AMERICAN PSYCHOLOGICAL ASSOCIATION

Journal of Applied Psychology

ISSN: 0021-9010

https://doi.org/10.1037/apl0001045

RESEARCH REPORT

The Rise of Robots Increases Job Insecurity and Maladaptive Workplace Behaviors: Multimethod Evidence

Kai Chi Yam[1], Pok Man Tang[2, 3], Joshua Conrad Jackson[4, 5], Runkun Su[6], and Kurt Gray[4]

[1] Department of Management and Organisation, National University of Singapore
[2] Department of Management, Texas A&M University
[3] Department of Management, University of Georgia
[4] Department of Psychology and Neuroscience, University of North Carolina, Chapel Hill
[5] Department of Management and Organizations, Northwestern University
[6] School of Business, Sun Yat-sen University

Robots are transforming the nature of human work. Although human–robot collaborations can create new jobs and increase productivity, pundits often warn about how robots might replace humans at work and create mass unemployment. Despite these warnings, relatively little research has directly assessed how laypeople react to robots in the workplace. Drawing from cognitive appraisal theory of stress, we suggest that employees exposed to robots (either physically or psychologically) would report greater job insecurity. Six studies—including two pilot studies, an archival study across 185 U.S. metropolitan areas (Study 1), a preregistered experiment conducted in Singapore (Study 2), an experience-sampling study among engineers conducted in India (Study 3), and an online experiment (Study 4)—find that increased exposure to robots leads to increased job insecurity. Study 3 also reveals that this robot-related job insecurity is in turn positively associated with burnout and workplace incivility. Study 4 reveals that self-affirmation is a psychological intervention that might buffer the negative effects of robot-related job insecurity. Our findings hold across different cultures and industries, including industries *not* threatened by robots.

Keywords: robots, job insecurity, burnout, incivility, self-affirmation

Supplemental materials: https://doi.org/10.1037/apl0001045.supp

Much has been written about the threat that robots, defined as "embodied, automatically controlled, reprogrammable multipurpose entities that perform useful tasks for humans or equipment" (International Federation of Robotics, 2017), pose to jobs (e.g., Lee et al., 2018). Frey and Osborne (2017) estimated that in the next 2 decades, robots will replace humans in 47% of jobs, especially manual labor job. A bricklaying robot can work six times faster than the average construction worker, without breaks and benefits (Murphy, 2017). Some economists are optimistic because the rise of robots will create new jobs and roles for humans (Acemoglu & Restrepo, 2018). Other experts are more pessimistic: Pundits have attributed the rise of populism to robots taking jobs (Frey et al., 2018)—especially those of middle-class men (Acemoglu & Autor, 2011)—and scholars predict that robots will create deep existential threats (Frase, 2016). It is true that there are some "technophobes" who—like the Luddites of the Industrial Revolution—explicitly dislike and fear robots (Dekker et al., 2017; McClure, 2018), but little work has examined how working adults generally react to the rise of robots at work (Brosnan, 2002). Uncertainty about how people respond to robots at work extends beyond the ivory tower, with less than 17% of senior business leaders saying they understand the consequences of this developing phenomenon (Davenport et al., 2017). In this article, we examine the work-related psychological and behavioral costs of exposure to robots at work.

In exploring reactions to the rise of robots at work, we draw from cognitive appraisal theory of stress (Lazarus & Folkman, 1984) to suggest that exposure to robots is positively associated with a sense of job insecurity, broadly defined as the subjective perception that one's job is threatened (Greenhalgh & Rosenblatt, 1984). Even if people's jobs are not actually threatened by robots, we predict that the prevalence of pessimistic societal rhetoric—along with the obvious superiority of robots within a narrow domain of tasks—will likely lead people to see robots as threat to their employment, resulting in a heightened sense of job insecurity. We also theorize feelings of robot-induced job insecurity will be associated with more maladaptive workplace behaviors, including burnout and workplace incivility.

Given these negative effects, we also test a psychological intervention that might buffer them: self-affirmation (Steele, 1988), broadly defined as the recognition and assertion of the existence and important values of one's individual self. After appraising robots as threats, self-affirmation may allow people to "realize

Kai Chi Yam https://orcid.org/0000-0001-7381-8039

This research is supported by a Singapore Ministry of Education Tier 1 (Grant R-317-000-149-115) awarded to Kai Chi Yam.

Correspondence concerning this article should be addressed to Kai Chi Yam, Department of Management and Organisation, National University of Singapore, BIZ1-8-37A, 15 Kent Ridge Drive, Singapore 119245, Singapore or Runkun Su, School of Business, Sun Yat-sen University, Haizhu District, 387 Yixian Road, Guangzhou, Guangdong Province 510276, China. Email: bizykc@nus.edu.sg or runkun.su@u.nus.edu

that their self-worth does not hinge on the evaluative implications of the immediate situation [exposure to robots]" (Sherman & Cohen, 2006, p. 187) and therefore experience less job insecurity and also exhibit fewer of the resultant maladaptive behaviors.

Our research makes several contributions. First, we answer the call from organizational scholars to study employee–robot interactions (e.g., von Krogh, 2018). Other articles have considered the effects of the rise of technology, automation, and robots on job insecurity, but our work is perhaps the most thorough test of this question to date, including multiple study designs and sampling participants across cultures and industries.[1] The sum result is a set of robust and generalizable findings that can further advanced this emerging literature. Second, we examine the downstream behavioral costs (i.e., burnout and workplace incivility) of exposure to robots. Understanding these costs can enable organizations to better examine whether the increased use of robots is a blessing or a curse. Third and finally, while some research has documented the negative effects of being exposed to robots, our work examines a simple, easily scalable, and practically important intervention to mitigate these negative effects, which might have lasting practical implications for organizations who wish to introduce robots.

Theoretical Background

Before moving to our theory, we first define exposure to robots as *being exposed, either physically or psychologically, to robots that take physical forms regardless of how autonomous the robots are.* We use this definition for several reasons. First, we only explore robots with physical forms (i.e., embodied robots) because research in social psychology has suggested that people's reactions to embodied technological agents are fundamentally different compared to their reactions to disembodied technological agents (Epley & Waytz, 2010). This definition sharpens our theoretical and empirical focus by excluding mere algorithms or computerized programs, which are both ubiquitous and relatively hard to circumscribe as a distinct social phenomenon. Although our work focuses on embodied robots, there is an emerging stream of work that has focused on employees' reactions to algorithms. We suggest that embodied robots are different compared to algorithms and as a result more threatening. First, robots are perceived to have some levels of agency but completely lack emotionality (Gray et al., 2007). Entities that possess this unique combination are often perceived to be threatening (Gray & Wegner, 2012; Wegner & Gray, 2016). Unlike robots, algorithms do not possess a physical form and often are perceived to be less agentic (Wegner & Gray, 2016). As a result, although both are likely to be perceived as infallible or at least would suppress humans' capabilities in the future, robots would have a much larger impact on employees' perceived job insecurity.

Second, we do not distinguish between fully autonomous robots (i.e., artificial intelligence [AI]-equipped) versus semi-autonomous or preprogrammed robots because AI-equipped robots are still in their infancy, and laypeople and employees are not commonly exposed to them. Moreover, people tend to infer a similar amount of mind across embodied robots (Wegner & Gray, 2016)—typically hinging on the humanness of their appearance (Gray & Wegner, 2012)—regardless of their actual autonomy and processing capacities. This suggests that experience with robots is driven primarily by the robot's appearance rather than their autonomy. Third, we examine both physical and psychological exposure because cognitive appraisal theory of stress applies to both physical and psychological stimuli (Lazarus & Folkman, 1984).

Cognitive Appraisal Theory of Stress

Job insecurity is a subjective appraisal, "a *perceived* threat to the continuity and stability of employment as it is currently experienced" (Shoss, 2017, p. 1914; italics added). As such, job insecurity is a perceptual process and is the result of a subjective appraisal of one's surrounding environmental stimuli. Per cognitive appraisal theory of stress (Lazarus & Folkman, 1984), when an individual encounters a self-relevant stimulus, he or she will engage in appraisal processes (Frijda, 1993; Ortony et al., 1988; Smith & Pope, 1992)—a stimulus is either cognitively appraised as being congruent or incongruent with one's goals. Goal congruent appraisals result in positive reactions, whereas goal incongruent appraisals trigger negative reactions, such as stress. During this process, the individual's cognitive assessment of coping potential and/or future expectations would also affect the specific reaction experienced (Lazarus, 1991). In line with this theory, past research has revealed that job insecurity represents individuals' cognitive appraisals of their surrounding threats (Greenhalgh & Rosenblatt, 1984; Kinnunen et al., 2014; Roskies & Louis-Guerin, 1990). In essence, cognitive appraisal theory of stress enables us to understand how environmental stimuli—in our context, being exposed to robots—might affect employees' appraisals of job insecurity (Lee et al., 2018). Importantly, appraisal theory of stress also enables us to theorize the action tendency as a result of the experienced job insecurity and interventions that can mitigate such negative effects.

We theorize that exposure to robots influences individuals' appraisal process, leading them to appraise robots as being incongruent with ones' goals. This is because most would agree that robots are already more efficient and competent than humans in some jobs. For example, robots can outperform humans in manual labor (Frey & Osborne, 2017; Murphy, 2017). Although knowledge workers might still outperform their robot counterparts at this point in time, many are well aware that robots are poised to outperform them in the near future. For example, a robot surgeon recently performed intestinal surgery on a pig and its results were better than the same surgery performed by human surgeons (Greenemeier, 2016). The pace of innovation in robotics may thus cause people to appraise the rise of robots as a threat to their jobs, leading to a goal incongruent appraisal which results in job insecurity.

Importantly, exposure to robots not only triggers appraisal processes that culminate in job insecurity but this sense of job insecurity would also be particularly strong relative to other sources of job threats. Appraisal theory of stress specifically discusses coping potential and/or future expectations as key determinants of one's reaction to external stimuli (Lazarus, 1991). Compared to competing with younger employees or skilled immigrants, individuals generally cannot learn new skills to outcompete robots in terms of efficiency or engage in political activism to safeguard employment from immigrants, thus putting coping potential in doubt. In addition, virtually, all pundits and scholars have suggested that robots will increasingly be integrated into the workplace, and that this future trend is inevitable. As such, we theorize that employees would

[1] See Supplemental Materials for a comprehensive review of the human–robot interaction at work literature to date.

largely appraise their exposure to robots as an obstacle to their future employability (Ashford et al., 1989; Lazarus & Folkman, 1984), leading to significant feelings of job insecurity.

Some studies have provided preliminary support for this hypothesis. Theoretically, Lee et al. (2018; also see Lu et al., 2020) suggest that the rise of robots will lead not only to job insecurity but also to career insecurity because entire careers and industries might be overtaken by robots. Empirically, scholars observed a link between job insecurity and new technologies, although the empirical rigor of these studies is limited (Lingmont & Alexiou, 2020; Vassileva, 2020). We posit the following hypothesis:

> *Hypothesis 1:* Exposure to robots is positively associated with a sense of job insecurity.

Downstream Impacts on Behaviors

Numerous qualitative and quantitative reviews have revealed the consequences of job insecurity (Cheng & Chan, 2008; De Witte, 2005; Lee et al., 2018; Shoss, 2017; Sverke et al., 2002). Scholars generally agree that an individual would engage in both avoidance- and approach-oriented coping behaviors (Lazarus & Folkman, 1984). Avoidance-oriented behaviors allow the individual to disengage from the negative stimuli, whereas approach-oriented behaviors allow the individual to regain control over the stressful situation. After individuals appraise robots as threatening and experience job insecurity, we theorize that employees will (a) disengage from their threatened work in the form of burnout and (b) ameliorate the situation and regain control via dysfunctional means in the form of incivility (Lazarus, 1993; Lazarus & Folkman, 1984).

Job-insecure employees have to invest extra energy from their resource reservoir to protect their existing resources (e.g., income, social connection, and status), thereby diverting that energy from the creation of new resources (Schaufeli et al., 2009). Therefore, individuals exposed to a threatened job situation usually experience a loss spiral of resources and eventually suffer from a resource shortage (Dekker & Schaufeli, 1995). As such, as a result of exposure to robots, job-insecure employees are more likely to experience burnout (Maslach et al., 2001). Indeed, meta-analyses have revealed a robust link between a sense of job insecurity and physical and psychological health outcomes (Cheng & Chan, 2008; Sverke et al., 2002). De Witte (1999) even suggested that the effects of job insecurity on one's well-being mirror the effects of actually losing one's job.

In addition to burnout, we also consider job insecurity's effects on employees' workplace incivility toward their colleagues (for a review, see Schilpzand et al., 2016). There are three reasons to expect a sense of job insecurity would increase workplace incivility. Job-insecure employees are motivated to keep their jobs and may thus mistreat or undermine their coworkers as a means to compete with rivals for limited positions (Shoss & Probst, 2012). Other research by Qin et al. (2018) and by Huang et al. (2017) shows that job-insecure employees will engage in more interpersonally deviant behavior to regain their control over the situation when confronted with stress (see also Van den Broeck et al., 2014). Finally, Huang et al. (2017) found that job-insecure employees are more likely to engage in deviance because they perceive an imbalanced social exchange between themselves and their employers, leading them to justify deviant behavior as appropriate.

> *Hypothesis 2:* The relationship between exposure to robots and (a) burnout and (b) workplace incivility is mediated by a heightened sense of job insecurity.

An Intervention to Reduce Job Insecurity: Self-Affirmation

Robots may create feelings of job insecurity, which can cause negative consequences, but these feelings—and consequences—may be mitigated by self-affirmation. Self-affirmation "can buffer stress . . . [and it is an] effective stress management approach" (Creswell et al., 2013, p. 1), by making the self to be more resilient to potential threats (Cohen & Sherman, 2014). The cognitive appraisal theory of stress argues that events are stressful when people appraise that they lack the capacity to cope with them. Self-affirmation therefore emphases that employees *can* cope by affirming one's self-worth and their ability to confront change at work (Dunning, 2005; Schmeichel & Vohs, 2009; Sherman & Cohen, 2006).

A common self-affirmation technique is "value essays," in which people reflect on their most important characteristics and values (e.g., Kinias & Sim, 2016), including friends and family, social skills, religion, and so forth. Creswell et al. (2005) found that these self-affirmation exercises reduce levels of cortisol—a biological stress marker—after a stressful exercise. Likewise, Sherman et al. (2009) found that college students who were instructed to self-affirm prior to their midterm examination period later reported lower stress compared to their counterparts who did not self-affirm. In line with these findings, we suggest that self-affirmation will help build a "flexible self-system" that prompts less threatening appraisals when people are exposed to robots. We posit

> *Hypothesis 3:* Self-affirmation moderates the effect of exposure to robots on a heightened sense of job insecurity such that the relationship is weakened when people practice self-affirmation.

Overview of Studies

We test our hypotheses in six studies, with two additional pilot studies (reported in the see Supplemental Materials) showing that robots are uniquely associated with job insecurity when compared to other threats to employment (e.g., immigrants, algorithms). Study 1 is an archival analysis of whether increases in the number of robots across major U.S. metropolitan areas predict corresponding job insecurity. Study 2 is a preregistered experiment that tests whether temporarily exposing people to the idea of robots at work leads to increased self-reported job insecurity. Study 3 is a field study that examines the psychological experiences of engineers who interact with robots on a daily basis. Finally, Study 4 is an online experiment that examines whether self-affirmation might buffer the negative effects of being exposed to robots.[2] All studies (except the archival

[2] All study materials, data, and syntax can be found via this link (https://osf.io/zxq52/?view_only=e67355419b274b7da997200499b33a7f). Study 2's preregistration report can be found via this link (https://osf.io/f7sd9/?view_only=b331d1193c3e410fbf72960ced5b5cc7).

