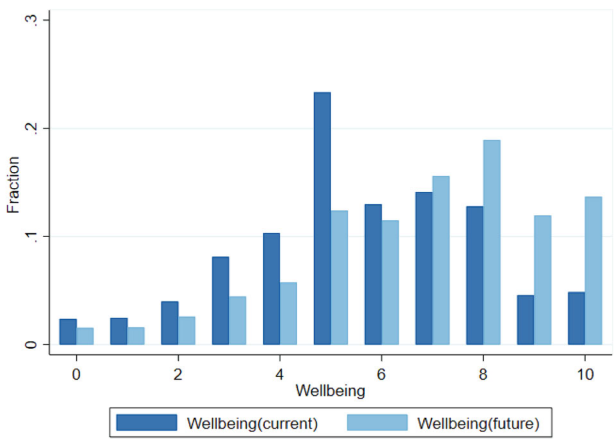

FIGURE 1 Fractional histograms of wellbeing.

Artificial intelligence

Identifying and measuring AI developments is fraught with difficulty (Baruffaldi et al., 2020). In this subsection, we use two measurements to (imperfectly) reflect a country's AI-related developments inspired by the literature: one captures the number of AI-related publications (*Publication*), and the other measures the number of industrial robots installed in one country (*Robot*).

Publication is defined as the total amount of yearly AI-related publications (journal articles or books) in each country, which is used to reflect the development status of AI science and technology in a country. To obtain the country-year panel dataset, we employ a three-step search strategy. In the first step, we identify keywords. According to Cockburn et al. (2018), the AI-related literature falls into three distinct fields, robotics, learning systems, and symbol systems, each comprising numerous subfields. Overall, there are 41 subfields (for details, refer to Cockburn et al. (2018)). In the second step, we identify the annual number of AI-related publications. To this end, we use each subfield as a keyword and conduct a year-by-year keyword search on Thompson Reuters' Web of Science database. In the last step, we determine which country an article belongs to according to the affiliations of all authors. If at least one author of an AI-related article is from country *j*, the article is considered as scientific research achieved by country *j*. For instance, if an article has three authors, and one of them is affiliated with an institution in Mexico and two with institutions in

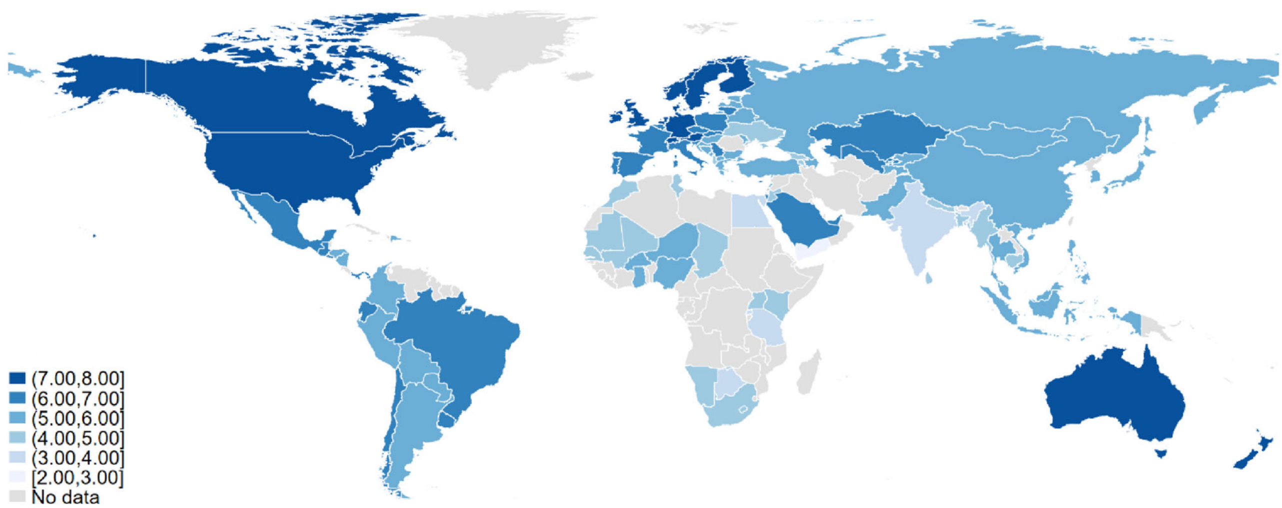

FIGURE 2 Wellbeing rating around the world, 2018.

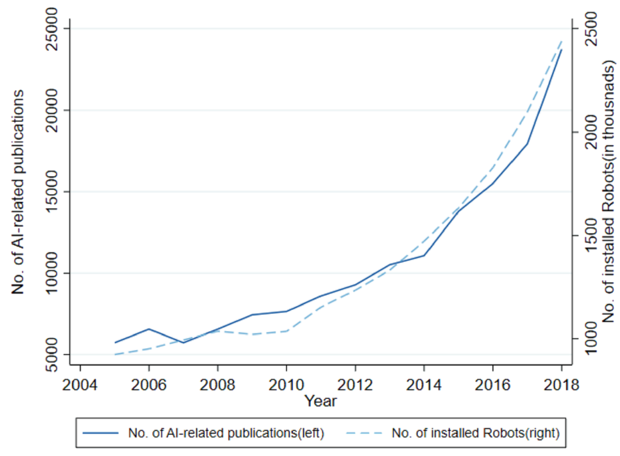

FIGURE 3 Trend for the number of robots and AI-related publications worldwide, 2005–2018.

Belgium, then we consider that Mexico and Belgium have each achieved one AI publication.

We also consider the number of industrial robots used in actual production in a country, Robot, to measure the degree of the country's exposure to AI. Following Artuc et al. (2020) and Acemoglu and Restrepo (2020), we use the stock of industrial robots in one country per year to measure the yearly use of robots in a country's production sector. The data is from the IFR, a professional organisation that provides data on the worldwide use of robots. The IFR conducts yearly surveys with 90% of the industrial robot suppliers worldwide and estimates the stock of industrial robots assuming that a robot has an average life expectancy of 12 years. The IFR data are considered the best information source on industrial robots, although they have some limitations (Acemoglu & Restrepo, 2020).

Figure 3 shows the dynamics (positive trends) for these two measures of AI: total numbers of AI-related publications and robots installed worldwide. The two measurements are strongly correlated with a correlation coefficient of 0.993 ($p = 0.0000$).

Figure 4 displays two residual-based diagnostic plots: (i) the partial-residual plots or the component-plus-residual plots (Larsen & McCleary, 1972); (ii) the partial-regression leverage plots, or the added-variable plots (Belsley et al., 2005). All plots reveal evidence of a negative relationship between the reported wellbeing score and AI-related development. It is worth mentioning that the diagnostic plots are just preliminary analysis to explore the linear relationship between AI and SWB while teasing out the potential effects of the confounding variables such as country- and year fixed effects, they provide no additional information regarding the causal relationship between AI and SWB. In the empirical analysis as follows, we will focus more on the causal effect of AI on individual SWB.

Control variables

Various individual- and country-level demographic and economic characteristics are known to affect self-rated wellbeing (Ejrnæs & Greve, 2017; Hendriks & Bartram, 2016; Ramia & Voicu, 2022). Age is a continuous variable denoting the age of respondents in years, where 100 and above is recorded as 100. Gender is a binary dummy variable with the value of 1 for male and 0 for female. Marital status is a binary dummy with the value of 1 if the respondent is married or having a domestic partner and 0 otherwise (single, never been married, separated, divorced, or widowed). Education measures the education level of the respondents and is divided into three categories: primary education level or below, secondary education, and tertiary education or above. Urban status is measured as a binary dummy variable, which equals 1 if the respondent lives in or close to a large city, and equals 0 if the respondent lives in rural area, farm, small town, or village (the reference group). With regard to the national-level covariates, GDP is expressed in constant 2011 US dollars and converted by purchasing power parity. Data are retrieved from the World Development Indicators (WDI) database of World Bank. GDP per capita is defined as GDP divided by the national population size. Data for population is from WDI. Unemployment rate is measured as the share of the labour force without work but available for and seeking employment. Data are from the WDI, being originally retrieved from the ILOSTAT database of the International Labour Organisation.

Table 1 presents the descriptive statistics of the main variables in our data.

EMPIRICAL STRATEGY

Baseline specification

The baseline model used to examine whether and how AI affects an individual's wellbeing is

$$Wellbeing_{njt} = \alpha + \delta AI_{jt} + \mathbf{X}\beta + \mu_j + \nu_t + \varepsilon_{njt} \qquad (1)$$

where $Wellbeing_{njt}$ is the wellbeing score rated by individual n from country j in year t. AI, denoted by $\ln(Publication)$ or $\ln(Robot)$, is defined as the natural log of one plus the number of AI-related publications or the

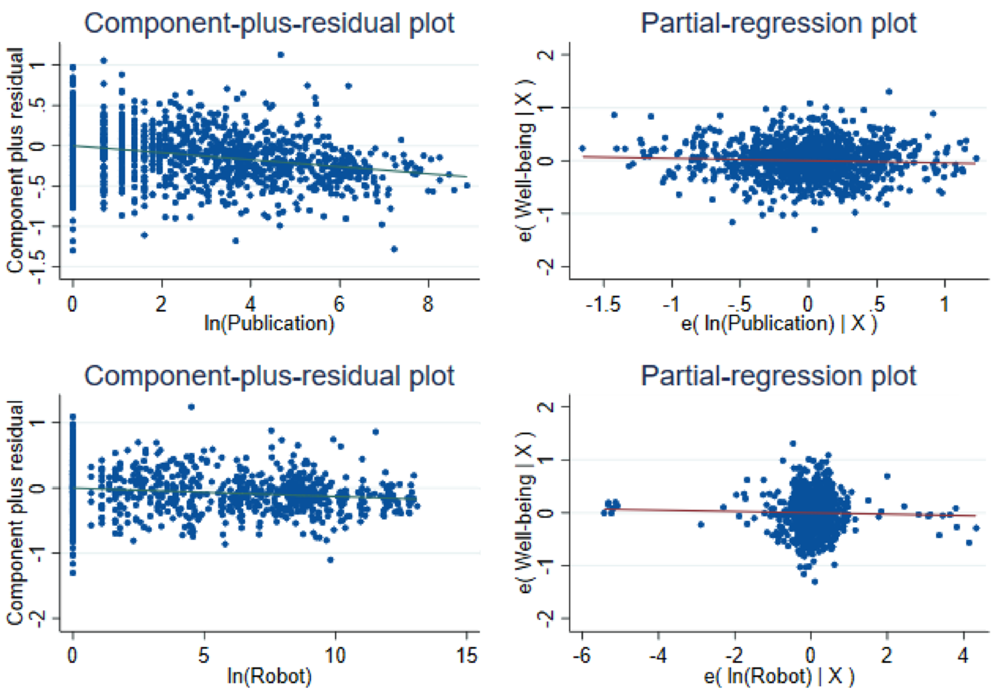

FIGURE 4 Partial residual and partial-regression leverage plots.

TABLE 1 Descriptive statistics.

Variable	Observation	Mean	SD	Min	Max
Dependent variables					
Subjective wellbeing (current)	1,466,109	5.62	2.28	0	10
Subjective wellbeing (future)	1,347,898	6.79	2.38	0	10
Key covariates					
ln(AI-related publications)	1,466,109	3.04	2.29	0	8.86
ln(Industrial robots)	1,466,109	4.13	4.32	0	13.11
Individual variables					
Age	1,466,109	42.16	17.82	15	100
Gender (1 = male)	1,466,109	0.46	0.50	0	1
Marital (1 = married)	1,466,109	0.59	0.49	0	1
Education level	1,466,109	1.87	0.68	1	3
Urban (ref = rural)	1,466,109	0.44	0.50	0	1
Country variables					
ln(GDP)	1,466,109	26.32	1.87	22.18	30.75
ln(GDP per capita)	1,466,109	9.47	1.05	6.56	11.73
Unemployment rate	1,466,109	0.08	0.06	0.00	0.35

number of installed industrial robots. It measures the extent to which AI develops in country j in year t. $\boldsymbol{X}$ is a series of control variables, including individual/country level variables—age, gender, education, GDP. μ_j and ν_t are, respectively, the country and year fixed effects. ε_{njt} is the random error term, assumed to be clustered at the country-year level. The key coefficient of interest is δ, measuring the relationship between AI and wellbeing. If $\delta > 0$, the use of AI improves the overall wellbeing of the individual; otherwise, it does not.

