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Veröffentlichungsversion / Published Version
Zeitschriftenartikel / journal article

AMERICAN PSYCHOLOGICAL ASSOCIATION

Technology, Mind, and Behavior

ISSN: 2689-0208

https://doi.org/10.1037/tmb0000078

SPECIAL COLLECTION: TECHNOLOGY, WORK, AND INEQUALITY

Are Robots/AI Viewed as More of a Workforce Threat in Unequal Societies? Evidence From the Eurobarometer Survey

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Although advanced technologies (i.e., artificial intelligence [AI], robots) are often discussed as drivers of societal inequality, our research examines whether people living in more unequal societies tend to view technology as a greater threat to jobs in general. Building from research that societal inequality heightens concerns about status hierarchies and future resource attainment, we anticipated that workers in more unequal societies would tend to view AI/robots as greater threats (e.g., AI/robots as job destroyers). Utilizing the Eurobarometer 87.1 data set, we found that country inequality, as operationalized via the Gini index, was positively associated with perceptions that AI/robots pose threats of general job loss. These relationships occurred when controlling for people's perceptions of technological threat to their own personal job, technology skills and interests, and demographics. Moreover, these findings are robust across alternative operationalizations of inequality including the Human Inequality Index and people's subjective perceptions of current and future inequality in their country. These findings advance theory on inequality and suggest that the broader context—both objective and perceived—may play a role in how people view disruption associated with AI/robots at work.

Keywords: inequality, robots, AI, threat perception

Supplemental materials: https://doi.org/10.1037/tmb0000078.supp

Inequality, defined as "the unequal dispersion of resources across society" (Wienk et al., 2022), has been growing at a staggering rate. According to the United Nations, more than 70% of the global population has experienced worsening income inequality over the past decade (United Nations, 2020). Moreover, many countries face inequality in terms of other resources, including health, social, and occupational opportunities (United Nations, 2013). A growing literature documents the harmful costs of inequality both to individual well-being and to the social fabric of societies (Buttrick et al., 2017; Easterbrook, 2021).

The current research examines whether people's perceptions of threats of general job loss engendered by robots and artificial intelligence (AI) are higher in more, as compared with less unequal societies. Stated otherwise, is there an association between the degree of inequality in a society and the degree to which its population views AI and robots as a threat to the workforce? Much attention has been directed to technology as a driver of inequality, especially income inequality (Acemoglu, 2002; Aghion et al., 2002; Grigoli et al., 2020; Prettner & Bloom, 2020). We advance the discussion of technology and inequality by inverting the typical direction of research questions

Special Collection Editors: Tara Behrend and Mindy K. Shoss
Action Editor: Tara Behrend was the action editor for this article.
ORCID iDs: Mindy K. Shoss https://orcid.org/0000-0001-5354-208X.
Funding: This article was supported by Grant T42OH008438, funded by the National Institute for Occupational Safety and Health (NIOSH) under the Centers for Disease Control and Prevention (CDC). Its contents are solely the responsibility of the authors and do not necessarily represent the official views of the NIOSH or CDC or the Department of Health and Human Services.
Disclosures: The authors have no conflicts of interest.
Data Availability: Data for this study are publicly available. Links to data, study materials, output, and analytical code are available on an Open Science Foundation page for this project at https://osf.io/r9qap/?view_only=96d0d3393fab4f6682544a1ec692dca8.
Open Science Disclosures:
The data are available at https://osf.io/r9qap/?view_only=96d0d3393fab4f6682544a1ec692dca8.
The experimental materials are available at https://osf.io/r9qap/?view_only=96d0d3393fab4f6682544a1ec692dca8.

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on this topic (i.e., technology as a driver of inequality) to examine how societal inequality may relate to how workforce robots and AI are perceived by workers. To be clear, our focus is on people's perceptions that AI and robots represent threats to the workforce *as a whole* (e.g., that robots and AI will steal jobs; Eurbarometer; 87.1, 2017), independent of threats to an individual's own job (see Brougham & Haar, 2020; Koen & Parker, 2020, for research on the latter).

Although little research has examined the connection between societal inequality and the public's perceptions of emerging technologies as job destroyers, such a relationship may be anticipated based on the psychological research on inequality (e.g., Wilkinson & Pickett, 2009). Inequality both attunes people to potential disruption in status-conferring systems, such as work, and makes people more likely to view disruption as a threat (Buttrick et al., 2017; Wilkinson & Pickett, 2017). As disruptive technologies, AI and robots have the potential to transform work, organizations, and societies more broadly (Azhar, 2021; Brynjolfsson & McAfee, 2012; Brynjolfsson & Mitchell, 2017; National Academies of Sciences, 2017). Although it is debated exactly how much and when this disruption will come (see Acemoglu & Restrepo, 2018; 2021; McGaughey, 2021), the wide variety of estimates and prognostications of short-term "disruptively painful" transitions contribute to a "hazy future" wherein there may be considerable variability in how people across societies view these technologies (Mokyr et al., 2015, p. 47, 43; see also Rughiniş et al., 2018). In more unequal societies, where resources are distributed in a zero-sum manner and people demonstrate greater concern about their abilities to maintain/increase status, we anticipate, on average, more negative views of the workforce threats engendered by AI and robots.

Our research contributes to the growing bodies of literature on work, inequality, and technology. We expand the field's understanding of inequality by examining how inequality relates to people's perceptions of job threats posed by AI and robot technologies in the workplace. In other words, although technological advances surrounding work may be a contributor to inequality, our research proposes that inequality is associated with more negative views toward these technologies. This sentiment is important to understand for several reasons. First, people are not merely passive recipients of technological advances. Rather, their ideas, attitudes, and behaviors toward technology shape the form and function of technologies that ultimately take hold (National Academies of Sciences, Engineering, & Medicine, 2017; McGaughey, 2021; Sinha et al., 2020). As Rughiniş et al. (2018, p. 115) write, "public receptivity of a specific technological transformation is one of the important engines of its progress." Second, people's beliefs about the collective threats engendered by advanced technologies have implications for a variety of individually and societally relevant outcomes, for example, people's well-being, attitudes toward others, and voting behaviors (Brougham & Haar, 2018; Engler & Weisstanner, 2020; Gamez-Djokic & Waytz, 2020). Third, given calls to design and deploy technology in a manner that takes into account stakeholders' views and concerns (e.g., Dobrosovestnova et al., 2022), it is worthwhile to understand how these concerns are embedded within a societal context.

The Consequences of Societal Inequality

Government leaders, think tanks, and researchers alike have described societal inequality as the "root of social ills" (Francis, 2013; United Nations, 2013; Wilkinson & Pickett, 2017). Generally, discussions about inequality have focused on income inequality, most commonly indexed by the Gini Index. The Gini index captures the extent to which a country's distribution of income across households differs from a perfectly equal distribution (World Bank, 2016).

