What are we learning from language? Associations between gender stereotypes and distributional structure in 25 languages

Supplementary Information

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Contents

This document was created from an R markdown file. The respository for the project can be found here: https://github.com/mllewis/IATLANG/.

NOTE: The SI is intended to be viewed interactively online at https://mollylewis.shinyapps.io/iatlang_SI/.

Description of IAT data

As described in the Main Text, the IAT data come from Project Implicit (https://implicit.harvard.edu/implicit/; Nosek, Banaji, & Greenwald, 2002), for a sample collected 2005 - 2016.

Demographics

N by country

Number of participants by country after exclusions. Our final sample 657,335 participants from 39 countries. Participants were exclude who:

- did not have complete gender, country, age, and implicit IAT measures (53%; the majority of these exclusions (69%) are due to missing IAT data - likely cases where the participant started but did not complete the IAT task).
- had average latencies for either critical block were over 1,800 ms or whose average overall latency was above 1,500 ms (as in Nosek, Banaji, & Greenwald, 2002; 5% of participants with complete data).
- made excess of 25% errors in any single critical block (as in Nosek, Banaji, & Greenwald, 2002; 14% of participants with complete data).
- were from countries with less than 400 participants (1% of remaining participants; in the "Correlations by language exclusion threshold" section below we show analyses with a range of threshold values)