The ordinary least squares (OLS) approach is used to estimate Equation (1), as the response scale can be considered as cardinal. Indeed, treating satisfaction scores as ordinal and cardinal numbers yields results that are quantitatively similar (Frey & Stutzer, 2000). One concern is that the baseline model might not follow a normal distribution, given that the dependent variable is a non-negative count number. For comparison purposes, we also use a Poisson model, which is common for count data (Cameron & Trivedi, 2005).

Instrument construction

Adding the control variables (such as market size, national income, and employment) and fixed effects eases some concerns regarding bias due to omitted variables. Using micro-level data may also mitigate reverse causality (as the aggregated AI variable affects individuals, but individual-level wellbeing or happiness generally does not affect the development of aggregated AI). However, the above treatments cannot entirely solve potential endogeneity. Hence, we will apply the IV approach delineated below to causally estimate the effect of AI on wellbeing when AI development is endogenous.

Our IV identification strategy is inferred from the trade gravity framework used by Feyrer (2009) and Blanchard and Olney (2017). There are two sources of installed robots in a country: domestically produced and imported. The installed volume determined by the former is affected by the country's own economic conditions, which also affects wellbeing. Installed volume via imports is determined both by the economic attributes of surveyed/importing country ('pull factors'), and by the economic attributes of its trading countries ('push factors'). 'Push factors' from exporting countries are more exogenous than 'pull factors', and their relationship with the domestic factors or wellbeing of the surveyed country is relatively weak. If we can tease out the endogenous 'pull factors' that affect the import (and hence installation) of industrial robots in that country, and use merely the variation in potentially exogenous drivers of robot imports to construct the IV, then the exogeneity condition of the IV variable can be better satisfied.

First, we estimate the following equation:

$$\ln\left(Imp.Robot_{ijt}\right) = \alpha + \beta \ln\left(Robot_{it}\right) + \gamma_t + \gamma_i + \gamma_j + \varepsilon_{ijt} \quad (2)$$

where $Imp.Robot_{ijt}$ is the bilateral flow of robots imported by country j (i.e., the surveyed country) from country i in year t. Following Acemoglu and Restrepo (2020), we identify imports of industrial robots at the Harmonised System (HS) six-digit level (i.e., HS6 code 847950). The data are retrieved from the Centre d'Etudes Prospectives et d'Informations Internationales BACI database. $Robot_{it}$ denotes the total amount of industrial robots installed in exporting country i in year t. γ_t, γ_i, and γ_j are year-, exporter, and importer-fixed effects, respectively. ε_{ijt} is the disturbance term. The coefficient estimates based on Equation (2) are provided in column 1 of Table 2.

Second, using the estimated coefficients, we can obtain the fitted value of the dependent variable in Equation (2), $\widehat{y}_{ijt}$. By construction, these predicted values are not a function of attributes in the surveyed importing country but a function of those in the exporting countries; therefore, we use them to construct the instrument. Third, we sum the fitted values of all the country's trading partners in each year, that is, we the instrument ($Robot\_IV_{jt}$) is defined as:

$$Robot\_IV_{jt} = \sum_{i=1}^{N_j} \widehat{y}_{ijt} \quad (3)$$

where $\widehat{y}_{ijt} = e^{\widehat{\alpha} + \widehat{\beta} \ln(Robot_{it}) + \widehat{\gamma_t} + \widehat{\gamma_i} + \widehat{\gamma_j}}$. N_j is the total number of exporting countries that an importing country j trades with.

We then adopt five different but complementary exogenous variation in bilateral robot trade: (1) based on the introduction of exporters' industrial robots to the model, including further bilateral geographical and cultural characteristics (indicator variables for a common border, a common language, and a colonial relationship) (Equation 4); (2) different from Feyrer (2009) who applies the time-varying effects of distances, we interact bilateral distance with year fixed effects to explore the heterogenous effect of distance on robot imports over time partially due to improved transportation technology (Equation 5); (3) adding further even more safely exogenous variables that affect importers' demand: exporters' natural disasters, such as droughts, earthquakes, and landslides. (Equation 6), data for which are retrieved from the EM-DAT international disaster database; (4) instead of controlling for γ_i and γ_j, we use a series of bilateral pair fixed effects (γ_{ij}) as instruments (Equation 7); and (5) considering that even the number of industrial robots installed in exporting countries might not be completely exogenous, the last equation drops the variable $\ln(Robot_{it})$ while keeps only the more exogenous variables (natural disasters) of exporting countries (Equation 8).

The above five approaches of constructing IV are summarized as follows:

TABLE 2 Construction of instrument using bilateral industrial robots trade data.

	Dependent variables: ln(robots imported)					
	Use only robot variable	Add bilateral attributes	Add distance-year FE	Add natural disasters	Use bilateral pair FE	Consider only natural disasters
ln(Industrial robots)	0.0449***	0.0759***	0.0789***	0.0784***	0.0735***	
	(0.0059)	(0.0056)	(0.0056)	(0.0056)	(0.0053)	
Common border (1 = yes)		0.4652***	0.4691***	0.4692***		
		(0.0322)	(0.0321	(0.0321)		
Common language (1 = yes)		0.4777***	0.4768***	0.4772***		
		(0.027)	(0.027)	(0.027)		
Colonial relationship (1 = yes)		0.6999***	0.6992***	0.6991***		
		(0.0346)	(0.0346)	(0.0346)		
ln(Distance)		−1.1150***	−0.9875***	−0.9882***		
		(0.0113)	(0.0374)	(0.0374)		
ln(Drought)				−0.1200***	−0.1064***	−0.1020***
				(0.0381)	(0.0341)	(0.0344)
ln(Earthquake)				−0.0532*	−0.0450*	−0.0505**
				(0.0283)	(0.0243)	(0.0244)
ln(Flood)				0.0251	0.0249	0.0330**
				(0.0181)	(0.016)	(0.016)
ln(Landslide)				0.0229	0.0071	−0.0057
				(0.031	(0.0269	(0.0271
ln(Storm)				0.0318*	0.0371**	0.0390**
				(0.0193)	(0.0167)	(0.0167)
ln(Extreme Temp)				−0.0025	0.0075	0.0022
				(0.0253)	(0.0218)	(0.022)
ln(Volcano)				0.1069	0.0565	0.0537
				(0.0781)	(0.0704)	(0.0702)
ln(Wildfire)				−0.0157	−0.0350	−0.0441
				(0.0321)	(0.0282)	(0.0283)
Constant	0.8809***	9.6833***	9.6693***	9.6549***	1.8327***	2.2613***
	(0.0418)	(0.1024)	(0.1024)	(0.104)	(0.2776)	(0.2764)
ln(Distance)*Year fixed-effects	No	No	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Importer fixed-effects	Yes	Yes	Yes	Yes	No	No
Exporter fixed-effects	Yes	Yes	Yes	Yes	No	No
Bilateral pair fixed-effects	No	No	No	No	Yes	Yes
Observations	85,006	78,283	78,283	78,283	76,148	76,148
R-squared	0.299	0.427	0.427	0.427	0.623	0.622

Note: *** <1%, ** <5%, and * <10%. Robust standard errors are in parentheses. The variable contiguous indicates whether two countries are geographically adjacent, which equals 1 when the two countries border, and 0 otherwise. Common language indicates whether two countries speak the same language. When more than 95% of the people speak the same language, this variable takes the value of 1, otherwise it is 0. Colonial relationship indicates whether two countries have colonial relationship in history, it is set to 1 if yes, and 0 otherwise. Distance is the geographical distance between two countries, which is represented by the spherical distance between the capitals of two countries. Drought, Drought, Earthquake, Flood, Landslide, Storm, Extreme Temperature, Volcano, and Wildfire measure the number of natural disasters that occur in each country each year, respectively. They are added by one and included in the regression equation by taking the logarithmic form. Gravity model variables such as geographical distance are obtained from the French Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) Database. Natural disaster data are obtained from EM-DAT, the International Disaster Database.

$$\ln\left(Imp.Robot_{ijt}\right) = \alpha + \beta\ln\left(Robot_{it}\right) + Bilat'_{ij}\lambda + \gamma_t + \gamma_i + \gamma_j + \varepsilon_{ijt} \quad (4)$$

$$\ln\left(Imp.Robot_{ijt}\right) = \alpha + \beta\ln\left(Robot_{it}\right) + Bilat'_{ij}\lambda + \sum_{s=1996}^{2018}\theta^s 1(t=s)\ln\left(Dist_{ij}\right) + \gamma_t + \gamma_i + \gamma_j + \varepsilon_{ijt} \quad (5)$$

$$\ln\left(Imp.Robot_{ijt}\right) = \alpha + \beta\ln\left(Robot_{it}\right) + Bilat'_{ij}\lambda + \sum_{s=1996}^{2018}\theta^s 1(t=s)\ln\left(Dist_{ij}\right) + Disaster'_{it}\phi + \gamma_t + \gamma_i + \gamma_j + \varepsilon_{ijt} \quad (6)$$

$$\ln\left(Imp.Robot_{ijt}\right) = \alpha + \beta\ln\left(Robot_{it}\right) + \sum_{s=1996}^{2018}\theta^s 1(t=s)\ln\left(Dist_{ij}\right) + Disaster'_{it}\phi + \gamma_t + \gamma_{ij} + \varepsilon_{ijt} \quad (7)$$

$$\ln\left(Imp.Robot_{ijt}\right) = \alpha + \sum_{s=1996}^{2018}\theta^s 1(t=s)\ln\left(Dist_{ij}\right) + Disaster'_{it}\phi + \gamma_t + \gamma_{ij} + \varepsilon_{ijt} \quad (8)$$

where $Bilat_{ij}$ is a vector of bilateral geographical and cultural variables introduced above. $Dist_{ij}$ is the geographical distance between countries i and j, $Disaster_{it}$ is a vector of natural disaster variables measured as the natural log of one plus the number of each type of natural disaster (drought, earthquake, flood, landslide, storm, extreme temperature, volcano, and wildfire) that occurred in exporting country i at year t. It is worth mentioning that although the occurrence of natural disasters is exogenous, its economic and social consequence is associated with the economic and social conditions of a country. Thus, different from Blanchard and Olney (2017) using damages caused by natural disasters, we quantify natural disasters based on number of occurrences instead of damages as the former is exogenous.

The coefficient estimates based on each of the five equations (Equations (4)–(8)) are provided in columns 2–6 of Table 2. We proceed to use these estimated coefficients to obtain fitted values of the dependent variable (i.e., bilateral trade flows of robots) and construct each set of IVs using Equation (3).

RESULTS AND DISCUSSIONS

Baseline results

Table 3 presents the baseline estimates based on Equation (1). The number of AI-related publications is used to proxy for the spread of AI. All model specifications control for country- and year-fixed effects, and cluster the standard errors at the country-year level, which has a desirable property to avoid the downward bias of the standard errors of the aggregated variables (Moulton, 1990). Columns 1–2 show the OLS results, while columns 3–4 report the Poisson regression results.