Objective income inequality (hereafter, inequality) has been linked to poorer life satisfaction and mental well-being across countries. At the within-country level, mental well-being has been demonstrated to be poorer in years where there is greater inequality (Delhey & Dragolov, 2014; Melgar & Rossi, 2010; Oishi, 2012; Oishi et al., 2018). Inequality has also been linked to lower levels of civic honesty, greater prejudice and violence, and lower social mobility (see Wilkinson & Pickett, 2009, 2017, for a review). The effects of inequality are generally predictive over general economic conditions, such as gross domestic product (GDP) and unemployment rate, suggesting that it is inequality in society rather than overall economic well-being that is more strongly associated with these negative outcomes (Caluori et al., 2021; Delhey & Dragolov, 2014; Roth et al., 2017; although see Kelley & Evans, 2017a, for contrary results). Moreover, the harmful impacts of societal inequality have been shown to occur across social strata (Roth et al., 2017) and extend beyond objective indicators of inequality to people's subjective perceptions of the extent to which wealth is unequally distributed (Du et al., 2021; Schmalor & Heine, 2022).

Several mechanisms have been proposed to account for inequality's negative effects. One explanation is that greater inequality engenders greater social distance and a greater sense of distrust of others (Delhey & Dragolov, 2014). Other research has suggested that inequality creates both actual deprivation for a large proportion of the population (i.e., lack of economic or social resources) as well as a sense of relative deprivation, leading individuals across the income spectrum to feel that they are lacking things that others have (Layte & Whelan, 2014; Walasek & Brown, 2015, 2016). A related account of inequality is the notion that societal inequality creates anxiety about status, conceptualized broadly as greater concern with status comparisons and fears of being looked down upon by others (Buttrick et al., 2017; Delhey & Dragolov, 2014; Layte & Whelan, 2014; Wilkinson & Pickett, 2009). As Brown-Iannuzzi et al. (2021, p. 2) described, "people automatically attune to social hierarchies (e.g., Kraus et al., 2017), and one of the most cross-culturally prevalent hierarchies is based on socioeconomic resources (e.g., income, wealth, social capital, etc.)." Inequality heightens people's awareness of where they fall in this hierarchy and creates concerns about being able to secure limited resources in the future (Buttrick et al., 2017; Delhey & Dragolov, 2014; Sommet et al., 2019).

According to Wilkinson and Pickett's (2009) status-based theory of inequality, people in highly unequal societies experience (a) anxiety about maintaining or increasing one's place and (b) vigilance to potential threats (e.g., Cheung & Lucas, 2016). This occurs because in more unequal societies, there is a greater cost—psychological, social, and economic—associated with a loss of status (Easterbrook, 2021). There is also a greater potential for gain, to the extent to which individuals can achieve higher status. In this vein, empirical work finds people in more unequal societies on average report greater fear of losing one's status as well as greater attempts to signal or enhance one's status through the purchase of status-signaling objects (Buttrick et al., 2017; Roth et al., 2017; Sommet et al., 2019; Walasek & Brown, 2015). Delhey and Dragolov (2014) argue that status anxiety goes beyond economic concerns and captures uncertainty and worry about the extent to which one will be afforded respect and dignity from others. Using the 2007 European Quality of Life Survey, they found that country-level inequality was associated with greater feelings that one is looked down upon by others based on one's income or job. Moreover, in more unequal nations, people on average reported lower trust in others and greater perceived class conflict, including conflict between management and workers. Similarly, Layte (2012) found that status anxiety and lower social capital can help explain the negative relationship between country income inequality and mental health (see also Layte & Whelan, 2014). These effects were observed when controlling for GDP, suggesting that how wealth is distributed matters above overall wealth.

Inequality and Perceived Threats of General Job Loss From AI and Robots

Work serves as a primary mechanism through which society allocates status, respect, and social and economic resources (e.g., pay, benefits, networks; Bapuji et al., 2020; Bidwell et al., 2013; van Dijk et al., 2019). Perhaps it should be no surprise that new social interactions often begin with the question: "what do you do?" (Hulin, 2002). People obtain status and power within the workplace, and organizations reinforce and create inequality through the distribution of pay, rewards, and benefits (van Dijk et al., 2019).

Building from the psychological research on inequality, we anticipate that people living in more unequal societies will, on average, perceive robots and AI as greater workforce threats.[1] Inequality, as Engler and Weisstanner (2020, p. 154, emphasis in original) describe,

> is an important indicator not only of the extent to which some groups have *fallen behind* compared to others, but also of the *potential decline* in society that people higher up in the social hierarchy could face.

Much of the discussion surrounding the use of robots and AI in the workplace highlights the potential for these tools to disrupt work, thereby disrupting existing status hierarchies and threatening work tasks and work itself (Acemoglu & Restrepo, 2020; Brynjolfsson & Mitchell, 2017; Liu, 2018). Although the extent of this disruption is debated, highly publicized estimates have yielded much discussion about the nature of jobs that will be replaced by technology and the extent to which job tasks will change to work alongside AI or robots (Autor, 2015; Arntz et al., 2016; Chui et al., 2015; Frey & Osborne, 2017; Mokyr et al., 2015). Rughiniş et al. (2018, p. 115) describe this well: "public attention has gradually been captured by the issue of automation and job displacement due to robots, a topic which raises both fears and hopes, and considerable uncertainty."