Study 1) were approved by the National University of Singapore's institutional review board (MNO-20-0626). The data reported in Study 3 were collected as part of a larger data collection. This is the first publication from this broader data set.

Study 1: Archival Evidence Across 50 U.S. States

Our first study tested whether the prevalence of robots across 185 metropolitan areas in the United States could predict people's efforts to safeguard job security through online job searches at popular job-recruiting sites. An association between the rising number of robots and an increased interest in such sites would imply that robots lead to greater job insecurity—manifested through looking for other jobs.

Method

Measures

Robot Prevalence. We measured robot prevalence using metro-level data originally gathered by the International Federation of Robotics and then organized and publicly shared by Brookings. Brookings contained data on (a) robot workers per 1,000 human workers in 2015 and (b) the percent change in robot workers within the metro areas from 2010 to 2015 (these are the most recent data published by both agencies). The robots tracked by these agencies are industrial robots, which all take physical forms and are not mere algorithms or computerized programs. One advantage of these data was that they were scaled to (a) the population of human workers in a metro area and (b) the level of robots in 2010, which avoided confounding robot density with metro area size. In Table 1, we present the five metro areas with the highest and lowest levels of robot prevalence.

Job Insecurity. We measured job insecurity through the frequency at which people searched for job-recruiting sites. We collected data for searches on the five most popular job-recruiting sites in the United States: LinkedIn, Glassdoor, ZipRecruiter, Indeed, and Monster. To measure cross-sectional (robots and job insecurity in the same year) and longitudinal variability (robots and job insecurity over the same multiyear period) in job insecurity, we downloaded data on how often people searched on these sites annually from 2010 to 2015 and then summed data across the four sites so that our relationships were not confounded with any individual site.

Table 1
Metro Areas With the Highest and Lowest Industrial Robot Density (Study 1)

Highest industrial robot density in 2015	Lowest industrial robot density in 2015
South Bend, IN (19.50)	Anchorage, AK (.10)
Lafayette, IN (13.20)	Fairbanks, AK (.10)
Toledo, OH (9.00)	Laredo, TX (.10)
Lima, OH (8.80)	Gainesville, FL (.20)
Bowling Green, KY (8.70)	Honolulu, HI (.20)
Most industrial robot increase (2010–2015)	**Least industrial robot change (2010–2015)**
Rapid City, *SD* (+35%)	Casper-Riverton, WY (−2%)
Albany-Schenectady-Troy, NY (+30%)	Shreveport, LA (2%)
Gainesville, FL (+29%)	Elmira, NY (4%)
Toledo, OH (+28%)	Syracuse, NY (8%)
Louisville, KY (27%)	Parkersburg, WV (9%)

Control Variable. We gathered unemployment data from the U.S. Bureau of Labor Statistics and controlled for it in our analyses. This is because unemployment rate is an often-used proxy for the economic condition of a given location (Bianchi, 2013). Controlling for it helps rule out the explanation that increases in prevalence of robots and job search are both driven by economic growth (results remained identical without this control; see Supplemental Materials).

Analytic Strategy

Google Trends scales its search data from 0 to 100 so that individual data points are not interpretable, but variations across geographic regions are meaningful. This means that we could not compare overall changes in search rates from 2010 to 2015, but we could compare variation across metro areas and analyze how variation across metro areas changed over time. Importantly, these scaled 0–100 values represent an interest in a search term *among all search terms*, rather than raw interest. This metric means that our results are not confounded with general internet (or search engine) activity, which is a strength.

Results

Table 2 presents the descriptive information for all the study variables in our analysis.

Cross-Sectional Results

Our multiple regression model revealed that job insecurity was robustly associated with robot density across all years (i.e., 2010–2015), $\beta = .23$, $p = .002$; and in 2015 alone, $\beta = .17$, $p = .02$. This suggests that the metro areas with the most prevalent rates of robots also have the highest rates of job-recruiting site searches, potentially because people are more insecure about losing their jobs. Figures 1 and 2 depict this relationship. Table 3 (Models 1 and 2) summarizes the regression results.

Longitudinal Results

We next tested for whether changes in robot density from 2010 to 2015 were associated with changes in job insecurity over the same period. Multilevel regression supported our hypothesis. Change in robot density from 2010 to 2015 was significantly and positively associated with change in job insecurity, both when intercepts were modeled as random, $\beta = .05$, $p = .03$; and when slopes and intercepts were modeled as random, $\beta = .05$, $p = .04$. Table 3 (Models 3 and 4) summarizes these statistics. Simple slope analysis revealed that, among metro areas that experienced low (−1 *SD*) change in robot density from 2010 to 2015, there was no effect of time on job insecurity, $b = .15$, $SE = .20$, $p = .45$, but among metro areas that experienced high (+1 *SD*) change in robot density, there was a positive and significant effect of time on job insecurity, $b = .61$, $SE = .21$, $p = .003$.

Supplementary Analyses

We tested whether robot density was associated with unemployment rate, and whether changes in robot density were associated

Table 2
Descriptive Statistics and Correlations (Study 1)

Variable	*M*	*SD*	1	2	3	4
1. Robots per 1,000 human workers (2015)	1.91	2.38	—			
2. Percent change in robot workers (2010–2015)	.18	.05	.09	—		
3. Job site interest	35.91	8.98	.23**	−.01	—	
4. Unemployment rate	6.65	2.15	.04	−.03	.06	—

Note. Robots per 1,000 human workers in 2015 is our operationalization of robot density. Percent change in robot workers from 2010 to 2015 is our operationalization of change in robot density.
** $p < .01$.

with changes in unemployment rate. These analyses showed no association between robot density in 2015 and unemployment rate from 2010 to 2015, $\beta = .04$, $p = .57$; or unemployment rate in 2015 alone, $\beta = -.05$, $p = .54$. A subsequent multilevel model showed that increases in robot density from 2010 to 2015 were actually negatively associated with unemployment during that time, $\beta = -.03$, $p = .006$, although this association was not significant when modeling slopes as random, $\beta = -.03$, $p = .11$. Taken together, these analyses suggest that robot density from 2010 to 2015 had very little—if any—effect on actual unemployment rates.

Although Study 1 provides support for Hypothesis 1, it has limitations as with most other archival studies (Barnes et al., 2018). First, our proxy for job insecurity is not perfect. Those who opted to use job search websites might do so because they (a) feel insecure about their current job (our hypothesis), (b) want to explore new career opportunities, (c) are dissatisfied with their current job, or a combination of the above. However, controlling for unemployment rate in a metro area partially ruled out the explanation that the rise of robots and economic growth stimulates more job searches. Second, correlational analyses cannot reveal causation. Third, our unit of analysis was at the metro area and we are unable to identify if this association would hold at the individual level. Fourth, the latest data only cover the years 2010–2015, and results might differ if more recent data are available. We conducted an experimental study next to address these limitations.

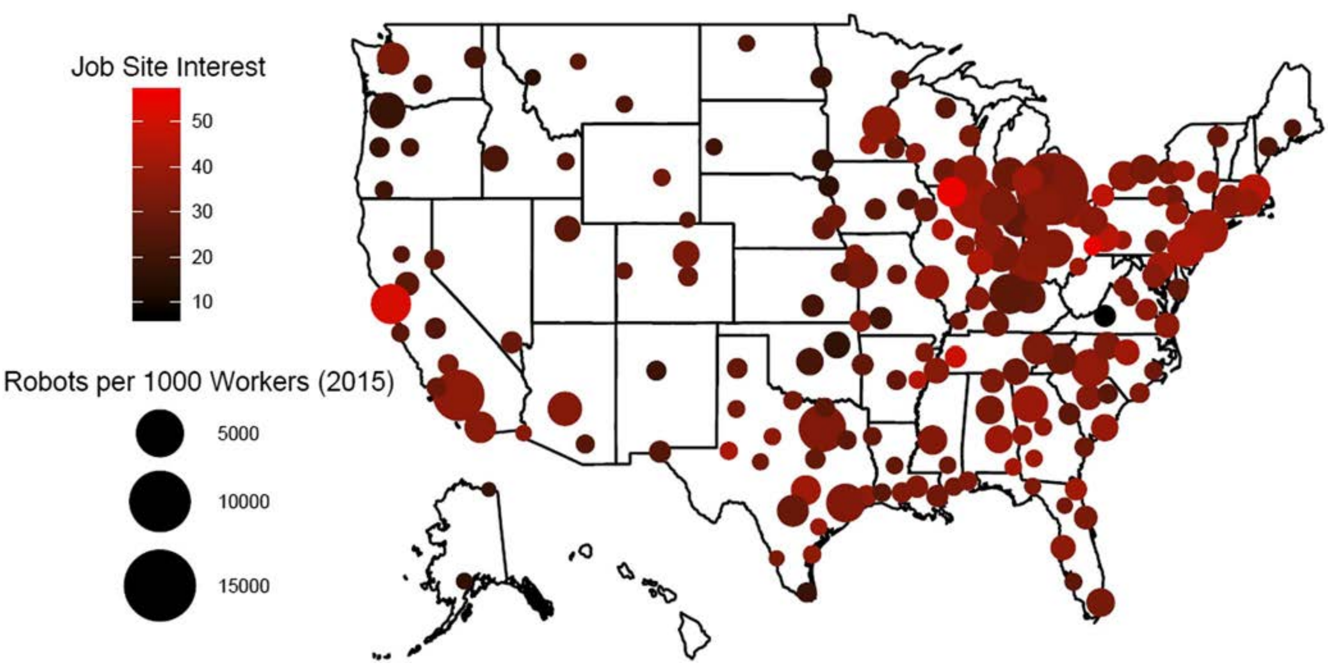
Study 2: Experimental Evidence From Singapore

Method

Participants and Procedure

We asked students from a large Singaporean university to invite one of their parents (who must be a full-time employee) to complete an online study in exchange for course credits. A total of 380 parents completed the study; we dropped 37 who reported to not currently be working, resulting in 343 parents ($M_{\text{age}} = 51.4$, 43% males). We

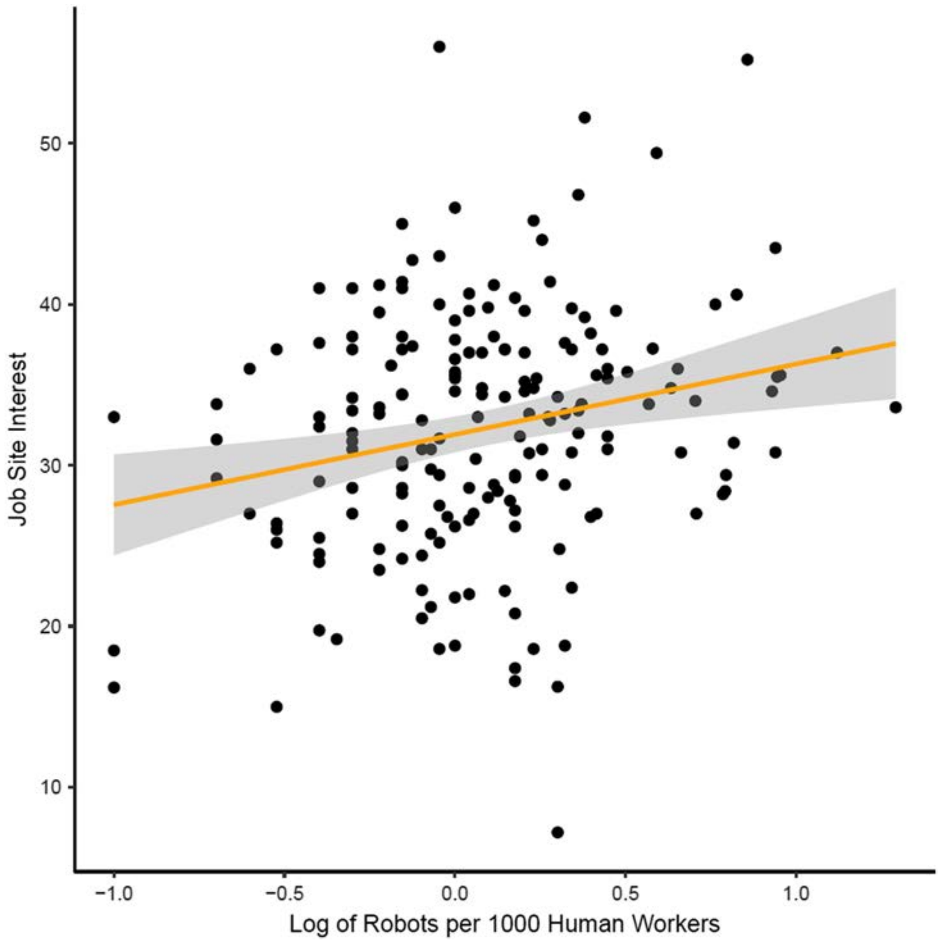
Figure 1
A Visual Display of Industrial Robot Density and Job Site Interest (Study 1)



Note. Industrial robot density is represented via node size. Analyses showed that job site interest was significantly correlated with industrial robot density, controlling for unemployment rate. See the online article for the color version of this figure.

Figure 2

A Scatterplot Display of the Relationship Between Industrial Robot Density in 2015 and Job Site Interest in 2015 (Study 1), Which Allows for Visualization of the Standard Error



Note. Industrial robot density has been log-transformed for visualization purposes. See the online article for the color version of this figure.

randomly assigned participants to one of three experimental conditions. In the experimental condition, participants read an article concerning the role of robots in businesses. In the robot mere-exposure control condition, participants read an article that merely discussed advanced robots, without mentioning their roles or applications in businesses. In the pure control condition, participants read a work culture article unrelated to robots. After reading the assigned article, participants rated their current levels of job insecurity with the same three items (1 = *strongly disagree* to 5 = *strongly agree*) adapted from De Witte et al. (2016; e.g., "Right now, I feel insecure about the future of my job;" all survey items and materials used across all studies are available in the Appendix B and C).

Ostensibly unrelated to the first part of the study, participants were told that the researchers were interested in examining consumers' preferences on five online services: career, music, online storage, online dating, and entertainment. We further asked participants to select the one in which they were the most interested at the moment and then directed them to answer some questions specific to this service. In reality, once participants made the selection they were debriefed. Participants' selection of the online career services option served as a behavioral manifestation of a sense of job insecurity (0 = others, 1 = online career services). A total of 21.6% of participants selected this option. This measure correlated significantly with the three-item measure of self-reported job insecurity ($r = .19$, $p < .001$).

Results

Descriptive statistics can be found in Table 4. A one-way analysis of variance (ANOVA) revealed that participants in the experimental condition reported significantly higher levels of job insecurity ($M = 3.64$, $SD = 1.55$) compared to participants in the robot mere-exposure condition ($M = 3.12$, $SD = 1.25$) and pure control condition ($M = 3.12$, $SD = 1.40$), $F(342) = 5.14$, $p = .006$. A Tukey's post hoc test[3] revealed that job insecurity was significantly higher in the experimental condition compared to the pure control (difference = .52, $p = .016$, $d = .35$) and robot mere-exposure (difference = .52, $p = .014$, $d = .37$) conditions. There was no

[3] We also used the more conservative Bonferroni post hoc tests in these analyses, and the two p values were .017 and .016, respectively.

