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Fears About Artificial Intelligence Across 20 Countries and Six Domains of Application

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The frontier of artificial intelligence (AI) is constantly moving, raising fears and concerns whenever AI is deployed in a new occupation. Some of these fears are legitimate and should be addressed by AI developers—but others may result from psychological barriers, suppressing the uptake of a beneficial technology. Here, we show that country-level variations across occupations can be predicted by a psychological model at the individual level. Individual fears of AI in a given occupation are associated with the mismatch between psychological traits people deem necessary for an occupation and perceived potential of AI to possess these traits. Country-level variations can then be predicted by the joint cultural variations in psychological requirements and AI potential. We validated this preregistered prediction for six occupations (doctors, judges, managers, care workers, religious workers, and journalists) on a representative sample of 500 participants from each of 20 countries (total N = 10,000). Our findings may help develop best practices for designing and communicating about AI in a principled yet culturally sensitive way, avoiding one-size-fits-all approaches centered on Western values and perceptions.

Public Significance Statement
There are widespread concerns about artificial intelligence (AI) systems taking over high-stakes occupations that used to be reserved for humans—such as doctors, judges, or managers. Using data from 20 countries, we show that these fears are not universal but systematically vary across cultures. We also explore the potential drivers of these cultural differences. Our results can help AI designers and policymakers anticipate how new AI developments will be received in different nations and address fears in a culturally sensitive manner by designing systems that meet culture-specific requirements.

Keywords: artificial intelligence, algorithmic aversion, mind perception, culture

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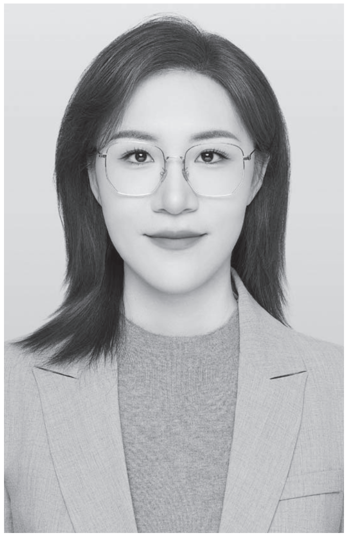

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People are no longer surprised by the sight of a robot in a warehouse or by the voice of a machine answering their call to customer service—the use of artificial intelligence (AI) in industrial or service roles has become part of everyday life and is no longer conjuring visions of technological dystopia (Huang & Rust, 2018; Kim et al., 2018). Fears about AI have not disappeared (Cave & Dihal, 2019; Kieslich et al., 2021; Liang & Lee, 2017), though—they have moved instead to new occupational roles, occupations that AI is poised to conquer but which feel like they should be reserved for humans. This shift in fear stems partly from the unique nature of AI: Unlike many other novel technologies (e.g., nuclear power, genetically modified food, 5G infrastructure), AI is capable of performing tasks and roles previously associated solely with humans. Figure 1A displays six such occupations (Bigman & Gray, 2018; Dong et al., 2024; Hudson et al., 2017; Jackson et al., 2023; Longoni et al., 2019; Perc et al., 2019), together with examples of media coverage highlighting associated fears and concerns.

Would you let a robot be the caretaker of your aging parents? Would you find fulfillment in a religious service conducted by a machine? Would you be comfortable with being treated by a medical AI? Importantly, most people do not yet have direct experience of seeing AI in these occupations, which means that their negative reaction is often not based on witnessing mistakes made by AI. In this article, we investigate the *fear* that people have about AI being deployed in human occupations, a future-oriented emotion that is typically based on risk, uncertainty, and potential for harm (Cave & Dihal, 2019; Kieslich et al., 2021). We do not investigate the dynamics that make people reject AI after seeing it fail at a task, even if the AI actually outperforms humans, a phenomenon known as *algorithm aversion* (De Freitas et al., 2023; Dietvorst et al., 2015; Mahmud et al., 2022).

Adverse effects can follow when AI is deployed in a new occupation and induce fear. An important task is to find a way to minimize adverse effects, maximize positive effects, and reach a state where the balance of effects is ethically acceptable. Finding this balance is not enough, though, since the technology has to be accepted and adopted by the public (Bonnefon et al., 2016; De Freitas et al., 2023; Glikson & Woolley, 2020). As a result, another important task is to measure, understand, and address the fears experienced by the public. Here, we propose a psychological model to understand and potentially mitigate public fears about introducing AI in different occupations and different countries. The model focuses on the unique humanlike dimension of AI, predicting that fears of AI are associated with the mismatch between psychological traits people deem necessary for an occupation and the perceived potential of AI to possess these traits.

Fear of AI Versus Other Novel Technologies

It is not the first time in human history that novel technologies evoke public fears about their future prospects. People feel frightened by nuclear power for its catastrophic consequences of failures and misuses (Peters & Slovic, 1996). People protest against genetically modified food and vaccination for safety concerns and lack of understanding (Marti et al., 2017; Siegrist & Hartmann, 2020). On the frontier of digitalization, people are also anxious about losing

Mengchen Dong played a lead role in data curation, investigation, methodology, and project administration and an equal role in conceptualization, formal analysis, writing–original draft, and writing–review and editing. Jane Rebecca Conway played a supporting role in methodology and writing–review and editing and an equal role in conceptualization. Jean-François Bonnefon played a lead role in visualization, a supporting role in supervision, and an equal role in conceptualization, formal analysis, funding acquisition, writing–original draft, and writing–review and editing. Azim Shariff played a supporting role in writing–review and editing and an equal role in conceptualization and funding acquisition. Iyad Rahwan played a lead role in supervision, a supporting role in writing–review and editing, and an equal role in conceptualization and funding acquisition.

The data are available at https://osf.io/mb5nz/

The experimental materials are available at https://osf.io/mb5nz/

The preregistered design and analysis plan is accessible at https://osf.io/mwbxj

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control over privacy, autonomy, and data security to 5G infrastructure (Frith et al., 2023). Moreover, different individuals may reject science and technology to different extents. Their worldviews, political and religious ideologies, objective knowledge, and subjective distance to science are associated with a general skepticism about various scientific and technological advances (for a review, see Rutjens & Hornsey, 2024).

Many of these concerns rooted in individual circumstances or regarding technological capabilities have also been shown to account for people's negative sentiments around AI (De Freitas et al., 2023; Li & Huang, 2020; Mahmud et al., 2022). For example, people who have lower income and education report more fear of autonomous robots and AI (Liang & Lee, 2017). These people may also experience more threat of job replacement by intelligent machines as a competing workforce (Li & Huang, 2020). Moreover, people often deem AI as lacking flexibility and transparency; therefore, they are reluctant to trust AI after seeing it err or for making high-stakes decisions (Cadario et al., 2021; Dietvorst et al., 2015).