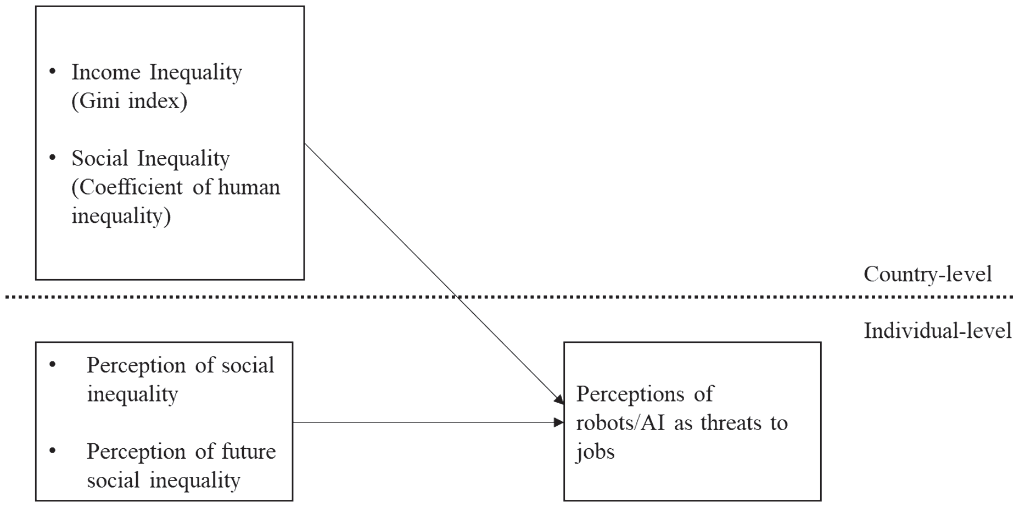
Given the centrality of work in the distribution of resources and in people's lives, disruption in the work arena raises questions about people's abilities to achieve and maintain status and has cascading implications for disruption across social and hierarchical elements of society (Azhar, 2021; Erebak & Turgut, 2021). It is important to note that when people think about the anticipated impact of AI and robots, they are thinking about the impact of technologies that are emerging at rapid rates, where the future capabilities of this technology are currently unknown and are sources of widespread speculation even among experts (Mokyr et al., 2015; McGaughey, 2021). The speculation goes, no longer are AI/robots only designed to replace repetitive and straightforward tasks. Rather, AI/robots can replace complex jobs including managerial, legal, medical, creative, caregiving, and social work (Dobrosovestnova et al., 2022; Carradore, 2022). Again, our focus is not on the objective potential impacts of AI/robots (for research on this, see Acemoglu & Restrepo, 2021), but rather people's beliefs. As the field of psychology and the research on societal inequality have demonstrated, background societal context plays an important role in shaping beliefs (see e.g., Buttrick et al., 2017; Johns, 2006; Sirola & Pitesa, 2017), including beliefs regarding advanced technologies.

Although limited, research provides some indications of the relations between macrolevel factors and attitudes toward advanced technologies in the context of work. For instance, using the Eurobarometer data sets, Gnambs and Appel (2019) reported on worsening attitudes toward robots assisting with work across 2012, 2014, and 2017 data collections. They attributed these worsening attitudes to the potential negative consequences of this technology becoming more salient as its deployment gets closer in time. Although this research did not examine country inequality, they also found that Northern European countries, which tend to be more equal, had more positive attitudes toward robots overall than southern European countries, which tend to have greater levels of inequality (World Bank, 2016). Dekker et al. (2017) suggested fears of negative workforce impacts of robots would be shaped by individual vulnerabilities as well as country-level contexts such as economic conditions (e.g., GDP) and safety net protections. Although they found approximately 10% of the variation in fears of robots to be attributable to country-level differences, the evidence for their country-level economic and safety net predictors was inconsistent and largely nonsignificant, and they did not examine country inequality.

From a technology acceptance standpoint, much of the research and theory has focused on people's personal perceptions and adoption of specific technologies (e.g., computers). Vu and Lim (2021, p. 1) recently argued for more research on societal perceptions of emerging technologies, which they note "could potentially be a key to whether the public and, perhaps, policymakers would welcome the applications of such technologies." In doing so, they argued that models of technology acceptance, such as the technology acceptance model, need to expand beyond narrow individual factors to also consider people's perceptions of the general impact of these technologies (AI and robots) on society. Using the Eurobarometer 87.1 (2017), they found that perceived threat of general job loss and digital technology efficacy negatively related to acceptance of AI and robots, suggesting that people take the broader context into account when forming opinions about adoption of emerging technologies. They discovered that both perceived threat and technology efficacy, in turn, were predicted by a factor capturing their conceptualization of society's engagement with technology, as captured by GDP per capita, government effectiveness, and innovation. Such findings again suggest that the social context of technology may matter when forming perceptions of their potential threats. In a similar vein and also utilizing the 2017 Eurobarometer survey, Carradore (2022) found that perceived threats of AI/robots for general job loss (the dependent variable in our study)

[1] Our focus here is on inequality in largely developed countries. As Kelley and Evans (2017a) and Easterbrook (2021) note, inequality may be viewed as positive in developing countries because it signals opportunities for social mobility.

Figure 1
Hypothesized Model



Note. AI = artificial intelligence.

were one of several factors associated with people's comfort with robots used for social situations (e.g., social service, companionship). They also observed unexplained country-level variance in the model. Likewise, Rughiniş et al. (2018) found that countries differed in profiles of people's general enthusiasm for the presence of robots in daily life (e.g., robots for medical operations, companionship, transportation).

Also relevant to this discussion is a historical perspective on workers protesting economic threats from technological change, especially those changes that threaten social orders and access to resources (see Acemoglu, 2002; McGaughey, 2021; Mokyr et al., 2015). McGaughey (2021) argued that fears of mass unemployment due to technological advances have historically occurred in contexts wherein policy made it such that only a small group of people could reap the benefits of economic returns to technology, which is more likely to be the case in highly unequal societies. Mokyr et al. (2015) observed that pessimistic prognostications of technology's impact on the workforce have tended to occur during times of poor economic growth. These perspectives suggest that people's perceptions about technology are in part connected to the broader economic context.

Based on the reasoning above, our overall hypothesis is that:

> *Hypothesis:* Societal inequality is positively associated with perceptions that AI/robots are threats to jobs in general.

Exploratory Research Questions

As previously noted, most studies on societal inequality have utilized the Gini index to operationalize inequality. We likewise use this inequality metric to test the main hypothesis. In addition, we examine whether the effects we find are robust across alternative operationalizations and conceptualizations of inequality. As another objective measure of inequality, we examine the United Nation's Human Inequality Index. The United Nations Development Programme Human Development Report (2018) conceptualizes human inequality as inequality in life expectancy, education, and income. Additionally, we examine whether subjective perceptions of the importance of inequality between social classes in one's country similarly predict perceived workforce threats by robots/AI after accounting for objective indicators of inequality (Figure 1).[2]

Although subjective perceptions of and objective economic inequality are correlated to some extent, subjective economic inequality captures people's individual perceptions of their society. These subjective views may be influenced by factors such as social networks, political beliefs, and personality traits (Schmalor & Heine, 2022). Schmalor and Heine (2022) linked subjective perceptions of inequality to greater stress, poorer well-being and trust, and higher status anxiety, indicating the importance of individual-level inequality perceptions. Although the Eurobarometer does not ask about people's perceptions of inequality per se, respondents are asked questions about inequality's importance in their country, both in the present and in the future, two of Kelley and Evan's (2017b) "worlds of well-being." These questions might be reasonably conceived to assess people's concern about inequality as well as anticipation about the future of the economy (Kelley & Evans, 2017b). Because we do not have any a priori expectations about differences in the findings across conceptualizations of inequality, we offer the following research questions:

> *Research Question 1:* Is the relationship between societal inequality and perceptions of AI/robot technology as workforce

[2] We also ran supplemental analyses looking at the effects of gender inequality, as measured by the gender inequality index, on perceptions that AI/robots are threats to jobs in general. Although different from income inequality, gender inequality reflects another way in which societal members are unequal. This relationship was nonsignificant and the output is available upon request.

threats robust across different objective and subjective operationalizations of societal inequality (human inequality, subjectively perceived current and future importance of inequality)?

