

Perceived AI Threat by Coders

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1 Abstract

As AI continues to increase in capabilities it is often heralded as a replacement for many jobs. Particularly, many believe AI will replace entry level software engineering jobs with some companies requiring its use for their employees. The veracity of these claims may be estimated by understanding how much the users of such tools believe their job to be under threat. Additionally an understanding of how this sentiment can vary across countries can

provide insight into the underlying reasoning for such sentiment. Fitting a multilevel model to survey data from stack overflow reveals that more professional coding slightly reduces the likelihood of believing AI to be a threat to one's job. Additionally respondents in similar geographic regions appear to produce similar levels of response likelihood.

2 Introduction

AI, a term typically referring to large language models (LLMs) is often characterized as an immense threat to many entry level jobs. Some companies go in so far as to mandating its use. In particular to software engineering, AI itself is already able to generate code via prompt. This raises the question as to whether software engineering jobs are safe from being replaced. One potential way of measuring this is via proxy: by asking understanding why developers may or may not feel that AI is a threat to their job, this may shed light on both the plausibility of these claims and also insight into new job niches. This paper first assesses the validity of claims relating to AI's capabilities and competence, then proceeds to understand what influences coders to believe AI is a threat, as well as how that differs between countries.

3 Literature Review / Hypothesis

AI is certainly capable, but how much so? In one study it was found that undergraduate students viewed AI feedback as better than human feedback (Zhang et al. 2025). This indicates at least in regards on giving feedback AI is very well equipped, so perhaps has use in response to coding problems or review on a high level. This speaks to the general capabilities of AI perhaps but what about opinion on it and its use. One study before the proliferation of LLMs recently found that people were generally positive about AI as a baseline measurement (Fast and Horvitz 2016). In a slight contrast to this another paper found that people actually have a general amount of concern regarding AI and additionally view it as both superior to and more impartial than humans (Araujo et al. 2020). This would support the assertion that AI may be a threat to not only coder's job but many other jobs. A more moderate finding indicates that AI is too primitive to replace jobs but automation itself has in fact replaced jobs (Thatikonda, n.d.). There is also evidence to indicate. Despite somewhat conflicting evidence it is clear that there is some sentiment by various groups towards AI, and an explaining factor is that increasing education about AI results in less fear about it (Brauner et al. 2024). Logically it follows then that where AI is more prevalent people will be less likely to view AI as a threat. The hypotheses then of this paper are as follows: A: * Coders with more experience will be less likely to view AI as a threat. B: * Coders from countries where AI development and use is more prevalent will be less likely to view AI as a threat.

4 Preprocessing

```
rm(list=ls())
library(tidyverse)
library(sjstats)
library(haven)
library(lme4) #For Estimating MLM
library(arm) #For Retrieving Random Effect SEs in a MLM
library(modelsummary) #For Displaying MLM
library(ggplot2)
library(stargazer)
library(janitor) #Quick cleaning of variable names
library(ggeffects)
library(skimr)
library(sjPlot)
library(glmmTMB)
library(glue)
library(tibble)
library(knitr)
library(html2latex)
data <-
  ↪ read.csv("~/Documents/School/790Q/FinalProject/stack-overflow-developer-survey-2024/survey_data.csv")
```

```
data <- clean_names(data)
```

```
data_clean <- data %>%
  dplyr::select(
    age,
    ed_level,
    country,
    years_code_pro,
    ai_sent,
    ai_complex,
    ai_threat
  )
```

```
data_clean <- data_clean %>%
  filter(!is.na(ai_threat), ai_threat != "I'm not sure")
```

```

ai_sent_map <- c(
  "Very favorable" = 5,
  "Favorable" = 4,
  "Indifferent" = 3,
  "Unfavorable" = 2,
  "Very unfavorable" = 1,
  "Unsure" = NA
)
ai_complex_map <- c(
  "Very well at handling complex tasks" = 5,
  "Good, but not great at handling complex tasks" = 4,
  "Neither good or bad at handling complex tasks" = 3,
  "Bad at handling complex tasks" = 2,
  "Very poor at handling complex tasks" = 1
)
ai_threat_map <- c(
  "Yes" = 1,
  "No" = 0
)

non_responses <- c(
  "Prefer not to say",
  "Something else",
  "I don't know"
)

data_edit <- data_clean %>%
  mutate(ai_sent = as.integer(ai_sent_map[ai_sent])) %>%
  mutate(ai_complex = as.integer(ai_complex_map[ai_complex])) %>%
  mutate(ai_threat = as.integer(ai_threat_map[ai_threat])) %>%
  mutate(across(where(is.character), ~ ifelse(. %in% non_responses, NA, .)))
  ↪ %>%
  mutate(years_code_pro = if_else(years_code_pro == "Less than 1 year", "0",
  ↪   years_code_pro))

data_edit$years_code_pro <- as.numeric(data_edit$years_code_pro)

# Fix Factor Order
data_edit$age <- factor(
  data_edit$age,
  levels = c(
    "Under 18 years old",

