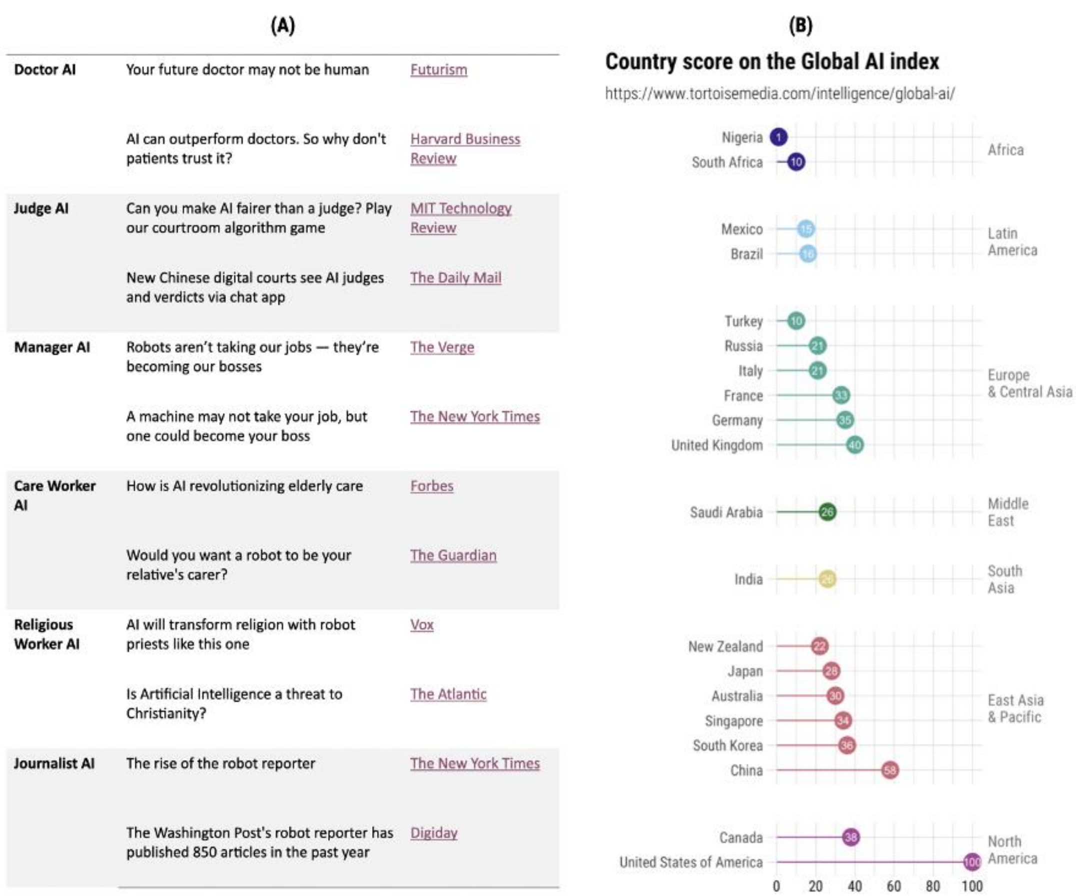
# Fears about Artificial Intelligence across 20 Countries and 6 Domains of Application

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. Fears about AI have not disappeared (Cave & Dihal, 2019; Morewedge, 2022), 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. Figure 1A displays six such occupations, 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?

**Figure 1.** An overview of the occupations and countries in the present study. (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.



(A)

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| **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 |

There are good reasons to be worried about the deployment of AI in new occupational roles: as research in AI ethics repeatedly showed us, whenever AI is deployed in a new occupation, adverse effects can follow (Bigman & Gray, 2018; Dietvorst et al., 2018; Glikson & Woolley, 2020). 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, 2020; Dietvorst et al., 2018). As a result, another important task is to measure, understand, and address the fears and psychological barriers experienced by the public.