From columns 1–2 of Table 3, which use a respondent's current and future wellbeing as dependent variables, respectively, the coefficients on the AI variables are negative and statistically significant at the 5% level. Comparing columns 3–4 with columns 1–2, the estimations using a Poisson model do not change essentially in terms of trend, as the estimated AI parameters bore the same negative signs and the estimated wellbeing effects are close in magnitude, as per the calculated marginal effects (−0.06318 in the 'wellbeing (current)' model and −0.06087 in the 'wellbeing (future)' model), which is simply computed as the AI coefficient estimate in Column (3) or (4) of Table 3 multiplies the mean value of wellbeing in Table 1 (Hilbe, 2011). These results suggest that the AI impact on wellbeing is substantial and the advancement of AI significantly reduces both current wellbeing and expectations of future wellbeing. Specifically, the coefficient on AI ($\beta = -0.0598$, s.e. $= 0.0228$) in column 1 reveals that a 10% increase in AI publication would reduce wellbeing by 0.6, which is about 10% (30%) of the sample mean (SD).

Turning to the control variables, each of them in these two models have the same sign and similar magnitude, except for the income variable, which is statistically insignificant. This result could indicate that the short- and long-run temporal relationships between wellbeing and income should be distinguished and, especially in the long run, wellbeing and income are unrelated (Easterlin et al., 2010). Moreover, women appear to be more satisfied than men, which align with the finding of Zweig (2015). Furthermore, those individuals that appear to be more satisfied than their counterparts are one of the following: married, highly educated, living in an urban area, or in a country with lower unemployment.

Alternative measure of AI

Table 4 shows an alternative proxy for AI, which uses the IFR stock of robots. Column 1 shows a strong negative

TABLE 3 Baseline results.

	OLS		Poisson	
	Subjective wellbeing (current)	**Subjective wellbeing (future)**	**Subjective wellbeing (current)**	**Subjective wellbeing (future)**
ln(AI-related publications)	−0.0598***	−0.0597**	−0.0112**	−0.0090**
	(0.0228)	(0.0284)	(0.0044)	(0.0042)
Age	−0.0109***	−0.0312***	−0.0020***	−0.0047***
	(0.0004)	(0.0006)	(0.0001)	(0.0001)
Gender (1 = male)	−0.0959***	−0.1013***	−0.0168***	−0.0146***
	(0.0066)	(0.0085)	(0.0012)	(0.0013)
Marital (1 = married)	0.1333***	0.1251***	0.0226***	0.0207***
	(0.0075)	(0.0082)	(0.0013)	(0.0012)
Education level	0.4809***	0.5027***	0.0857***	0.0754***
	(0.0072)	(0.0085)	(0.0015)	(0.0014)
Urban (ref = rural)	0.1726***	0.1941***	0.0307***	0.0285***
	(0.0111)	(0.0116)	(0.0020)	(0.0017)
ln(GDP)	−0.5802**	0.3738	−0.1141**	0.0511
	(0.2478)	(0.3036)	(0.0467)	(0.0458)
ln(GDP per capita)	1.0965***	0.2141	0.2155***	0.0403
	(0.3064)	(0.3382)	(0.0593)	(0.0517)
Unemployment rate	−4.2721***	−4.2453***	−0.7965***	−0.6679***
	(0.6731)	(0.7173)	(0.1289)	(0.1134)
Constant	10.4639**	−4.3340	2.5499***	0.1475
	(4.7615)	(5.9426)	(0.8849)	(0.8783)
Year fixed-effects	Yes	Yes	Yes	Yes
Country fixed-effects	Yes	Yes	Yes	Yes
Observations	1,466,109	1,347,898	1,466,109	1,347,898
R-squared	0.227	0.180		

Note: *** <1%, ** <5%, and * <10%. Robust standard errors in parentheses are clustered at the country-year level.

association between robot adoption and wellbeing (current), with an estimated coefficient of −0.0324 (standard error 0.0109) in the OLS model. This estimate implies that a 10% increase in robot adoption is related with a decrease in wellbeing of 0.3 (about 5% (15%) of the sample mean (SD)). The coefficient estimate remains close and statistically significant when using wellbeing (future) as the explained variable (column 2 of Table 4). Although the resulting Poisson estimations (columns 3 and 4) are marginally different from those obtained using the OLS method (e.g., −0.0324 in the OLS model vs. a calculated marginal effect of −0.0289 in the Poisson model), reassuringly, the negative and significant effect of robot adoption still held.

IV results

The above empirical analysis could be plagued with endogeneity and simultaneity bias using either proxy for AI, even after a battery of variables and fixed effects have been controlled. This may have arisen from omitted variables (e.g., labour union power or the COVID-19 pandemic), measurement error due to the inaccurate measurement of AI, or direct reverse causality (i.e., varying subjective wellbeing, regardless of whether the individuals are happier or unhappier than before, may influence the decision of a country to robotise its production or incentivise AI researchers to research and publish articles on AI more or less). Thus, we adopt a two-stage least squares (2SLS) approach to test the causal relationship between AI and subjective wellbeing. As described earlier in Section 4.2, our instruments are obtained using variation in the potentially drivers of a country's robot import.

Table 5 shows the IV results. First, the IV estimates of the AI coefficients are in general robust to all IV specifications. Second, the estimated association between AI and wellbeing reinforces considerably when the AI variable is instrumented. For instance, the coefficients on

TABLE 4 Alternative AI measure.

	OLS		Poisson	
	Subjective wellbeing (current)	**Subjective wellbeing (future)**	**Subjective wellbeing (current)**	**Subjective wellbeing (future)**
ln(Industrial robots)	−0.0324***	−0.0497***	−0.0051***	−0.0069***
	(0.0109)	(0.0138)	(0.0017)	(0.0019)
Age	−0.0109***	−0.0312***	−0.0020***	−0.0047***
	(0.0004)	(0.0006)	(0.0001)	(0.0001)
Gender (1 = male)	−0.0959***	−0.1014***	−0.0168***	−0.0146***
	(0.0066)	(0.0085)	(0.0012)	(0.0013)
Marital (1 = married)	0.1330***	0.1246***	0.0225***	0.0207***
	(0.0075)	(0.0082)	(0.0013)	(0.0012)
Education level	0.4806***	0.5024***	0.0856***	0.0753***
	(0.0072)	(0.0084)	(0.0015)	(0.0014)
Urban (ref = rural)	0.1725***	0.1939***	0.0307***	0.0285***
	(0.0111)	(0.0115)	(0.0020)	(0.0017)
ln(GDP)	−0.6837***	0.2293	−0.1324***	0.0307
	(0.2487)	(0.3054)	(0.0465)	(0.0459)
ln(GDP per capita)	1.1997***	0.3616	0.2325***	0.0600
	(0.3022)	(0.3337)	(0.0584)	(0.0509)
Unemployment rate	−4.3660***	−4.3680***	−0.8162***	−0.6895***
	(0.6694)	(0.7071)	(0.1286)	(0.1122)
Constant	12.1697**	−1.8932	2.8799***	0.5071
	(4.8400)	(6.0121)	(0.8874)	(0.8840)
Year fixed-effects	Yes	Yes	Yes	Yes
Country fixed-effects	Yes	Yes	Yes	Yes
Observations	1,466,109	1,347,898	1,466,109	1,347,898
R-squared	0.227	0.180		

Note: *** <1%, ** <5%, and * <10%. Robust standard errors in parentheses are clustered at the country-year level.

ln(*Publication*) and ln(*Robot*) (−0.8031 and −0.7006, respectively) in the 'wellbeing (current)' model (columns 1 and 2 of Table 5) suggest that a 1% increase in AI-related publications and robot adoption would reduce wellbeing by 0.8 and 0.7, respectively, which correspond to a reduction size of about 45% (18%) and 40% (15%), respectively, of the sample mean (SD). This result also suggests that there is a large bias in the results of OLS. From the perspective of bias direction, the overestimation of the OLS results is more likely to origin from other omitted variables that have a positive correlation with the error term in the model. In fact, when a country has a high level of AI, it will also have a relatively high level of institutional governance, living environment and convenience. However, these variables are not included in the empirical study due to data availability, teasing out these variables will overestimate the impact of AI in the OLS regression, while after accounting for the omitted variable bias issue in the IV regression, the strengthening of the negative impact of AI is hence a natural result.

Third, the estimation results might be challenged by weak instruments as most Kleibergen-Paap (KP) F values lie between 6.5 and 10.8, some of which are lower than the commonly used critical value 10. Nevertheless, we argue that the results are not affected substantially for two reasons: (i) As inferred from the Anderson-Rubin (AR) test that is robust to weakness of the instruments (Anderson & Rubin, 1949), the p-values for the tests in all IV models are less than 0.01, suggesting that the null hypothesis can be rejected, that is, the impact of AI is significant. (ii) In settings with weak instruments, IV estimates are 'biased toward' the corresponding OLS estimates (Angrist & Pischke, 2009). As the corresponding OLS estimates in Table 3 are substantially smaller

TABLE 5 IV results.

	Use only robot variable		Add bilateral attributes		Add distance-year FE		Use natural disasters		Use bilateral pair FE		Consider only natural disasters	
Panel A: *Subjective wellbeing (current) model*												
ln(AI-related publications)	−0.8031**		−0.7493		−0.7059*		−0.7387*		−0.8575*		−0.8591*	
	(0.3620)		(0.4622)		(0.3929)		(0.3928)		(0.4498)		(0.4799)	
ln(Industrial robots)		−0.7006***		−0.6622**		−0.6934**		−0.6716**		−0.6617**		−0.7830**
		(0.2477)		(0.3278)		(0.3134)		(0.2968)		(0.2954)		(0.3701)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
KP *F*-statistic	6.800	7.981	6.895	7.085	7.436	7.134	7.441	7.075	7.888	10.81	7.438	8.881
AR *F*-statistic	14.26	14.26	6.290	6.290	8.447	8.447	9.544	9.544	8.272	8.272	7.037	7.037
AR *p*-value	0.0002	0.0002	0.0123	0.0123	0.0037	0.0037	0.0021	0.0021	0.0041	0.0041	0.0081	0.0081
Observations	1,466,109	1,466,109	1,466,109	1,466,109	1,466,109	1,466,109	1,466,109	1,466,109	1,466,109	1,466,109	1,466,109	1,466,109
Panel B: *Subjective wellbeing (future) model*												
ln(AI-related publications)	−1.7895***		−1.7397***		−1.5073***		−1.5539***		−1.8895***		−1.8810**	
	(0.5132)		(0.6151)		(0.4988)		(0.5059)		(0.7070)		(0.7525)	
ln(Industrial robots)		−1.5058***		−1.5077***		−1.4645***		−1.3900***		−1.4375***		−1.6884***
		(0.3430)		(0.4555)		(0.4461)		(0.4201)		(0.4154)		(0.5656)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
KP *F*-statistic	6.619	7.692	6.578	6.762	7.185	6.834	7.190	6.792	7.483	10.28	7.066	8.341
AR *F*-statistic	12.75	12.75	13.57	13.57	14.37	14.37	14.50	14.50	20.72	20.72	19.69	19.69
AR *p*-value	0.0004	0.0004	0.0002	0.0002	0.0002	0.0002	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000
Observations	1,347,898	1,347,898	1,347,898	1,347,898	1,347,898	1,347,898	1,347,898	1,347,898	1,347,898	1,347,898	1,347,898	1,347,898

Note: *** <1%, ** <5%, and * <10%. Robust standard errors in parentheses are clustered at the country-year level.

TABLE 6 Using aggregated Gallup data.