Different from other novel technologies, though, AI can be imbued with humanlike characteristics, has the potential to fulfill roles once reserved exclusively for humans, and is increasingly compared with human counterparts on psychological dimensions (Bonnefon et al., 2024; De Freitas et al., 2023; Morewedge, 2022). AI language models can possess different personality profiles and make different social impressions through aggregable or neurotic verbal expressions (Pellert et al., 2024; Safdari et al., 2023). Anthropomorphizing robots can often induce more trust in service contexts through their humanlike appearances (Kim et al., 2018; Waytz et al., 2014). And as they do for human peers, people prefer AI systems that demonstrate warmth rather than competence (Harris-Watson et al., 2023; McKee et al., 2023). But people reject AI in subjective tasks for its lack of psychological attributes such as emotions and intuitions (Bigman & Gray, 2018; Castelo et al., 2019; Huang & Rust, 2018). In sum, people may be worried about AI for various reasons given their personal circumstances and the technological or psychological capabilities of AI; however, the psychological capabilities may be a unique mechanism for fear of AI, not other novel technologies.

A Psychological Model Across Domains and Countries

What does it mean for AI to be humanlike, and what are the exact psychological features of humans people expect AI to mimic? Research on mind perception and social impression provides a good foundation to map out the psychological dimension for both humans and AI. As they do for other persons and social groups, people perceive various AI products (e.g., virtual assistants and recommendation systems) on psychological dimensions of warmth and competence (Fiske & Dupree, 2014; Fiske et al., 2007; McKee et al., 2023). People also use similar concepts of thinking and feeling to assess the psychological capabilities of both humans and machines (Gray et al., 2007; Waytz et al., 2010) and trust some intelligent machines (e.g., robots and autonomous vehicles) to the extent that they are perceived as having these humanlike capabilities or a humanlike mind (Kim et al., 2018; Waytz et al., 2014).

However, humanlike AI is not always desirable; it is also important to consider people's psychological requirements when predicting fears across different occupations. Without considering the psychological requirements in the applied contexts, previous theories on mind perception and social impression could not explain other facts well, for example, that people prefer AI for some than other human roles (Castelo et al., 2019; Glikson & Woolley, 2020; Huang & Rust, 2018) and that people sometimes accept AI even though AI does not demonstrate high potential on psychological traits (Bigman et al., 2021; Logg et al., 2019). Indeed, for different occupations, people have different psychological requirements for job holders. In the United States, for example, people think that a doctor must be warm and competent, whereas a manager must be competent but need not be warm (Fiske & Dupree, 2014). These findings suggest that both occupation- and AI-side perceptions are integral to predicting their fears about AI in a given occupation, and people may have a psychological checklist to signify whether the potential of AI satisfies their requirements for an occupation.

We therefore posit an integrative psychological model for fears about AI: When AI is introduced into a new job, a person evaluates the humanlike traits needed for that job against AI's capability to mimic those traits, and the level of fears corresponds to the mismatch between these evaluations. Our model is consistent with recent reviews on the mind-role fit perspective: In both professional and personal domains,

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people's reactions to machine replacement depend on the fit between the perceived mind of the machine and their ideal conception of the mind deemed suitable for that particular role (Yam et al., 2024). As such, different occupations may elicit different psychological expectations; different individuals may also perceive the capacities and limitations of AI differently, for example, in that AI can make moral decisions (Bigman & Gray, 2018; Bonnefon et al., 2024) and that AI reproduces human bias and discrimination (Bigman et al., 2021; Jago & Laurin, 2022). Together, the perception that AI may fail to live up to expectations would predict fears about AI for different occupations and individuals.

Fears of AI may also vary at the country level, given the systematic variations in the traits that people require for an occupation (Cuddy et al., 2009; Fiske & Dupree, 2014; Fiske et al., 2007), as well as in their perception of AI's potential to match these traits (Weisman et al., 2021; Yam et al., 2023). Different countries have different traditions of depicting AI as benevolent or malicious, different historical interactions with intelligent machines, and have been exposed to different governmental policies about AI (Mehta & Hamke, 2019; Tortoise, 2021; Yam et al., 2023; Zhang et al., 2021). For example, compared to European Americans, Chinese people place less importance on controlling AI and more on connecting with AI (Ge et al., 2024). Moreover, each specific occupation may raise fear for specific reasons, and these reasons may play out differently in different world regions (Lim et al., 2021; Weisman et al., 2021). For example, U.S. residents are concerned about the ability of medical AI to take into account their unique circumstances as patients (Longoni et al., 2019) or the ability of AI to transparently explain its recommendations (Cadario et al., 2021). U.S. residents are also concerned about the propensity of AI management to reduce their performance to quantifiable metrics (Newman et al., 2020), while participants in Japan and Singapore are concerned about the credibility of AI preachers' faith (Jackson et al., 2023). As a result, we expect that our model would predict country-level variations in AI-related fear by leveraging country-level variations in its two main inputs of occupational requirements and perceived AI potential. Consistently, anxiety about the harmful potential of AI varies across different world regions. Whereas 47% of North Americans are worried about harmful AI, only 25% of Southeast Asians and 11% of East Asians have similar feelings (Neudert et al., 2020).

The Current Research

Through a representative sample survey on 10,000 participants from 20 different countries, we provide a descriptive contribution by documenting cross-national fears about AI in six controversial occupations, as well as cross-national variations in the traits that people require for these occupations and the potential they see for AI to achieve these traits. As results will show, these cross-national variations are in far excess of what would be expected from individual variations alone. This data set goes beyond existing theories and descriptive data, most of which come from Western countries (e.g., Gray et al., 2007; McKee et al., 2023; Waytz et al., 2010), and can provide useful insights when deploying AI in cross-functional roles (Bubeck et al., 2023) or when deployment requires international collaboration and customer-oriented localization (Lim et al., 2021; Yang et al., 2020). More importantly, our results allow us to test the power of a simple, universal psychological model for predicting what level of fear AI will raise when deployed in a specific country and occupation.

Transparency and Openness

We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study, and the study follows Journal Article Reporting Standards (Appelbaum et al., 2018). All data, analysis code, and research materials are publicly accessible at https://osf.io/mb5nz/. Data were analyzed using R, Version 4.3.1. The preregistration can be accessed at https://osf.io/mwbxj.

Method

Overview

To test our model, we surveyed nationally representative samples of participants in 20 countries (see Figure 1B). First, participants rated the requirements of the six occupations displayed in Figure 1A on eight psychological traits (warm, sincere, tolerant, fair, competent, determined, intelligent, and imaginative). Second, they rated the extent to which AI, at its full potential, may display each of these eight psychological

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traits. Third, they rated their fear of seeing AI deployed in each of the six occupations.

As a proof of concept, before the main study, we conducted a pilot study on 971 MTurk participants from India and the United States. The full description of the sample and results of this pilot study can be found in the Supplemental Material. The pilot and main studies (NO. C2021-5 and C2021-5b) were approved by the ethics committee at the Max Planck Institute for Human Development. We preregistered our main study, including the hypothesis, sampling plan, and analysis scripts, on the Open Science Framework (https://osf.io/mwbxj) before commencing data collection.