```

```

    "18-24 years old",
    "25-34 years old",
    "35-44 years old",
    "45-54 years old",
    "55-64 years old",
    "65 years or older"
  )
)

data_edit$ed_level <- factor(
  data_edit$ed_level,
  levels = c(
    "Primary/elementary school",
    "Secondary school (e.g. American high school, German Realschule or
    ↪ Gymnasium, etc.)",
    "Some college/university study without earning a degree",
    "Associate degree (A.A., A.S., etc.)",
    "Bachelor's degree (B.A., B.S., B.Eng., etc.)",
    "Master's degree (M.A., M.S., M.Eng., MBA, etc.)",
    "Professional degree (JD, MD, Ph.D, Ed.D, etc.)"
  )
)

```

5 Research Design

5.1 Data Overview

The data is the Stack Overflow 2024 developer survey. This survey is conducted yearly and administered to stack overflow users. This means the sample is explicitly contained to stack overflow. That does not necessarily denote professional developers however, and also covered a wide range of anyone who codes. It includes questions about preferred tooling, enjoyment of career and work, and challenges professional coders face. I expect the sample is supposed to generalize to coders, with a general focus on software engineering vs say data workers based on the questions asked.

5.2 Variable Overview

DV: This is whether coders view AI as a threat or not to their current job. It has three options: yes, no, and I'm not sure, with the latter filtered out as a non substantial answer. Since part of the hypothesis proposed here is how the DV varies by country and there are a lot of countries

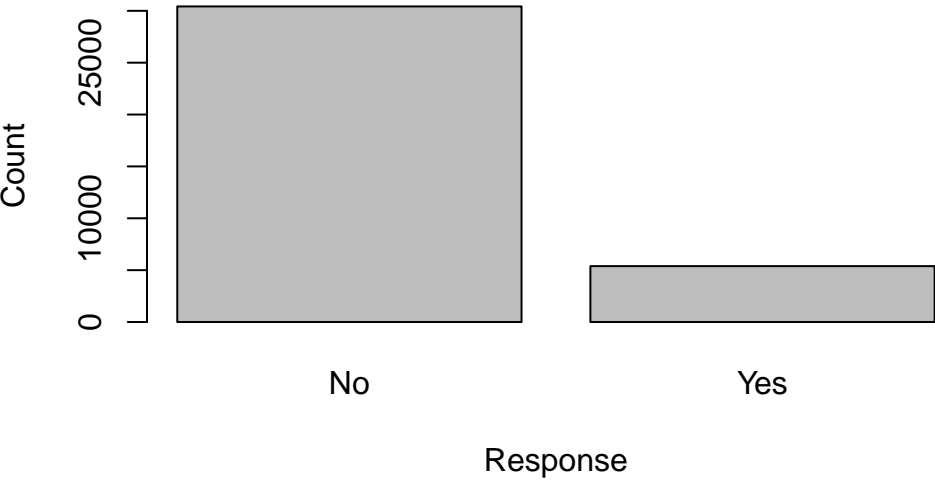
multilevel modeling will be used to estimate the effects of the IVs on the DV. Both an OLS and Logit model will be fit and the better model will be used for interpretation. OLS will be used since it is the traditional and more easily interpretable choice and Logit because the DV is coded as binary after removal of insubstantial responses.