	OLS		2SLS (Equation 8)		Rolling window		Long difference from 2008 to 2018[a]	
Panel A: *Subjective wellbeing (current) model*								
ln(AI-related publications)	−0.0567*		−1.0675**		−0.0998***		−0.1687*	
	(0.0327)		(0.5353)		(0.0278)		(0.0958)	
ln(Industrial robots)		−0.0298**		−0.8371**		−0.0393***		−0.0800**
		(0.0132)		(0.4100)		(0.0089)		(0.0314)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Country fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No
KP *F*-statistic			4.678	5.099				
AR *F*-statistic			6.581	6.581				
AR *p*-value			0.0115	0.0115				
Observations	1238	1238	1238	1238	982	982	66	66
Panel B: *Subjective wellbeing (future) model*								
ln(AI-related publications)	−0.0540		−2.3277**		−0.0967***		−0.1766*	
	(0.0390)		(1.0838)		(0.0360)		(0.0997)	
ln(Industrial robots)		−0.0437**		−1.7730***		−0.0533***		−0.0721**
		(0.0177)		(0.7229)		(0.0114)		(0.0325)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Country fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No
KP *F*-statistic			4.497	5.061				
AR *F*-statistic			18.56	18.56				
AR *p*-value			0.0000	0.0000				
Observations	1237	1237	1237	1237	982	982	66	66

Note: *** <1%, ** <5%, and * <10%. Robust standard errors in parentheses are clustered at the country level.
[a]Notice that, for the long-differencing model, the core independent variables are measured in changes (i.e., Δln(Publication) and Δln(Robot)).

(in absolute value) than the IV estimates, we can infer that weak instruments only underestimate rather than overestimate the relationship between AI and wellbeing. Indeed, we also attempt to develop a new set of instrumental variables viz (Artuc et al., 2020). These results are provided in Table A2. In brief, the regression results showed that the negative relationship between AI and wellbeing remains valid.

Using aggregated gallup data

The GWP survey data are repeated cross-section data (i.e., not a panel-type data) as interviewees differ year by year, yet, repeated cross-sectional data can be used to consider patterns of change at the aggregate level. In this subsection, as a robustness check, we convert the repeated cross-sectional survey data to a panel data type by averaging data at the country level for all variables in Equation (1) to assess the relationship between AI and subjective wellbeing using some panel data approaches such as panel IV, rolling window, or long-differencing approaches. Specifically, the country-level model is specified as: $Wellbeing_{jt} = \alpha + \delta AI_{jt} + \boldsymbol{Z}\beta + \mu_j + \nu_t + \varepsilon_{jt}$, where Z is a series of country-level control variables (GDP, GDP per capita, and unemployment rate) and the mean values of these individual covariates used in Equation (1) such as the respondent's age, gender, marital status, education level and urban status. This model specification yields a total of 1237–1238 country-level observations.

The OLS results using aggregated data are presented in columns 1 and 2 of Table 6. In this part, we also implement a battery of robustness checks. The results are shown in the remaining columns of the table.

First, following the OLS regression, we continue running an IV regression based on Equation (8) which use a set of more exogenous factors (exporter natural disasters, bilateral pair fixed effects, and time-varying effects of distances) as instruments.

Second, we will implement a rolling window regression while using the same model setup as before except we construct a slightly different version of the dependent variable and independent variables. Motivated by Artuc et al. (2020), the new dependent variable and each independent variable are defined so that each variable is smoothed over three consecutive years, where the current year has the same weight as the year before and the year after. For instance, the new dependent variable is defined as: $Wellbeing_{jt} = 1/3\left(Wellbeing_{j,t} + Wellbeing_{j,t-1} + Wellbeing_{j,t-2}\right)$. The simple smoothing method has some good properties to reduce the noise (transient or irregular fluctuations) hidden in the data.

Third, given that our main analysis is firmly rooted in short-run year-to-year AI-related developments, we use a long difference regression method that overcome the limitation of the traditional panel approach by considering only short-run year-to-year variation. To this end, we regress the change in average wellbeing rating from 2008 to 2018 on the change in either the number of AI-related publications or the number of industrial robots installed. Our first sample includes 66 countries for which there is data.

$$\begin{aligned} Wellbeing_{j,2018} - Wellbeing_{j,2008} = \delta\left(AI_{j,2018} - AI_{j,2008}\right) \\ +\beta\left(X_{j,2018} - X_{j,2008}\right) + \varepsilon_{j,2018} - \varepsilon_{j,2008} \end{aligned} \tag{9}$$

Last, we also try to investigate the effect of AI on wellbeing by combining the long-difference and (5- and 10-year) rolling window regression approaches. The results are presented in Appendix A.3.

Table 6 shows the results of these robustness checks. It reveals that the key variable of interest is qualitatively similar with that of previous analysis, confirming that our baseline OLS or IV findings are not affected by the transient/irregular fluctuations potentially existed in the sampled data, the time-invariant omitted variables, or large countries.

Other robustness checks

Finally, four more robustness checks are performed, as follows:

1. *Extracting a subsample of interviewees*: We limit the respondents to those adults aged 24–65 years.
2. *Removing extreme values*: We delete possible outliers by removing the country-year groups that have average wellbeing falling in the bottom or top 5th percentile of the distribution.
3. *Weighted least-square (WLS) regression*: The WLS approach is desirable and 'often employed in linear regression using complex survey data…deal with the bias in OLS arising from informative sampling' (Magee, 1998). The weight used in the WLS regression models is provided by Gallup, which after collecting and processing survey data, assigns a weight to each respondent belonging to the same country, so that the demographic characteristics of the total weighted sample of respondents matches the national demographics of a country. Readers may refer to https://www.gallup.com or http://www.oecd.org/sdd/43017172.pdf for details on the sampling and weighting methodologies.
4. *Removing some covariates*: We remove potentially endogenous control variables such as individual's marital status, urban status, and level of education in the baseline OLS model.

Panels A–B of Table 7 display the results of robustness checks for the four cases using two versions of the wellbeing measurement (current vs. future) as the dependent variable. Columns 1–4 (5–8) present results using AI-related publications (install robots as a proxy for AI). The empirical results are comparable to the baseline results in columns 1–2 in Table 3. Table 7 reveals that, when using either measure of AI proxy, the qualitative or quantitative results on the nexus between AI and wellbeing are not appreciably altered, implying that they are not likely driven by the updated age group, extreme values, re-weighting, or controlling potentially endogenous covariates. It is worth mentioning that we also re-run the IV regression after removing these potentially endogenous covariates. The results are reported in Table A4 and suggest that the updated IV results remain comparable to the baseline results in Table 3.

Heterogeneity analysis: Who is afraid of AI?

We proceed by examining how the impacts of AI on wellbeing vary across different demographic subgroups. Such analysis will not only help to further understand the heterogeneous responses of different individuals, but also help to better identify the specific mechanism by which AI may affect wellbeing in the next section. To this end, we rewrite the econometric model as follows:

$$\begin{aligned} Wellbeing_{njt} = \alpha + \delta AI_{jt} + \eta AI_{jt} \times M_{njt} + \theta M_{njt} + \boldsymbol{W}\beta + \mu_j \\ + \nu_t + \varepsilon_{njt} \end{aligned} \tag{10}$$

where M denotes a vector of six variables. The first two variables, age and gender, are introduced earlier, and the

TABLE 7 Other robustness checks (OLS).

	Aged between 24 and 65	Remove extreme values	WLS	Remove endogenous covariates	Aged between 24 and 65	Remove extreme values	WLS	Remove endogenous covariates
Panel A: *Subjective wellbeing (current) model*								
ln(AI-related publications)	−0.0654***	−0.0517**	−0.0568**	−0.0530**				
	(0.0235)	(0.0222)	(0.0231)	(0.0234)				
ln(Industrial robots)					−0.0283**	−0.0477***	−0.0315***	−0.0325***
					(0.0110)	(0.0133)	(0.0105)	(0.0114)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	994,384	1,320,161	1,466,109	1,466,109	994,384	1,320,161	1,466,109	1,466,109
R-squared	0.235	0.178	0.225	0.208	0.235	0.178	0.225	0.208
Panel B: *Subjective wellbeing (future) model*								
ln(AI-related publications)	−0.0695**	−0.0459*	−0.0574**	−0.0512*				
	(0.0300)	(0.0274)	(0.0289)	(0.0291)				
ln(Industrial robots)					−0.0488***	−0.0367***	−0.0511***	−0.0498***
					(0.0142)	(0.0124)	(0.0135)	(0.0141)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	917,352	1,218,008	1,347,898	1,347,898	917,352	1,218,008	1,347,898	1,347,898
R-squared	0.169	0.149	0.181	0.161	0.169	0.149	0.181	0.161

Note: *** <1%, ** <5%, and * <10%. Robust standard errors in parentheses are clustered at the country-year level.

remaining four variables are: (i) relative income or income gap: defined as the ratio of personal income to national per capita GDP (2009–2018). This variable is used to reflect the relative income of an individual compared to the national average. (ii) skilled worker: following Aksoy et al. (2018), we define it as a binary dummy variable indicating whether the respondent is a skilled worker. This variable is coded as 1 if the person aged 25–64 years has at least tertiary education, and 0 otherwise. (iii) manufacturing worker: a binary dummy which equals 1 if a person aged 25–64 is working in the manufacturing sector, and 0 otherwise. (iv) democracy index: a dummy variable taking a value of 1 if the respondent is from a high demographic country, defined as a country obtaining an EIU democracy index (https://www.eiu.com/topic/democracy-index) above 75, and 0 otherwise. The EIU index is a leading index covering 60 indicators for 5 dimensions (electoral process and pluralism, civil liberties, government functioning, political participation, and political culture) in more than 160 countries. $\boldsymbol{W}$ is a set of control variables which are introduced before, such as the respondent's marital status, level of education, urban status, national GDP, GDP per capita, and national unemployment rate.

Table 8 shows the regression results of these five regression models. Panel A shows the results based on Equations (10) using AI-related publications, and Panel B shows the corresponding results using robots as a proxy for *AI*. Table 8 reveals strong evidence that, for younger, male, higher-income individuals (in the AI publication model), skilled workers, and workers in manufacturing, wellbeing is negatively affected to a higher extent by AI in both cases than the elderly, women, lower-income individuals, unskilled workers, and non-manufacturing workers. However, there is some evidence indicating that the negative AI effect on wellbeing differs between democracies and non-democracies and affects more those individuals in the democratic countries ($\beta = -0.0017$, s.e. $= 0.0008$).

Women seem to have been less affected than men, which is a similar result to that of Webb (2019), who find that 'occupations whose workers are predominantly male

TABLE 8 Heterogeneity analysis for different groups.

	Age	Gender (1 = male)	Income Gap	Skilled Worker	Manufacturing Worker	Democracy
Panel A: *Using the number of AI-related publications to reflect a country's AI-related developments*						
ln(AI-related publications) × Age	0.0015***					
	(0.0002)					
ln(AI-related publications) × Gender(1 = male)		−0.0157***				
		(0.0031)				
ln(AI-related publications) × Relative income			−0.0074**			
			(0.0033)			
ln(AI-related publications) × Skilled worker(1 = yes)				−0.0209***		
				(0.0049)		
ln(AI-related publications) × Manufacturing worker(1 = yes)					−0.0237***	
					(0.0071)	
ln(AI-related publications) × Democracy index						−0.0017**
						(0.0008)
ln(AI-related publications)	−0.1191***	−0.0527**	−0.0622***	−0.0569**	−0.0260	0.0242
	(0.0234)	(0.0229)	(0.0236)	(0.0229)	(0.0343)	(0.0426)
Panel B: *Using the number of industrial robots installed to reflect AI-related developments*						
ln(Industrial robots) × Age	0.0007***					
	(0.0001)					
ln(Industrial robots) × Gender(1 = male)		−0.0046***				
		(0.0016)				
ln(Industrial robots) × Relative income			0.0015			
			(0.0010)			
ln(Industrial robots) × Skilled worker(1 = yes)				−0.0097***		
				(0.0026)		
ln(Industrial robots) × Manufacturing worker(1 = yes)					−0.0073**	
					(0.0035)	
ln(Industrial robots) × Democracy index						0.0002
						(0.0005)

TABLE 8 (Continued)

	Age	Gender (1 = male)	Income Gap	Skilled Worker	Manufacturing Worker	Democracy
ln(Industrial robots)	−0.0647***	−0.0304***	−0.0423***	−0.0308***	−0.0147	−0.0468
	(0.0118)	(0.0110)	(0.0120)	(0.0110)	(0.0152)	(0.0365)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,466,109	1,466,109	1,273,838	1,466,109	421,738	1,459,871

Note: Robust standard errors in parentheses are clustered at the country-year level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

are much more exposed to robots than occupations with a primarily female workforce'. This may reflect the fact that women's heavy involvement in 'interpersonal' occupations in such areas as education, healthcare support, and personal care services may shelter them from negative shocks due to the spread of AI. Chiacchio et al. (2018) focus on six European Union member states, and show that men are more vulnerable to displacement through automation than women, and younger workers' jobs are more likely to be replaced than older workers' jobs. This may, to some extent, mean that the wellbeing of young people is more adversely affected by machines. This is consistent with our findings that the welfare of the elderly is less affected. Another possible explanation is that the elderly pay less attention to privacy and their understanding of AI is inadequate, which, to a certain extent, alleviates the negative impacts of AI.