Participants

Participants were recruited from 20 countries: Australia, Brazil, Canada, China, France, Germany, India, Italy, Japan, Saudi Arabia, Mexico, New Zealand, Nigeria, Russia, Singapore, South Africa, South Korea, Turkey, the United Kingdom, and the United States. As shown in Figure 1B, these countries were selected from each inhabited continent and varied to a great extent in public AI attitudes, governmental readiness, and research and development (Mehta & Hamke, 2019; Zhang et al., 2021), as summarized by their score on the global AI index (Tortoise, 2021).

As specified in the preregistered sampling plan, we recruited representative samples (on age and gender) of $n = 500$ participants from each of the 20 countries (i.e., total $N = 10{,}000$). Before collecting data, we performed 1,000 power simulations with the R package *simr* (Green & MacLeod, 2016), using the parameters from the pilot study and extending the sample structure from $N = 971$ in two countries to $N = 10{,}000$ in 20 countries. The power simulations yielded higher than 99% power (95% CI [99.63, 100.00]) to detect our hypothesized correlation at an α level of .01. Participants were recruited through the panel company Toluna. See Supplemental Table S1 and Figures S1–S3 for details about participants' demographic information. Prior to the survey, participants were asked to provide online informed consent. Participants who did not approve of the consent form or failed to pass any of the attention or comprehension check questions (see the Procedure section) were not permitted to complete the survey or be included in further analyses. Upon completion, participants were compensated financially given local standard rates.

Procedure

Participants were recruited to complete a study on "Impressions of Occupations and Artificial Intelligence" and provided demographic information. The main survey had three parts: (a) psychological requirements, (b) AI potential, and (c) fears about AI. Where the survey was conducted in a non-English-speaking country, study materials (including both the survey contents and the video subtitles) were translated following a forward- and back-translation procedure.

First, participants evaluated the psychological requirements for the six occupations in a randomized order. As shown in Figure 1A, the prospect of deploying AI in all these occupations has raised controversies and public concerns. For each occupation, participants read a short description (as shown below). We referred to occupational definitions from the Cambridge and Merriam-Webster dictionaries and adapted them for cultural generalizability.

- A *journalist* is a person who writes for newspapers, magazines, or news websites or prepares news to be broadcast.
- A *religious worker* is a person who is trained to perform sacred rituals and religious duties.
- A *manager* is a person who is responsible for controlling or administering an organization or group of staff.
- A *care worker* is a person who is employed to support and supervise vulnerable, infirm, or disadvantaged people.
- A *judge* is a person who is appointed by public office to decide cases in a law court.
- A *doctor* is a person who is qualified to treat people who are ill.

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After reading the description of each occupation, participants read the question, "To what extent do you think a good journalist/religious worker/manager/care worker/judge/doctor should be … ?" and indicated their answers on a 100-point scale (ranging from 0 = *not at all* to 100 = *extremely*) regarding the eight traits presented in a randomized order: warm, sincere, tolerant, fair, competent, determined, intelligent, and imaginative. To the best of our knowledge, there is no universally agreed set of traits that could fully describe the psychological requirements of our eight target occupations in a cross-cultural context. However, we selected them based on previous research mapping the space of possible psychological traits (Fiske et al., 2007; Rosenberg et al., 1968), so that they would cover a reasonably large portion of that space and belong to different clusters. Put differently, instead of clustering together to represent higher level facets (e.g., warmth and competence; Fiske et al., 2007; McKee et al., 2023), the traits were processed as unique attributes that are desirable in practical contexts (e.g., fairness for managers, Newman et al., 2020; sincerity for doctors, Cadario et al., 2021). Two attention check questions were inserted: (a) "This question is a little different. Please select the color purple from the list below." (answers: "Orange, Green, Blue, Purple, Yellow"; "Purple" as correct); (b) "Please click on the smallest number displayed." (Answers: "33, 45, 87, 35"; "33" as correct.)

Second, participants watched a 1-min video with English voiceover and subtitles adapted to local languages, which can be accessed at https://tinyurl.com/cultureAIfear. The video depicts what AI is at both abstract and concrete levels. At the abstract level, we described AI as "a technology for making decisions that usually require human intelligence." And at the concrete level, we presented different forms of popular AI applications—including physical ("self-driving car"), virtual ("Siri"), and embedded ("online ads and news feeds") representations (Glikson & Woolley, 2020)—and explained their mechanisms ("trained on massive human dialogues" and "analyzing what contents we click"). After watching the video, participants answered two comprehension check questions: (a) "Can AI be embedded in physical forms like a robot or an autonomous vehicle?" (answers: "yes/no"; "yes" as correct); (b) "Can AI run on a computer, such as a laptop or a server in the 'cloud'?" (answers: "yes/no"; "yes" as correct). They then answered the question, "To what extent do you think AI, at its full potential, can be … ?" on the same eight traits and 100-point scale as before.

Last, following the descriptions of the six occupations presented in a randomized order, participants respectively indicated their own fear of AI ("To what extent are you afraid of AI being … ?") and most other people's fear of AI in their society ("To what extent do you think most people in [participants' country] are afraid of AI being … ?") again on a 100-point scale ranging from 0 = *not at all afraid* to 100 = *extremely afraid.* We selected two countries (South Korea and the United Kingdom) and manipulated the incentive underlying predictions of others' fear. In the nonincentivized condition, participants were simply asked to give their best estimate. In the incentivized condition, participants were also informed that they would receive bonus points that could later redeem gifts for each accurate guess that fell within ±10 of the actual country-average fear about AI. This latter group received the bonuses after the completion of data collection.

Results

Descriptive Statistics: Fear of AI

We report descriptive statistics based on our numerical measures, but our publicly available data set easily allows researchers to convert these measures into ranks—if, for example, they wish to investigate differential scale use across countries or cultural areas (Harzing, 2006). Figure 2 displays the average levels of fear about seeing AI deployed in each occupation in each country. Country-level fears were the highest in India, Saudi Arabia, and the United States (with average fear higher than 64) and the lowest in Turkey, Japan, and China (with average fear lower than 53; see Supplemental Table S2 for specifics). Some patterns are common across countries: For example, AI judges are feared the most or the second-most in all 20 countries, while AI journalists are feared the least or the second-least in 17 countries out of 20.