We also consider, in an exploratory manner, whether the relationship between inequality and perceptions of AI/robots as workforce threats depends on one's social standing. In other words, does individual-level social status moderate the impact of societal inequality on AI/robots attitudes? Here, the literature is unclear as to whether we should anticipate a difference and what a difference might look like. On the one hand, those most disadvantaged by inequality suffer from deprivation of resources and experience greater economic insecurity (Jetten et al., 2017; Manstead, 2018). Furthermore, AI and robots are often discussed in terms of their impact on more routine, often lower wage jobs (Acemoglu, 2002; Brynjolfsson & McAfee, 2012). Research suggests that workers displaced by technology may have difficulty finding new jobs (Grigoli et al., 2020). As a result, those who already perceive themselves to have lower status may be particularly concerned about negative effects of AI/robots in more unequal societies (Dodel & Mesch, 2020; Manstead, 2018).

However, as Manstead (2018, p. 279) noted, "higher-class people may be more concerned about losing their privileged position in society if they perceive a large gap between the rich and the poor." Thus, those in positions of higher status may see robots/AI as greater workforce threats due to concerns about workplace disruption (Easterbrook, 2021). Accordingly, Roth et al. (2017) found that among middle- and high-income groups, economic worries (which they conceptualize as status anxiety) mediated the impact of inequality on life satisfaction. In experimental work, Jetten et al. (2017) found that although those with lower income generally experience greater angst about the future vitality of their income group, wealthier individuals were more reactive to conditions of economic instability. Given that prognosticators increasingly predict that high-skilled work will not be untouched by the robot/AI revolution, these changes may create concerns about instability even to the highly advantaged (Wajcman, 2017).

However, there are also alternative viewpoints. Research suggests that people tend to justify the social systems in which they live and that people may be concerned about justifying their privileged position in a highly unequal environment (Manstead, 2018). Given that those with higher social status have been successful under the system that is giving rise to inequality, their justification of this system may make them less willing to see it as a threat. Indeed, Dodel (2021, p. 1) argued that "digital skills mediate the impact of structural inequalities" and Dodel and Mesch (2020) found that people employed in higher status jobs viewed technology as having a positive impact on their careers. Given that people's past experiences shape how they think about events in the future (Szpunar & McDermott, 2008), this might suggest that higher status individuals may view robots/AI more positively in more unequal contexts. Thus, we explore:

Research Question 2: Is the relationship between inequality and perceptions of workforce threat from AI/robots moderated by an individual's social status?

Method

Participants and Procedure

Individual-level data for this study came from the Eurobarometer 87.1 (2017), a Eurobarometer survey covering specialty topics including "The impact of digitisation and automation on daily life." Eurobarometer 87.1 data were collected via in-person interviews executed during March 2017 with a representative sample of European citizens (15 years of age and older). The total sample included responses from 27,901 participants representing 28 EU member states. We limited our sample to 13,294 employed participants, 51.5% female, $M_{\text{age}} = 44.06$ ($SD = 12.20$), because of our study's specific focus on the effects of advanced technology on the workforce and because we planned to use variables related to technology use on one's job as control variables.

Samples for West and East Germany, and Northern Ireland and Great Britain, were respectively combined to provide for the analysis as a whole of Germany (total $N = 650$) and the U.K. (total $N = 620$). Table 1 contains country-level sample sizes including basic demographics for each country (i.e., gender, age, and percentage employed). Country-level economic and inequality metrics were compiled from the World Bank's World Development Indicators (WDI; World Bank, 2016) and the United Nation's Human Development Report (United Nations Development Programme, 2018).

Measures

A listing of all items and scoring is available on an Open Science Foundation page for this project at https://osf.io/r9qap/?view_only=96d0d3393fab4f6682544a1ec692dca8.

Table 1
Country-Level Demographics (Employed Sample): Gender and Age

Country	N	Gender (% female)	Age
1. France	412	52.4%	42.19 (11.85)
2. Belgium	430	50.0	43.81 (11.98)
3. Netherlands	544	48.7%	47.36 (12.12)
4. Germany	650	50.7%	44.49 (12.22)
5. Italy	471	54.0%	45.72 (10.50)
6. Luxembourg	221	52.7%	43.13 (11.51)
7. Denmark	495	49.9%	48.52 (11.94)
8. Ireland	509	47.9%	43.62 (12.01)
9. United Kingdom	620	50.4%	43.40 (13.76)
10. Greece	442	45.5%	43.24 (12.06)
11. Spain	408	45.6%	42.67 (11.49)
12. Portugal	600	55.2%	43.07 (11.92)
13. Finland	403	52.3%	45.38 (12.77)
14. Sweden	507	40.8%	48.64 (13.52)
15. Austria	588	50.9%	42.31 (11.58)
16. Cyprus	233	46.4%	44.16 (11.70)
17. Czech Republic	621	55.9%	43.55 (11.58)
18. Estonia	489	60.9%	47.34 (12.27)
19. Hungary	525	49.7%	43.55 (11.72)
20. Latvia	493	61.3%	44.67 (13.62)
21. Lithuania	404	57.2%	45.00 (12.86)
22. Malta	187	48.7%	43.72 (14.35)
23. Poland	514	55.3%	42.08 (11.68)
24. Slovakia	481	56.8%	43.41 (11.40)
25. Slovenia	438	55.7%	43.89 (11.59)
26. Bulgaria	589	52.1%	43.83 (11.14)
27. Romania	528	49.2%	40.14 (11.02)
28. Croatia	492	58.3%	40.13 (11.05)
Total	13,294	51.5%	44.06 (12.20)

Individual-Level Variables

Perceived Workforce Threat From Robots/AI

Items assessing individuals' perceptions of the effects of robots and AI on the workforce (i.e., "Robots and artificial intelligence steal peoples' jobs" and "Due to the use of robots and artificial intelligence, more jobs will disappear than new jobs will be created") were measured on 4-point Likert scales (1 = *totally disagree* to 4 = *totally agree*) and combined to form a two-item measure of attitudes toward AI/robots as general threats to jobs ($\alpha = .77$; Carradore, 2022). Responses were scored such that higher values indicated greater agreement that AI/robots were threatening to jobs.