We find that high-skilled workers are more affected by the spread of AI than low-skilled ones. This result is consistent with Moravec's paradox, which states that high-level reasoning (e.g., as demonstrated by performing intelligence tests, mathematical programming, and playing checkers) requires very little computation, but low level sensory based motor skills (e.g., crawling, walking, face recognising) require enormous computational resources (Moravec, 1998). Therefore, it is conceivable that new technologies would make it easy to replace some high-skilled workers, but difficult to substitute low-skilled jobs (e.g., security personnel, chefs, and receptionists). Another reason for the larger impact in the high-skilled group may be that these people are high-income earners and value personal privacy more. Therefore, if AI raises additional privacy issues, these individuals will be affected even more. The result is consistent with the findings of recent empirical works. For instance, Muro et al. (2019) reveal that employees with a bachelor's degree are more exposed to AI than those with a high school diploma. Similarly, Webb (2019) finds that high-skilled workers are most exposed to the spread of AI technology. We also find that manufacturing workers feel less satisfied due to the spread of AI than non-manufacturing workers. This result is consistent with Dauth et al. (2018), who argue that, although the use of robots increase employment in the business service sector, it reduces the demand for workers in the manufacturing industries. If this mechanism holds, workers' wellbeing in the manufacturing sector will be more adversely affected than those in other sectors. Li et al. (2020) come to a similar conclusion, that the use of robots in the manufacturing sector reduces the ratio of front-line staff, with low-skilled and even skilled workers being replaced by robots.

These findings, to a certain extent, provide evidence for the existence of the employment and income

TABLE 9 Mechanism analysis: Income.

Dependent variable	Subjective wellbeing (current)	ln(Income)	Subjective wellbeing (current)	Subjective wellbeing (current)	ln(Income)	Subjective wellbeing (current)
Panel A: *Whole sample*						
ln(AI-related publications)	−0.0652***	−0.0248	−0.0599***			
	(0.0236)	(0.0200)	(0.0231)			
ln(Industrial robots)				−0.0417***	−0.0268**	−0.0359***
				(0.0121)	(0.0105)	(0.0124)
ln(Income)			0.2164***			0.2163***
			(0.0061)			(0.0061)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,273,838	1,273,838	1,273,838	1,273,838	1,273,838	1,273,838
R-squared	0.228	0.488	0.243	0.228	0.488	0.243
Panel B: *High-income group*						
ln(AI-related publications)	−0.0779***	−0.003	−0.0771***			
	(0.023)	(0.0059)	(0.0231)			
ln(Industrial robots)				−0.0411***	−0.0095**	−0.0384**
				(0.0154)	(0.0046)	(0.0159)
ln(Income)			0.2842***			0.2839***
			(0.0114)			(0.0114)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	320,646	320,646	320,646	320,646	320,646	320,646
R-squared	0.218	0.822	0.222	0.218	0.822	0.222
Panel C: *Low-income group*						
ln(AI-related publications)	−0.0483	−0.0869*	−0.0454			
	(0.0302)	(0.0497)	(0.0300)			
ln(Industrial robots)				−0.0207	−0.0458*	−0.0191
				(0.0140)	(0.0276)	(0.0144)
ln(Income)			0.0341***			0.0342***
			(0.0058)			(0.0058)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	318,073	318,073	318,073	318,073	318,073	318,073
R-squared	0.222	0.462	0.222	0.222	0.462	0.222

Note: *** <1%, ** <5%, and * <10%. Robust standard errors in parentheses are clustered at the country-year level.

mechanisms mentioned in Section 2. However, the findings reported herein should be interpreted with caution. The consensus is that AI could impact nearly all aspects of society: the labour market, transport, healthcare, education, national security, and so on; however, there is less agreement on whether the impact differs by occupation type. Unfortunately, there is a lack of disaggregated industry or sector-level data, which exacerbates the substantial uncertainty in the debate on the impacts of AI.

TABLE 10 Mechanism analysis: Employment.

Dependent variable	**Subjective wellbeing (current)**	**Employment**	**Subjective wellbeing (current)**	**Subjective wellbeing (current)**	**Employment**	**Subjective wellbeing (current)**
Panel A: *Whole sample*						
ln(AI-related publications)	−0.0799***	−0.0147***	−0.0789***			
	(0.0246)	(0.0042)	(0.0246)			
ln(Industrial robots)				−0.0385***	−0.0042*	−0.0382***
				(0.0121)	(0.0024)	(0.0121)
Employment (ref: unemployment)			0.0669***			0.0674***
			(0.0079)			(0.0079)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,253,103	1,253,103	1,253,103	1,253,103	1,253,103	1,253,103
R-squared	0.229	0.136	0.229	0.229	0.136	0.229
Panel B: *High-skilled group*						
ln(AI-related publications)	−0.0623**	−0.0094	−0.0593**			
	(0.0291)	(0.0062)	(0.0292)			
ln(Industrial robots)				−0.0334***	0.0008	−0.0337***
				(0.0102)	(0.0014)	(0.0101)
Employment (ref: unemployment)			0.3178***			0.3182***
			(0.0145)			(0.0145)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	174,061	174,061	174,061	174,061	174,061	174,061
R-squared	0.200	0.066	0.204	0.200	0.066	0.204
Panel C: *Low-skilled group*						
ln(AI-related publications)	−0.0791***	−0.0154***	−0.0783***			
	(0.0255)	(0.0044)	(0.0254)			
ln(Industrial robots)				−0.0402***	−0.0049*	−0.0399***
				(0.0130)	(0.0029)	(0.0130)
Employment (ref: unemployment)			0.0500***			0.0504***
			(0.0082)			(0.0082)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,079,041	1,079,041	1,079,041	1,079,041	1,079,041	1,079,041
R-squared	0.211	0.127	0.211	0.211	0.127	0.211

Note: *** <1%, ** <5%, and * <10%. Robust standard errors in parentheses are clustered at the country-year level.

MECHANISM ANALYSIS

We have suggested four theoretical mechanisms that may link AI to individual SWB in Section 2 and verified that there is a significant negative relationship between them in Section 5. In this section, we begin to empirically test some of these channels, as understanding these channels would enable us to refine policies or develop new

TABLE 11 Mechanism analysis: Risks of future job loss.

	High risk group		Low risk group	
ln(AI-related publications)	−0.0791*		0.0774	
	(0.0422)		(0.0501)	
ln(Industrial robots)		−0.1008*		0.0251
		(0.0547)		(0.0490)
Control variables	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes
Country fixed-effects	Yes	Yes	Yes	Yes
Observations	398,726	398,726	382,943	382,943
R-squared	0.154	0.154	0.233	0.233

Note: *** <1%, ** <5%, and * <10%. Robust standard errors in parentheses are clustered at the country-year level.

strategies to improve individual wellbeing. In this part, we follow the mediation methodology developed by Baron and Kenny (1986). The mediation analysis focuses mainly on the estimation of the indirect effect of AI on wellbeing through an intermediary mediator variable M (say, income, employment, privacy) in a model of the form $AI \rightarrow M \rightarrow Wellbeing$. Specifically, it proceeds with the following two regressions:

$$\begin{aligned} M &= \gamma_0 + \gamma_1 AI + \varepsilon \\ Wellbeing &= \beta_0 + \beta_1 AI + \beta_2 M + \nu \\ Wellbeing &= \alpha_0 + \alpha_1 AI + \mu \end{aligned} \tag{11}$$

For the mediation hypothesis to be valid, the following four prerequisites must be satisfied (Baron & Kenny, 1986): (1) $\gamma_1 \neq 0$; (2) $\beta_2 \neq 0$; (3) the direct effect of AI, $\beta_1 \neq 0$ or $|\beta_1| < \alpha_1$ (total effect); (4) $\alpha_1 \neq 0$. While β_1 measures the direct effect of AI on wellbeing, controlling for the mediation variable and other covariates, the product of γ_1 and β_2 then measures the indirect effect of AI on wellbeing, that is, how much the effect of AI on wellbeing can be mediated at least in part by M.

Income

First, we use income as the mediator variable, which is defined as the natural log of one plus per capita annual income in international dollars (ln(*Income*)). As the income data, which are from GWP, are only available after year 2009, this part of analysis covers the period 2009–2018.

Table 9 presents the empirical results of income as one of the potential mechanisms, where Panel A the results for the full sample. When using AI-related publications as a proxy variable, we find no evidence that AI affects income ($\gamma_1 = -0.0248$, s.e. $= 0.02$). The statistically insignificant coefficient estimate seems not to satisfy the prerequisite for the presence of mediation effect. In contrast, when using robot adoption as a proxy for the development of AI, we find that robot adoption has a negative and statistically significant effect on individual wellbeing, in addition, the coefficient in absolute value on ln(*Robot*) reduces from −0.0417 ($\alpha_1 = -0.0417$, s.e. $= 0.0121$, Column 4) to −0.0359 ($\alpha_1 = -0.0359$, s.e. $= 0.0124$, Column 6). These results indicate that the effect of AI on wellbeing can be mediated at least in part by income.

Panels B and C examine whether the mediating effect differs across two different income groups: an individual whose income is in the top 25% percentile in a given year in her country is classified into the high-income group, and an individual whose income is in the bottom 25% percentile in that year in her country is classified into the low-income group. For both income groups, the results are similar in that increased AI is found to reduce income in most cases except the coefficient is negative but statistically insignificant when using AI-related publications as a proxy in the high-income group ($\gamma_1 = -0.0030$, s.e. $= 0.0059$, Column 2 in Panel B). Thus, strong mediation effects still hold in general for both high-income and low-income groups. Especially, for the low-income group, the effect of AI on wellbeing is completely mediated by income, as implied by the statistically insignificant coefficient of income ($\beta_1 = -0.0030$, s.e. $= 0.0059$, Column 6 in Panel B) when the AI variable is added into the full model.

Employment

We next assess the significance of the mediating effect of employment and identify whether it partially or fully

TABLE 12 Mechanism analysis: Privacy.

	Countries with data privacy laws and bills		Countries without data privacy laws and bills	
ln(AI-related publications)	0.0061		−0.0830**	
	(0.0314)		(0.0330)	
ln(Industrial robots)		−0.0153		−0.0071
		(0.0101)		(0.0170)
Control variables	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes
Country fixed-effects	Yes	Yes	Yes	Yes
Observations	907,704	907,704	558,405	558,405
R-squared	0.238	0.238	0.176	0.175

Note: *** <1%, ** <5%, and * <10%. Robust standard errors in parentheses are clustered at the country-year level.

mediates the relationship between AI and wellbeing. GWP classifies respondents into one of six categories of employment: employed full time for an employer, self-employed full time, employed part time and does not want to work full time, employed part time and wants to work full time, unemployed, and out of the workforce. We create a binary dummy variable (*Employment*) which equals 0 if the respondent is unemployed or out of the workforce, and 1 otherwise.