To assess the magnitude of country-level variations, we performed a bootstrap analysis to compare variations between the real countries in our data set to a sample of 20 synthetic countries. Each synthetic country had 500 observations of the fear raised by each occupation. These observations were sampled randomly (with replacement) from the whole survey population. For example, to construct the distribution of fear

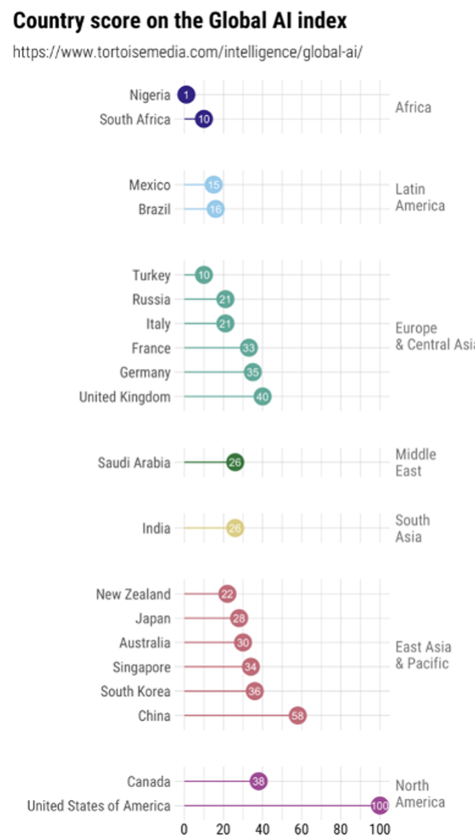
Figure 1

An Overview of the Occupations and Countries in the Present Study

(A)

Doctor AI	Your future doctor may not be human	Futurism
	AI can outperform doctors. So why don't patients trust it?	Harvard Business Review
Judge AI	Can you make AI fairer than a judge? Play our courtroom algorithm game	MIT Technology Review
	New Chinese digital courts see AI judges and verdicts via chat app	The Daily Mail
Manager AI	Robots aren't taking our jobs — they're becoming our bosses	The Verge
	A machine may not take your job, but one could become your boss	The New York Times
Care Worker AI	How is AI revolutionizing elderly care	Forbes
	Would you want a robot to be your relative's carer?	The Guardian
Religious Worker AI	AI will transform religion with robot priests like this one	Vox
	Is Artificial Intelligence a threat to Christianity?	The Atlantic
Journalist AI	The rise of the robot reporter	The New York Times
	The Washington Post's robot reporter has published 850 articles in the past year	Digiday

(B)



Note. (A) Sample media coverage of fears about deploying AI in the six human occupations included in the design. (B) Current AI index of the 20 countries we studied. Scores are based on the current levels of AI implementation, investment, and innovation. The United States ranks first on all three dimensions and thus receives a full score of 100, from which all other countries are benchmarked. AI = artificial intelligence. See the online article for the color version of this figure.

about AI judges in one synthetic country, we randomly sampled (with replacement) 500 observations of the fear about AI judges in the whole survey population, regardless of country of origin. As a result, the 20 synthetic countries provide us with an estimate of the country-level variations that might be expected from individual variations alone. As shown in Figure 3A, the variation between real countries is in far excess of the variation between synthetic countries: Many real countries fall out of the 95% quantiles of the distribution of the synthetic countries. In the 20 synthetic countries, the variance in the fear about AI for the six occupations ranged from 1.0 to 4.2. In the 20 real countries, the variance ranged from 13.2 to 37.1. Full results are available in Supplemental Table S4.

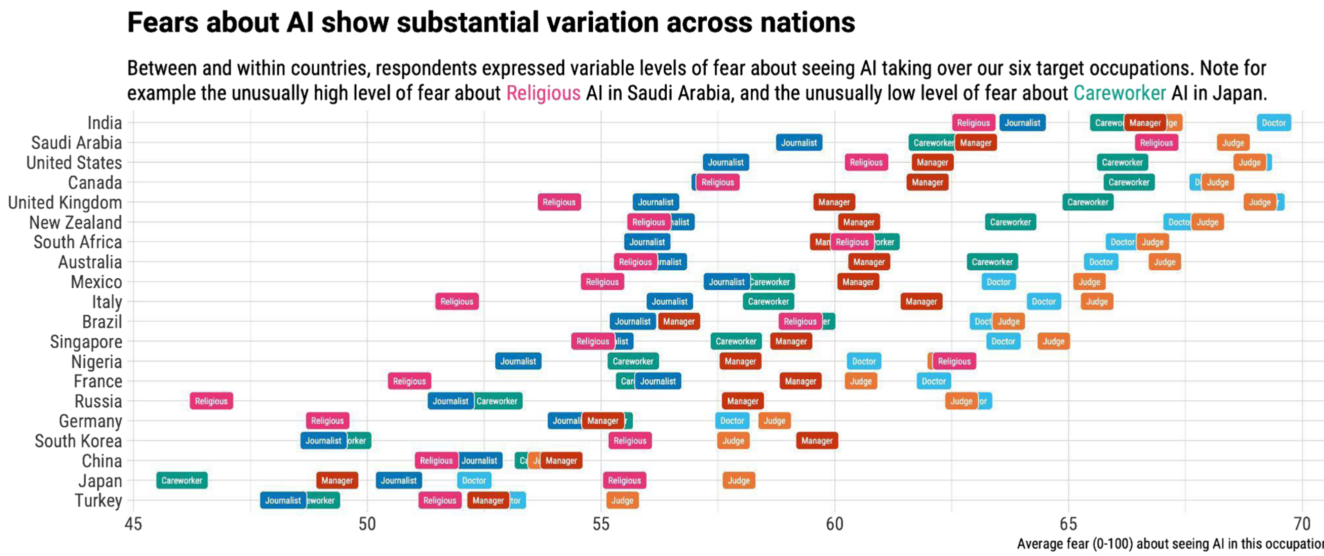
For convergent evidence, we also compared the performance of a model nesting participants within their countries (fear = 1 + (1|country/participant)) to a model without such nesting (fear = 1 + (1|participant)). The chi-square test suggested that the model with country nesting (Akaike information criterion [AIC] = 684,807, Bayesian information criterion [BIC] = 684,844) was significantly better than the model without (AIC = 685,413, BIC = 685,441), $\chi^2(1) = 198.0$, $p < .001$.

Descriptive Statistics: Psychological Requirements and AI Potential

In each country, we asked participants about the degree to which each occupation required each of eight psychological traits. The colored bars in Figure 4 depict participants' responses to these questions in India and in the United States, as an illustration. The full data set is described in the Supplemental Material: While there are some patterns across countries (e.g., care workers should be warm, judges should be fair, doctors should be sincere, journalists should be determined), we observe substantial variations in the psychological traits that people required for various occupations in different countries. To assess the magnitude of these variations, we performed a bootstrap analysis similar to that we conducted for AI fears.