Subjective Inequality

Perceived inequality was measured with a single item, "in your opinion, are the inequalities between the different social classes in (OUR COUNTRY) currently very important, fairly important, not very important or not at all important?," on a 4-point Likert scale (1 = *not very important* to 4 = *very important*). A one-item measure, "do you think that in 5 years' time, the inequalities between the different social classes in (OUR COUNTRY) will be ... ," was used to assess perceptions of the future importance of social inequality on a scale from 1 = *much less important than today* to 5 = *much more important than today*.

Social Class

Participants rated the social class of themselves and their household using a 5-point scale (1 = *the working class of society* to 5 = *the higher class of society*), such that higher scores indicated perceived membership in a higher social stratum.

Individual-Level Control Variables

We examined several individual-level demographic and technology-related variables that may predict people's perceptions of threats posed by AI/robots. Demographic variables include education, gender, age, community size, and political beliefs (McClure, 2018). Additionally, the Eurobarometer survey included several variables that captured individuals' experiences with, and knowledge of, advanced technology, which may influence attitudes toward advanced technology at work (Vu & Lim, 2021). These include respondent digital technology skills (i.e., whether these skills are sufficient for success in one's current or future jobs), respondent knowledge about artificial intelligence (i.e., whether they have read or seen anything about AI in the last year), and respondent use of robots at work (i.e., whether they currently use or have ever used a robot at work). Dodel and colleagues' research suggests that such variables may be relevant to how people view technology, consistent with job polarization and self-interest hypotheses of the impact of technological change (2020; 2021). Previous analyses of the Eurobarometer data set have also found these variables to be related to people's perceptions of the effects of technology and their acceptance of technology (Carradore, 2022; Hunady et al., 2020; Rughiniş et al., 2018). Finally, individual's perceptions of whether a robot or AI could do their current job in the future was controlled because the threat of advanced technology to replace one's specific job may affect individuals' general perceptions of the threatening nature of this technology. Including these control variables allows us greater confidence that the findings are not due to systematic differences across countries on these factors.

Country-Level Variables

We selected to utilize country-level inequality and economic indicators from 2016, rather than 2017, because we believed these values would be more representative of the level inequality and economic output actually present in each country when the Eurobarometer 87.1 responses were collected (i.e., March 2017).

Income Inequality

Income inequality was operationalized using the Gini index and was retrieved from the World Development Indicators (World Bank, 2016). The Gini is a measure of the distribution of income in an economy, which estimates inequality based on how far the distribution of income across households deviates from a perfectly equal distribution. A Gini score of 0 indicates complete equality and a score of 100 indicates complete inequality.

Human Inequality

The United Nation's coefficient of human inequality was used to estimate the level of general social inequality in each country, based on inequities in health, income, and education outcomes. The coefficient of human inequality is an unweighted average of inequalities using multiple indicators of human development, including life expectancy at birth (life expectancy index), mean years of schooling (education index), and gross national income (GNI) per capita (GNI index).

Country-Level Control Variables

Consistent with other research on inequality (e.g., Delhey & Dragolov, 2014), we controlled for gross domestic product per capita (GDP per capita), an annual estimate of a country's economic output divided by its population. This information came from the World Development Indicators (World Bank, 2016). To ensure the normality of the data, we took the logarithm of GDP per capita (ln(GDP)) and utilized these log-transformed values in all analyses.

Analytical Strategies

To test our hypothesis and exploratory research questions, we estimated a series of multilevel models using SPSS Version 28.0. We used full-maximum likelihood estimation to establish model fit because of our large sample size and number of Level 2 groups (i.e., countries; Raudenbush & Bryk, 2002). In an initial examination of our control variables (Level 1), where the slopes of controls were allowed to vary randomly, no random slopes were identified as significant ($p < .05$) beyond the intercept. Consequently, the random effects of controls were not estimated in subsequent models due to our large number of control variables and concerns regarding model convergence. The random slopes for the Level 1 predictors included in the hypotheses, for example, individual-level social inequality and future social inequality, were included in our analyses. Output and analytical code are available on an Open Science

Foundation page for this project at https://osf.io/r9qap/?view_only=96d0d3393fab4f6682544a1ec692dca8.

Results

Descriptive statistics and correlations are presented in Table 2. As seen there, each inequality metric was positively related to, and social class was negatively related to, perceptions of robots and AI as threatening to jobs. Demographic and technology controls were also significantly related to perceptions of robots and AI as threats, with the exception of age and political orientation.

A null random intercept model was estimated to calculate the ICC(1) value associated with perceptions of robots and AI as threatening to jobs; the proportion of the total variance in the robots/AI as threats outcome that is attributable to country grouping (i.e., whether there are significant between-country differences in variance; Raudenbush & Bryk, 2002). The intraclass correlation coefficient (ICC = .10) indicates that 10.0% of variance is attributable to country, suggesting that there is between-country variance in this variable, which is implied by our hypotheses and necessary to test our hypotheses related to country-level inequality.

As noted above, we examined our hypotheses and research questions through a series of systematic analyses. First, we ran a preliminary model to determine whether our control variables were significantly related to individual's perceptions of robots and AI as threats to the workforce (Model 1; Table 3). We found that coefficients for demographic controls (i.e., gender, community, and education) were significant (ps $< .001$). Technology control variables were also significant predictors (ps $< .01$), with individuals who reported higher work-related technological skills and greater exposure to AI information rating robots/AI as less generally threatening to jobs. Those who currently or have in the past worked with robots at work also indicated less negative views of the effects of advanced technology on the workforce ($\gamma = -.10$, $SE = .03$, $p < .001$), whereas individuals who reported that their current job could be done by a robot in the future tended to rate robots/AI as more generally threatening ($\gamma = .04$, $SE = .01$, $p < .001$). Country-level GDP per capita was not a significant predictor ($\gamma = -.10$, $SE = .07$, $p = .148$).

We entered each country-level inequality index in Models 2 and 3 (Table 3). The coefficient for the Gini index was significant ($\gamma = .03$, $SE = .01$, $p = .013$), such that higher levels of income inequality were associated with more negative technology perceptions (Model 2). Similarly, the coefficient of human inequality was significantly related to perceptions of technology ($\gamma = .06$, $SE = .01$, $p < .001$), such individuals from countries with greater social inequality were more likely to view advanced technology as generally threatening to jobs (Model 3).

We then considered people's subjective perceptions of social class inequality, first as a predictor alongside the controls and then as a predictor alongside each respective country-level inequality variable (Models 4, 4a, and 4b; Table 4). Subjective perceptions of social inequality were significant in each model ($p < .001$), suggesting that subjective perceptions of the importance of social inequality were positively related to threatening perceptions of technology regardless of country-level inequality. At the same time, when accounting for subjective perceptions of social inequality, both the Gini index (Model 4a, $\gamma = .03$, $SE = .01$, $p = .020$) and the coefficient of human inequality (Model 4b, $\gamma = .05$, $SE = .01$, $p = .002$) were significant predictors.