Table 10 presents the mediation results using *Employment* as the mediation variable. For the whole sample, Columns 2 and 5 show that AI reduces employment, which is consistent with Dauth et al. (2018) and Acemoglu and Restrepo (2020), and Columns 3 and 6 then show that AI development has a direct impact on reducing individual wellbeing and an indirect impact on reducing individual wellbeing through reducing employment. Combining with the fact that the coefficient magnitude (in absolute value) of AI reducing from $|\alpha_1| = 0.0799$ (Column 1) to $|\beta_1| = 0.0789$ (Column 3), or $|\alpha_1| = 0.0385$ (Column 4) to $|\beta_1| = 0.0382$ (Column 6), the above results suggest that employment is also one of the key mediating factors. In other words, our study verified the paths through which employment mediates the relationship between AI and individual wellbeing.

Furthermore, we use the dummy variable (*Skilled worker*) defined in Section 5.6, classify the whole sample into two groups by skill type, and examine whether the mediation effect differ between them. Panels B and C show the mediation results for high-skilled group and low-skilled group, respectively. For the high-skilled group, there is no apparent mediation effect of employment implied by the statistically insignificant coefficient estimate of either AI proxy, while for the low-skilled group, we observe that the impact of AI on individual wellbeing is partly mediated by employment. This result may imply that AI has more channels to negatively affect the wellbeing of low-skilled workers than it does on high-skilled workers.

One more concern is that, in addition to directly causing unemployment, AI may increase anxiety from future job loss. To test such possible causal channel, we first obtain the data on the probability (*Prob*) of each occupation type *i* being computerized from Frey and Osborne (2017), multiply it by the total number of employments (*Emp_i*) in occupation *i*, then sum all these products for each occupation type to obtain the total number of employments that is susceptible to automation in each country. Last, we divide it by the national total employment (*Emp*) to obtain a country's overall risk (*Risk*) of job replaced by automation. Specifically, the formula is defined as $Risk = \sum_i Prob_i \times Emp\_i_i / Emp$ where the occupation employment data are obtained from International Labour Organization (ILO) database (https://ilostat.ilo.org/data). As the calculated probabilities of automation from Frey and Osborne (2017) are based on data of the SOC occupational classification, while the ILO provides the employment data on ISCO 2-digit occupational classification, following Hardy et al. (2018), the SOC code are converted to the corresponding ISCO 2-digit level code in the probability calculation.

Eventually, based on the calculated job loss probability in each country, we can classify the whole sample into two groups. An individual falls into the 'high-risk' ('low-risk') country group if the *Risk* score in her country during the sample period lies in the top (bottom) 25% percentile. Table 11 shows that the AI coefficient is negative and statistically significant for the 'high-risk' country group, however, it is statistically insignificant for the 'low-risk' countries. This result reveals that high-risk countries are more responsive to the spread of AI due to its negative shock to future job loss of the country.

Privacy

We are unable to directly test the potential channel of privacy, which is discussed theoretically in Section 2.4, on affecting the link between AI and wellbeing, as individual or country-level privacy data are not available. However, we can provide some side evidence. World Legal Information Institute (http://www.worldlii.org) released a series of reports on Data Privacy Laws and Bill in 2011, 2012, 2013, 2015, 2017, and 2019. According to these reports, 76 countries have introduced relevant bills in 2011, 109 countries in 2015, 120 countries in 2017, and 132 countries in 2019. We first define a dummy variable (*Privacy*), which equals 1 if a given year is after the year of original data privacy law or bill enacted, and 0 otherwise, then we divide the sample countries into two groups according to whether they had data privacy laws or bills, and last, we perform these two subgroup regressions.

This part of analysis rests on the idea that, if we expect that AI development will affect individual privacy negatively and consequently the individual wellbeing, as discussed earlier in Section 2.4, then compared to countries enacted data privacy laws or bills, the negative impact of AI on individual wellbeing in countries without data privacy laws or bills shall be stronger. Thinking of an extreme case where AI can only affect wellbeing through one channel—privacy, we would expect that AI would not affect individual wellbeing in countries with privacy fully protected. Table 12 presents the empirical results of these groups of countries in terms of whether privacy laws or bills are enacted, and verifies to some extent the above conjecture. Thus, it seems that privacy does form a possible channel on linking AI and wellbeing.

CONCLUSIONS

AI has been evolving rapidly in recent years, leading to notable changes, in both positive and negative ways, in nearly every sphere of people's lives. With these changes in lifestyle, questions about what AI means for humans and whether it affects our quality of life are emerging.

This study investigates the relatively unexplored dimension of the impacts of AI on individual subjective wellbeing using a large dataset of 137 countries over 2005–2018 from the GWP. First, we empirically evaluate whether AI could affect how people feel about their lives. Our gravity-based IV results reveal a causal negative impact of the rise in AI on individual subjective wellbeing. We find that not only people's current wellbeing levels, but also their expectations of future wellbeing have decreased with the advance of AI technology and its applications. We further test the robustness of the findings using different metrics, estimation methods, and samples, and find the conclusions to be robust. Second, we investigate whether the impact of AI on individual wellbeing depends on the interaction between individual characteristics and countries' AI exposure, and find that the impact of AI varies significantly with age, gender, income, and job type. The elderly and women are less negatively affected by AI than the young and men, respectively, while the life quality of high-income and high-skilled groups and manufacturing workers are more negatively impacted than those with low income, low skills, and non-manufacturing workers.

The present study contributes to a better understanding of how AI is likely to influence an individual's wellbeing. However, it has the following limitations: First, it uses yearly repeated cross-sectional survey data, in which the same respondents are not followed over time. A genuine panel data type, if available, may better identify the relationships between wellbeing and its determinants for the same individuals. Second, in line with Diener et al. (2018), subjective wellbeing from self-reported surveys suffers from potential measurement error bias; thus, it should be verified whether the findings can be replicated using a wider range of wellbeing measurements. Third, we have AI data that is only aggregated at the country level, but many important policy questions require disaggregated data. These can be potential avenues for future research.

FUNDING INFORMATION

This study received support from the National Social Science Foundation of China (No. 20BJY195).

CONFLICT OF INTEREST STATEMENT

There are no conflicts of interest to declare.

DATA AVAILABILITY STATEMENT

The dataset used in this study are available from the corresponding author on reasonable request.

ORCID

Yihua Yu https://orcid.org/0000-0003-2709-6092

REFERENCES

Abrardi, L., Cambini, C., & Rondi, L. (2019). The economics of artificial intelligence: A survey. In *Robert Schuman Centre for Advanced Studies Research Paper No. RSCAS, 58*. European University Institute.

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, *128*(6), 2188–2244.

Aghion, P., Jones, B., & Jones, C. (2017). Artificial intelligence and economic growth. *NBER Working Paper Series*, *23928*. https://doi.org/10.3386/w23928

Ahuvia, A., & Friedman, D. (1998). Income, consumption, and subjective well-being: Toward a composite macromarketing model. *Journal of Macromarketing*, *18*(2), 153–168.

Aksoy, C., Guriev, S., & Treisman, D. (2018). Globalization, government popularity, and the great skill divide. *NBER Working Paper Series*, *25062*. https://doi.org/10.3386/w25062

Anderson, T., & Rubin, H. (1949). Estimation of the parameters of a single equation in a complete system of stochastic equations. *The Annals of Mathematical Statistics*, *20*(1), 46–63.

Angrist, J., & Pischke, J. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Arntz, M., Gregory, T., & Zierahn, U. (2016). The risk of automation for jobs in OECD countries: A comparative analysis. *OECD Social, Employment and Migration Working Papers*, *189*. https://doi.org/10.1787/5jlz9h56dvq7-en

Artuc, E., Bastos, P., & Rijkers, B. (2020). Robots, tasks, and trade. *CEPR Discussion Paper*, *DP14487*. https://papers.ssrn.com/abstract=3560294

Ateca-Amestoy, V., Gerstenblüth, M., Mussio, I., & Rossi, M. (2016). How do cultural activities influence happiness? Investigating the relationship between self-reported well-being and leisure. *Estudios Económicos (México, DF)*, *31*(2), 217–234.

Athey, S. (2019). The impact of machine learning on economics. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda* (pp. 507–547). University of Chicago Press.

Autor, D., & Salomons, A. (2017). Robocalypse now: Does productivity growth threaten employment. *Proceedings of the ECB Forum on Central Banking: Investment and Growth in Advanced Economies*, pp. 45–118. https://www.economicsofai.com/nber-conference-toronto-2017

Barbieri, L., Mussida, C., Piva, M., & Vivarelli, M. (2019). Testing the employment impact of automation, robots and AI: A survey and some methodological issues. *IZA Discussion Paper*, *12612*, 1–23. https://doi.org/10.2139/ssrn.3457656

Baron, R., & Kenny, D. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *51*(6), 1173–1182.

Baruffaldi, S., Beuzekom, B. van, Dernis, H., Harhoff, D., Rao, N., Rosenfeld, D., & Squicciarini, M. (2020). Identifying and measuring developments in artificial intelligence. *OECD Science, Technology and Industry Working Papers*, *2020*(5), 1–68. https://doi.org/10.1787/5f65ff7e-en

Batz, C., & Tay, L. (2018). Gender differences in subjective well-being. In E. Diener, S. Oishi, & L. Tay (Eds.), *Handbook of well-being*. DEF Publishers.

Belsley, D., Kuh, E., & Welsch, R. (2005). *Regression diagnostics: Identifying influential data and sources of collinearity*. John Wiley & Sons.

Benzell, S., Kotlikoff, L., LaGarda, G., & Sachs, J. (2015). Robots are us: Some economics of human replacement. *NBER Working Paper Series*, *20941*. https://doi.org/10.3386/w20941

Bessen, J. (2018). AI and jobs: The role of demand. *NBER Working Paper Series*, *24235*. https://doi.org/10.3386/w24235

Bessen, J., Goos, M., Salomons, A., & van den Berge, W. (2019). Automatic reaction-what happens to workers at firms that automate? *Boston University School of Law, Law and Economics Research Paper*, *19–2*. https://scholarship.law.bu.edu/faculty_scholarship/584

Biermann, P., Bitzer, J., & Gören, E. (2022). The relationship between age and subjective well-being: Estimating within and between effects simultaneously. *The Journal of the Economics of Ageing*, *21*, 100366.

Blanas, S., Gancia, G., & Lee, S. T. (2019). Who is afraid of machines? *Economic Policy*, *34*(100), 627–690. https://doi.org/10.1093/epolic/eiaa005

Blanchard, E., & Olney, W. (2017). Globalization and human capital investment: Export composition drives educational attainment. *Journal of International Economics*, *106*, 165–183. https://doi.org/10.1016/j.jinteco.2017.03.004

Blanchflower, D. (2021). Is happiness U-shaped everywhere? Age and subjective well-being in 145 countries. *Journal of Population Economics*, *34*(2), 575–624. https://doi.org/10.1007/s00148-020-00797-z

Blanchflower, D., & Oswald, A. (2008). Is well-being U-shaped over the life cycle? *Social Science & Medicine*, *66*(8), 1733–1749. https://doi.org/10.1016/j.socscimed.2008.01.030

Brynjolfsson, E., Hui, X., & Liu, M. (2019). Does machine translation affect international trade? Evidence from a large digital platform. *Management Science*, *65*(12), 5449–5460. https://doi.org/10.1287/mnsc.2019.3388

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company.

Bughin, J., Seong, J., Manyika, J., Chui, M., & Joshi, R. (2018). Notes from the AI frontier: Modeling the impact of AI on the world economy. *Kinsey Global Institute Discussion Paper*. https://www.mckinsey.com/featured-insights/artificial-intelligence/notes-from-the-ai-frontier-modeling-the-impact-of-ai-on-the-world-economy

Cameron, A., & Trivedi, P. (2005). *Microeconometrics: Methods and applications*. Cambridge University Press.

Cantril, H. (1965). *The pattern of human concerns*. Rutgers University Press.