Figure 2

The Average Levels of Fear Expressed in 20 Countries (n = 500 Respondents per Country) About the Deployment of AI in Each of Our Six Target Occupations

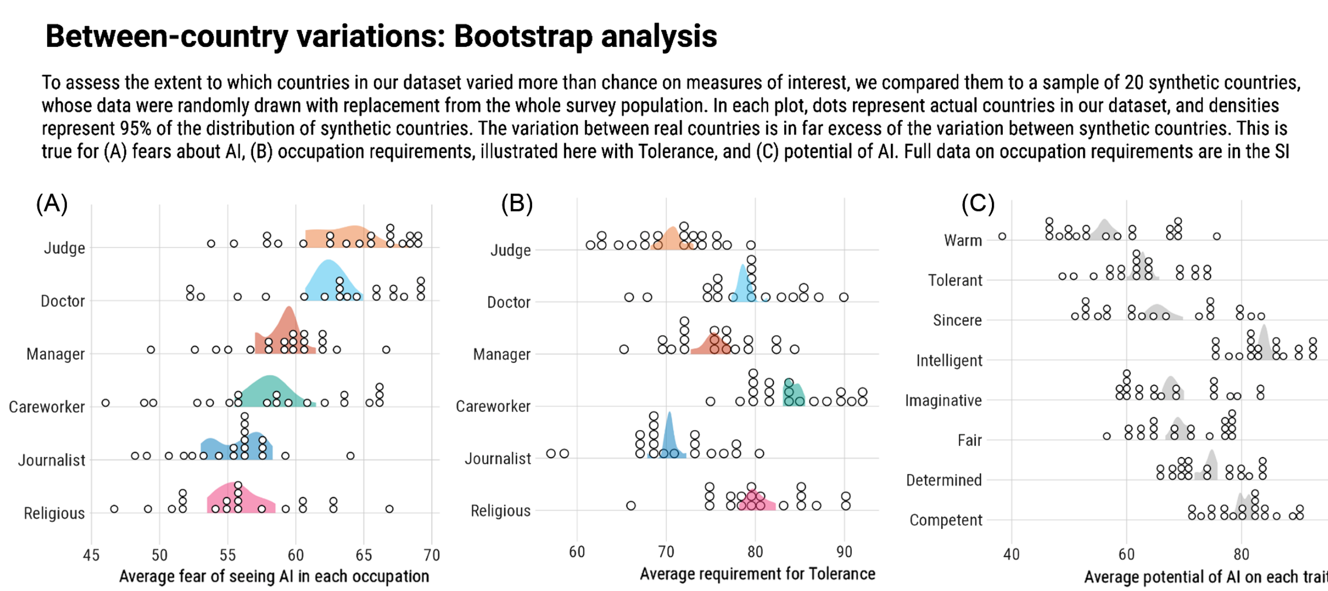


Note. AI = artificial intelligence. See the online article for the color version of this figure.

Figure 3B illustrates the results for the trait tolerance; full results are available in Supplemental Table S4 and Figure S5. Just as in the case of AI fears, the variance observed in real countries was in excess of the variance observed in synthetic countries. Many real countries fall outside the 95% quantile of the synthetic countries distribution. In the 20 synthetic countries, the variance in requirements ranged from 0.4 to 2.6. In the 20 real countries, the variance ranged from 14.8 to 65.1. Furthermore, for each occupation, the model with country nesting (requirement = 1 + (1|country/participant); AIC = 698,367, BIC = 698,404) significantly outperformed the model without (requirement = 1 + (1|participant); AIC = 699,240,

Figure 3

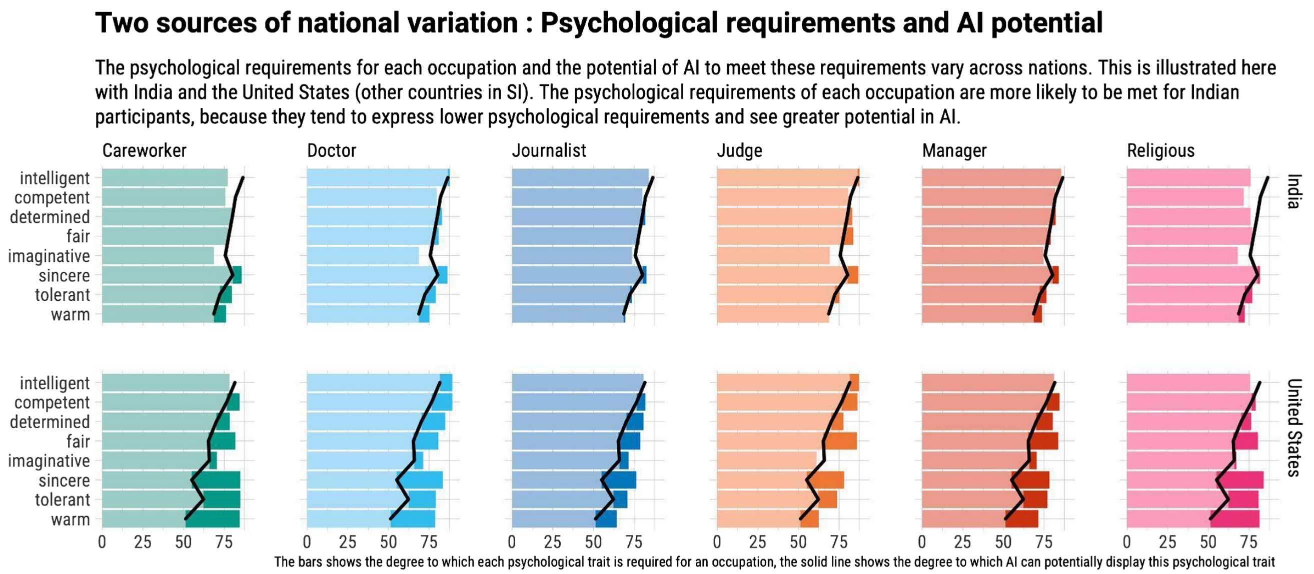
Bootstrap Analyses That Show Substantial Country Variations Across the Measures of Fears About AI, Psychological Requirements, and AI Potential



Note. AI = artificial intelligence; SI = supplementary information. See the online article for the color version of this figure.

Figure 4

Comparison Between the Perceived Potential of AI to Display Each of the Eight Psychological Traits and the Degree to Which Each of These Traits Is Perceived to be Required for Each Occupation



Note. For the sake of simplicity, only data from India and the United States are shown here (see Supplemental Figure S4 for a full display of the 20 countries). AI = artificial intelligence; SI = supplementary information. See the online article for the color version of this figure.

BIC = 699,268), $\chi^2(1) = 870.78$, $p < .001$. Full results are available in Supplemental Table S5.

Participants also indicated the potential of AI to display each of the eight traits. This AI potential is shown as a black line in Figure 4, for India and the United States. When a colored bar stays to the left of the black line, it means that the psychological requirement for the relevant trait remains below what people think is achievable by AI. When a colored bar crosses the black line, it means that the psychological requirement for the considered trait exceeds what people think is achievable by AI. Once more, we assessed the magnitude of the observed country-level variations with a bootstrap analysis. Results are shown in Figure 3C. Once more, the variance observed between real countries was in excess of the variance observed between synthetic countries. Many real countries fall outside the 95% quantile of the synthetic countries distribution. In the 20 synthetic countries, the variance in potential ranged from 0.8 to 3.3. In the 20 real countries, the variance ranged from 31.5 to 120.5 (see also Supplemental Table S4). Furthermore, the model with country nesting (AI potential = 1 + (1|country/participant); AIC = 4,285,082, BIC = 4,285,126) was significantly better than the model without (AI potential = 1 + (1|participant)); AIC = 4,286,065, BIC = 4,286,098), $\chi^2(1) = 981.23$, $p < .001$.