- IVs:
 - Years of coding professionally: A continuous variable denoting how long one has been coding professionally
- Controls:
 - Education Level: categorical / factor ranging from primary school to professional degrees; demographic control
 - Age: categorical / factor, youngest group is <18 oldest is >65; demographic control
 - AI Sentiment: Likert scale 1-5 (actually 6 but unsubstantial). Stance on using AI tools in workflow, higher is more favorable, don't want this as a component of years coding
 - AI Complexity: Likert scale 1-5. How well one respondent trusts AI for complex tasks higher is more favorable; included for the same reason as AI sentiment
- Grouping:
 - Country: country of residence for respondent

Notably the responses for the DV are incredibly imblanaced

```
barplot(table(data_edit$ai_threat), ylab = "Count", xlab = "Response",  
  ↪ names.arg = c("No", "Yes"))  
title("Response to 'Do you believe AI is a threat to your current job'")
```

Response to 'Do you believe AI is a threat to your current j



Mean of AI Threat Responses 0.150456563625702

Variance of AI Threat Responses 0.127822955464472

Number of countries in sample: 181

```
skim(data_edit)
```

Table 1: Data summary

Name	data_edit
Number of rows	35811
Number of columns	7
Column type frequency:	
character	1
factor	2
numeric	4
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
country	957	0.97	4	52	0	180	0

Variable type: factor

skim_variable	n_missing	complete_rate	ordered	n_unique	top_counts
age	108	1.00	FALSE	7	25-: 13650, 35-: 8280, 18-: 7385, 45-: 3505
ed_level	1170	0.97	FALSE	7	Bac: 14728, Mas: 9174, Som: 4334, Sec: 3116

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
years_code_pro	5210	0.85	9.84	8.75	0	3	7	14	50	
ai_sent	969	0.97	3.90	0.88	1	3	4	4	5	
ai_complex	6780	0.81	2.81	1.12	1	2	3	4	5	
ai_threat	0	1.00	0.15	0.36	0	0	0	0	1	

```
icc_mod_lm <- lmer(  
  ai_threat ~ +  
    (1 | country),  
  data = data_edit  
)
```

```
icc_mod_logit <- glmer(  
  ai_threat ~ +  
    (1 | country),  
  data = data_edit,  
  family = binomial(link = "logit")  
)
```

5.3 Interclass Correlation


```

tab_model(
  transform = NULL,
  icc_mod_lm,
  icc_mod_logit,
  title = "ICC Models",
  dv.labels = c("Linear Model", "Logit Model"),
  show.icc = T,
  file = "temp1.html"
)

```

ICC Models						
Predictors	Linear Model			Logit Model		
	Estimates	CI	p	Log-Odds	CI	p
(Intercept)	0.16	0.15 – 0.17	<0.001	-1.71	-1.80 – -1.62	<0.001
Random Effects						
σ^2	0.12			3.29		
τ_{00}	0.00	country		0.16	country	
ICC	0.02			0.05		
N	180	country		180	country	
Observations	34854			34854		
Marginal R ² / Conditional R ²	0.000 / 0.024			0.000 / 0.046		

With extremely low interclass correlation (ICC) values, varying intercept is what will be used for the multilevel model. Low ICC indicates that there isn't much variance between groupings indicating MLM isn't strictly necessary, however using it will make country differences much more interpretable.

5.4 Model Fitting

```
lm_mod <- lmer(
  ai_threat ~
    age +
    ed_level +
    years_code_pro +
    ai_sent +
    ai_complex +
    (1|country),
  data = data_edit
)
```

```
logit_mod <- glmmTMB(
  ai_threat ~
    age +
    ed_level +
    years_code_pro +
    ai_sent +
    ai_complex +
    (1|country),
  data = data_edit,
  family = binomial(link = "logit")
)
```

5.5 Linear vs Logit Model Comparison

```
tab_model(
  transform = NULL,
  lm_mod,
  logit_mod,
  title = "Varying Intercept Models for Perceived AI Threat by Stack Overflow
  ↪ Developers",
  dv.labels = c("Linear Model Varying Intercept (AI Threat)", "Logit Model
  ↪ Varying Intercept(AI Threat)"),
  pred.labels = c(
    "(Intercept)",
    "18-24 Years Old",
    "25-34 Years Old",
  )
)
```

```
"35-44 Years Old",  
"45-54 Years Old",  
"55-64 Years Old",  
"65 Years or Older",  
"Secondary School",  
"Some College",  
"Associate",  
"Bachelor's",  
"Master's",  
"Professional Degree",  
"Years Coding Professionally",  
"AI Sentiment",  
"Trust in AI for Complex Tasks"  
)  
show.loglik = T,  
show.aic = T,  
show.r2 = F  
)
```