The scale of this task can be daunting. First, 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. Second, each specific occupation may raise fear for specific reasons, and these reasons may play out differently in different world regions. Third, different people may have different perceptions of the technical capacities and limitations of AI, which can in turn affect their fear about seeing AI deployed in some occupations.

In sum, there are many different reasons for people in different countries to fear the deployment of AI in different occupations. Despite this, our goal is to show that a relatively simple psychological model can predict AI-related fears across countries and occupations. The model works uniformly at the individual level. In a nutshell, it posits that when AI is introduced into a new job, a person evaluates the human traits needed for that job against AI's capability to mimic those traits. The level of fear corresponds to the mismatch between these evaluations. Critically, while we expect this model to be universally applicable for all individuals and occupations, we also expect country-level variations in the traits that people require for an occupation, as well as in their perception of AI's potential to match these traits. As a result, we expect that our simple, universal psychological model will predict country-level variations in AI-related fear by leveraging country-level variations in its two main inputs.

## Method

### Overview

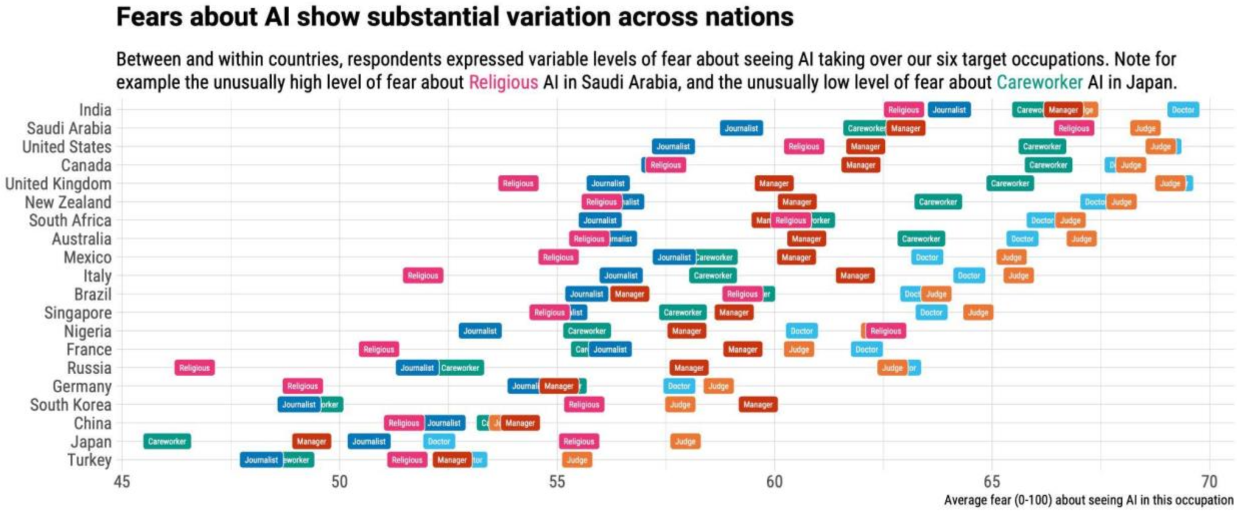
To test our model, we surveyed nationally representative samples of participants in 20 countries (*n* = 500 for each country; see Figure 1B). First, participants rated the requirements of the six occupations displayed in Figure 1A, on eight psychological traits (warm, sincere, tolerant, fair, competent, determined, intelligent, and imaginative). Second, they rated the extent to which AI, at its full potential, may display each of these eight psychological traits. Third, they rated their fear of seeing AI deployed in each of the six occupations. We pre-registered the study, including the hypothesis, sampling plan, and analysis scripts, on the Open Science Framework ([https://tinyurl.com/cultureAIfearPreregister](https://tinyurl.com/cultureAIfearPreregister)), before commencing data collection.