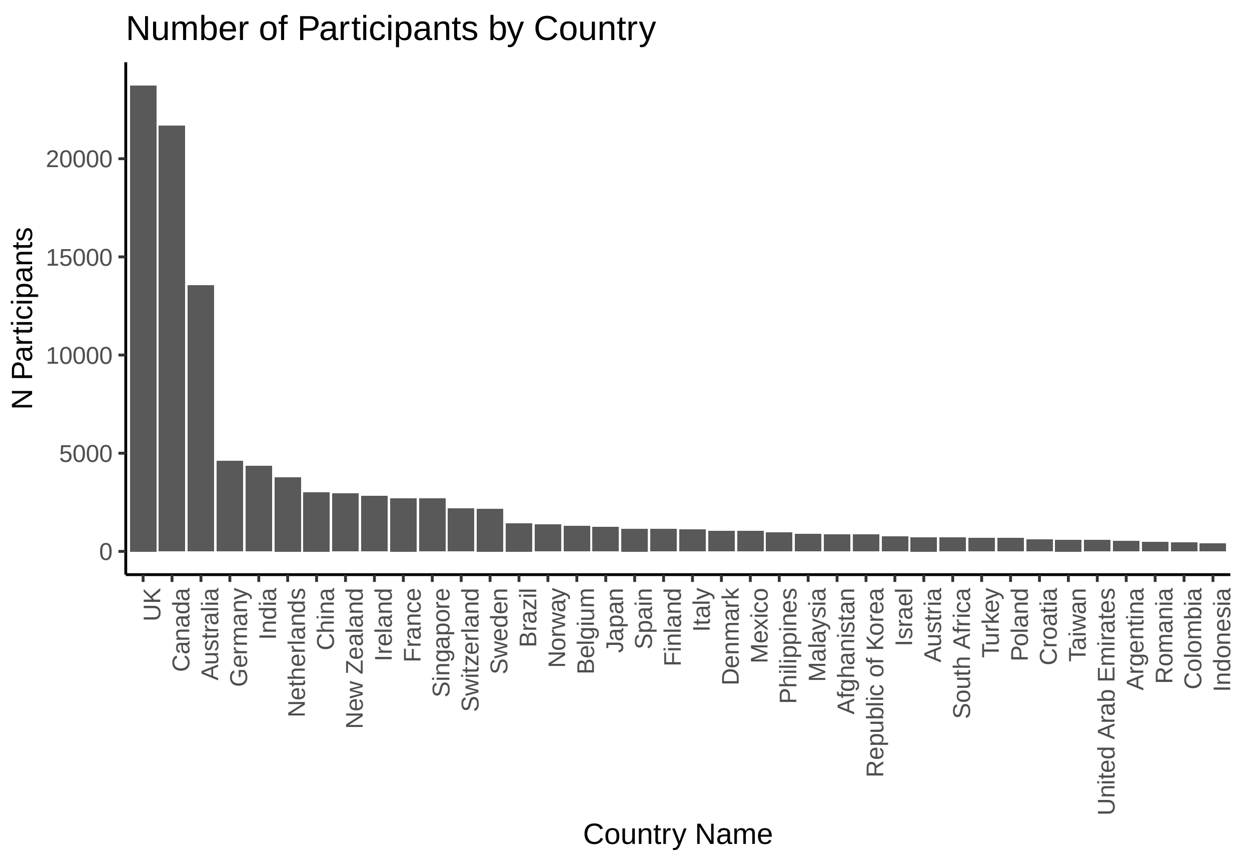
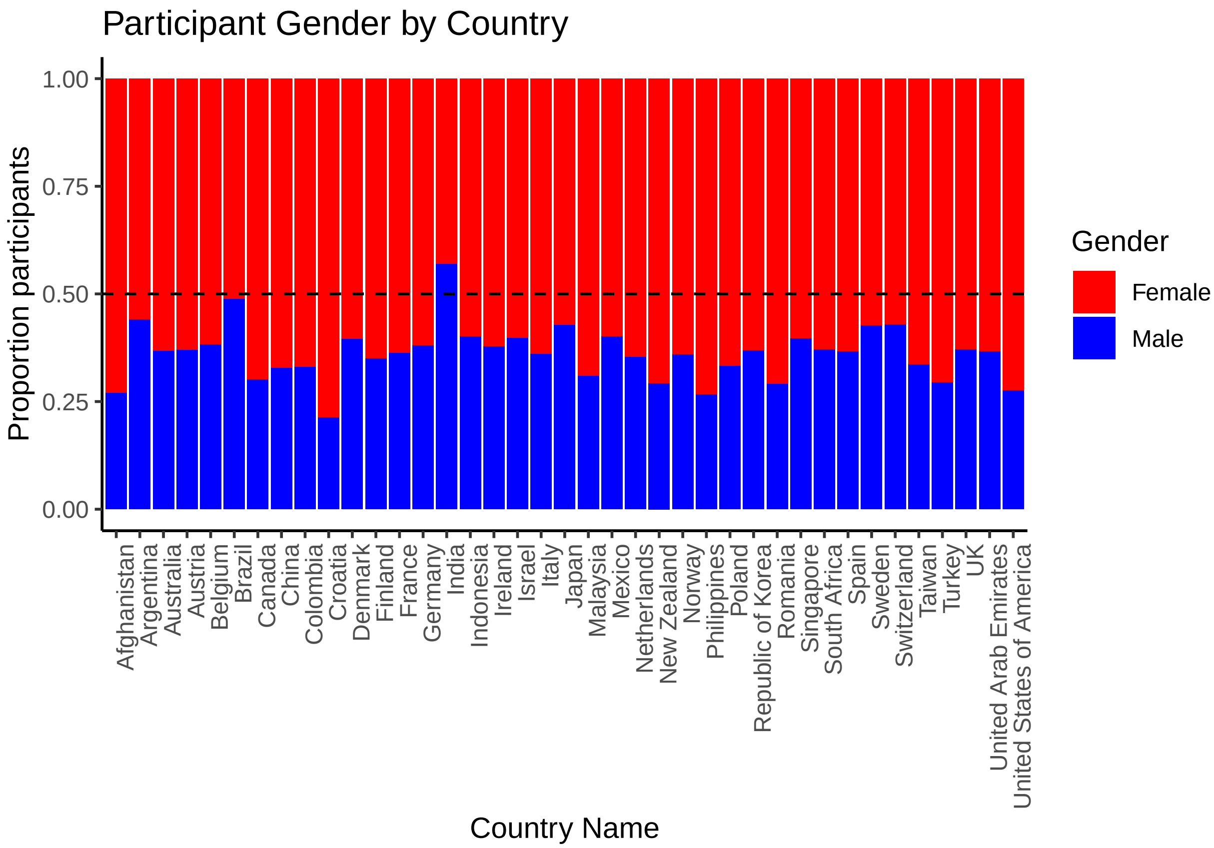


Figure 1: Note: Data from the US are excluded from this plot because of the large number of participants (N = 638,082).