Varying Intercept Models for Perceived AI Threat by Stack Overflow Developers

<i>Predictors</i>	Linear Model Varying Intercept (AI Threat)			Logit Model Varying Intercept(AI Threat)		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>	<i>Log-Odds</i>	<i>CI</i>	<i>p</i>
(Intercept)	0.17	0.10 – 0.24	<0.001	-1.70	-2.22 – -1.18	<0.001
18-24 Years Old	-0.01	-0.06 – 0.04	0.768	-0.05	-0.45 – 0.35	0.811
25-34 Years Old	0.01	-0.04 – 0.06	0.807	0.07	-0.34 – 0.47	0.751
35-44 Years Old	0.04	-0.01 – 0.09	0.141	0.34	-0.07 – 0.76	0.103
45-54 Years Old	0.07	0.01 – 0.12	0.019	0.57	0.13 – 1.01	0.011
55-64 Years Old	0.05	-0.01 – 0.11	0.112	0.38	-0.12 – 0.89	0.140
65 Years or Older	0.04	-0.04 – 0.13	0.310	0.26	-0.54 – 1.06	0.522
Secondary School	-0.05	-0.10 – 0.01	0.093	-0.33	-0.73 – 0.07	0.110
Some College	-0.05	-0.10 – 0.00	0.054	-0.37	-0.77 – 0.02	0.062
Associate	-0.04	-0.10 – 0.02	0.164	-0.28	-0.71 – 0.15	0.197
Bachelor's	-0.06	-0.11 – -0.01	0.031	-0.42	-0.80 – -0.03	0.034
Master's	-0.07	-0.12 – -0.01	0.014	-0.49	-0.88 – -0.10	0.014
Professional Degree	-0.10	-0.15 – -0.04	0.001	-0.79	-1.22 – -0.36	<0.001
Years Coding Professionally	-0.00	-0.00 – -0.00	<0.001	-0.03	-0.03 – -0.02	<0.001
AI Sentiment	-0.00	-0.01 – 0.00	0.354	-0.02	-0.07 – 0.03	0.402
Trust in AI for Complex Tasks	0.02	0.01 – 0.02	<0.001	0.15	0.11 – 0.19	<0.001
Random Effects						
σ^2	0.12			3.29		
τ_{00}	0.00 country			0.13 country		
ICC	0.02			0.04		
N	168 country			168 country		
Observations	24208			24208		
AIC	17348.314			19356.142		
log-Likelihood	-8656.157			-9661.071		

5.6 Top and Bottom 5 Countries by Intercept

```
country_re <- round(ranef(lm_mod)$country, digits = 3)

country_re_df <- as_tibble(country_re, rownames = "country")

ordered_re <- country_re_df %>%
  arrange(desc(`(Intercept)`))

ranked_re <- ordered_re %>%
  mutate(rank = row_number())

bottom_5_ranked <- head(ranked_re, 5)
top_5_ranked <- tail(ranked_re, 5)
```

```
top_bottom_10_ranked <- bind_rows(top_5_ranked, bottom_5_ranked) %>%
  arrange(rank)

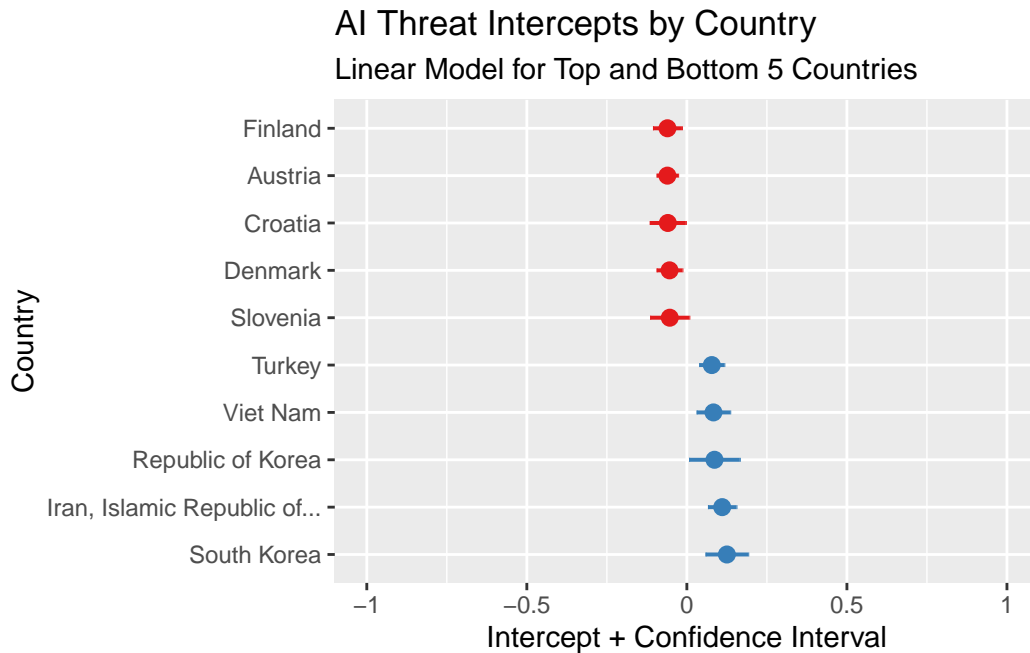
kable(top_bottom_10_ranked, caption = "Top and Bottom 5 Country Intercepts")
```