## Results

### Descriptive Statistics: Fear of AI

Figure 2 displays the average levels of fear about seeing AI deployed in each occupation in each country. Country-level fears were highest in India, Saudi Arabia, and the US (with average fear higher than 64) and lowest in Turkey, Japan, and China (with average fear lower than 53). 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.

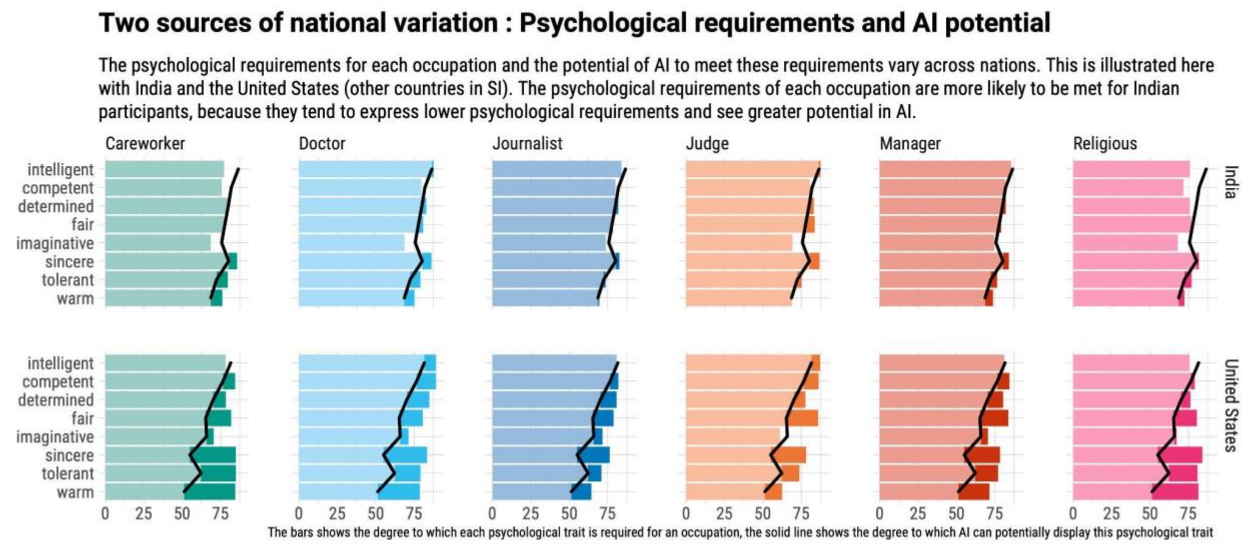
**Figure 2.** The average level of fear expressed in each country (*n* = 500 respondents per country) about the deployment of AI in each of our six target occupations.




### 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 3 depict participants' responses to these questions in India and in the United States, as an illustration. While there are some patterns that show 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. 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 3, for India and the US. 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.