Table 3
Statistical Analyses (Study 1)

Predictor	R^2	*b* (*SE*)	β	*t*	*p*
Model 1: Job insecurity across all years					
Robot density	.05	.86 (.27)	.23	3.14	.002
Unemployment	.002	.20 (.30)	.05	.65	.52
Model 2: Job insecurity in 2015					
Robot density	.03	.54 (.23)	.17	2.31	.02
Unemployment	.008	.32 (.26)	.09	1.25	.21
Model 3: Job insecurity over time (random intercepts)					
Rise in robot density		−.35.78 (13.26)	−.10	−2.70	.007
Unemployment		.67 (.17)	.20	3.99	<.001
Year		−.54 (.45)	.07	−1.19	.23
Year × Rise in Robot Density		5.01 (2.33)	.05	2.15	.03
Model 4: Job insecurity over time (random intercepts and slopes)					
Rise in robot density		−.35.91 (12.94)	−.10	−2.77	.006
Unemployment		.74 (.17)	.22	4.46	<.001
Year		−.49 (.49)	.09	−1.01	.32
Year × Rise in Robot Density		5.07 (2.52)	.05	2.01	.04

Note. *SE* = standard error. We do not report R^2 coefficients for the multilevel models (Models 3 and 4) because there is variance explained at multiple levels of analysis, which means that there is no single R^2 statistic.

statistically significant difference between the robot mere-exposure and pure control conditions. Furthermore, we found that participants in the experimental condition were significantly more likely to select the online career services option ($n = 36$) compared to participants in the pure control ($n = 19$) and robot mere-exposure ($n = 19$) conditions, $\chi^2(2, N = 343) = 12.39$, $p = .002$ (see Figure 3).[4]

Study 3: Experience-Sampling Evidence From India

The first two studies reveal that increasing roles for robots in the workplace can increase job insecurity, but key questions remain. First, it is unclear whether these effects extend to people interacting directly with robots. Second, it is unclear whether these effects generalize to people with highly technical jobs that are less likely to be threatened by the rise of robots in the workplace. Third, it is unclear to what extent increased feelings of job insecurity would translate to behavioral outcomes. We address these issues in Study 3.[5]

Method

Participants and Procedure

We recruited participants from one of Asia's largest automobile manufacturing companies, which is headquartered in Western India. With the assistance of senior management, we initially contacted 202 engineers; 118 agreed to participate (see Appendix A, for further descriptions of this firm).

Across 10 consecutive workdays. we sent daily surveys to the participants at three fixed timeslots: before work, middle of the workday, and end of work. The before-work survey (average completion time: 7:28 a.m.) contained measures of daily positive and negative affect, which we included as control variables. The middle-of-workday survey (average completion time: 12:29 p.m.) contained measures of daily adoptions of robots at work and daily job insecurity. The end-of-work survey (average completion time: 4:31 p.m.) contained measures of daily burnout and daily workplace incivility. Our final sample included 118 engineers who completed 915 day-level observations (see Table 5).

Measures

We translated the measures from English to Marathi following Brislin's (1980) back-translation procedure. We used the same scale anchors (1 = *strongly disagree* to 7 = *strongly agree*) for our measures.[6]

Before-Work Survey

We measured baseline positive affect (PA) and negative affect (NA) at the beginning of the participants' workday with five items for each (Mackinnon et al., 1999). A sample item for PA[NA] is "Right now, I feel excited [distressed]."

Middle-of-Workday Survey

We measured daily robot adoption by adapting four items from the measurements used in Campion's (1988) and von Krogh's (2018) studies. A sample item is "Today, many of the decision-making activities of this job are automated or assisted by robots." We measured job insecurity using the three items as in Study 2.

End-of-Work Survey

We measured burnout using the three-item scale from Boswell et al.'s (2004) study. A sample item is "Today, I felt burned out from my work." We measured workplace incivility using five items from Lim and Cortina (2005). A sample item is "Today, I put a co-worker down."

[4] We also conducted supplementary analyses to probe the indirect effects of experimental condition → self-reported job insecurity → selection of career service (see Figure 3 and Suppplemental Materials).

[5] We replicated Study 3's core results with a multiwave, between-person design in a Taiwanese firm. For details, please refer to the Supplemental Materials (Item 6)

[6] The coefficient αs of the scales across 10 days of observation were presented on the diagonal in Table 5.

Table 4
Descriptive Statistics and Correlations (Study 2)

Variable	*M*	*SD*	1	2	3	4	5
1. Conditions	.98	.81	—				
2. Job insecurity (survey measure)	3.29	1.42	.15**	(.90)			
3. Job insecurity (behavioral measure)	.22	.41	.16**	.19**	—		
4. Age	51.40	5.70	.05	.02	−.02	—	
5. Gender	1.57	.50	−.02	−.00	−.04	−.13*	—

Note. Conditions (0 = control, 1 = robots mere-exposure, 2 = robots at work); job insecurity behavioral measure (0 = others, 1 = online career services); gender (1 = male, 2 = female); race (1 = White, 0 = others).
* $p < .05$. ** $p < .01$.

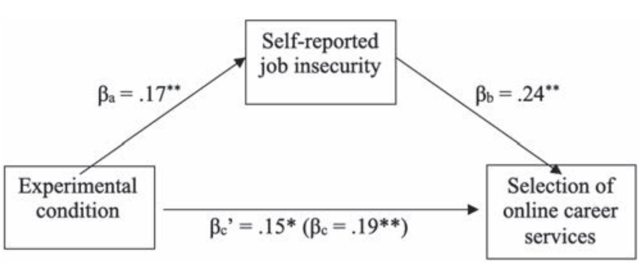
Control Variables

Although we controlled for a number of variables in testing our hypothesized model, all results remained unchanged when control variables were removed; these results can be found in the Supplemental Materials. As noted, we included baseline affect in our analyses because daily moods can affect people's perceptions of job insecurity (Huang et al., 2012). To rule out plausible serial dependence and enable us to capture changes in our dependent variables, we included prior-day measures (i.e., day $t - 1$) for each dependable variable to control for the potential influence of serial dependence (e.g., Judge & Ilies, 2004).

Analytic Strategy

Because our data are multilevel, we used multilevel modeling with robust full maximum likelihood estimations in Mplus 7.4 (Muthén & Muthén, 2015). A multilevel confirmatory factor analysis on the four study variables indicated acceptable model fit (χ^2 = 220.14, *df* = 84, comparative fit index [CFI] = .98, root-mean-square error of approximation [RMSEA] = .04, standardized root-mean-square residual [SRMR] = .03). Following the recommendations by Hofmann and Gavin (1998) and Hofmann et al. (2000), we person-mean-centered exogenous variables measured at the daily level (Level 1) and grand-mean-centered between-person variables (Level 2). Following the recommendations of Preacher et al. (2010), we utilized a parametric bootstrap to estimate and assess the significance of indirect effects simultaneously. We then applied Monte Carlo simulation with 20,000 replications to construct confidence intervals around the estimated indirect effect.

Figure 3
Mediation Effect in Study 2



Note. Odds ratios for the *b* and *c* paths have been converted to standardized betas.
* $p < .05$. ** $p < .01$.

Results

Descriptive statistics are presented in Table 5; Table 6 summarizes the results of the multilevel analyses. The relationship between daily robot adoption and daily job insecurity was significant ($\gamma = .22$, $p < .01$). We also find that the relationship between daily job insecurity and burnout was significant ($\gamma = .18$, $p < .01$), as with the relationship between daily job insecurity and instigated incivility ($\gamma = .20$, $p < .01$). Incremental variance explained in job insecurity, burnout, and incivility were 4%, 4%, and 7%, respectively.

Monte Carlo simulations revealed that the indirect effect of daily robot adoption on daily burnout through daily job insecurity was positive (*effect size of indirect effect* = .04), and the 95% confidence interval excluded zero [.020, .062]. The same analysis also revealed that the indirect effect of daily robot adoption on daily instigated incivility through daily job insecurity was positive (*effect size of indirect effect* = .04), and the 95% confidence interval excluded zero [.023, .067] (see Table 6, for the full results).

Study 4: Self-Affirmation as an Intervention

The first three studies reveal that when being exposed to robots either physically (Studies 1 and 3) or psychologically (Study 2), people tend to experience a sense of job insecurity. Study 3 also demonstrates two negative downstream consequences—increased burnout and incivility at work, via the mechanism of increased job insecurity. As such, it is important to examine an intervention that might buffer the negative effect that robot exposure has on people, which is the goal of Study 4 (i.e., to test Hypothesis 3).[7]

Method

Participants and Procedure

We recruited 400 full-time employees (M_{age} = 30.97, 42.5% females) from Prolific to participate in a 2 (robot exposure vs. control) × 2 (self-affirmation vs. no self-affirmation) between-subjects experiment. We randomly assigned participants to one of four experimental conditions. We first presented participants with a news article that either exposes them to robots or not. Then, participants were either asked to engage in a self-affirmation

[7] We conducted an additional study to replicate the buffering effects of self-affirmation with another experimental paradigm. We omitted this study due to length requirements. Interested readers can contact the first author for more information about this replication study.

Table 5
Descriptive Statistics and Correlations Among Study Variables (Study 3)

Variable	*M*	*SD*	Correlation 1	2	3	4	5	6	7
Within-person variables									
1. Daily positive affect (T1)	4.42	1.44	(.92)						
2. Daily negative affect (T1)	2.03	1.24	−.13**	(.92)					
3. Daily robot adoption (T2)	5.36	1.05	.31**	−.16**	(.89)				
4. Daily job insecurity (T2)	4.29	1.40	−.02	.22**	.12**	(.80)			
5. Daily burnout (T3)	3.78	1.61	−.45**	.38**	−.21**	.22**	(.91)		
6. Daily instigated incivility (T3)	3.26	1.42	−.47**	.39**	−.22**	.26**	.65**	(.90)	
7. Daily job performance (T3; supplementary)	4.71	1.43	.76**	−.14**	.41**	.08	−.42**	−.40**	(.84)
Between-person variables (demographics)									
8. Gender	1.84	0.37	−.12	.43**	.14	.75**	.43**	.45**	.05
9. Education	2.98	0.54	.25**	−.20	−.25**	−.14	.22	−.16	−.09
10. Age (in years)	29.79	4.57	.11	−.02	−.02	−.01	.10	.11	.10
11. Tenure (in years)	2.98	1.60	−.21	−.15	.01	−.22	−.45**	−.24**	.05

Note. Gender (1 = female, 2 = male); education (1 = primary school, 2 = secondary school, 3 = professional diploma or vocational school, 4 = undergraduate or above). Day-level $N = 915$; person-level $N = 118$; T1 = Time 1; T2 = Time 2; T3 = Time 3; coefficient α estimates of reliability are in parentheses on the diagonal. The reliabilities were the mean αs across 10 days of observation.
** $p < .01$.

writing exercise or not. Finally, participants rated their job insecurity at the moment and completed a manipulation check item.

Robot Exposure Manipulation

In the experimental condition, participants read the same article concerning the role of robots in businesses as in Study 2. In the control condition, participants read the same travel article unrelated to robots as in Study 2. We did not present a robot control condition because Study 2 has already established that the "robots in businesses" condition is significantly different compared to the robot control condition.

Self-Affirmation Manipulation

After the robot exposure manipulation, we used a well-established writing task to manipulate participants' self-affirmation (see McQueen & Klein, 2006, for a review). We presented participants with a list of 11 characteristics and values (e.g., sense of humor, athletics, relations with friends and family, social skills) and asked them to rank order these characteristics and values in order of importance to them. After the ranking, participants in the self-affirmation condition were asked to write a couple of sentences to explain why their top-ranked value is important to them. Participants in the no self-affirmation condition were asked to write a

Table 6
Multilevel Path Analysis and Indirect Effects (Study 3)

Variable	Daily job insecurity (T2) γ	*SE*	Daily burnout (T3) γ	*SE*	Daily instigated incivility (T3) γ	*SE*
Control variables						
Daily positive affect (T1)	−.03	.04	−.44**	.03	−.40**	.03
Daily negative affect (T1)	.27**	.04	.37**	.04	.32**	.04
Lagged control variables						
Day $t - 1$ job insecurity	−.10*	.04	—	—	—	—
Day $t - 1$ burnout	—	—	−.07*	.03	—	—
Day $t - 1$ instigated incivility	—	—	—	—	−.08*	.03
Predictors						
Daily robot adoption (T2)	.22**	.05	−.12*	.05	−.11*	.05
Daily job insecurity (T2)	—	—	.18**	.03	.20**	.03
Indirect effects				**.04** **95% CI [.020, .062]**		**.04** **95% CI [.023, .068]**

Note. CI = confidence interval; *SE* = standard error. Day-level $N = 915$; T1 = Time 1; T2 = Time 2; T3 = Time 3. Effects that are significant are bolded for multilevel mediation analysis. Estimates reflect unstandardized coefficients; we used random slopes for our final analysis. We also examined whether including the direct effects of daily adoption of robot on outcome variables influenced our results; it did not, so we omitted these paths in our final model for the sake of parsimony.
* $p < .05$. ** $p < .01$.

couple of sentences to explain why their eighth-ranked value is important to the average college student.

Job Insecurity Measure

Participants rated their current levels of job insecurity with the same three-item job insecurity measure used in Studies 2 and 3.

Manipulation Check

At the end of the study, participants were asked "which of these societal innovations will impact the future of business the most?" (1 = not at all to 7 = very much). The option "robotics" was embedded with four other response options (i.e., globalization, cloud storage, democratization, and remote communication). As expected, participants in the robot exposure condition rated the item "robotics" to be significantly higher ($M = 5.13$, $SD = 1.19$) than participants in the control condition ($M = 4.75$, $SD = 1.37$), $t(398) = 2.99$, $p = .006$, $d = .30$.

Results

Descriptive statistics can be found in Table 7. A *t* test revealed that participants in the robot exposure experimental condition reported significantly higher levels of job insecurity ($M = 3.75$, $SD = 1.78$) compared to participants in the control condition ($M = 2.93$, $SD = 1.52$), $t(398) = 4.98$, $p < .001$, $d = .50$. This result supports Hypothesis 1.

A two-way ANOVA revealed that there is a significant interaction between the robot exposure manipulation and the self-affirmation manipulation predicting a sense of job insecurity, $F(1, 396) = 5.20$, $p = .023$, $\eta_p^2 = .013$, such that the effect of robot exposure on job insecurity was stronger for participants who did not engage in self-affirmation ($M = 4.24$, $SE = .17$) than participants who did engage in self-affirmation ($M = 3.31$, $SE = .16$, $p < .001$, $d = .40$; Figure 4). There was no statistically significant difference for participants in the control condition as a function of self-affirmation (self-affirmation: $M = 2.83$, $SE = .17$ vs. no self-affirmation: $M = 3.02$, $SE = .16$; $p = .417$). These results provide support for Hypothesis 3.