CEA. (2016). *2016 economic report of the president*. Council of Economic Advisers. http://go.wh.gov/7J6qNx

Chapman, B., & Guven, C. (2016). Revisiting the relationship between marriage and wellbeing: Does marriage quality matter? *Journal of Happiness Studies*, *17*(2), 533–551. https://doi.org/10.1007/s10902-014-9607-3

Cheng, T., Powdthavee, N., & Oswald, A. (2017). Longitudinal evidence for a midlife nadir in human well-being: Results from four data sets. *Economic Journal*, *127*(599), 126–142. https://doi.org/10.1111/ecoj.12256

Chevalier, A., & Feinstein, L. (2006). Sheepskin or prozac: The causal effect of education on mental health. *IZA Discussion Paper*, *2231*. https://doi.org/10.2139/ssrn.923530

Chiacchio, F., Petropoulos, G., & Pichler, D. (2018). The impact of industrial robots on EU employment and wages: A local labour market approach. *Bruegel Working Paper*, *2018/02*. http://hdl.handle.net/10419/207001

Cockburn, I., Henderson, R., & Stern, S. (2018). The impact of artificial intelligence on innovation. *NBER Working Paper Series*, *24449*. https://doi.org/10.3386/w24449

D'Ambrosio, C., Jäntti, M., & Lepinteur, A. (2020). Money and happiness: Income, wealth and subjective well-being. *Social Indicators Research*, *148*(1), 47–66. https://doi.org/10.1007/s11205-019-02186-w

Dauth, W., Findeisen, S., Suedekum, J., & Woessner, N. (2018). Adjusting to robots: Worker-level evidence. *Federal Reserve*

Banks of Minneapolis Working Paper, *13*. https://doi.org/10.21034/iwp.13

DeCanio, S. (2016). Robots and humans – Complements or substitutes? *Journal of Macroeconomics*, *49*, 280–291. https://doi.org/10.1016/j.jmacro.2016.08.003

Diener, E., & Diener, C. (1996). Most people are happy. *Psychological Science*, *7*(3), 181–185. https://doi.org/10.1111/j.1467-9280.1996.tb00354.x

Diener, E., Oishi, S., & Tay, L. (2018). Advances in subjective well-being research. *Nature Human Behaviour*, *2*(4), 253–260. https://doi.org/10.1038/s41562-018-0307-6

Easterlin, R. (2011). In H. Hinte & K. Zimmermann (Eds.), *Happiness, growth, and the life cycle*. Oxford University Press.

Easterlin, R., Angelescu, L., & Zweig, J. (2011). The impact of modern economic growth on urban–rural differences in subjective well-being. *World Development*, *39*(12), 2187–2198. https://doi.org/10.1016/j.worlddev.2011.04.015

Easterlin, R., McVey, L., Switek, M., Sawangfa, O., & Zweig, J. (2010). The happiness–income paradox revisited. *Proceedings of the National Academy of Sciences*, *107*(52), 22463–22468. https://doi.org/10.1073/pnas.1015962107

Ejrnæs, A., & Greve, B. (2017). Your position in society matters for how happy you are. *International Journal of Social Welfare*, *26*(3), 206–217. https://doi.org/10.1111/ijsw.12233

Feyrer, J. (2009). Trade and income – Exploiting time series in geography. *NBER Working Paper Series*, *14910*. https://doi.org/10.3386/w14910

Ford, M. (2015). *Rise of the robots: Technology and the threat of a jobless future*. Basic Books.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Frey, B., & Stutzer, A. (2000). Happiness, economy and institutions. *The Economic Journal*, *110*(466), 918–938. https://doi.org/10.1111/1468-0297.00570

Frijters, P., Lalji, C., & Pakrashi, D. (2020). Daily weather only has small effects on wellbeing in the US. *Journal of Economic Behavior & Organization*, *176*, 747–762. https://doi.org/10.1016/j.jebo.2020.03.009

Glaeser, E., Gottlieb, J., & Ziv, O. (2016). Unhappy cities. *Journal of Labor Economics*, *34*(S2), S129–S182. https://doi.org/10.1086/684044

Goldfarb, A., & Trefler, D. (2018). AI and international trade. *NBER Working Paper Series*, *24254*. https://doi.org/10.3386/w24254

Goyal, A., & Aneja, R. (2020). Artificial intelligence and income inequality: Do technological changes and worker's position matter? *Journal of Public Affairs*, *20*(4), e2326. https://doi.org/10.1002/pa.2326

Graafland, J., & Compen, B. (2015). Economic freedom and life satisfaction: Mediation by income per capita and generalized trust. *Journal of Happiness Studies*, *16*(3), 789–810. https://doi.org/10.1007/s10902-014-9534-3

Graetz, G., & Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, *100*(5), 753–768. https://doi.org/10.1162/rest_a_00754

Graham, C., & Chattopadhyay, S. (2013). Gender and well-being around the world. *International Journal of Happiness and Development*, *1*(2), 212–232.

Grossi, E., Tavano Blessi, G., Sacco, P., & Buscema, M. (2012). The interaction between culture, health and psychological well-being: Data mining from the Italian culture and well-being project. *Journal of Happiness Studies*, *13*(1), 129–148. https://doi.org/10.1007/s10902-011-9254-x

Guerreiro, J., Rebelo, S., & Teles, P. (2022). Should robots be taxed? *Review of Economic Studies*, *89*(1), 279–311. https://doi.org/10.1093/restud/rdab019

Hardy, W., Keister, R., & Lewandowski, P. (2018). Educational upgrading, structural change and the task composition of jobs in Europe. *Economics of Transition*, *26*(2), 201–231. https://doi.org/10.1111/ecot.12145

Helliwell, J., Huang, H., Grover, S., & Wang, S. (2018). Empirical linkages between good governance and national well-being. *Journal of Comparative Economics*, *46*(4), 1332–1346. https://doi.org/10.1016/j.jce.2018.01.004

Hendriks, M., & Bartram, D. (2016). Macro-conditions and immigrants' happiness: Is moving to a wealthy country all that matters? *Social Science Research*, *56*, 90–107. https://doi.org/10.1016/j.ssresearch.2015.11.006

Hilbe, J. M. (2011). *Negative binomial regression* (2nd ed.). Cambridge University Press. Cambridge Core. https://doi.org/10.1017/CBO9780511973420

IDC. (2020). *Strong growth for artificial intelligence market in 2020*. International Data Corporation. https://usdc.vn/strong-growth-for-ai-market-in-2020

IFR. (2020). *World robotics report 2020*. International Federation of Robotics. https://ifr.org/downloads/press2018/Presentation_WR_2020.pdf

Jäger, A., Moll, C., Som, O., & Zanker, C. (2015). *Analysis of the impact of robotic systems on employment in the European Union: Final report*. Publications Office of the European Union. https://data.europa.eu/doi/10.2759/516348

Jin, G. (2018). Artificial intelligence and consumer privacy. *NBER Working Paper Series*, *2453*. https://doi.org/10.3386/w24253

Klinger, J., Mateos-Garcia, J., & Stathoulopoulos, K. (2018). Deep learning, deep change? Mapping the development of the artificial intelligence general purpose technology. *SSRN Working Paper*. https://doi.org/10.2139/ssrn.3233463

Korinek, A., & Stiglitz, J. (2021). Artificial intelligence, globalization, and strategies for economic development. *NBER Working Paper Series*, *28453*. https://doi.org/10.3386/w28453

Lacey, H., Smith, D., & Ubel, P. (2006). Hope I die before I get old: Mispredicting happiness across the adult lifespan. *Journal of Happiness Studies*, *7*(2), 167–182. https://doi.org/10.1007/s10902-005-2748-7

Larsen, W., & McCleary, S. (1972). The use of partial residual plots in regression analysis. *Technometrics*, *14*(3), 781–790. https://doi.org/10.1080/00401706.1972.10488966

Li, Q., & An, L. (2020). Corruption takes away happiness: Evidence from a cross-national study. *Journal of Happiness Studies*, *21*(2), 485–504. https://doi.org/10.1007/s10902-019-00092-z

Li, X., Hui, E., Lang, W., Zheng, S., & Qin, X. (2020). Transition from factor-driven to innovation-driven urbanization in China: A study of manufacturing industry automation in Dongguan City. *China Economic Review*, *59*, 101382. https://doi.org/10.1016/j.chieco.2019.101382

Magee, L. (1998). Improving survey-weighted least squares regression. *Journal of the Royal Statistical Society: Series B (Statistical*

Methodology), *60*(1), 115–126. https://doi.org/10.1111/1467-9868.00112

Michaels, G., Natraj, A., & van Reenen, J. (2014). Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years. *The Review of Economics and Statistics*, *96*(1), 60–77. https://doi.org/10.1162/REST_a_00366

Moravec, H. (1998). When will computer hardware match the human brain. *Journal of Evolution and Technology*, *1*(1), 10.

Moulton, B. (1990). An illustration of a pitfall in estimating the effects of aggregate variables on micro units. *Review of Economics and Statistics*, *72*(2), 334–338. https://doi.org/10.2307/2109724

Muro, M., Whiton, J., & Maxim, R. (2019). What jobs are affected by AI? Better-paid, better-educated workers face the most exposure. *Metropolitan Policy Program Report*. http://hdl.voced.edu.au/10707/531845

Nikolova, M., & Graham, C. (2015). In transit: The well-being of migrants from transition and post-transition countries. *Journal of Economic Behavior & Organization*, *112*, 164–186. https://doi.org/10.1016/j.jebo.2015.02.003

Noy, S., & Sin, I. (2021). The effects of neighbourhood and workplace income comparisons on subjective wellbeing. *Journal of Economic Behavior & Organization*, *185*, 918–945. https://doi.org/10.1016/j.jebo.2020.11.008

Ramia, I., & Voicu, M. (2022). Life satisfaction and happiness among older Europeans: The role of active ageing. *Social Indicators Research*, *160*(2), 667–687. https://doi.org/10.1007/s11205-020-02424-6

Reyes-García, V., Babigumira, R., Pyhälä, A., Wunder, S., Zorondo-Rodríguez, F., & Angelsen, A. (2016). Subjective wellbeing and income: Empirical patterns in the rural developing world. *Journal of Happiness Studies*, *17*(2), 773–791. https://doi.org/10.1007/s10902-014-9608-2

Rock, D. (2019). Engineering value: The returns to technological talent and investments in artificial intelligence. *SSRN Working Paper*. https://doi.org/10.2139/ssrn.3427412

Ruiu, G., & Ruiu, M. (2019). The complex relationship between education and happiness: The case of highly educated individuals in Italy. *Journal of Happiness Studies*, *20*(8), 2631–2653. https://doi.org/10.1007/s10902-018-0062-4

Sachs, J. (2019). R&D, structural transformation, and the distribution of income. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda* (pp. 329–348). University of Chicago Press.

Sacks, D., Stevenson, B., & Wolfers, J. (2012). The new stylized facts about income and subjective well-being. *Emotion*, *12*, 1181–1187. https://doi.org/10.1037/a0029873

Senik, C. (2017). Gender gaps in subjective wellbeing: A new paradox to explore. *Review of Behavioral Economics*, *4*(4), 349–369. https://doi.org/10.1561/105.00000076

Soulsby, L., & Bennett, K. (2015). Marriage and psychological wellbeing: The role of social support. *Psychology*, *6*(11), 1349–1359.