We then ran these same models, substituting people's perceptions of future social inequality in place of people's perceptions of current inequality (Table 5; Models 5, 5a, and 5b). People's perceptions of future social inequality were also a significant predictor in each model (ps $< .001$), indicating that subjective perceptions of the future importance of social inequality are also positively related to perceptions of robots and AI. At the same time, when accounting for subjective perceptions of the importance of future social inequality, both the Gini index (Model 5a, $\gamma = .02$, $SE = .01$, $p = .042$) and the coefficient of human inequality (Model 5b, $\gamma = .04$, $SE = .02$, $p = .013$) were significant predictors.

These results indicate that inequality is positively associated with perceptions that AI/robots are general threats to jobs. Thus, Hypothesis 1 was supported. These findings also indicate that different forms of inequality relate differently to perceptions of AI/robot technology as workforce threats (Research Question 1).

The cross-level interaction models corresponding to Research Question 2 are displayed in Table 6. As seen there, subjectively reported social class (Model 6) was a significant predictor of advanced technology perceptions ($\gamma = -.08$, $SE = .02$, $p < .001$) and continued to be so following the addition of country-level inequality metrics (at $p < .01$; Models 7a and 8a). In Models 7b and 8b, the cross-level interaction between social class and the Gini index ($\gamma = .00$, $SE = .00$, *ns*) and social class and the coefficient of human inequality ($\gamma = .00$, $SE = .00$, *ns*) were both nonsignificant, indicating no significant interaction effect between social class and country-level income inequality and social inequality. This fails to support our expectation that the relationship between inequality and perceptions of workforce threat from AI/robots differs based on individuals' relative advantaged or disadvantaged status (Research Question 2).

Discussion

Much has been written about the supposed forthcoming revolution in AI and robotics. Some prognostications have been positive, focusing on the ability of emerging technology to aid workers and advance societal capabilities (Schepman & Rodway, 2020). Others are more negative, focusing on widespread technological employment and the yet-unknown disruption that these technologies will enact on jobs and society more broadly (Frank et al., 2019). As Walsh (2018; p. 637) noted, "It remains an open question whether more jobs will be created than destroyed" and McGaughey (2021) pointed out that the ultimate impact will likely be decided by a country's institutional framework and people's economic voice (see also Grigoli et al., 2020). There are many sides to these important discussions. Our concern here is focused on people's perceptions of AI and robots as job destroyers in general (rather than concerns about displacement of one's own job). Building on inequality research, we anticipated that societal inequality would be positively associated with the degree to which people in a given country view AI/robots as general threats to jobs.

Our findings were in line with this prediction. Accounting for a variety of individual-level factors such as age, gender, education, policies, and technology use and skills, as well as country-level GDP per capita, societal inequality was associated with greater perceptions of AI/robots as a threat. This finding held when inequality was

Table 2
Individual-Level Correlations and Descriptive Statistics

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Gender[a]	—																
2. Age	.01	—															
3. Community	.00	−.02**	—														
4. Education	−.04**	0.02+	.12**	—													
5. Politics	.05**	.01	.01	−.04**	—												
6. Tech. skills	−.00	−.18**	.07**	.28**	−.01	—											
7. Tech. skills (future job)	.01	−.26**	.08**	.25**	−.01	.72**	—										
8. Job done by robot	.06**	−.08**	.04**	−.05**	.02*	.01	.03**	—									
9. Read tech.[b]	.09**	−.01	.06**	.25**	−.04**	.29**	.26**	.03**	—								
10. Robot use[c] (at work)	.10**	−.03**	.00	.04**	.02+	.08**	.08**	.13**	.12**	—							
11. GDPln	.04**	.08**	−.04**	.17**	−.14**	.18**	.17**	−.10**	.23**	.07**	—						
12. Social class	−.02**	.02+	.12**	.32**	.05**	.24**	.22**	−.06**	.19**	.05**	.18**	—					
13. Social inequality	−.04**	.02*	.03**	.02+	−.11**	.01	.00	−.02+	.05**	−.03**	−.00	−.08**	—				
14. Future social inequality	−.02*	.01	.01	.03**	−.06**	.02*	.02*	−.01	.06**	−.00	.05**	−.02*	.40**	—			
15. Gini index	0.01	−.03**	.08**	−.13**	.02+	−.06**	−.03**	.06**	−.14**	−.08**	−.30**	−.19**	.13**	.02*	—		
16. Human ineq.	.02*	−.05**	−.01	−.15**	−.03**	−.07**	−.04**	.04**	−.12**	−.06**	−.24**	−.19**	.13**	.03**	.79**	—	
17. Robot/AI threat to jobs	−.06**	−.01	−.06**	−.18**	−.01	−.14**	−.13**	.05**	−.15**	−.07**	−.13**	−.19**	.11**	.07**	.18**	.22**	—
M	.49	44.06	1.98	20.55	5.38	3.18	3.03	1.71	.53	.08	10.15	2.47	3.22	3.84	31.66	9.44	3.06
SD	0.50	12.20	0.79	4.75	2.15	0.92	0.93	0.88	0.50	0.27	0.61	0.97	0.75	1.10	3.91	2.45	0.79

Note. N = 11,073–13,294. Job done by robot = current job could be done by robot in the future; human ineq. = coefficient of human inequality. AI = artificial intelligence; GDP = gross domestic product; *SD* = standard deviation.
[a] Gender (0 = female; 1 = male). [b] Read tech. = heard/read about AI in last 12 months (0 = no; 1 = yes). [c] Robot use (work; 0 = no; 1 = yes).
$^{+}p < .10$. $^{*}p < .05$. $^{**}p < .01$.