General Discussion

Theoretical Contributions

Our studies heed the call from organizational scholars (Bamberger, 2018; von Krogh, 2018) to explore the dynamic and nuanced interactions between robots and humans at work. We find that employees generally feel insecure when being exposed to robots. This sense of job insecurity also leads them to feel more burnout and be less civil to coworkers, both of which are very costly. As such, our work suggests that, despite some positive effects of robots at work (e.g., reduced personnel costs), it may also have unintended psychological costs. Meanwhile, in extending work from scholars about the impacts of technologies on job opportunities in other literatures (e.g., Autor, 2010; Autor et al., 2003), our multimethod and multicultural findings specifically demonstrate that the adoption of robots can perhaps be equally influential in inducing job insecurity among employees working in both low-skilled and intellectually demand jobs. Thus, our work sheds further lights on the consistently threatening nature of robots.

Pioneers of robotics forecasted that robots might soon replace humans in many jobs (Frey & Osborne, 2017), but—as with the hover car and interstellar travel—many of these projected robot powers remain more science fiction than science. Study 1 provides some indirect evidence for this, suggesting that robot prevalence is not associated with actual unemployment rate. This seems to imply that robots' capacities are advancing at an increasingly rapid pace, but then so are the opportunities they create. All in all, while being exposed to robots leads people to feel anxious in terms of job insecurity, these feelings might have been largely due to subjective appraisal rather than objective loss of employment.

Finally, we hope that our work can open up a new line of inquiry in the organizational literature. Extant works in employee–robot interaction have largely been theoretical in nature due to its recency (Gregory et al., 2021). Our work provides a foundation for future scholars to explore nuances associated with the increased use of robots at work. All in all, we hope our work can spark additional works in this emerging domain.

Practical Implications

Our work suggests that top managers who wish to introduce a robot workforce should be mindful of its negative effects on their employees. Intuitively, such a strategy would improve organizational efficiency and performance (e.g., Murray et al., 2021), but our work has shown that there are unintended costs in the form of employee job insecurity, burnout, and incivility that must be accounted for (Studies 1–3). Fortunately, our results from Study 4 demonstrate that these negative effects can be significantly mitigated with a costless self-affirmation intervention. Employees want to think positively of themselves, and we encourage managers and leaders to encourage self-affirmation whenever possible. Importantly, the positive effects of self-affirmation appear to be sustained

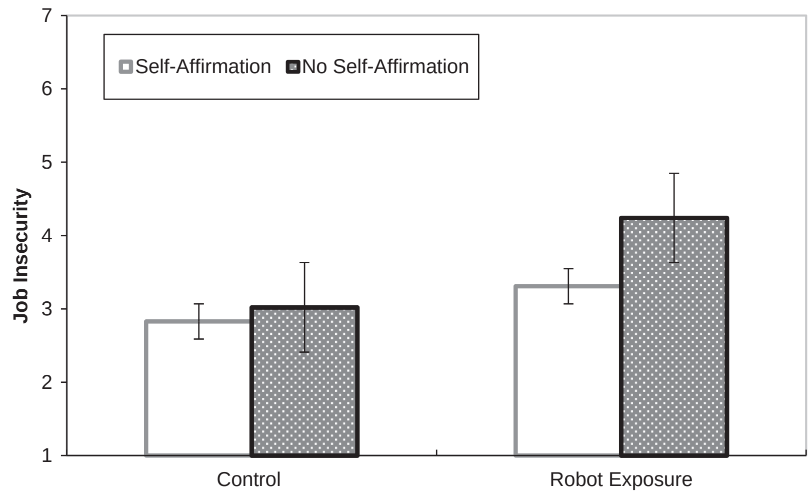
Table 7
Descriptive Statistics and Correlations (Study 4)

Variable	*M*	*SD*	1	2	3	4	5
1. Robot exposure manipulation	.50	.50	—				
2. Self-affirmation manipulation	.50	.50	.05	—			
3. Job insecurity	3.34	1.70	.24**	−.15**	(.92)		
4. Age	30.97	11.43	.02	.04	.03	—	
5. Gender	1.42	.50	.03	.03	.02	.10*	—

Note. Robot exposure manipulation (0 = control, 1 = robot); self-affirmation manipulation (0 = control, 1 = self-affirmation); gender (1 = male, 2 = female).
* $p < .05$. ** $p < .0$.

Figure 4

The Interactive Effect of Robot Exposure and Self-Affirmation Predicting Job Insecurity (Study 4)



even after a year after such interventions (Cohen et al., 2009) because "a moment of validation at a threatening transition could improve a trajectory" (Cohen & Sherman, 2014, p. 343). For example, employees who self-affirm could trigger a cascade of positive effects (e.g., greater confidence in collaborating with the robots, working with other coworkers). As a result, we strongly encourage organizations to adopt self-affirmation interventions to combat the rising robot workforce and its resultant job insecurity.

Limitations and Future Directions

We note several limitations. First, these studies focused primarily on a single construct—job insecurity. We also examine only two downstream consequences of job insecurity: burnout and incivility. It is interesting that we observed direct negative effects to these outcomes and indirect positive effects, which suggest that there are competing mechanisms at play. We encourage future research to explore such mechanism. For example, collaborating with robots at work may help employees to improve their skills development and job satisfaction, which thus reduce their burnout (Smids et al., 2020). In addition, there are also competing perspectives in terms of whether robots can indeed increase employees' job performance; robots at work may help effectively augment employees' pursuit of work goals, which thus providing them more self-regulatory resources and reduce the occurrence of these deleterious outcomes (Fernandez et al., 2012; Wilson & Daugherty, 2018). On the one hand, robots can obviously enhance human employees' performance because they enhance efficiency. On the other hand, however, our stress account suggests that this increased efficiency might be offset by increased job insecurity. We provide a preliminary exploration of this in Study 3 by asking employees to report their job performance with a three-item scale from Mitchell et al. (2019) at the end of the workday. A multilevel path analysis revealed that the relationship between daily robot adoption and daily task performance was significant ($\gamma = .25$, $p < .01$). Although we note the self-report nature of our job performance scale, this result does provide some insights into whether robots at work can increase or decrease employees' performance.

Second, our empirical studies focused on embodied robots but did not distinguish the level of "humanness" of the robots, which we note as a limitation. This limitation is consistent with recent taxonomies of human–robot interactions (e.g., Onnasch & Roesler, 2021; Yanco & Drury, 2004), where scholars have specified the type of task robots performed, the appearance of the robots, and the autonomy of the robots all as boundary conditions in determining the consequences of such interactions. In addition, our studies focused on embodied robots and did not consider disembodied algorithms. Although our pilot studies provide some evidence that exposure to algorithms is generally less threatening compared to exposure to robots, we encourage future work to consider algorithms in their theorizing as well.

Lastly, we did not conduct a study to explore whether self-affirmation can moderate the two mediation effects. That is, while we have evidence that self-affirmed individuals do experience lower levels of job insecurity after being exposed to robots, we do not know if this reduced job insecurity would in turn lower burnout and incivility. Although likely, we suggest future research to test the moderating effects of self-affirmation in other settings and with an expanded list of dependent variables.

Conclusion

No one knows with certainty how robots will shape our future society, and that uncertainty itself can be unnerving (Knyazev et al., 2005). Technology may have fundamentally changed the nature of work, but people seem fundamentally unchanged: We still fear that a workplace with robots is a workplace without us.

References

Abubshait, A., & Wiese, E. (2017). You look human, but act like a machine: Agent appearance and behavior modulate different aspects of human-robot interaction. *Frontiers in Psychology*, *8*, Article 1393. https://doi.org/10.3389/fpsyg.2017.01393

Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. *Handbook of Labor Economics*, *4*, 1043–1171. https://doi.org/10.1016/S0169-7218(11)02410-5

Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *The American Economic Review*, *108*(6), 1488–1542. https://doi.org/10.1257/aer.20160696

Admoni, H., & Scassellati, B. (2017). Social eye gaze in human–robot interaction: A review. *Journal of Human–Robot Interaction*, *6*(1), 25–63. https://doi.org/10.5898/JHRI.6.1.Admoni

Akalin, N., Kristoffersson, A., & Loutfi, A. (2022). Do you feel safe with your robot? Factors influencing perceived safety in human–robot interaction based on subjective and objective measures. *International Journal of Human–Computer Studies*, *158*, Article 102744. https://doi.org/10.1016/j.ijhcs.2021.102744

Aleksander, I. (2017). Partners of humans: A realistic assessment of the role of robots in the foreseeable future. *Journal of Information Technology*, *32*(1), 1–9. https://doi.org/10.1057/s41265-016-0032-4

Alexander, V., Blinder, C., & Zak, P. J. (2018). Why trust an algorithm? Performance, cognition, and neurophysiology. *Computers in Human Behavior*, *89*, 279–288. https://doi.org/10.1016/j.chb.2018.07.026

Anelli, M., Colantone, I., & Stanig, P. (2021). Individual vulnerability to industrial robot adoption increases support for the radical right. *Proceedings of the National Academy of Sciences of the United States of America*, *118*(47), Article e2111611118. https://doi.org/10.1073/pnas.2111611118

Anson, R., Bostrom, R., & Wynne, B. (1995). An experiment assessing group support system and facilitator effects on meeting outcomes. *Management Science*, *41*(2), 189–208. https://doi.org/10.1287/mnsc.41.2.189

Appel, J., von der Pütten, A., Krämer, N. C., & Gratch, J. (2012). Does humanity matter? Analyzing the importance of social cues and perceived agency of a computer system for the emergence of social reactions during human-computer interaction. *Advances in Human–Computer Interaction*, *2012*, 1–10. https://doi.org/10.1155/2012/324694

Appel, M., Izydorczyk, D., Weber, S., Mara, M., & Lischetzke, T. (2020). The uncanny of mind in a machine: Humanoid robots as tools, agents, and experiencers. *Computers in Human Behavior*, *102*, 274–286. https://doi.org/10.1016/j.chb.2019.07.031

Asatiani, A., Penttinen, E., Ruissalo, J., & Salovaara, A. (2020). Knowledge workers' reactions to a planned introduction of robotic process automation—Empirical evidence from an accounting firm. In R. Hirschheim, A. Heinzl, & J. Dibbern (Eds.), *Information systems outsourcing: The era of digital transformation* (pp. 413–452). Springer Publishing. https://doi.org/10.1007/978-3-030-45819-5_17

Ashford, S. J., Lee, C., & Bobko, P. (1989). Content, cause, and consequences of job insecurity: A theory-based measure and substantive test. *Academy of Management Journal*, *32*(4), 803–829. https://doi.org/10.5465/256569

Autor, D. (2010). The polarization of job opportunities in the U.S. labor market: Implications for employment and earnings. *Center for American Progress and The Hamilton Project*, *6*, 11–19.

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, *118*(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Avelino, J., Correia, F., Catarino, J., Ribeiro, P., Moreno, P., Bernardino, A., & Paiva, A. (2018, October). *The power of a hand-shake in human–robot interactions* [Conference session]. 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Madrid, Spain. https://doi.org/10.1109/IROS.2018.8593980

Azhar, M. Q., & Sklar, E. I. (2017). A study measuring the impact of shared decision making in a human–robot team. *International Journal of Robotics Research*, *36*(5–7), 461–482. https://doi.org/10.1177/0278364917710540

Bainbridge, W. A., Hart, J. W., Kim, E. S., & Scassellati, B. (2011). The benefits of interactions with physically present robots over video-displayed agents. *International Journal of Social Robotics*, *3*(1), 41–52. https://doi.org/10.1007/s12369-010-0082-7

Baltrusch, S. J., Krause, F., de Vries, A. W., van Dijk, W., & de Looze, M. P. (2022). What about the human in human robot collaboration? *Ergonomics*, *65*(5), 719–740. https://doi.org/10.1080/00140139.2021.1984585

Bamberger, P. A. (2018). AMD—Clarifying what we are about and where we are going. *Academy of Management Discoveries*, *4*(1), 1–10. https://doi.org/10.5465/amd.2018.0003

Bankins, S., & Formosa, P. (2020). When AI meets PC: Exploring the implications of workplace social robots and a human–robot psychological contract. *European Journal of Work and Organizational Psychology*, *29*(2), 215–229. https://doi.org/10.1080/1359432X.2019.1620328

Baraglia, J., Cakmak, M., Nagai, Y., Rao, R. P., & Asada, M. (2017). Efficient human–robot collaboration: When should a robot take initiative? *International Journal of Robotics Research*, *36*(5–7), 563–579. https://doi.org/10.1177/0278364916688253

Barnes, C. M., Dang, C. T., Leavitt, K., Guarana, C. L., & Uhlmann, E. L. (2018). Archival data in micro-organizational research: A toolkit for moving to a broader set of topics. *Journal of Management*, *44*(4), 1453–1478. https://doi.org/10.1177/0149206315604188

Bartneck, C., Kulić, D., Croft, E., & Zoghbi, S. (2009). Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. *International Journal of Social Robotics*, *1*(1), 71–81. https://doi.org/10.1007/s12369-008-0001-3

Beal, D. J. (2015). ESM 2.0: State of the art and future potential of experience sampling methods in organizational research. *Annual Review of Organizational Psychology and Organizational Behavior*, *2*(1), 383–407. https://doi.org/10.1146/annurev-orgpsych-032414-111335

Bhave, D. P., Teo, L. H., & Dalal, R. S. (2020). Privacy at work: A review and a research agenda for a contested terrain. *Journal of Management*, *46*(1), 127–164. https://doi.org/10.1177/0149206319878254

Bianchi, E. C. (2013). The bright side of bad times: The affective advantages of entering the workforce in a recession. *Administrative Science Quarterly*, *58*(4), 587–623. https://doi.org/10.1177/0001839213509590

Bigman, Y. E., & Gray, K. (2018). People are averse to machines making moral decisions. *Cognition*, *181*, 21–34. https://doi.org/10.1016/j.cognition.2018.08.003

Bigman, Y. E., Waytz, A., Alterovitz, R., & Gray, K. (2019). Holding robots responsible: The elements of machine morality. *Trends in Cognitive Sciences*, *23*(5), 365–368. https://doi.org/10.1016/j.tics.2019.02.008

Binns, R., Van Kleek, M., Veale, M., Lyngs, U., Zhao, J., & Shadbolt, N. (2018, April). *'It's reducing a human being to a percentage': Perceptions of justice in algorithmic decisions* [Conference session]. Proceedings of the 2018 CHI conference on human factors in computing systems, Montreal, Canada. https://doi.org/10.1145/3173574.3173951

Bondarouk, T., Parry, E., & Furtmueller, E. (2017). Electronic HRM: Four decades of research on adoption and consequences. *International Journal of Human Resource Management*, *28*(1), 98–131. https://doi.org/10.1080/09585192.2016.1245672

Boswell, W. R., Olson-Buchanan, J. B., & LePine, M. A. (2004). Relations between stress and work outcomes: The role of the felt challenge, job control, and psychological strain. *Journal of Vocational Behavior*, *64*(1), 165–181. https://doi.org/10.1016/S0001-8791(03)00049-6

Bowden, V. K., Griffiths, N., Strickland, L., & Loft, S. (2021). Detecting a single automation failure: The impact of expected (but not experienced) automation reliability. *Human Factors*. Advance online publication. https://doi.org/10.1177/00187208211037188

Breazeal, C., Kidd, C. D., Thomaz, A. L., Hoffman, G., & Berlin, M. (2005, August). *Effects of nonverbal communication on efficiency and robustness in human-robot teamwork* [Conference session]. 2005 IEEE/RSJ international conference on intelligent robots and systems, Edmonton, Canada. https://doi.org/10.1109/IROS.2005.1545011

Brislin, R. W. (1980). Translation and content analysis of oral and written materials. In H. C. Triandis, & J. W. Berry, (Eds.), *Handbook of cross-cultural psychology: Methodology* (pp. 389–444). Allyn and Bacon.