Model Testing: Individual Level (Preregistered)

As specified in our preregistration, we fitted the following mixed model using the lme4 R package (Bates et al., 2014): Fear = Match + (1|country/participant), where *Fear* is the fear expressed by a given participant about a given occupation, *Match* is the number of psychological requirements that are potentially met by AI for this occupation according to this participant, and the last term stands for random intercepts for each country and participant, participants being nested within countries. The *Match* variable is an integer between 0 and 8. It takes the value zero for a given occupation and participant if this participant rated the potential of AI on every trait as lower than its required value for that occupation. It would take the value 1 if this participant had rated the potential of AI on a trait as equal or greater than its required value for one single trait out of 8; and so on (see Supplemental Table S3 for the proportion of AI's matched psychological requirements for each occupation's each trait in the 20 countries).

This model showed a good fit to the data—in particular, and in line with our preregistered prediction, we detected a negative and significant relation between the Match variable and the Fear variable ($\beta = -0.06$, $t = -12.92$, $p < .001$, 95% CI [−0.07, −0.05], Nakagawa's $R^2 = 0.004$). Generally speaking, each occupational psychological requirement satisfied by AI is related to the decrease of fear about AI in this occupation by about 1 point. Given the large sample size, we also fitted the mixed model following the Bayesian approach using the R packages rstanarm (Goodrich et al., 2020) and bayestestR (Makowski et al., 2019; see Supplemental Table S6 for specific parameters of the posterior distribution). The Bayesian model again strongly supported the significant association between Match and Fear with a $BF_{10} > 10{,}000.00$, suggesting that the data were 10,000 times more probable under our hypothesis than the null hypothesis.

Our model demonstrated unique advantages over other alternative models, based on a series of robustness checks (see Supplemental Table S7 for a summary). First, none of people's psychological requirements ($\beta = 0.03$, $t = 27.67$, $p < .001$, 95% CI [0.03, 0.03], Nakagawa's $R^2 = 0.001$; in the model: Fear = Requirement + (1|country/participant)), their perceived AI potential ($\beta = 0.03$, $t = 1.58$, $p = .115$, 95% CI [<0.01, <0.01], Nakagawa's $R^2 < 0.001$; in the model: Fear = AI potential + (1|country/participant)), or both as predictors (Nakagawa's $R^2 = 0.001$; in the model: Fear = Requirement + AI potential + (1|country/participant)), were more successful regarding the variance explained. Second, even after controlling for people's psychological requirements ($\beta = 0.12$, $t = 18.02$, $p < .001$, 95% CI [<0.10, 0.13]) and perceived AI potential ($\beta = 0.08$, $t = 7.95$, $p < .001$, 95% CI [0.06, 0.10]), the prediction of the Match variable remained significant ($\beta = -0.03$, $t = -3.92$, $p < .001$, 95% CI [−0.04, −0.01]; in the model: Fear = Requirement + AI potential + Match + (1|country/participant)). Third, to test the robustness of our model across different occupations, we added the random intercept for occupation to our original model (i.e., Fear = Match + (1|country/participant) + (1|occupation)), in which Match variable remained as a significant predictor ($\beta = -0.04$, $t = -8.14$, $p < .001$, 95% CI [−0.05, −0.03], Nakagawa's $R^2 = 0.002$). We additionally explored occupation as a fixed-factor predictor. The model did not converge, but after removing the random intercept for occupation, the simplified model showed that the match effect was still significant ($\beta = -0.04$, $t = -8.12$, $p < .001$, 95% CI [−0.05, −0.03]). And the occupations significantly differed from each other in fear levels ($p < .01$).

Model Testing: Country Level (Exploratory)

Our preregistered model testing revealed that the correlation between Match and Fear holds for individuals across different countries. The next step is to perform the same analysis at the country level to show that the aggregated number of Matches for a given occupation in a given country predicts the fear expressed about AI for this occupation in this country. Figure 5 displays the relation between the Match and Fear variables in each country, binning data by occupation (this visualization was included in the preregistration). At the country level, the model Fear = Match + (1|country)) reveals a strong association between Match and Fear ($\beta = -0.94$, $t = -8.22$, $p < .001$, 95% CI [−1.16, −0.71], Nakagawa's $R^2 = 0.40$). Note, in particular, the variance explained by this model is much greater than the variance explained by the individual model.

Figure 5 also points to a few interesting anomalies. First, three countries of 20 do not show a correlation in the expected direction: China, Japan, and Turkey. These three countries also happen to be the ones in which fears of AI are the lowest. However, we will refrain from speculating about this result too much, though, since it is expected (given statistical fluctuations) that we would find a few exceptions to the general pattern when testing a model across 20 nations. Furthermore, Figure 5 indicates that our model typically and substantially underestimates fear about judge AIs. This suggests that people's concerns in this sector are largely driven by factors that our model fails to capture.