Table 5: Top and Bottom 5 Country Intercepts

country	(Intercept)	rank
South Korea	0.125	1
Iran, Islamic Republic of...	0.110	2
Republic of Korea	0.086	3
Viet Nam	0.083	4
Turkey	0.078	5
Slovenia	-0.053	164
Denmark	-0.054	165
Croatia	-0.060	166
Austria	-0.061	167
Finland	-0.061	168

5.7 Intercept Graph

```
sjPlot::plot_model(lm_mod, type="re", terms = selected_countries) +
  scale_x_discrete(limits=top_bottom_10_ranked$country) +
  ggtitle(label = "AI Threat Intercepts by Country", subtitle = "Linear Model
  ↪ for Top and Bottom 5 Countries") +
  ylab("Intercept + Confidence Interval") +
  xlab("Country")
```



6 Results / Interpretation / Conclusion

6.1 Models

Looking at the model results it is clear from both the lower AIC and log-Likelihood that the linear model is a better model, which is somewhat surprising given the output is a binary variable. This may be due to the very imbalanced responses. Regardless in both models the same variables are significant. Someone aged 45-54 years old is more likely to view AI as a threat as compared to someone <18 years old with that amount being 0.07 of an increase holding all other variables constant. Additionally, somewhat consistently with the literature more educated people are less likely to view AI as a threat as compared to those with a primary school education. Those who trust AI for complex tasks are also significantly more likely to view AI as a threat holding all other variables constant (intercept of 0.02). This somewhat intuitively makes sense; if one believes AI to be competent at complex tasks then they will view it as more of a threat to their job. The IV of interest to the hypothesis, years coding professionally, proves to be significant and also a nearly zero effect. Someone who has more years coding professionally is less likely to view AI as a threat holding all other variables constant but the effect is *extremely* small. This to some extent supports the postulated hypothesis but the effects are so small that it's essentially meaningless. The intercept is also statistically significant which is good for the varying intercept portion of the model.

6.2 Table

The table shows an interesting trend. The table about denotes the top and bottom 5 country intercepts. Interestingly there seems to be some amount of regional similarity between the two groups (Asian countries vs Northern European), although the reasons for this are unclear. This would be an excellent avenue for further research, in addition to mapping trends using the survey from previous years as well. This doesn't really indicate any evidence to support the country hypothesis as neither group really captures any of the large AI players (China, US) at all.

6.3 Conclusions

Using multilevel modeling, on the Stack Overflow Developer Survey from 2024, results for the included variables show that education, years of coding experience, and trust in AI complex tasks have significant effects mostly in the negative direction indicating a lower likelihood to respond that AI is a threat to their job. Multilevel modeling was selected to interpret the many countries that are present in the sample. The actual substantial significance of these effects however is extremely small and nearly negligible, particularly for years of professional coding experience. Additionally between countries there is some interesting variation, however the interpretability of this variation is difficult and requires further research or literature review. Overall these findings are novel and lead to clear further questioning. Including the "I'm not sure" response may provide further insight.

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