Broadbent, E. (2017). Interactions with robots: The truths we reveal about ourselves. *Annual Review of Psychology*, *68*(1), 627–652. https://doi.org/10.1146/annurev-psych-010416-043958

Brosnan, M. J. (2002). *Technophobia: The psychological impact of information technology*. Routledge. https://doi.org/10.4324/9780203436707

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization*, *24*(2), 239–257. https://doi.org/10.1017/jmo.2016.55

Business Insider. (2016, July 9). *Meet the smart robots joining the workforce*. https://www.businessinsider.com/sc/robots-will-change-manufacturing?r=US&IR=T

Campion, M. A. (1988). Interdisciplinary approaches to job design: A constructive replication with extensions. *Journal of Applied Psychology*, *73*(3), 467–481. https://doi.org/10.1037/0021-9010.73.3.467

Chang, W. L., White, J. P., Park, J., Holm, A., & Šabanović, S. (2012). *The effect of group size on people's attitudes and cooperative behaviors toward robots in interactive gameplay* [Conference session]. 2012 IEEE RO-MAN: The 21st IEEE International Symposium on Robot and Human Interactive Communication, Paris, France. https://doi.org/10.1109/ROMAN.2012.6343857

Chao, G. T., & Kozlowski, S. W. J. (1986). Employee perceptions on the implementation of robotic manufacturing technology. *Journal of Applied Psychology*, *71*(1), 70–76. https://doi.org/10.1037/0021-9010.71.1.70

Cheng, G. H. L., & Chan, D. K. S. (2008). Who suffers more from job insecurity? A meta-analytic review. *Applied Psychology*, *57*(2), 272–303. https://doi.org/10.1111/j.1464-0597.2007.00312.x

Chong, L., Zhang, G., Goucher-Lambert, K., Kotovsky, K., & Cagan, J. (2022). Human confidence in artificial intelligence and in themselves: The evolution and impact of confidence on adoption of AI advice. *Computers in Human Behavior*, *127*, Article 107018. https://doi.org/10.1016/j.chb.2021.107018

Cohen, G. L., & Sherman, D. K. (2014). The psychology of change: Self-affirmation and social psychological intervention. *Annual Review of Psychology*, *65*(1), 333–371. https://doi.org/10.1146/annurev-psych-010213-115137

Cohen, G. L., Aronson, J., & Steele, C. M. (2000). When beliefs yield to evidence: Reducing biased evaluation by affirming the self. *Personality and Social Psychology Bulletin*, *26*(9), 1151–1164. https://doi.org/10.1177/01461672002611011

Cohen, G. L., Garcia, J., Purdie-Vaughns, V., Apfel, N., & Brzustoski, P. (2009). Recursive processes in self-affirmation: Intervening to close the minority achievement gap. *Science*, *324*(5925), 400–403. https://doi.org/10.1126/science.1170769

Correia, F., Mascarenhas, S. F., Gomes, S., Arriaga, P., Leite, I., Prada, R., Melo, F. S. , & Paiva, A. (2019, March). *Exploring prosociality in human-robot teams* [Conference session]. 2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI), Daegu, Korea. https://doi.org/10.1109/HRI.2019.8673299

Correia, F., Petisca, S., Oliveira, P. A., Ribeiro, T., Melo, F. S., & Paiva, A. (2017, July). *Groups of humans and robots: Understanding membership preferences and team formation* [Conference session]. Robotics: Science and Systems 2017 (RSS), Vancouver, Canada. https://doi.org/10.15607/RSS.2017.XIII.024

Coupe, T. (2019). Automation, job characteristics and job insecurity. *International Journal of Manpower*, *40*(7), 1288–1304. https://doi.org/10.1108/IJM-12-2018-0418

Creswell, J. D., Dutcher, J. M., Klein, W. M., Harris, P. R., & Levine, J. M. (2013). Self-affirmation improves problem-solving under stress. *PLOS ONE*, *8*(5), Article e62593. https://doi.org/10.1371/journal.pone.0062593

Creswell, J. D., Welch, W. T., Taylor, S. E., Sherman, D. K., Gruenewald, T. L., & Mann, T. (2005). Affirmation of personal values buffers neuroendocrine and psychological stress responses. *Psychological Science*, *16*(11), 846–851. https://doi.org/10.1111/j.1467-9280.2005.01624.x

Damholdt, M. F., Vestergaard, C., Nørskov, M., Hakli, R., Larsen, S., & Seibt, J. (2020). Towards a new scale for assessing attitudes towards social robots: The attitudes towards social robots scale (ASOR). *Interaction Studies: Social Behaviour and Communication in Biological and Artificial Systems*, *21*(1), 24–56. https://doi.org/10.1075/is.18055.fle

Dang, J., & Liu, L. (2021). Robots are friends as well as foes: Ambivalent attitudes toward mindful and mindless AI robots in the United States and China. *Computers in Human Behavior*, *115*, Article 106612. https://doi.org/10.1016/j.chb.2020.106612

Davenport, T., Loucks, J., & Schatsky, D. (2017). *Bullish on the business value of cognitive*. www2.deloitte.com/us/en/pages/deloitte-analytics/articles/cognitive-technology-adoption-survey.html

de Kleijn, R., van Es, L., Kachergis, G., & Hommel, B. (2019). Anthropomorphization of artificial agents leads to fair and strategic, but not altruistic behavior. *International Journal of Human-Computer Studies*, *122*, 168–173. https://doi.org/10.1016/j.ijhcs.2018.09.008

de Melo, C. M., & Gratch, J. (2015, September). *People show envy, not guilt, when making decisions with machines* [Conference session]. 2015 International Conference on Affective Computing and Intelligent Interaction (ACII), Xi'an, China. https://doi.org/10.1109/ACII.2015.7344589

De Witte, H. (1999). Job insecurity and psychological well-being: Review of the literature and exploration of some unresolved issues: Job insecurity. *European Journal of Work and Organizational Psychology*, *8*(2), 155–177. https://doi.org/10.1080/135943299398302

De Witte, H. (2005). Job insecurity: Review of the international literature on definitions, prevalence, antecedents and consequences. *SA Journal of Industrial Psychology*, *31*(4), 1–6. https://doi.org/10.4102/sajip.v31i4.200

De Witte, H., Pienaar, J., & De Cuyper, N. (2016). Review of 30 years of longitudinal studies on the association between job insecurity and health and well-being: Is there causal evidence? *Australian Psychologist*, *51*(1), 18–31. https://doi.org/10.1111/ap.12176

Dekker, F., Salomons, A., & van der Waal, J. (2017). Fear of robots at work: The role of economic self-interest. *Socio-economic Review*, *15*, 539–562. https://doi.org/10.1093/ser/mwx005

Dekker, S. W., & Schaufeli, W. B. (1995). The effects of job insecurity on psychological health and withdrawal: A longitudinal study. *Australian Psychologist*, *30*(1), 57–63. https://doi.org/10.1080/00050069508259607

Destephe, M., Brandao, M., Kishi, T., Zecca, M., Hashimoto, K., & Takanishi, A. (2015). Walking in the uncanny valley: Importance of the attractiveness on the acceptance of a robot as a working partner. *Frontiers in Psychology*, *6*, Article 204. https://doi.org/10.3389/fpsyg.2015.00204

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, *144*(1), 114–126. https://doi.org/10.1037/xge0000033

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. *Management Science*, *64*(3), 1155–1170. https://doi.org/10.1287/mnsc.2016.2643

Dolan, S., & Tziner, A. (1988). Implementing computer-based automation in the office: A study of experienced stress. *Journal of Organizational Behavior*, *9*(2), 183–187. https://doi.org/10.1002/job.4030090209

Dunning, D. (2005). *Self-insight: Roadblocks and detours on the path to knowing thyself*. Psychology Press.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., ... Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, Article 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Dzindolet, M. T., Peterson, S. A., Pomranky, R. A., Pierce, L. G., & Beck, H. P. (2003). The role of trust in automation reliance. *International Journal of Human-Computer Studies*, *58*(6), 697–718. https://doi.org/10.1016/S1071-5819(03)00038-7

Edwards, C., Edwards, A., Albrehi, F., & Spence, P. (2021). Interpersonal impressions of a social robot versus human in the context of performance evaluations. *Communication Education*, *70*(2), 165–182. https://doi.org/10.1080/03634523.2020.1802495

Efendić, E., Van de Calseyde, P. P. F. M., & Evans, A. M. (2020). Slow response times undermine trust in algorithmic (but not human) predictions. *Organizational Behavior and Human Decision Processes*, *157*, 103–114. https://doi.org/10.1016/j.obhdp.2020.01.008

Epley, N., & Waytz, A. (2010). Mind perception. In S. T. Fiske, D. T. Gilbert, & G. Lindzey (Eds.), *The handbook of social psychology* (5th ed., pp. 498–541). Wiley. https://doi.org/10.1002/9780470561119.socpsy001014

Eyssel, F. (2017). An experimental psychological perspective on social robotics. *Robotics and Autonomous Systems*, *87*, 363–371. https://doi.org/10.1016/j.robot.2016.08.029

Eyssel, F., & Hegel, F. (2012). (S)he's got the look: Gender stereotyping of robots. *Journal of Applied Social Psychology*, *42*(9), 2213–2230. https://doi.org/10.1111/j.1559-1816.2012.00937.x

Eyssel, F., & Kuchenbrandt, D. (2012). Social categorization of social robots: Anthropomorphism as a function of robot group membership. *British Journal of Social Psychology*, *51*(4), 724–731. https://doi.org/10.1111/j.2044-8309.2011.02082.x

Eyssel, F., De Ruiter, L., Kuchenbrandt, D., Bobinger, S., & Hegel, F. (2012, March). *'If you sound like me, you must be more human': On the interplay of robot and user features on human-robot acceptance and anthropomorphism* [Conference session]. 2012 7th ACM/IEEE International Conference on Human–Robot Interaction (HRI), Boston, MA, USA. https://doi.org/10.1145/2157689.2157717

Fernandez, G. C., Gutierrez, S. M., Ruiz, E. S., Perez, F. M., & Gil, M. C. (2012). Robotics, the new industrial revolution. *IEEE Technology and Society Magazine*, *31*(2), 51–58. https://doi.org/10.1109/MTS.2012.2196595

Ferràs-Hernández, X. (2018). The future of management in a world of electronic brains. *Journal of Management Inquiry*, *27*(2), 260–263. https://doi.org/10.1177/1056492617724973

Fleming, P. (2019). Robots and organization studies: Why robots might not want to steal your job. *Organization Studies*, *40*(1), 23–38. https://doi.org/10.1177/0170840618765568

Foroughi, C. K., Devlin, S., Pak, R., Brown, N. L., Sibley, C., & Coyne, J. T. (2021). Near-perfect automation: Investigating performance, trust, and visual attention allocation. *Human Factors*. Advance online publication. https://doi.org/10.1177/00187208211032889

Fox, J., & Gambino, A. (2021). Relationship development with humanoid social robots: Applying interpersonal theories to Human–Robot interaction. *Cyberpsychology, Behavior and Social Networking*, *24*(5), 294–299. https://doi.org/10.1089/cyber.2020.0181

Frase, P. (2016). *Four futures: Life after capitalism*. Verso.

Fraune, M. R. (2020). Our robots, our team: Robot anthropomorphism moderates group effects in Human–Robot teams. *Frontiers in Psychology*, *11*, Article 1275. https://doi.org/10.3389/fpsyg.2020.01275

Fraune, M. R., Šabanović, S., Smith, E. R., Nishiwaki, Y., & Okada, M. (2017, March). *Threatening flocks and mindful snowflakes: How group entitativity affects perceptions of robots* [Conference session]. 2017 12th ACM/IEEE International Conference on Human-Robot Interaction (HRI), Vienna, Austria. https://doi.org/10.1145/2909824.3020248

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, C. B., Berger, T., & Chen, C. (2018). Political machinery: Did robots swing the 2016 U.S. presidential election? *Oxford Review of Economic Policy*, *34*(3), 418–442. https://doi.org/10.1093/oxrep/gry007

Frieder, R. E., Wang, G., & Oh, I.-S. (2018). Linking job-relevant personality traits, transformational leadership, and job performance via perceived meaningfulness at work: A moderated mediation model. *Journal of Applied Psychology*, *103*, 324–333. https://doi.org/10.1037/apl0000274

Frijda, N. H. (1993). *Appraisal and beyond: The issue of cognitive determinants of emotion*. Lawrence Erlbaum. https://doi.org/10.1080/02699939308409188

Furlough, C., Stokes, T., & Gillan, D. J. (2021). Attributing blame to robots: I. the influence of robot autonomy. *Human Factors*, *63*(4), 592–602. https://doi.org/10.1177/0018720819880641

Gallimore, D., Lyons, J. B., Vo, T., Mahoney, S., & Wynne, K. T. (2019). Trusting robocop: Gender-based effects on trust of an autonomous robot. *Frontiers in Psychology*, *10*, Article 482. https://doi.org/10.3389/fpsyg.2019.00482

Gamez-Djokic, M., & Waytz, A. (2020). Concerns about automation and negative sentiment toward immigration. *Psychological Science*, *31*(8), 987–1000. https://doi.org/10.1177/0956797620929977

Ghazali, A. S., Ham, J., Barakova, E., & Markopoulos, P. (2018). The influence of social cues in persuasive social robots on psychological reactance and compliance. *Computers in Human Behavior*, *87*, 58–65. https://doi.org/10.1016/j.chb.2018.05.016

Ghimire, R., Skinner, J., & Carnathan, M. (2020). Who perceived automation as a threat to their jobs in metro Atlanta: Results from the 2019 Metro Atlanta Speaks Survey. *Technology in Society*, *63*, Article 101368. https://doi.org/10.1016/j.techsoc.2020.101368

Gladden, M. E. (2014). The social robot as 'charismatic leader': A phenomenology of human submission to nonhuman power. In J. Seibt, R. Hakli & M. Nørskov (eds.), *Sociable robots and the future of social relations: Proceedings of robo-philosophy 2014* (pp. 329–339). IOS Press.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *The Academy of Management Annals*, *14*(2), 627–660. https://doi.org/10.5465/annals.2018.0057

Gnambs, T., & Appel, M. (2019). Are robots becoming unpopular? Changes in attitudes towards autonomous robotic systems in Europe. *Computers in Human Behavior*, *93*, 53–61. https://doi.org/10.1016/j.chb.2018.11.045

Granulo, A., Fuchs, C., & Puntoni, S. (2019). Psychological reactions to human versus robotic job replacement. *Nature Human Behaviour*, *3*(10), 1062–1069. https://doi.org/10.1038/s41562-019-0670-y

Gray, H. M., Gray, K., & Wegner, D. M. (2007). Dimensions of mind perception. *Science*, *315*(5812), 619. https://doi.org/10.1126/science.1134475

Gray, K., & Wegner, D. M. (2012). Feeling robots and human zombies: Mind perception and the uncanny valley. *Cognition*, *125*(1), 125–130. https://doi.org/10.1016/j.cognition.2012.06.007