Table 3

Multilevel Estimates: Country-Level Inequality and Perceptions of Robots/AI as Threats to Jobs

Predictors	Model 1		Model 2		Model 3	
	γ	*SE*	γ	*SE*	γ	*SE*
Level 1						
Gender[a]	−.08**	.02	−.08**	.02	−.08**	.02
Age	.00	.00	.00	.00	.00	.00
Community	−.03**	.01	−.03**	.01	−.03**	.01
Education	−.01**	.00	−.01**	.00	−.01**	.00
Politics	−.01	.00	−.01	.00	−.01	.00
Tech. skills	−.04**	.01	−.04**	.01	−.04**	.01
Tech. skills (future job)	−.03*	.01	−.03*	.01	−.03*	.01
Job done by robot	.04**	.01	.04**	.01	.04**	.01
Read tech.[b]	−.12**	.02	−.12**	.02	−.12**	.02
Robot use (work)[c]	−.10**	.03	−.10**	.03	−.10**	.03
Level 2						
GDPln	−.10	.07	−.05	.06	−.05	.05
Gini index			.03*	.01		
Human inequality					.06**	.01
Level 1 residual variance	.55**		.55**		.55**	
Intercept variance	.04**		.03**		.02**	
−2 Log likelihood	21,461.83		21,455.56		21,447.53	

Note. $N = 9{,}555$. Job done by robot = current job could be done by robot in the future; human inequality = coefficient of human inequality. AI = artificial intelligence; GDP = gross domestic product; *SE* = standard error.
[a] Gender (0 = female; 1 = male). [b] Read tech. = heard/read about AI in last 12 months (0 = no; 1 = yes). [c] Robot use (work; 0 = no; 1 = yes).
* $p < .05$. ** $p < .01$.

operationalized via the Gini index, the most common operationalization of income inequality, and the coefficient of human inequality, which includes life expectancy and education in addition to income. These findings also extended to people's perceptions of the extent to which inequality is a problem now and will be a problem in the future (i.e., subjective inequality) and are consistent with the general reasoning in the inequality literature that threats are more salient and disruption may be viewed as more threatening in places where resources are distributed in a more unequal manner (Buttrick et al., 2017; Oishi et al., 2018).

These findings extend the inequality literature, which has tended to focus mainly on well-being and intergroup outcomes, by suggesting that people's perceptions of emerging technologies may also differ in more or less unequal societies. Such findings are important given that public perceptions of these technologies may play a role in people's support for certain technology policies and adoption behaviors (Vu & Lim, 2021). Beyond this, Engler and Weisstanner (2020) suggested there may be a link between fears of being left behind, for example, by advanced technologies, and people's voting behaviors. As Kelley and Evans (2017b) submitted, the connection between inequality and people's perceptions of the future is a fascinating one, and one deserving of greater research attention.

Interestingly, when included in the same model, both subjective perceptions of social inequality's importance now and in the future, as well as objective indicators of inequality were significantly related to perceptions of robots/AI as workforce threats. Such findings are in line with Schmalor & Heine's (2022) argument that subjective and objective economic phenomena are related but, at the same time, can have distinct impacts. There have been calls for research, especially on the former, as Kelley and Evans (2017b) noted that people's perceptions about the present and the future may be a powerful way that inequality exerts effects. In the present study, our subjective inequality items asked about the extent to which people believed that inequality is an important issue. Our findings may therefore reflect that, beyond country-level inequality, whether the person specifically views inequality as an issue is associated with perceptions of AI/robots as workforce threats. This finding is consistent with social and organizational psychologists' ideas that context can impact people's cognitions and behaviors outside and in addition to specific perceptions (e.g., Johns, 2006; Kunst et al., 2017).

Neither the Gini index nor the coefficient of human inequality interacted with the person's own perceived social class. As noted above, it may be that people with different social status develop these perceptions for different reasons, which would be an interesting question to unpack in future research. We encourage future research on societal inequality to further examine the psychology of income inequality and whether/how/when the effects of income or social inequality differ depending on a person's social or economic status.

Our research also suggests that people's perceptions of AI/robots as general threats are broader than concerns about their own jobs being replaced. Rather, people's perceptions of the workforce impact of AI/robots are associated with demographic factors (e.g., rural or urban communities), their own experiences, skills, and interests in technology, and the broader social context—both objectively and as participants perceive it. Models of technology acceptance and use may therefore benefit from taking into account

Table 4

Multilevel Estimates: Perceptions of Social Inequality, Country-Level Inequality and Perceptions of Robots/AI as Threats to Jobs

Predictors	Model 4		Model 4a		Model 4b	
	γ	*SE*	γ	*SE*	γ	*SE*
Level 1						
Gender[a]	−.07**	.02	−.07**	.02	−.07**	.02
Age	.00	.00	.00	.00	.00	.00
Community	−.04**	.01	−.04**	.01	−.04**	.01
Education	−.01**	.00	−.01**	.00	−.01**	.00
Politics	−.00	.00	−.00	.00	−.00	.00
Tech. skills	−.04**	.01	−.04**	.01	−.04**	.01
Tech. skills (future job)	−.03*	.01	−.03*	.01	−.03*	.01
Job done by robot	.04**	.01	.04**	.01	.04**	.01
Read tech.[b]	−.13**	.02	−.13**	.02	−.13**	.02
Robot use (work)[c]	−.10**	.03	−.10**	.03	−.10**	.03
Social inequality	.10**	.01	.10**	.01	.10**	.01
Level 2						
GDPln	−.05	.07	−.01	.06	−.02	.05
Gini index			.03*	.01		
Human inequality					.05**	.01
Level 1 residual variance	.54**		.54**		.54**	
Intercept variance	.03*		.02*		.02*	
Slope variance (social inequality)	.00+		.00*		.00+	
−2 Log likelihood	21,011.61		21,006.091		21,001.52	

Note. $N = 9{,}555$. Job done by robot = current job could be done by robot in the future social inequality = importance of social inequality (in country); human inequality = coefficient of human inequality. AI = artificial intelligence; *SE* = standard error; GDP = gross domestic product.
[a] Gender (0 = female; 1 = male). [b] Read tech. = heard/read about AI in last 12 months (0 = no; 1 = yes). [c] Robot use (work; 0 = no; 1 = yes).
+ $p < .10$. * $p < .05$. ** $p < .01$.

Table 5
Multilevel Estimates: Perceptions of Future Social Inequality, Country-Level Inequality and Perceptions of Robots/AI as Threats to Jobs

Predictors	Model 5		Model 5a		Model 5b	
	γ	*SE*	γ	*SE*	γ	*SE*
Level 1						
Gender[a]	−.08**	.02	−.08**	.02	−.08**	.02
Age	.00	.00	.00	.00	.00	.00
Community	−.04**	.01	−.04**	.01	−.04**	.01
Education	−.01**	.00	−.01**	.00	−.01**	.00
Politics	−.00	.00	−.00	.00	−.00	.00
Tech. skills	−.04**	.01	−.04**	.01	−.04**	.01
Tech. skills (future job)	−.03*	.01	−.03*	.01	−.03*	.01
Job done by robot	.04**	.01	.04**	.01	.04**	.01
Read tech.[b]	−.13**	.02	−.13**	.02	−.13**	.02
Robot use (work)[c]	−.09**	.03	−.09**	.03	−.09**	.03
Future social inequality	.06**	.01	.06**	.01	.06**	.01
Level 2						
GDPln	−.11	.07	−.08	.07	−.08	.06
Gini index			.02*	.01		
Human inequality					.04*	.02
Level 1 residual variance	.54**		.54**		.54**	
Intercept variance	.04**		.03**		.03**	
Slope variance (future social inequality)	.00*		.00*		.00	
−2 Log likelihood	20,453.96		20,449.74		20,448.38	