Spruk, R., & Kešeljević, A. (2016). Institutional origins of subjective well-being: Estimating the effects of economic freedom on national happiness. *Journal of Happiness Studies*, *17*(2), 659–712. https://doi.org/10.1007/s10902-015-9616-x

Tucker, C. (2019). In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *Privacy, algorithms, and artificial intelligence*. University of Chicago Press. https://doi.org/10.7208/chicago/9780226613475.001.0001

Veenhoven, R. (2012). Cross-national differences in happiness: Cultural measurement bias or effect of culture? *International Journal of Wellbeing*, *2*(4), 333–353. https://internationaljournalofwellbeing.org/index.php/ijow/article/view/98

Veenhoven, R., & Berg, M. (2013). Has modernization gone too far? Happiness and modernity in 141 contemporary nations. *International Journal of Happiness and Development*, *1*(2), 172–195. https://doi.org/10.1504/IJHD.2013.055645

Walsh, T., Levy, N., Bell, G., Elliott, A., Maclaurin, J., Mareels, I., & Wood, F. (2019). *The effective and ethical development of artificial intelligence: An opportunity to improve our wellbeing*. Australian Council of Learned Academies Melbourne. http://hdl.voced.edu.au/10707/518873

Wang, Y., & Kosinski, M. (2018). Deep neural networks are more accurate than humans at detecting sexual orientation from facial images. *Journal of Personality and Social Psychology*, *114*, 246–257. https://doi.org/10.1037/pspa0000098

Webb, M. (2019). The impact of artificial intelligence on the labor market. *SSRN Working Paper*. https://doi.org/10.2139/ssrn.3482150

Wilson, C., & Oswald, A. (2005). How does marriage affect physical and psychological health? A survey of the longitudinal evidence. *IZA Discussion Paper, 1619*. https://ssrn.com/abstract=735205

Zhang, P. (2019). Automation, wage inequality and implications of a robot tax. *International Review of Economics & Finance*, *59*, 500–509. https://doi.org/10.1016/j.iref.2018.10.013

Zhang, X., Zhang, X., & Chen, X. (2017). Happiness in the air: How does a dirty sky affect mental health and subjective well-being? *Journal of Environmental Economics and Management*, *85*, 81–94. https://doi.org/10.1016/j.jeem.2017.04.001

Zhou, Y., & Tyers, R. (2019). Automation and inequality in China. *China Economic Review*, *58*, 101202. https://doi.org/10.1016/j.chieco.2018.07.008

Zuckerman, M., Li, C., & Diener, E. (2017). Societal conditions and the gender difference in well-being: Testing a three-stage model. *Personality and Social Psychology Bulletin*, *43*(3), 329–336. https://doi.org/10.1177/0146167216684133

Zweig, J. (2015). Are women happier than men? Evidence from the Gallup world poll. *Journal of Happiness Studies*, *16*(2), 515–541. https://doi.org/10.1007/s10902-014-9521-8

How to cite this article: Zhao, Y., Yin, D., Wang, L., & Yu, Y. (2024). The rise of artificial intelligence, the fall of human wellbeing? *International Journal of Social Welfare*, *33*(1), 75–105. https://doi.org/10.1111/ijsw.12586

APPENDIX A

A.1 | COUNTRY LIST

Table A1 shows the list of countries and corresponding numbers of surveyed respondents.

TABLE A1 Country list.

Country code	Observations	Country code	Observations	Country code	Observations	Country code	Observations
AFG	8684	DZA	7957	LBR	3883	QAT	5898
ALB	10,628	ECU	9946	LKA	12,133	RUS	22,125
ARE	17,968	EGY	18,599	LTU	10,565	RWA	9926
ARG	10,755	ESP	12,914	LUX	8834	SAU	16,157
ARM	11,868	EST	11,094	LVA	10,858	SDN	3732
AUS	13,004	ETH	997	MAR	9742	SEN	10,075
AUT	11,840	FIN	10,624	MDA	12,743	SGP	13,529
AZE	12,704	FRA	12,511	MDG	996	SLE	991
BDI	1990	GBR	22,360	MEX	10,661	SLV	12,370
BEL	11,719	GEO	12,946	MKD	10,950	SRB	22,103
BEN	979	GHA	9392	MLI	10,454	SVK	9953
BFA	8826	GRC	10,815	MLT	8807	SVN	10,875
BGD	12,250	GTM	9269	MMR	3358	SWE	11,501
BGR	10,791	HND	11,338	MNE	10,571	TCD	10,078
BHR	930	HRV	10,556	MNG	9892	TGO	2965
BIH	11,752	HUN	10,876	MOZ	972	THA	11,878
BLR	13,249	IDN	14,827	MRT	12,724	TJK	13,876
BOL	11,430	IND	45,775	MUS	3845	TKM	979
BRA	11,986	IRL	10,842	MWI	1990	TUN	13,126
BTN	3008	IRN	13,554	MYS	11,012	TUR	12,868
BWA	8868	IRQ	14,242	NAM	1929	TZA	10,920
CAN	12,727	ISL	2069	NER	9625	UGA	10,784
CHE	6927	ISR	11,828	NGA	9422	UKR	9678
CHL	11,987	ITA	12,790	NIC	11,375	URY	12,295
CHN	44,860	JAM	532	NLD	10,630	USA	13,928
CIV	2927	JOR	14,875	NOR	8750	UZB	11,753
CMR	8665	JPN	15,852	NPL	12,578	VEN	6668
COD	995	KAZ	11,549	NZL	10,957	VNM	10,290
COL	12,701	KEN	9919	PAK	14,235	YEM	13,061
CRI	1990	KGZ	12,824	PAN	10,590	ZAF	10,879
CYP	8488	KHM	11,311	PER	11,374	ZMB	1980
CZE	11,884	KOR	14,784	PHL	14,091	ZWE	987
DEU	31,660	KWT	12,645	POL	12,570		
DNK	11,565	LAO	808	PRT	12,715		
DOM	12,406	LBN	13,982	PRY	9837		

Note: Full name of each country is available at https://unstats.un.org/unsd/tradekb/knowledgebase/country-code.

A.2 | ALTERNATIVE INSTRUMENT CONSTRUCTION

In this subsection, we develop a different measure of an instrumental variable viz. Artuc et al. (2020). Specifically, we use the following instrument for variable AI: $IV_{jt} = \ln(PGDP)_{j,2005} \times \ln(World\_AI)_t$, where $\ln(PGDP)_{j,2005}$ is the logarithm of country *j*'s initial GDP per capita. It is a predetermined variable that can be considered a proxy variable for labour costs and the economic incentives for robotization. $World\_AI_t$ denotes the world total publications or total installed robots in year *t*. It is a proxy for the price of robots, measuring the development of AI technology worldwide that is less affected by residents' wellbeing in a single country. Table A2 presents the IV results. The negative relationship between AI and wellbeing remains holding in the IV model.

TABLE A2 Instrumental variable estimation.

	Dependent variables			
	Subjective wellbeing (current)		**Subjective wellbeing (future)**	
ln(AI-related publications)	−0.3750**		−0.4099*	
	(0.1777)		(0.2318)	
ln(Industrial robots)		−0.2658**		−0.2506*
		(0.1295)		(0.1462)
Age	−0.0110***	−0.0109***	−0.0312***	−0.0311***
	(0.0004)	(0.0004)	(0.0006)	(0.0006)
Gender (1 = male)	−0.0954***	−0.0956***	−0.1007***	−0.1010***
	(0.0066)	(0.0066)	(0.0084)	(0.0084)
Marital (1 = married)	0.1331***	0.1308***	0.1248***	0.1226***
	(0.0075)	(0.0076)	(0.0081)	(0.0082)
Education level	0.4828***	0.4815***	0.5052***	0.5032***
	(0.0071)	(0.0071)	(0.0084)	(0.0083)
Urban (ref = rural)	0.1717***	0.1708***	0.1932***	0.1925***
	(0.0111)	(0.0111)	(0.0116)	(0.0116)
ln(GDP)	−0.4778*	−1.2887***	0.4640	−0.2933
	(0.2762)	(0.4134)	(0.3413)	(0.4560)
ln(GDP per capita)	1.0505***	1.8794***	0.1975	0.9472*
	(0.3274)	(0.4779)	(0.3720)	(0.5261)
Unemployment rate	−4.0189***	−4.6964***	−3.9419***	−4.6548***
	(0.7170)	(0.6749)	(0.7958)	(0.7161)
Year fixed-effects	Yes	Yes	Yes	Yes
Country fixed-effects	Yes	Yes	Yes	Yes
KP *F*-statistic	18.138	26.732	17.261	26.157
Observations	1,466,109	1,466,109	1,347,898	1,347,898

Note: *** <1%, ** <5%, and * <10%. Robust standard errors in parentheses are clustered at the country-year level.

A.3 | LONG-DIFFERENCE WITH ROLLING WINDOW REGRESSION

We try to explore the nexus between AI and individual wellbeing by combining the long-difference and (5- and 10-year) rolling window regression approaches. Specifically, we estimate the following equation using countries from 2005 to 2018

$$Wellbeing_{j,t} - Wellbeing_{j,t-k} = \delta\left(AI_{j,t} - AI_{j,t-k}\right) + \beta\left(X_{j,t} - X_{j,t-k}\right) + \mu_j + \nu_t + \varepsilon_{jt} \tag{11}$$

where the dependent variable denotes the change in averaged wellbeing rating between the end of year t and the end of year $t-k$ of country j ($k = 5$ or 10). Independent variable is the change in AI-related developments.

Table A3 presents the long-difference regression while considering the 5- or 10-year rolling windows. The negative and significant relationship remains unchanged.

TABLE A3 Long-differencing and rolling window results.

	Form year $t-5$ to t		**Form year $t-10$ to t**	
Panle A: *Subjective wellbeing (current) model*				
Δln(AI-related publications)	−0.1045***		−0.1002	
	(0.0373)		(0.0846)	
Δln(Industrial robots)		−0.0257*		−0.0576**
		(0.0139)		(0.0256)
Control variables	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes
Country fixed-effects	No	No	No	No
Observations	637	637	148	148
R-squared	0.247	0.235	0.232	0.236
Panel B: *Subjective wellbeing (future) model*				
Δln(AI-related publications)	−0.0841*		−0.1385	
	(0.0434)		(0.0991)	
Δln(Industrial robots)		−0.0399**		−0.0622*
		(0.0154)		(0.0354)
Control variables	Yes	Yes	Yes	Yes
Year fixed-effects	Yes	Yes	Yes	Yes
Country fixed-effects	No	No	No	No
Observations	636	636	148	148
R-squared	0.263	0.261	0.332	0.326

Note: *** <1%, ** <5%, and * <10%. Robust standard errors in parentheses are clustered at the country level.

Table A4

TABLE A4 Removing some potentially endogenous covariates (IV results).

	Dependent variables			
	Subjective wellbeing (current)		**Subjective wellbeing (future)**	
ln(AI-related publications)	−0.7825*		−1.6005***	
	(0.4002)		(0.5150)	
ln(Industrial robots)		−0.7111**		−1.4308***
		(0.3025)		(0.4292)
Age	−0.0134***	−0.0132***	−0.0338***	−0.0334***
	(0.0004)	(0.0004)	(0.0005)	(0.0006)
Gender (1 = male)	−0.0592***	−0.0597***	−0.0636***	−0.0645***
	(0.0067)	(0.0066)	(0.0088)	(0.0089)
ln(GDP)	−0.3633	−2.4615***	0.7665	−3.3671***
	(0.3742)	(0.8671)	(0.5979)	(1.2547)
ln(GDP per capita)	0.9138**	3.1001***	0.0460	4.2932***
	(0.4152)	(0.9958)	(0.6745)	(1.4773)
Unemployment rate	−3.8053***	−5.4392***	−3.0331**	−6.4587***
	(0.8916)	(0.9055)	(1.3239)	(1.4422)
Year fixed-effects	Yes	Yes	Yes	Yes
Country fixed-effects	Yes	Yes	Yes	Yes
KP *F*-statistic	7.436	7.068	7.184	6.786
AR *F*-statistic	11.21	11.21	15.57	15.57
AR *p*-value	0.0008	0.0008	8.38e−05	8.38e−05
Observations	1,466,109	1,466,109	1,347,898	1,347,898

Note: *** <1%, ** <5%, and * <10%. Robust standard errors in parentheses are clustered at the country level.