**Figure 3.** 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.




## Model Testing: Individual-Level (Pre-registered)

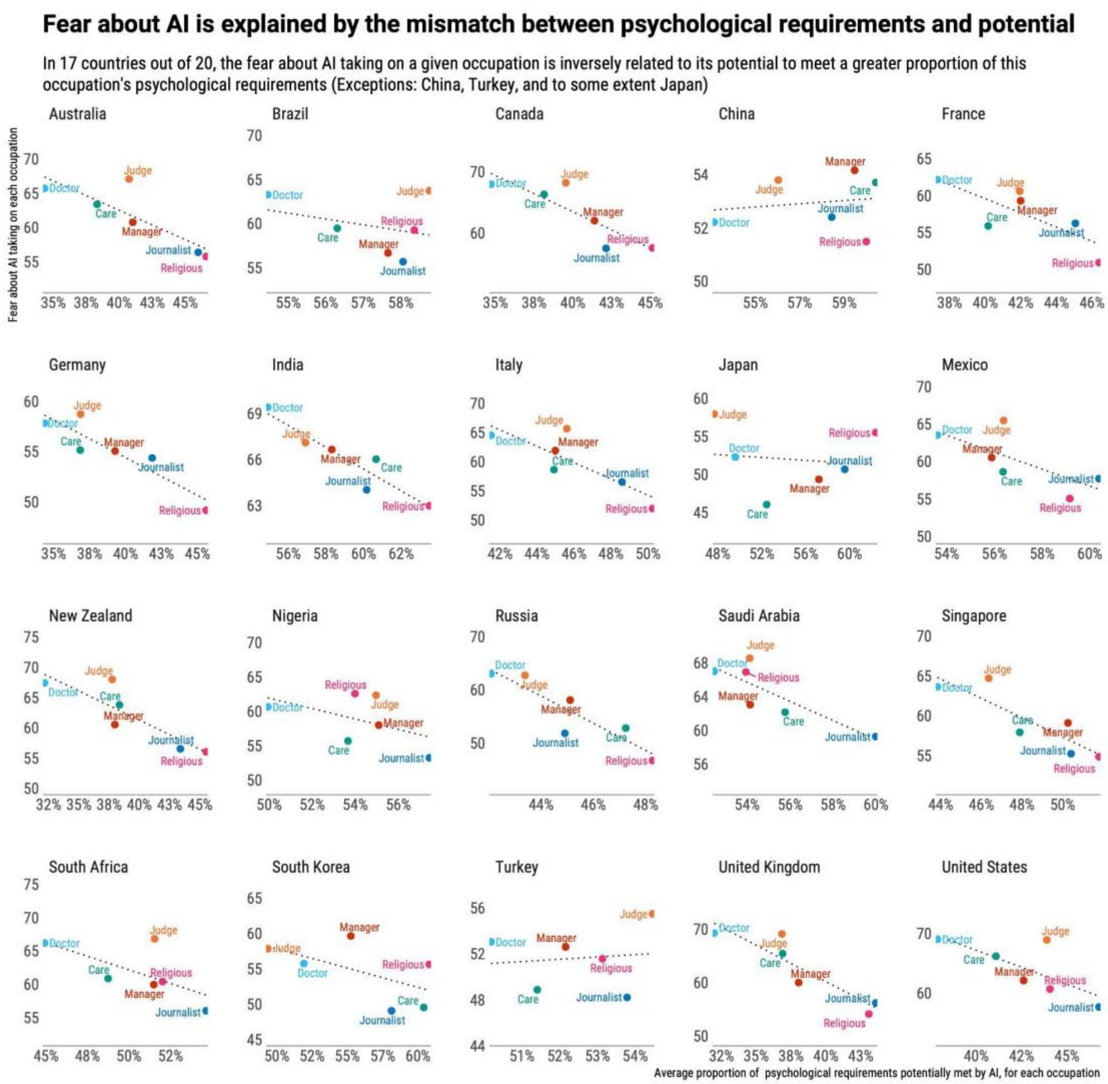
As specified in our pre-registration, we fitted the following mixed model using the lme4 R package (Bates et al., 2014): Fear = Match + (1 | country/participant), where *Fear* is the fear expressed by a given participant about a given occupation, *Match* is the number of psychological requirements that 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. This model showed a good fit to the data – in particular, and in line with our pre-registered 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, for each occupational psychological requirement satisfied by AI, fear about AI in this occupation decreased by about one point.

## Model Testing: Country-Level (Exploratory)

Our pre-registered 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 3 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) detects 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, which is much greater than the variance explained by the individual model. Figure 3 points to a few interesting anomalies. First, 3 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. Finally, Figure 3 also 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.

**Figure 3.** Fears of AI in the 20 countries, as a function of the proportion of AI's matched psychological requirements across the six occupations.



## Discussion

Beyond the descriptive value of our dataset 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, or increasing the transparency required from medical algorithms (Longoni et al., 2019). 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 a social other, and use subtle linguistic cues that convey the kind of psychological traits we investigated in this article. We hope that our results emphasize the need to be vigilant about such communication.

## References

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