Note. $N = 9{,}555$. Job done by robot = current job could be done by robot in the future future social inequality = future importance of social inequality (in country); human inequality = coefficient of human inequality. AI = artificial intelligence; *SE* = standard error; GDP = gross domestic product.
[a] Gender (0 = female; 1 = male). [b] Read tech. = heard/read about AI in last 12 months (0 = no; 1 = yes). [c] Robot use (work; 0 = no; 1 = yes).
* $p < .05$. ** $p < .01$.

elements of context, both objective and subjectively perceived. Additionally, these findings suggest that surveys and polls related to advanced technologies in the workplace should not assume that people's perceptions of threats of robots/AI to their own jobs are equivalent to people's perceptions of the threats that AI/robots pose more generally for jobs in society.

From a practical implications perspective, our findings suggest that technology companies, workplaces considering implementing

Table 6
Cross-Level Interactions: Social Class, Inequality, and Perceptions of Robots/AI as General Threats to Jobs

Predictors	Model 6		Model 7a		Model 7b		Model 8a		Model 8b	
	γ	*SE*	γ	*SE*	γ	*SE*	γ	*SE*	γ	*SE*
Gender[a]	−.08**	.02	−.08**	.02	−.08**	.02	−.08**	.02	−.08**	.02
Age	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Community	−.03**	.01	−.03**	.01	−.03**	.01	−.03**	.01	−.03**	.01
Education	−.01**	.00	−.01**	.00	−.01**	.00	−.00**	.00	−.01**	.00
Politics	−.00	.00	−.00	.00	−.00	.00	−.00	.00	−.00	.00
Tech. skills	−.03*	.01	−.03*	.01	−.03*	.01	−.03*	.01	−.03*	.01
Tech. skills (future job)	−.02*	.01	−.02*	.01	−.02*	.01	−.02*	.01	−.02*	.01
Job done by robot	.03**	.01	.03**	.01	.03**	.01	.03**	.01	.03**	.01
Read tech.[b]	−.11**	.02	−.11**	.02	−.11**	.02	−.11**	.02	−.11**	.02
Robot use (work)[c]	−.10**	.03	−.10**	.03	−.10**	.03	−.10**	.03	−.10**	.03
GDPln	−.07	.06	−.04	.06	−.04	.06	−.03	.05	−.03	.05
Social class	−.08**	.02	−.08**	.02	−.15	.12	−.08**	.02	−.11+	.06
Gini index			.02*	.01	.02*	.01				
Gini × Social class					.00	.00				
Human inequality							.05**	.01	.05**	.01
Human inequality × Social class									.00	.01
Level 1 residual variance	.54**		.54**		.54**		.54**		.54**	
Intercept variance	.04**		.03**		.03**		.02**		.02**	
Slope variance (social class)	.00*		.00*		.00*		.00*		.00*	
−2 Log likelihood	20,888.18		20,883.27		20,882.93		20,875.33		20,875.07	

Note. $N = 9{,}555$. Job done by robot = current job could be done by robot in the future; human inequality = coefficient of human inequality. GDP = gross domestic product; AI = artificial intelligence.
[a] Gender (0 = female; 1 = male). [b] Read tech. = heard/read about AI in last 12 months (0 = no; 1 = yes). [c] Robot use (work; 0 = no; 1 = yes).
+ $p < .10$. * $p < .05$. ** $p < .01$.

advanced technologies, and policymakers should account for the broader context of inequality when anticipating how people may react to these technologies. There should be concern about not only technology driving inequality but also about inequality being related to people's view of technology. To the extent to which people's views about technology limit the successful introduction of advanced technologies (Thibodeau, 2013), one might wonder whether, or if, this countervailing force could serve to temper the growth of inequality-producing technologies. Although this is beyond the scope of this project, future research should examine the dynamics of inequality, technology views, and technology adoption to shed greater light on the relationships we found here.

Limitations and Future Directions

Our research is limited in several ways that should be taken into account when interpreting the findings. We included only the countries available in the Eurobarometer data set. Kelley and Evans (2017a, 2017b) make the important point that inequality may mean different things in different countries given development status, political past, and so forth. Future research is thus needed to examine boundary conditions of the relationships we found here. For instance, in developing countries, inequality may represent hope for the future, depending on opportunities for social mobility. Perhaps in this context, potential disruption from robots/AI could be viewed positively in countries with greater inequality. Additionally, we only included individuals who are currently employed. This was done to be able to control for technology use on the job in estimating the models. As a result, our research is unable to speak to the perceptions of people who are unemployed or out of the labor force, who are likely to hold more negative views of displacement by technology, particularly if they blame technology for this displacement (Dodel & Mesch, 2020).

Our research is unable to determine causality or explanatory mechanisms for these effects. In our theoretical development, we speculate that the positive association between inequality and perceptions of AI/robots as job destroyers may in part be due to greater sensitivity to threat, zero-sum thinking, and fears of disruption to work as a key institution in society behind income and status that are associated with greater inequality. However, the data available do not allow us to test these specific ideas. It may also be the case that, given people's general preferences for equality in their societies (Alesina et al., 2004), people in more unequal societies may simply be more reactive to the technologies that are thought to underlie these trends. Future research is needed to explore the potential mechanisms underlying these relationships.

Our research also provides only a snapshot of this relationship at a given point in time. We encourage future work to examine these questions with more recent data sets as well as to track potential societal changes over time (e.g., Shoss & Kueny, 2022). In this vein, future work might examine trajectories of inequality and perceptions of threats from robots/AI. This work might also utilize other sources of data, for example, the content of media coverage about these technologies across different countries. It also would be beneficial for future research to build on our findings by examining other variables and outcomes that may be related to people's perceptions of robots/AI as job destroyers (e.g., policy preferences).

Conclusions

Although emerging technologies may give rise to inequality (Hong & Shell, 2018), our study of the Eurobarometer data suggests that societal inequality—both objective and perceived—is associated with the extent to which people view AI/robots as threats to jobs in general. This relationship occurs even when accounting for people's perceptions of technology-related threats to their own jobs as well as demographic factors and technology experience. These findings point to the importance of context for understanding how people react to potentially transformative workplace technologies. To the extent to which society is organized in a zero-sum manner and economic returns to technology are concentrated among a small proportion of society (i.e., higher inequality), people are more likely to view technology as a threat.

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Received December 8, 2021
Revision received April 2, 2022
Accepted April 21, 2022 ■