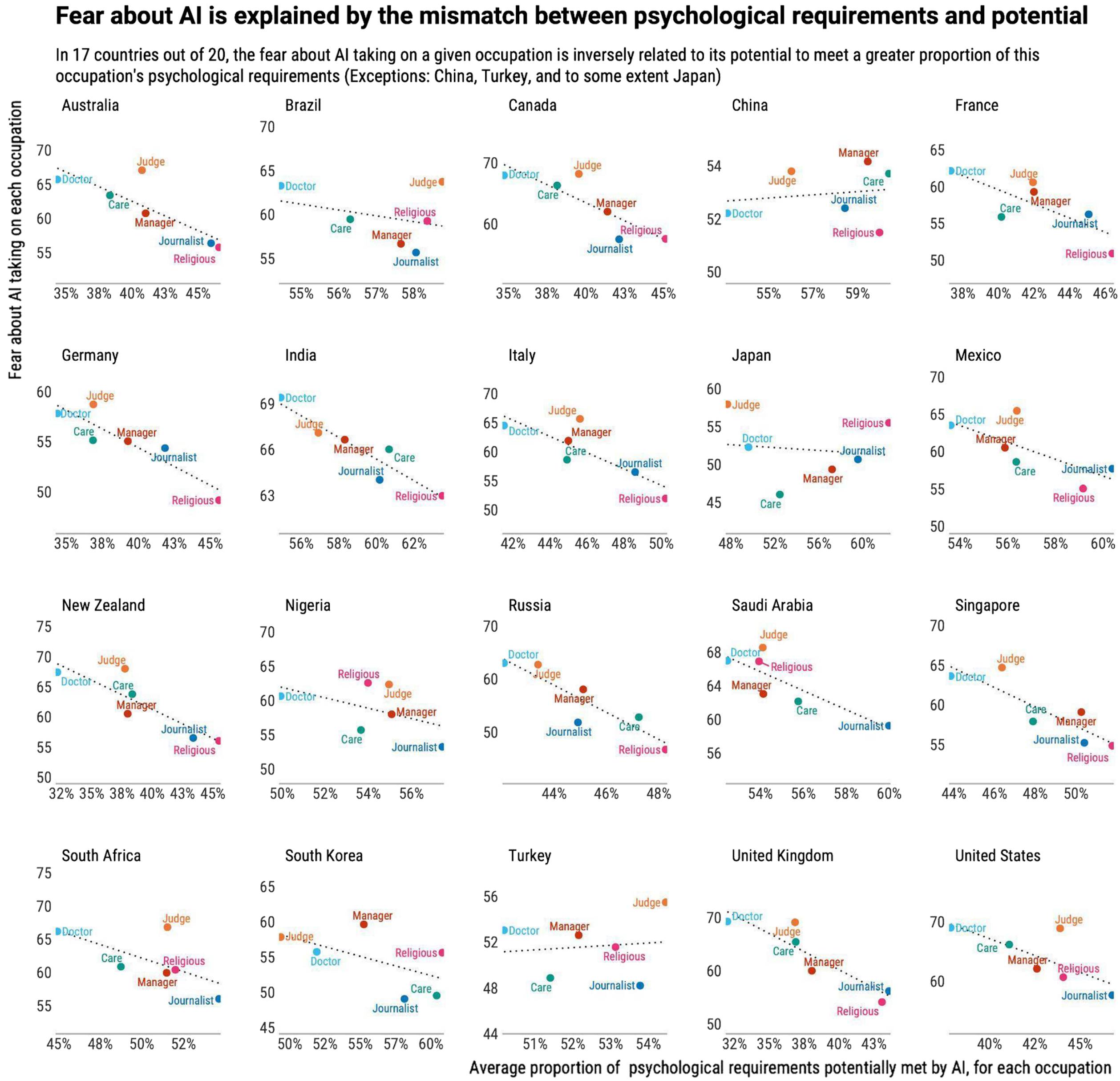
We performed similar robustness checks for the country-level model as in the individual-level analyses (see Supplemental Table S8 for a summary). First, none of people's psychological requirements ($\beta = 0.63$, $t = 5.86$, $p < .001$, 95% CI [0.42, 0.84], Nakagawa's $R^2 = 0.285$; in the model: Fear = Requirement + (1|country)), their perceived AI potential ($\beta = 0.01$, $t = 0.08$, $p = .936$, 95% CI [−0.32, 0.35], Nakagawa's $R^2 < 0.001$; in the model: Fear = AI potential + (1|country)), or both as predictors (Nakagawa's $R^2 = 0.267$; in the model: Fear = Requirement + AI potential + (1|country)) were more successful regarding the country-level variance explained. Second, the country-level correlation between Match and Fear remained significant after controlling for psychological requirements and AI potential ($\beta = -2.15$, $t = -7.41$, $p < .001$, 95% CI [−2.73, −1.58]; in the model: Fear = Requirement + AI potential + Match + (1|country)). Third, after adding the random intercept for occupation, Match remained as a significant predictor ($\beta = -0.42$, $t = -3.27$, $p = .002$, 95% CI [−0.67, −0.17], Nakagawa's $R^2 = 0.152$; in the model: Fear = Match + (1|country) + (1|occupation)). We additionally explored occupation as a fixed-factor predictor. Again, the model did not converge, but after removing the random intercept for occupation, the simplified model showed that the match effect was still significant ($\beta = -0.36$, $t = -2.79$, $p = .007$, 95% CI [−0.62, −0.11]). Except for the similar fear of AI journalists and religious workers ($p = .30$), other occupations significantly differed from each other in fear levels ($p < .01$).

Ancillary Results

For exploratory purposes, we asked respondents to rate the fear that other people felt in their country about seeing AI deployed in each occupation (see Supplemental Table S9 for descriptive information). This allowed us to assess how calibrated people were about the state of concerns in their home country. Results suggest that people found this question quite difficult. In a nutshell, people strongly anchored on the fear that they themselves felt (the correlation between the two measures ranged from .49 in South Africa to .74 in China; see Supplemental Table S10 for details) and slightly adjusted upward, with the result that most people overestimated the average level of fear in their country (from 51% responses in China to 64% in Nigeria). Note that in two countries (South Korea and the United Kingdom), we offered half the sample a financial incentive for accuracy, which did not significantly

Figure 5

Fears of AI in the 20 Countries as a Function of the Proportion of AI's Matched Psychological Requirements Across the Six Occupations



Note. AI = artificial intelligence. See the online article for the color version of this figure.

improve calibration (β = −0.02, *t* = −0.89, *p* = .37, 95% CI [−0.07, 0.02]; see Supplemental Material for detailed data and results).

We also explored whether various country-level social and economic indices would correlate with fears about AI for different occupations. For this analysis, we used the AI index depicted in Figure 1B, as well as the rule of law, gross domestic product, religiosity, cultural looseness, relational mobility (all featured in Awad et al., 2018), and Hofstede cultural dimensions (i.e., individualism, power distance, masculinity, long-term orientation, and indulgence; Hofstede, 2011). None of these correlations was significant for any of the six occupations (see Supplemental Figure S7).

General Discussion

The frontier of AI is constantly moving, raising fears and concerns every time machines are deployed in an occupation that used to be reserved for humans (Bigman & Gray, 2018; Dong et al., 2024; Hudson et al., 2017; Jackson et al., 2023;

Longoni et al., 2019; Perc et al., 2019). As with many other novel technologies, people are concerned about technological deficiencies, such as AI's biases and mistakes, controllability and transparency, and invasion of privacy and autonomy (De Freitas et al., 2023; Li & Huang, 2020; Mahmud et al., 2022). Many of these fears are also related to personal circumstances, such as education and knowledge, job replacement, and discrimination (Bigman et al., 2021; Jago & Laurin, 2022; Li & Huang, 2020; Liang & Lee, 2017). Importantly, people often apply their standards for humans to AI—but not most other technologies—and reject AI in situations where it fails to present certain psychological traits as human experts do (Bonnefon et al., 2024; De Freitas et al., 2023; Harris-Watson et al., 2023; Kim et al., 2018; Morewedge, 2022). The rejection of AI should be addressed, especially when AI can produce societal benefits. For example, whereas AI chatbots can help more people access mental health services (Habicht et al., 2024), people are not easily satisfied with the empathetic traits AI possesses as compared to human therapists (Yin et al., 2024). Then, how good would it be good enough for AI to have psychological traits? And to what extent can the psychological capabilities account for public fear of AI?