Greenemeier, L. (2016, May 04). *Robot surgeon successfully sews pig intestine*. https://www.scientificamerican.com/article/robot-surgeon-successfully-sews-pig-intestine/

Greenhalgh, L., & Rosenblatt, Z. (1984). Job insecurity: Toward conceptual clarity. *Academy of Management Review*, *9*(3), 438–448. https://doi.org/10.5465/amr.1984.4279673

Gregory, R. W., Henfridsson, O., Kaganer, E., & Kyriakou, S. H. (2021). The role of artificial intelligence and data network effects for creating user value. *Academy of Management Review*, *46*(3), 534–551. https://doi.org/10.5465/amr.2019.0178

Han, S., Shanafelt, T. D., Sinsky, C. A., Awad, K. M., Dyrbye, L. N., Fiscus, L. C., Trockel, M., & Goh, J. (2019). Estimating the attributable cost of physician burnout in the United States. *Annals of Internal Medicine*, *170*(11), 784–790. https://doi.org/10.7326/M18-1422

Haring, K. S., Satterfield, K. M., Tossell, C. C., de Visser, E. J., Lyons, J. R., Mancuso, V. F., Finomore, V. S., & Funke, G. J. (2021). Robot authority in human-robot teaming: Effects of human-likeness and physical embodiment on compliance. *Frontiers in Psychology*, *12*, Article 625713. https://doi.org/10.3389/fpsyg.2021.625713

Häring, M., Kuchenbrandt, D., & André, E. (2014, March). *Would you like to play with me? How robots' group membership and task features influence* *human–robot interaction* [Conference session]. 2014 9th ACM/IEEE International Conference on Human-Robot Interaction (HRI), Bielefeld, Germany. https://doi.org/10.1145/2559636.2559673

Hertz, N., & Wiese, E. (2019). Good advice is beyond all price, but what if it comes from a machine? *Journal of Experimental Psychology: Applied*, *25*(3), 386–395. https://doi.org/10.1037/xap0000205

Hinds, P., Roberts, T., & Jones, H. (2004). Whose job is it anyway? A study of human-robot interaction in a collaborative task. *Human-Computer Interaction*, *19*(1), 151–181. https://www.cs.cmu.edu/~kiesler/anthropomorphism-org/pdf/Hindsetal_HCI1912.pdf

Hoff, K. A., & Bashir, M. (2015). Trust in automation: Integrating empirical evidence on factors that influence trust. *Human Factors*, *57*(3), 407–434. https://doi.org/10.1177/0018720814547570

Hoffmann, L., Bock, N., & vd Pütten, A. M. R. (2018, March). *The peculiarities of robot embodiment (EmCorp-Scale): Development, validation and initial test of the embodiment and corporeality of artificial agents scale* [Conference session]. 2018 13th ACM/IEEE International Conference on Human-Robot Interaction (HRI), Chicago, IL, USA. https://doi.org/10.1145/3171221.3171242

Hofmann, D. A. (1997). An overview of the logic and rationale of hierarchical linear models. *Journal of Management*, *23*(6), 723–744. https://doi.org/10.1177/014920639702300602

Hofmann, D. A., & Gavin, M. B. (1998). Centering decisions in hierarchical linear models: Implications for research in organizations. *Journal of Management*, *24*(5), 623–641. https://doi.org/10.1177/014920639802400504

Hofmann, D. A., Griffin, M. A., & Gavin, M. B. (2000). The application of hierarchical linear modeling to organizational research. In K. J. Klein & S. W. J. Kozlowski (Eds.), *Multilevel theory, research, and methods in organizations: Foundations, extensions, and new directions* (pp. 467–511). Jossey-Bass.

Horstmann, A. C., & Krämer, N. C. (2019). Great expectations? Relation of previous experiences with social robots in real life or in the media and expectancies based on qualitative and quantitative assessment. *Frontiers in Psychology*, *10*, Article 939. https://doi.org/10.3389/fpsyg.2019.00939

Huang, G. H., Niu, X., Lee, C., & Ashford, S. J. (2012). Differentiating cognitive and affective job insecurity: Antecedents and outcomes. *Journal of Organizational Behavior*, *33*(6), 752–769. https://doi.org/10.1002/job.1815

Huang, G. H., Wellman, N., Ashford, S. J., Lee, C., & Wang, L. (2017). Deviance and exit: The organizational costs of job insecurity and moral disengagement. *Journal of Applied Psychology*, *102*(1), 26–42. https://doi.org/10.1037/apl0000158

Hutchinson, J., Strickland, L., Farrell, S., & Loft, S. (2022). The perception of automation reliability and acceptance of automated advice. *Human Factors*. Advance online publication. https://doi.org/10.1177/00187208211062985

Im, Z. J., & Komp-Leukkunen, K. (2021). Automation and public support for workfare. *Journal of European Social Policy*, *31*(4), 457–472. https://doi.org/10.1177/09589287211002432

Im, Z. J., Mayer, N., Palier, B., & Rovny, J. (2019). The “losers of automation”: A reservoir of votes for the radical right? *Research & Politics*, *6*(1), 1–7. https://doi.org/10.1177/2053168018822395

International Federation of Robotics. (2017). *The impact of robots on productivity, employment and jobs*. https://ifr.org/img/office/IFR_The_Impact_of_Robots_on_Employment.pdf

Jackson, J. C., Castelo, N., & Gray, K. (2020). Could a rising robot workforce make humans less prejudiced? *American Psychologist*, *75*(7), 969–982. https://doi.org/10.1037/amp0000582

Jago, A. S. (2019). Algorithms and authenticity. *Academy of Management Discoveries*, *5*(1), 38–56. https://doi.org/10.5465/amd.2017.0002

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human–AI symbiosis in organizational decision making. *Business Horizons*, *61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

Jeffrey, K. (2021). Automation and the future of work: How rhetoric shapes the response in policy preferences. *Journal of Economic Behavior & Organization*, *192*, 417–433. https://doi.org/10.1016/j.jebo.2021.10.019

Judge, T. A., & Ilies, R. (2004). Affect and job satisfaction: A study of their relationship at work and at home. *Journal of Applied Psychology*, *89*(4), 661–673. https://doi.org/10.1037/0021-9010.89.4.661

Jung, M. F. (2017, March). *Affective grounding in human-robot interaction* [Conference session]. 2017 12th ACM/IEEE International Conference on Human–Robot Interaction (HRI), Vienna, Austria. https://doi.org/10.1145/2909824.3020224

Jung, M. F., Martelaro, N., & Hinds, P. J. (2015, March). *Using robots to moderate team conflict: The case of repairing violations* [Conference session]. Proceedings of the Tenth Annual ACM/IEEE International Conference on Human–Robot Interaction, Portland, OR, USA. https://doi.org/10.1145/2696454.2696460

Kashi, S., & Levy-Tzedek, S. (2018). Smooth leader or sharp follower? Playing the mirror game with a robot. *Restorative Neurology and Neuroscience*, *36*(2), 147–159. https://doi.org/10.3233/RNN-170756

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *The Academy of Management Annals*, *14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174

Khalil, O. E. M. (1993). Artificial decision-making and artificial ethics: A management concern. *Journal of Business Ethics*, *12*(4), 313–321. https://doi.org/10.1007/BF01666535

Kim, T. W., & Duhachek, A. (2020). Artificial intelligence and persuasion: A construal-level account. *Psychological Science*, *31*(4), 363–380. https://doi.org/10.1177/0956797620904985

Kim, T. W., & Scheller-Wolf, A. (2019). Technological unemployment, meaning in life, purpose of business, and the future of stakeholders. *Journal of Business Ethics*, *160*(2), 319–337. https://doi.org/10.1007/s10551-019-04205-9

Kinias, Z., & Sim, J. (2016). Facilitating women’s success in business: Interrupting the process of stereotype threat through affirmation of personal values. *Journal of Applied Psychology*, *101*(11), 1585–1597. https://doi.org/10.1037/apl0000139

Kinnunen, U., Mäkikangas, A., Mauno, S., De Cuyper, N., & De Witte, H. (2014). Development of perceived job insecurity across two years: Associations with antecedents and employee outcomes. *Journal of Occupational Health Psychology*, *19*(2), 243–258. https://doi.org/10.1037/a0035835

Knyazev, G. G., Savostyanov, A. N., & Levin, E. A. (2005). Uncertainty, anxiety, and brain oscillations. *Neuroscience Letters*, *387*(3), 121–125. https://doi.org/10.1016/j.neulet.2005.06.016

Kolbjørnsrud, V., Amico, R., & Thomas, R. J. (2017). Partnering with AI: How organizations can win over skeptical managers. *Strategy and Leadership*, *45*(1), 37–43. https://doi.org/10.1108/SL-12-2016-0085

Kong, H., Yuan, Y., Baruch, Y., Bu, N., Jiang, X., & Wang, K. (2021). Influences of artificial intelligence (AI) awareness on career competency and job burnout. *International Journal of Contemporary Hospitality Management*, *33*(2), 717–734. https://doi.org/10.1108/IJCHM-07-2020-0789

Koo, B., Curtis, C., & Ryan, B. (2021). Examining the impact of artificial intelligence on hotel employees through job insecurity perspectives. *International Journal of Hospitality Management*, *95*, Article 102763. https://doi.org/10.1016/j.ijhm.2020.102763

Krach, S., Hegel, F., Wrede, B., Sagerer, G., Binkofski, F., & Kircher, T. (2008). Can machines think? Interaction and perspective taking with robots investigated via fMRI. *PLOS ONE*, *3*(7), Article e2597. https://doi.org/10.1371/journal.pone.0002597

Kühnlenz, B., Kühnlenz, K., Busse, F., Förtsch, P., & Wolf, M. (2018, August). *Effect of explicit emotional adaptation on prosocial behavior of humans towards robots depends on prior robot experience* [Conference session]. 2018 27th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN), Tai’an, China. https://doi.org/10.1109/ROMAN.2018.8525515

Kwon, M., Jung, M. F., & Knepper, R. A. (2016, March). *Human expectations of social robots* [Conference session]. 2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI), Christchurch, New Zealand. https://doi.org/10.1109/HRI.2016.7451807

Langer, M., & Landers, R. N. (2021). The future of artificial intelligence at work: A review on effects of decision automation and augmentation on workers targeted by algorithms and third-party observers. *Computers in Human Behavior*, *123*, Article 106878. https://doi.org/10.1016/j.chb.2021.106878

Latikka, R., Turja, T., & Oksanen, A. (2019). Self-efficacy and acceptance of robots. *Computers in Human Behavior*, *93*, 157–163. https://doi.org/10.1016/j.chb.2018.12.017

Lawler, J. J., & Elliot, R. (1996). Artificial intelligence in HRM: An experimental study of an expert system. *Journal of Management*, *22*(1), 85–111. https://doi.org/10.1177/014920639602200104

Lazarus, R. S. (1991). Psychological stress in the workplace. *Journal of Social Behavior and Personality*, *6*, 1–13.

Lazarus, R. S. (1993). Coping theory and research: Past, present, and future. *Psychosomatic Medicine*, *55*(3), 234–247. https://doi.org/10.1097/00006842-199305000-00002

Lazarus, R. S., & Folkman, S. (1984). *Stress, appraisal, and coping*. Springer Publishing.

Lazarus, R. S., & Folkman, S. (1986). Cognitive theories of stress and the issue of circularity. In M. H. Appley & R. Trumbull (Eds.), *Dynamics of stress: Physiological, psychological and social perspectives* (pp. 63–80). Springer Publishing. https://doi.org/10.1007/978-1-4684-5122-1_4

Lee, C., Huang, G. H., & Ashford, S. J. (2018). Job insecurity and the changing workplace: Recent developments and the future trends in job insecurity research. *Annual Review of Organizational Psychology and Organizational Behavior*, *5*(1), 335–359. https://doi.org/10.1146/annurev-orgpsych-032117-104651

Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big Data & Society*, *5*(1), 1–16. https://doi.org/10.1177/2053951718756684

Lee, M. K., Kiesler, S., Forlizzi, J., & Rybski, P. (2012, May). *Ripple effects of an embedded social agent: A field study of a social robot in the workplace* [Conference session]. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Austin, TX, USA. https://doi.org/10.1145/2207676.2207776

Lee, M. K., Kusbit, D., Metsky, E., & Dabbish, L. (2015, April). *Working with machines: The impact of algorithmic and data-driven management on human workers* [Conference session]. Proceedings of the 33rd annual ACM conference on human factors in computing systems, Seoul, South Korea. https://doi.org/10.1145/2702123.2702548

Lei, X., & Rau, P. L. P. (2021). Effect of relative status on responsibility attributions in human–robot collaboration: Mediating role of sense of responsibility and moderating role of power distance orientation. *Computers in Human Behavior*, *122*, Article 106820. https://doi.org/10.1016/j.chb.2021.106820

Li, J., & Huang, J. (2020). Dimensions of artificial intelligence anxiety based on the integrated fear acquisition theory. *Technology in Society*, *63*, Article 101410. https://doi.org/10.1016/j.techsoc.2020.101410

Li, J., Bonn, M. A., & Ye, B. H. (2019). Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: The moderating roles of perceived organizational support and competitive psychological climate. *Tourism Management*, *73*, 172–181. https://doi.org/10.1016/j.tourman.2019.02.006

Lim, S., & Cortina, L. M. (2005). Interpersonal mistreatment in the workplace: The interface and impact of general incivility and sexual harassment. *Journal of Applied Psychology*, *90*(3), 483–496. https://doi.org/10.1037/0021-9010.90.3.483

Lingmont, D. N. J., & Alexiou, A. (2020). The contingent effect of job automating technology awareness on perceived job insecurity: Exploring the moderating role of organizational culture. *Technological Forecasting and Social Change*, *161*, Article 120302. https://doi.org/10.1016/j.techfore.2020.120302

Loft, S., Bhaskara, A., Lock, B. A., Skinner, M., Brooks, J., Li, R., & Bell, J. (2021). The impact of transparency and decision risk on human–automation teaming outcomes. *Human Factors*. Advance online publication. https://doi.org/10.1177/00187208211033445

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, *151*, 90–103. https://doi.org/10.1016/j.obhdp.2018.12.005

Lu, V. N., Wirtz, J., Kunz, W. H., Paluch, S., Gruber, T., Martins, A., & Patterson, P. G. (2020). Service robots, customers and service employees: What can we learn from the academic literature and where are the gaps? *Journal of Service Theory and Practice*, *30*(3), 361–391. https://doi.org/10.1108/JSTP-04-2019-0088

Lund, B. D., Omame, I., Tijani, S., & Agbaji, D. (2020). Perceptions toward artificial intelligence among academic library employees and alignment with the diffusion of innovations' adopter categories. *College & Research Libraries*, *81*, 865–882. https://doi.org/10.5860/crl.81.5.865

Mackinnon, A., Jorm, A. F., Christensen, H., Korten, A. E., Jacomb, P. A., & Rodgers, B. (1999). A short form of the Positive and Negative Affect Schedule: Evaluation of factorial validity and invariance across demographic variables in a community sample. *Personality and Individual Differences*, *27*(3), 405–416. https://doi.org/10.1016/S0191-8869(98)00251-7

Maslach, C., Schaufeli, W. B., & Leiter, M. P. (2001). Job burnout. *Annual Review of Psychology*, *52*(1), 397–422. https://doi.org/10.1146/annurev.psych.52.1.397

McClure, P. K. (2018). "You're fired," says the robot: The rise of automation in the workplace, technophobes, and fears of unemployment. *Social Science Computer Review*, *36*(2), 139–156. https://doi.org/10.1177/0894439317698637

McQueen, A., & Klein, W. M. (2006). Experimental manipulations of self-affirmation: A systematic review. *Self and Identity*, *5*(4), 289–354. https://doi.org/10.1080/15298860600805325

Merritt, S. M., Ako-Brew, A., Bryant, W. J., Staley, A., McKenna, M., Leone, A., & Shirase, L. (2019). Automation-induced complacency potential: Development and validation of a new scale. *Frontiers in Psychology*, *10*, Article 225. https://doi.org/10.3389/fpsyg.2019.00225

Mitchell, M. S., Greenbaum, R. L., Vogel, R. M., Mawritz, M. B., & Keating, D. J. (2019). Can you handle the pressure? The effect of performance pressure on stress appraisals, self-regulation, and behavior. *Academy of Management Journal*, *62*(2), 531–552. https://doi.org/10.5465/amj.2016.0646

Moniz, A., & Krings, B. (2016). Robots working with humans or humans working with robots? Searching for social dimensions in new human–robot interaction in industry. *Societies*, *6*(3), 1–23. https://doi.org/10.3390/soc6030023

Murphy, M. (2017, March 27). *This bricklaying robot is going to destroy construction jobs*. https://nypost.com/2017/03/27/this-bricklaying-robot-is-going-to-destroy-construction-jobs

Murray, A., Rhymer, J., & Sirmon, D. G. (2021). Humans and technology: Forms of conjoined agency in organizations. *Academy of Management Review*, *46*(3), 552–571. https://doi.org/10.5465/amr.2019.0186

Muthen, B. O., & Satorra, A. (1995). Complex sample data in structural equation modeling. *Sociological Methodology*, *25*, 267–316. https://doi.org/10.2307/271070

Muthén, L. K., & Muthén, B. O. (2015). *Mplus Version 7.4 software* (7th ed.).

Mutlu, B., & Forlizzi, J. (2008, March). *Robots in organizations: The role of workflow, social, and environmental factors in human–robot interaction* [Conference session]. 2008 3rd ACM/IEEE International Conference on Human–Robot Interaction (HRI), Amsterdam, The Netherlands. https://doi.org/10.1145/1349822.1349860

Nazareno, L., & Schiff, D. S. (2021). The impact of automation and artificial intelligence on worker well-being. *Technology in Society*, *67*, Article 101679. https://doi.org/10.1016/j.techsoc.2021.101679

Nuti, S. V., Wayda, B., Ranasinghe, I., Wang, S., Dreyer, R. P., Chen, S. I., & Murugiah, K. (2014). The use of google trends in health care research: A systematic review. *PLOS ONE*, *9*(10), Article e109583. https://doi.org/10.1371/journal.pone.0109583

Oistad, B. C., Sembroski, C. E., Gates, K. A., Krupp, M. M., Fraune, M. R., & Šabanović, S. (2016, November). *Colleague or tool? Interactivity increases positive perceptions of and willingness to interact with a robotic co-worker* [Conference session]. International Conference on Social Robotics, Kansas City, MO, USA. https://doi.org/10.1007/978-3-319-47437-3_76

Onnasch, L., & Roesler, E. (2021). A taxonomy to structure and analyze human–robot interaction. *International Journal of Social Robotics*, *13*(4), 833–849. https://doi.org/10.1007/s12369-020-00666-5

Oosthuizen, R. M. (2019). Smart technology, artificial intelligence, robotics and algorithms (STARA): Employees' perceptions and wellbeing in future workplaces. In I. Potgieter, N. Ferreira, & M. Coetzee (Eds.), *Theory, research and dynamics of career wellbeing* (pp. 17–40). Springer Publishing. https://doi.org/10.1007/978-3-030-28180-9_2

Ortony, A., Clore, G. L., & Collins, A. (1988). *The cognitive structure of emotions*. Cambridge University Press. https://doi.org/10.1017/CBO9780511571299

Ötting, S. K., & Maier, G. W. (2018). The importance of procedural justice in human–machine interactions: Intelligent systems as new decision agents in organizations. *Computers in Human Behavior*, *89*, 27–39. https://doi.org/10.1016/j.chb.2018.07.022

Ötting, S. K., Masjutin, L., Steil, J. J., & Maier, G. W. (2020). Let's work together: A meta-analysis on robot design features that enable successful human–robot interaction at work. *Human Factors*. Advance online publication. https://doi.org/10.1177/0018720820966433

Paesano, A. (2021). Artificial intelligence and creative activities inside organizational behavior. *The International Journal of Organizational Analysis*. Advance online publication. https://doi.org/10.1108/IJOA-09-2020-2421

Paetzel-Prüsmann, M., Perugia, G., & Castellano, G. (2021). The influence of robot personality on the development of uncanny feelings. *Computers in Human Behavior*, *120*, Article 106756. https://doi.org/10.1016/j.chb.2021.106756

Parasuraman, R., & Manzey, D. H. (2010). Complacency and bias in human use of automation: An attentional integration. *Human Factors*, *52*(3), 381–410. https://doi.org/10.1177/0018720810376055

Park, R. (2018). The roles of OCB and automation in the relationship between job autonomy and organizational performance: A moderated mediation model. *International Journal of Human Resource Management*, *29*(6), 1139–1156. https://doi.org/10.1080/09585192.2016.1180315

Parry, K., Cohen, M., & Bhattacharya, S. (2016). Rise of the machines: A critical consideration of automated leadership decision making in organizations. *Group & Organization Management*, *41*(5), 571–594. https://doi.org/10.1177/1059601116643442

Patel, P. C., Devaraj, S., Hicks, M. J., & Wornell, E. J. (2018). County-level job automation risk and health: Evidence from the United States. *Social Science & Medicine*, *202*, 54–60. https://doi.org/10.1016/j.socscimed.2018.02.025

Payne, B. K., Brown-Iannuzzi, J. L., & Hannay, J. W. (2017). Economic inequality increases risk taking. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(18), 4643–4648. https://doi.org/10.1073/pnas.1616453114

Pearson, C., & Porath, C. (2009). *The cost of bad behavior: How incivility is damaging your business and what to do about it*. Penguin.

Porath, C., & Pearson, C. (2013). The price of incivility. *Harvard Business Review*, *91*(1–2), 114–146.

Prahl, A., & Van Swol, L. (2017). Understanding algorithm aversion: When is advice from automation discounted? *Journal of Forecasting*, *36*(6), 691–702. https://doi.org/10.1002/for.2464

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, *40*(3), 879–891. https://doi.org/10.3758/BRM.40.3.879

Preacher, K. J., Zyphur, M. J., & Zhang, Z. (2010). A general multilevel SEM framework for assessing multilevel mediation. *Psychological Methods*, *15*(3), 209–233. https://doi.org/10.1037/a0020141

Preis, T., Moat, H. S., & Stanley, H. E. (2013). Quantifying trading behavior in financial markets using Google Trends. *Scientific Reports*, *3*(1), Article 1684. https://doi.org/10.1038/srep01684

Prewett, M. S., Johnson, R. C., Saboe, K. N., Elliott, L. R., & Coovert, M. D. (2010). Managing workload in human–robot interaction: A review of empirical studies. *Computers in Human Behavior*, *26*(5), 840–856. https://doi.org/10.1016/j.chb.2010.03.010

Probst, T. M., Stewart, S. M., Gruys, M. L., & Tierney, B. W. (2007). Productivity, counterproductivity and creativity: The ups and downs of job insecurity. *Journal of Occupational and Organizational Psychology*, *80*(3), 479–497. https://doi.org/10.1348/096317906X159103

Qin, X., Chen, C., Yam, K. C., Cao, L., Li, W., Guan, J., Zhao, P., Dong, X., & Lin, Y. (2022). Adults still can't resist: A social robot can induce normative conformity. *Computers in Human Behavior*, *127*, Article 107041. https://doi.org/10.1016/j.chb.2021.107041

Qin, X., Huang, M., Johnson, R. E., Hu, Q., & Ju, D. (2018). The short-lived benefits of abusive supervisory behavior for actors: An investigation of recovery and work engagement. *Academy of Management Journal*, *61*(5), 1951–1975. https://doi.org/10.5465/amj.2016.1325

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, *46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072

Rau, P. P., Li, Y., & Liu, J. (2013). Effects of a social robot's autonomy and group orientation on human decision-making. *Advances in Human-Computer Interaction*, *2013*, 1–13. https://doi.org/10.1155/2013/263721

Richards, D. (2017). Escape from the factory of the robot monsters: Agents of change. *Team Performance Management*, *23*(1/2), 96–108. https://doi.org/10.1108/TPM-10-2015-0052

Richert, A., Müller, S., Schröder, S., & Jeschke, S. (2018). Anthropomorphism in social robotics: Empirical results on human–robot interaction in hybrid production workplaces. *AI & Society*, *33*(3), 413–424. https://doi.org/10.1007/s00146-017-0756-x

Robert, L. P. (2018, August). *Personality in the human robot interaction literature: A review and brief critique* [Conference session]. Proceedings of the 24th Americas Conference on Information Systems, New Orleans, LA, USA.

Roesler, E., Onnasch, L., & Majer, J. I. (2020). The effect of anthropomorphism and failure comprehensibility on human–robot trus. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *64*(1), 107–111. https://doi.org/10.1177/1071181320641028

Roskies, E., & Louis-Guerin, C. (1990). Job insecurity in managers: Antecedents and consequences. *Journal of Organizational Behavior*, *11*(5), 345–359. https://doi.org/10.1002/job.4030110503

Salem, M., Lakatos, G., Amirabdollahian, F., & Dautenhahn, K. (2015, March). *Would you trust a (faulty) robot? Effects of error, task type and personality on human-robot cooperation and trust* [Conference session]. 2015 10th ACM/IEEE International Conference on Human-Robot Interaction (HRI), Portland, OR, USA. https://doi.org/10.1145/2696454.2696497

Sanders, T., Oleson, K. E., Billings, D. R., Chen, J. Y. C., & Hancock, P. A. (2011). A model of human–robot trust: Theoretical model development. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *55*(1), 1432–1436). https://doi.org/10.1177/1071181311551298

Sauppé, A., & Mutlu, B. (2015, April). *The social impact of a robot co-worker in industrial settings* [Conference session]. Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, Seoul, South Korea. https://doi.org/10.1145/2702123.2702181

Savela, N., Kaakinen, M., Ellonen, N., & Oksanen, A. (2021a). Sharing a work team with robots: The negative effect of robot co-workers on in-group identification with the work team. *Computers in Human Behavior*, *115*, Article 106585. https://doi.org/10.1016/j.chb.2020.106585

Savela, N., Turja, T., Latikka, R., & Oksanen, A. (2021b). Media effects on the perceptions of robots. *Human Behavior and Emerging Technologies*, *3*(5), 989–1003. https://doi.org/10.1002/hbe2.296

Schaufeli, W. B., Bakker, A. B., & Van Rhenen, W. (2009). How changes in job demands and resources predict burnout, work engagement, and sickness absenteeism. *Journal of Organizational Behavior*, *30*(7), 893–917. https://doi.org/10.1002/job.595

Schilpzand, P., de Pater, I., & Arez, A. (2016). Workplace incivility: A review of the literature and agenda for future research. *Journal of Organizational Behavior*, *37*, 57–88. https://doi.org/10.1002/job.1976

Schmeichel, B. J., & Vohs, K. (2009). Self-affirmation and self-control: Affirming core values counteracts ego depletion. *Journal of Personality and Social Psychology*, *96*(4), 770–782. https://doi.org/10.1037/a0014635

Schwartz, T., Zinnikus, I., Krieger, H. U., Bürckert, C., Folz, J., Kiefer, B., Hevesi, P., Lüth, C., Pirkl, G., Spieldenner, T., Schmitz, N., Wirkus, M., & Straube, S. (2016). Hybrid teams: Flexible collaboration between humans, robots and virtual agents. *German Conference on Multiagent System Technologies* (pp. 131–146). https://doi.org/10.1007/978-3-319-45889-2_10

Selig, J. P., & Preacher, K. J. (2008). *Monte Carlo method for assessing mediation: An interactive tool for creating confidence intervals for indirect effects* [Computer software]. http://quantpsy.org/

Sembroski, C. E., Fraune, M. R., & Šabanović, S. (2017, August). *He said, she said, it said: Effects of robot group membership and human authority on people's willingness to follow their instructions* [Conference session]. 2017 26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN), Lisbon, Portugal. https://doi.org/10.1109/ROMAN.2017.8172280

Seo, S. H., Griffin, K., Young, J. E., Bunt, A., Prentice, S., & Loureiro-Rodríguez, V. (2018). Investigating people's rapport building and hindering behaviors when working with a collaborative robot. *International Journal of Social Robotics*, *10*(1), 147–161. https://doi.org/10.1007/s12369-017-0441-8

Shank, D. B., Graves, C., Gott, A., Gamez, P., & Rodriguez, S. (2019). Feeling our way to machine minds: People's emotions when perceiving mind in artificial intelligence. *Computers in Human Behavior*, *98*, 256–266. https://doi.org/10.1016/j.chb.2019.04.001

Sheridan, T. B. (2019). Individual differences in attributes of trust in automation: Measurement and application to system design. *Frontiers in Psychology*, *10*, Article 1117. https://doi.org/10.3389/fpsyg.2019.01117

Sherman, D. K., & Cohen, G. L. (2006). The psychology of self-defense: Self-affirmation theory. In M. P. Zanna (Ed.), *Advances in experimental social psychology* (pp. 183–242). Academic.

Sherman, D. K., Bunyan, D. P., Creswell, J. D., & Jaremka, L. M. (2009). Psychological vulnerability and stress: The effects of self-affirmation on sympathetic nervous system responses to naturalistic stressors. *Health Psychology*, *28*(5), 554–562. https://doi.org/10.1037/a0014663

Shirado, H., & Christakis, N. A. (2017). Locally noisy autonomous agents improve global human coordination in network experiments. *Nature*, *545*(7654), 370–374. https://doi.org/10.1038/nature22332

Shoss, M. K. (2017). Job insecurity: An integrative review and agenda for future research. *Journal of Management*, *43*(6), 1911–1939. https://doi.org/10.1177/0149206317691574

Shoss, M. K., & Probst, T. M. (2012). Multilevel outcomes of economic stress: An agenda for future research. In P. Perrewe, C. Rosen, & J. Halbesleben (Eds.), *The role of economic context on occupational stress and well-being* (pp. 43–86). Emerald Group Publishing. https://doi.org/10.1108/S1479-3555(2012)0000010006

Siino, R. M., & Hinds, P. J. (2004). Making sense of new technology as a lead-in to structuring: The case of an autonomous mobile robot. *Academy of Management Proceedings*, *2004*(1), E1–E6. https://doi.org/10.5465/ambpp.2004.13862508

Smids, J., Nyholm, S., & Berkers, H. (2020). Robots in the workplace: A threat to—or opportunity for—meaningful work? *Philosophy & Technology*, *33*(3), 503–522. https://doi.org/10.1007/s13347-019-00377-4

Smith, C. A., & Pope, L. K. (1992). Appraisal and emotion: The interactional contributions of dispositional and situational factors. In M. S. Clark (Ed.), *Emotion and social behavior* (pp. 32–62). Sage Publications.