While important progress can be achieved piecemeal by studying the fear that participants from a single country have about a single application of AI, a useful step would be to formulate and test a model that would predict the fear that participants from different countries would have about the introduction of AI in different occupations. Whereas most previous studies examined the acceptance of AI in a specific domain among people from one or a few Western countries, it is increasingly realistic that one AI system can serve cross-functional roles (Bubeck et al., 2023), or its deployment requires global collaboration or customer-oriented localization (Lim et al., 2021; Yang et al., 2020). However, the process of AI taking over human tasks and occupations is unfolding at a pace and at a scale that makes it seemingly impossible to predict how citizens of one country or another will react to the deployment of AI in one new occupation or another. Even if we know how much French people fear AI doctors, we may find it hard to predict how much they will fear AI managers—and knowing about the fears of French people is hardly helpful when trying to predict the fears of people in Japan.

Indeed, our data collected from 20 representative samples (total $N = 10{,}000$) showed cross-national variations in the average fear that people felt about seeing AI deployed in new occupations—as well as variations in the way different occupations ranked in the fears expressed by each nation. What we proposed and tested in this article is that there is an underlying psychological structure to these variations, which can accordingly be predicted by a psychological model applied across nations and occupations. After measuring the psychological traits that people from 20 nations deemed necessary for each of six occupations (doctors, judges, managers, care workers, religious workers, and journalists) and the expectations they had about the potential of AI to display these traits, we were able to predict the fear they had about seeing AI deployed in these occupations, using the same statistical model in every nation.

Theoretical Implications

The psychological model we document in this article advances previous research in at least three important ways. First, we present a partial but useful picture of the requirements that people from different countries can have for different occupations. Though these requirements leave out some nuanced technological capabilities that people desire for a particular occupation in a particular country, they can provide a set of generalizable standards across countries and AI roles. The psychological and technological capabilities of AI may not be independent, though. For example, for AI to be intelligent and competent, it may be translated into technical requirements for accuracy, efficiency, adaptability, and explainability across many domains of application. But under the hood of being competent and fair, different domains may also have different performance metrics for defining what competence and fairness mean (Bonnefon et al., 2024; Mehrabi et al., 2021).

Second, we document people's perceptions of AI on eight psychological traits across 20 countries. Though numerous studies suggest that people like intelligent machines to the extent that they are perceived as humanlike or possessing humanlike psychological traits, most of these studies were conducted in Western countries (De Freitas et al., 2023; Mahmud et al., 2022; Waytz et al., 2010). Interestingly, when we applied these psychological traits to more culturally diverse samples, perceived AI potential did not stand alone to predict public fear of AI at either individual ($p = .115$) or country level ($p = .936$). This null finding again points to the importance of considering both the supply and demand sides of psychological traits to predict cross-domain, cross-nation public reactions to AI.

Last and more importantly, we provide empirical evidence for the unique value of the mind-role fit perspective on human reactions to AI (Yam et al., 2024). Our model distinguished people's psychological requirements from the perceived potential of AI on these requirements, which successfully predicted fears about AI being deployed in an occupation. The link between their mismatch and fear of AI was robust even after controlling for variations of each source independently. This distinction can be potentially useful for interpreting more nuanced reactions to AI, for example, where people like the same described AI in one but not another role (Castelo et al., 2019; Dong et al., 2024; Glikson & Woolley, 2020; Huang & Rust, 2018), or when people prefer AI for a task originally completed by humans (Bigman et al., 2021; Logg et al., 2019).

Practical Implications

Beyond the descriptive value of our data set and the theoretical value of our model, our results can inform the efforts of policymakers to communicate about AI with their citizens in a principled yet culturally sensitive way. If, for example, citizens in a given country are worried about AI doctors because they think AI does not have the high sincerity they expect from human doctors, then policymakers may address this concern by implementing AI in a way that supports rather than replaces human doctors (Longoni et al., 2019) or increasing the transparency required from medical algorithms (Cadario et al., 2021).

We do not mean, however, that policymakers should mislead the public and emphasize human oversight when there are no formal regulations or manipulatively anthropomorphize AI and pretend that it possesses any kind of psychological trait that citizens deem important for an occupation (Shneiderman, 2016). Indeed, our results point to the risk of seeing other stakeholders (such as the companies that create AI or promote its deployment) rely on this anthropomorphization strategy. This could be done either by using language that describes AI as possessing the psychological traits that people require for a given occupation in a given nation or by endowing AI with natural language interfaces (using large language models), which make it easier to frame AI as a social other and use subtle linguistic cues that convey the kind of psychological traits we investigated in this article (Pellert et al., 2024; Safdari et al., 2023). We hope that our results emphasize the need to be vigilant about such communication.

Constraints on Generalizability

Our work validates a psychological model that can potentially predict public fears about artificial intelligence across different countries and domains of application. However, we acknowledge that our empirical test was limited to 20 countries and six domains, which may not necessarily generalize to other countries or domains. Indeed, the model did not seem to predict fear of AI in the expected direction in three out of the 20 countries we studied (i.e., Turkey, China, and Japan). And our choice of occupations was biased toward occupations that would be at least somewhat controversial somewhere and away from occupations that would not be controversial anywhere. As a result, the data we have provide a stronger test of our model for the former sort of occupation than for the latter. It is possible that in cultural and occupational contexts where there is little fear of AI, the psychological requirements and their matching would no longer be a major concern.

To cast a wide range of countries and occupations, we prioritized generalizability over realism and presented simplified descriptive information to participants. Ideally, we should introduce more contextual details (e.g., type of AI, incentive structure, and human–AI interaction dynamics) to approximate the reality of AI being used in each occupation. However, doing so for multiple occupations may introduce uncontrolled variations in the description of each occupation and the way AI would share its duties with humans in each different occupation. We therefore simplified the descriptions so that our model can better generalize across occupational and cultural contexts. Moreover, the psychological model was demonstrated by eight sample traits. Future research may use more detailed descriptions of in-context AI and a larger set of traits to capture a more complete picture of our matching model in specific domains of application.

The robustness checks of our model focused on the psychological constructs, including the psychological traits that people require and the potential for AI to achieve these traits. Even though the mismatch model was proven robust after controlling for each and both of these variables, we did not control for other potential predictors such as anxieties about job displacement, privacy concerns, fears of increased systemic discrimination (Bigman et al., 2021; Cave & Dihal, 2019; Granulo et al., 2019), or more broadly, people's mistrust in science or underlying ideological views (Rutjens & Hornsey, 2024). We therefore could not infer the extent to which our model can predict AI-related fears over and beyond these factors that we did not measure. For future research, it would be interesting to develop a more complete picture of antecedents to AI-related fears, examining how individual differences, technological capabilities, and psychological perceptions complement or substitute each other.

Given our main focus on fear of AI, the research may have missed out on the positive sentiments around AI. Also, the explicit questions regarding fears about AI may have primed respondents' negative feelings about AI and even cause an overestimation of fear levels. In real life, people may hold both hopes and fears regarding AI across many domains and countries, but for different reasons. They may also evaluate the realistic trade-offs of the positive and negative sides and show more nuanced attitudinal or behavioral reactions to the deployment of AI. Future research may replicate our findings with more implicit measures of fear or with a more neutral or balanced framing of questions.

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