Smith, E. R., Sherrin, S., Fraune, M. R., & Šabanović, S. (2020). Positive emotions, more than anxiety or other negative emotions, predict willingness to interact with robots. *Personality and Social Psychology Bulletin*, *46*(8), 1270–1283. https://doi.org/10.1177/0146167219900439

Spencer, D. A. (2018). Fear and hope in an age of mass automation: Debating the future of work. *New Technology, Work and Employment*, *33*(1), 1–12. https://doi.org/10.1111/ntwe.12105

Steele, C. M. (1988). The psychology of self-affirmation: Sustaining the integrity of the self. *Advances in Experimental Social Psychology*, *21*, 261–302. https://doi.org/10.1016/S0065-2601(08)60229-4

Stein, J. P., & Ohler, P. (2017). Venturing into the uncanny valley of mind-The influence of mind attribution on the acceptance of human-like characters in a virtual reality setting. *Cognition*, *160*, 43–50. https://doi.org/10.1016/j.cognition.2016.12.010

Strait, M. K., Floerke, V. A., Ju, W., Maddox, K., Remedios, J. D., Jung, M. F., & Urry, H. L. (2017). Understanding the uncanny: Both atypical features and category ambiguity provoke aversion toward humanlike robots. *Frontiers in Psychology*, *8*, Article 1366. https://doi.org/10.3389/fpsyg.2017.01366

Strohkorb Sebo, S., Traeger, M., Jung, M., & Scassellati, B. (2018, March). *The ripple effects of vulnerability: The effects of a robot's vulnerable behavior on trust in human-robot teams* [Conference session]. Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction, Chicago, IL, USA. https://doi.org/10.1145/3171221.3171275

Sverke, M., Hellgren, J., & Näswall, K. (2002). No security: A meta-analysis and review of job insecurity and its consequences. *Journal of Occupational Health Psychology*, *7*(3), 242–264. https://doi.org/10.1037/1076-8998.7.3.242

Swiderska, A., & Küster, D. (2020). Robots as malevolent moral agents: Harmful behavior results in dehumanization, not anthropomorphism. *Cognitive Science*, *44*(7), Article e12872. https://doi.org/10.1111/cogs.12872

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review*, *61*(4), 15–42. https://doi.org/10.1177/0008125619867910

Tang, P. M., Koopman, J., McClean, S. T., Zhang, J. H., Li, C. H., De Cremer, D., Lu, Y. & Ng, C. T. S. (2021). When conscientious employees meet intelligent machines: An integrative approach inspired by complementarity theory and role theory. *Academy of Management Journal*. Advance online publication. https://doi.org/10.5465/amj.2020.1516

Tsai, C., Marshall, J. D., Choudhury, A., Serban, A., Tsung-Yu Hou, Y., Jung, M. F., Dionne, S. D., & Yammarino, F. J. (2022). Human-robot collaboration: A multilevel and integrated leadership framework. *The Leadership Quarterly*, *33*(1), Article 101594. https://doi.org/10.1016/j.leaqua.2021.101594

Van den Broeck, A., Sulea, C., Vander Elst, T., Fischmann, G., Iliescu, D., & De Witte, H. (2014). The mediating role of psychological needs in the relation between qualitative job insecurity and counterproductive work behavior. *Career Development International*, *19*(5), 526–547. https://doi.org/10.1108/CDI-05-2013-0063

Vassileva, T. (2020). *Do androids dream of unemployment? Examining moderators of the association between perceived AI threat and job insecurity* [Thesis]. San Diego State University.

Von der Pütten, A. M., Krämer, N. C., Gratch, J., & Kang, S.-H. (2010). "It doesn't matter what you are!" Explaining social effects of agents and avatars. *Computers in Human Behavior*, *26*(6), 1641–1650. https://doi.org/10.1016/j.chb.2010.06.012

von Krogh, G. (2018). Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. *Academy of Management Discoveries*, *4*(4), 404–409. https://doi.org/10.5465/amd.2018.0084

von Krogh, G., Ben-Menahem, S. M., & Shrestha, Y. R. (2021). Artificial Intelligence in Strategizing: Prospects and challenges. In I. M. Duhaime,

M. A. Hitt, & M. A. Lyles (Eds.), *Future of strategic management* (pp. 625–646). Oxford University Press.

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. *International Journal of Human Resource Management*, *33*(6), 1237–1266. https://doi.org/10.1080/09585192.2020.1871398

Wegner, D. M., & Gray, K. (2016). *The mind club: Who thinks, what feels, and why it matters*. Viking Press.

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: Humans and AI are joining forces. *Harvard Business Review*, *96*, 114–123.

Wright, S. A., & Schultz, A. E. (2018). The rising tide of artificial intelligence and business automation: Developing an ethical framework. *Business Horizons*, *61*(6), 823–832. https://doi.org/10.1016/j.bushor.2018.07.001

Yam, K. C., Bigman, Y., & Gray, K. (2021). Reducing the uncanny valley by dehumanizing humanoid robots. *Computers in Human Behavior*, *125*, Article 106945. https://doi.org/10.1016/j.chb.2021.106945

Yanco, H. A., & Drury, J. (2004, October). *Classifying human-robot interaction: An updated taxonomy* [Conference session]. 2004 IEEE International Conference on Systems, Man and Cybernetics, The Hague, Netherlands. https://doi.org/10.1109/ICSMC.2004.1400763

Yu, K., Berkovsky, S., Conway, D., Taib, R., Zhou, J., & Chen, F. (2018). Do I trust a machine? Differences in user trust based on system performance. In J. Zhou & F. Chen (Eds), *Human and machine learning* (pp. 245–264). Springer Publishing. https://doi.org/10.1007/978-3-319-90403-0_12

Appendix A

Sample Pictures and Description of the Industrial Robots in Study 3

Brief Description

This organization deploys smart technology solutions in their robots to smoothen the robot-assisted manufacturing processes. The engineers in our sample are the primary "handlers" of the robots, wherein a major part of their job involves jointly coordinating work-related activities with the robots in the production line. For example, to manage the complex daily production cycle, engineers need to collaborate and interact with robots to execute a series of complicated commands in order to track the production progress and respond to deviations. In addition, the robot adoption in this context enables these engineers to acquire real-time data and information in order to make accurate work decisions throughout the production cycles. This integration of robots into the daily work activities of skilled workers (e.g., engineers) indeed mirrors worldwide robotic adoption trends (Business Insider, 2016). Thus, our sample is illustrative of a rapidly developing phenomenon affecting employees in organizations worldwide.

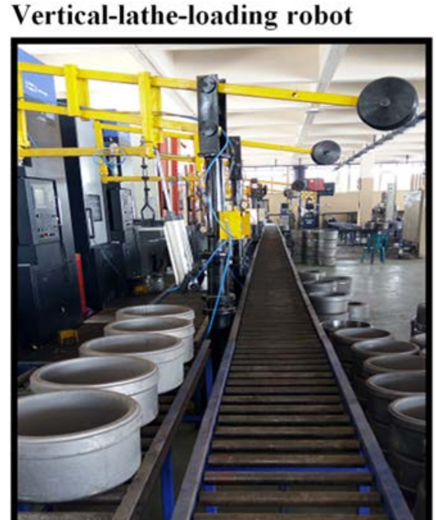
Apart from the extraordinary capability in handling assembly, moving, packaging, transporting, and other challenging physical task, these robots are "intelligent" in a way that they are able to be collaborative, working together, and giving each other feedback. As highlighted earlier in our Method section, this company has specifically combined the professional techniques of data analytics, the use of smart sensors and actuators, together with the machine learning algorithms to facilitate smart manufacturing processes associated with efficiency optimizations. The robot operators (engineers) in the company have to interact with these robots in coming up with real-time figures and data in monitoring and streamlining the daily operation flows. Meanwhile, they have to coordinate with the robots in acquiring timely information about the operational progress on a daily basis.

Each engineer is responsible for managing the manufacturing line infrastructure and, more importantly, must jointly coordinate work activities with advanced robots during the production processes on a daily basis.

Brake drum manufacturing robot

Note. See the online article for the color version of this figure.

Vertical-lathe-loading robot



Note. See the online article for the color version of this figure.

(*Appendices continue*)

Appendix B

Scenarios Used in Studies 2 and 4

Experimental Condition (Studies 2 and 4)

The Increasing Role of Robots at Work

Autonomous cleaning robots that can sing, rap, speak in the four official languages here will be deployed around Singapore.

Local robotics firm LionsBot International (LionsBot) announced that they will be building 300 autonomous professional cleaning robots locally.

And as part of a special agreement between LionsBot and six cleaning partners, the robots will be progressively deployed around Singapore from Wednesday through to March 2020.

The robots come in different shapes and sizes.

For example, the LeoBots Family robot is 63 cm wide and has the ability to navigate through doorways and tight corridor spaces.

Since the beginning of the year, the company has developed 13 different models of cleaning robots that are able to scrub, mop, vacuum, sweep, shine, and even transport cleaning equipment.

The robots can operate indoors and outdoors.

In April last year, LionsBot launched its first two cleaning robots at the National Gallery Singapore and Jewel Changi Airport.

At Changi Airport, wine-loving passengers arriving at Terminal 2 (T2) will now have a special robotic assistant to help them select duty-free wines at Duty Free Stores (DFS) Singapore.

This initiative is part of a trial by Changi Airport Group (CAG), in collaboration with DFS Singapore, Temasek Polytechnic, and SoftBank Telecom Singapore.

> Through observations, on-ground feedback and surveys, we found that many arriving passengers would like to purchase duty-free wine, but do not know where to start, given the large selection available. Leveraging TP's deep wine expertise and STS's social robotics capabilities, we hope to make the wine selection process hassle-free and exciting for our passengers, as they discover new products and personalised retail offerings that are tailored to their preferences

said Ms Teo Chew Hoon, Group Senior Vice President of Airside Concessions, CAG.

With the introduction of robots, the airport hopes to enhance the shopping experience of passengers by making it seamless and more enjoyable.

Robot Control (Study 2 Only)

Boston Dynamics' First Consumer Product Might Be a Battle Bot

Boston Dynamics' faintly terrifying quadruped dog robot—SpotMini—was first announced in 2016. The robot has a whole lot of whizzy sensors and cameras, spindly mechanical legs, a creepy grabber arm that opens doors, and mind-bogglingly impressive robotics technology. It is expected to carry a five-digit price tag—a fitting sum to bring the uncanny valley direct to your home.

But it is never been very clear what, exactly, the point of Spot is—especially as a consumer product.

Speaking in Las Vegas at Amazon's inaugural public conference on robotics, machine learning, automation and space this evening, Boston Dynamics CEO Marc Raibert gave an audience of engineers, astronauts, and Robert Downey Jr. a key clue: entertainment. In the future, multiple players might fight Spots against each other, he said, as a "network game with physical actors," basically allowing remote players to control Spot as BattleBots. There were also reports that Spot is being β tested for use on playgrounds. In a video shown to the audience, four of the robots were shown tussling over a blue ball in an orange enclosure, before tumbling to the ground.

And, like any new technology, they sometimes malfunction. During a live demo, one of the Spot robots collapsed without explanation, folding up its legs and nose-diving to the floor before a replacement trotted onstage. But as the robots' handlers demonstrated, they are eminently simple to control—so simple even I could do it. Using a D-pad, you can steer the robot as you would any RC car or mechanical toy. A quick tap on the video feed streamed live from the robot's front-facing camera lets you select a destination for it to walk to, and another tap lets you assume control of a robot arm mounted on top of the chassis. It all feels very intuitive.

These entertainment robots are expected to go on sale in 2020 in Singapore.

Pure Control (Studies 2 and 4)

Working the Singaporean Way

Singapore, a cosmopolitan melting pot of cultures where east meets west, has a work culture made up of a unique mix of Asian and Western cultural influences. These cultural themes bring about unwritten cultural rules and regulations that govern the way Singaporeans act in a place—and in this case, your workplace. The noninterventionist approach taken by the Singapore government provides a relaxed environment for cultural tendencies to predominate. Large western Multinational corporations (MNCs) located in Singapore will often exhibit predominantly western-style work culture, whereas majority of the local government and private companies will have greater influence of traditional Asian culture in their work environment. Local firms are mainly influenced by cultural characteristics: high power distance, collectivism, high uncertainty avoidance, and long-term orientation.

While it may be true that some Singaporeans (especially the younger and more modern ones) may not wholly practice the Singaporean traditional values of group-centredness, respecting hierarchical relationships and preserving "face," you are strongly advised to learn and understand the behavioral patterns of the Chinese, Indians, and Malays of Singapore for one reason: The majority of Singaporeans you will be working still preserve traditional values—regardless of how Westernized they may seem.

In terms of work hours, many companies in Singapore have moved from 6 days to 5 days per week schedule. This is especially true for MNCs and companies engaged in white collar work. Normal working hours are 40–45 hr per week. However, depending on the workload you may end up spending more hours per week. Normally, there is half-an-hour to one-hour lunch break. Overtime is not applicable to most of the professional and managerial jobs.

Overall, Singaporeans have a predominantly strict attitude to life, marked by clear authority structures and distinct social status lines.

(*Appendices continue*)

Appendix C

Survey Items Used in Pilot Studies 1–2, Studies 2–4

Job Insecurity Scale (Pilot Studies 1–2, Studies 2, 4)

1. Right now, I think that I will soon lose my job.
2. Right now, I feel insecure about the future of my job.
3. Right now, I think that I may lose my job in the near future.

Online Career Service Selection (Study 2)

Please note that we counterbalanced the ordering of the five options in the actual study.

As part of the study, we are also examining people's preferences on various online services. List below are five different online services. *Please select the one that you are the most interested in right now* and we will direct you to some follow up questions specific to that service.

Career: Linkedin Premium Career Services (USD 9.99 per month)

Music: Spotify Premium Music (USD 9.99 per month)

Online storage: Dropbox Professional (USD 9.99 per month)

Online dating: Coffee Meets Bagel Premium (USD 9.99 per month)

Entertainment: Netflix Streaming (USD 9.99 per month)

Positive Affect (Study 3)

1. Inspired
2. Alert
3. Excited
4. Enthusiastic
5. Determined

Negative Affect (Study 3)

1. Afraid
2. Upset
3. Nervous
4. Scared
5. Distressed

Robot Adoption (Study 3)

1. Today, many of the decision-making activities of this job were automated or assisted by robot.
2. Today, many of the problem-solving activities of this job were automated or assisted by robot.
3. Today, many of the learning activities for this job were automated or assisted by robot.
4. Today, many of the reasoning needed for this job were automated or assisted by robot.

Job Insecurity Scale (Study 3)

1. Today, I thought that I will soon lose my job.
2. Today, I felt insecure about the future of my job.
3. Today, I thought that I might lose my job in the near future.

Burnout (Study 3)

1. Today, I felt emotionally drained from my work.
2. Today, I felt burned out from my work.
3. Today, I felt exhausted when I think about having to face another day on the job.

Incivility (Study 3)

1. Today, I put a coworker down or acted condescendingly toward a coworker.
2. Today, I paid little attention to a coworker's statements or showed little interest in a coworker's opinion.
3. Today, I made demeaning or derogatory remarks about a coworker.
4. Today, I addressed a coworker in unprofessional terms publicly or privately.
5. Today, I ignored or excluded a coworker from professional camaraderie.

Received January 14, 2020
Revision received July 12, 2022
Accepted July 18, 2022 ■