Gender by country

Across countries, there tended to be more female participants, compared to male participants ($M = 0.36$ proportion males; $SD = 0.06$)



Age by country

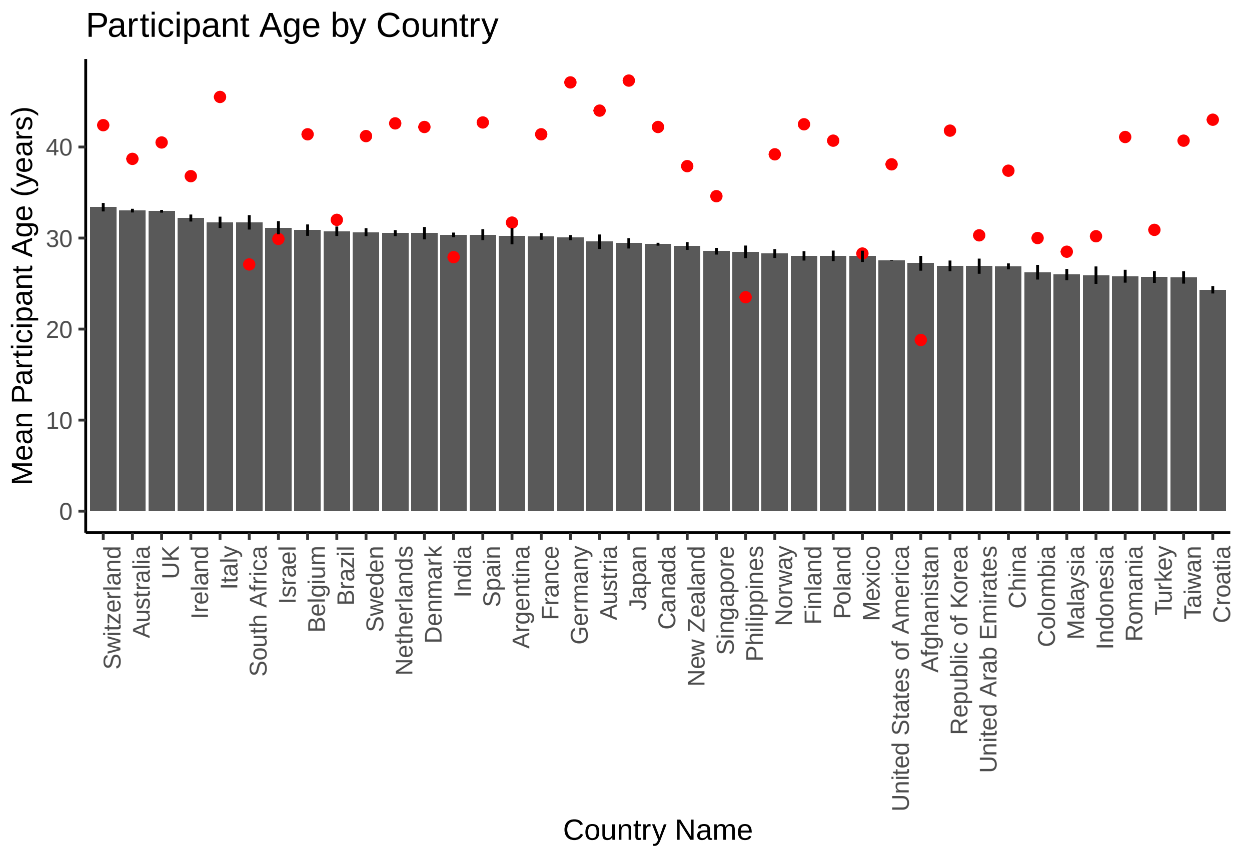


Figure 2: Bars show mean participant age by country; ranges correspond to 95% CIs. Red points show median age by country from CIA factbook data.

Language by country

For each country, we identified the language with the most speakers using Ethnologue (Simons & Charles, 2018). Note that Ethnologue reports "Bavarian" as the primary language of Germany, and "Daric" as the primary language of Afghanistan. In order to map between the other data sources in our study, we used the more general language variant for these countries, German and Persian, respectively.

NOTE: See online version for this content (https://mollylewis.shinyapps.io/iatlang_SI/)

Show 10 entries Search:

	Country	Language	Language Family
1	Afghanistan	Persian	Indo-European
2	Argentina	Spanish	Indo-European
3	Australia	English	Indo-European
4	Austria	German	Indo-European
5	Belgium	Dutch	Indo-European
6	Brazil	Portuguese	Indo-European
7	Canada	English	Indo-European
8	China	Chinese	Sino-Tibetan
9	Colombia	Spanish	Indo-European
10	Croatia	Croatian	Indo-European

Showing 1 to 10 of 39 entries Previous 1 2 3 4 Next

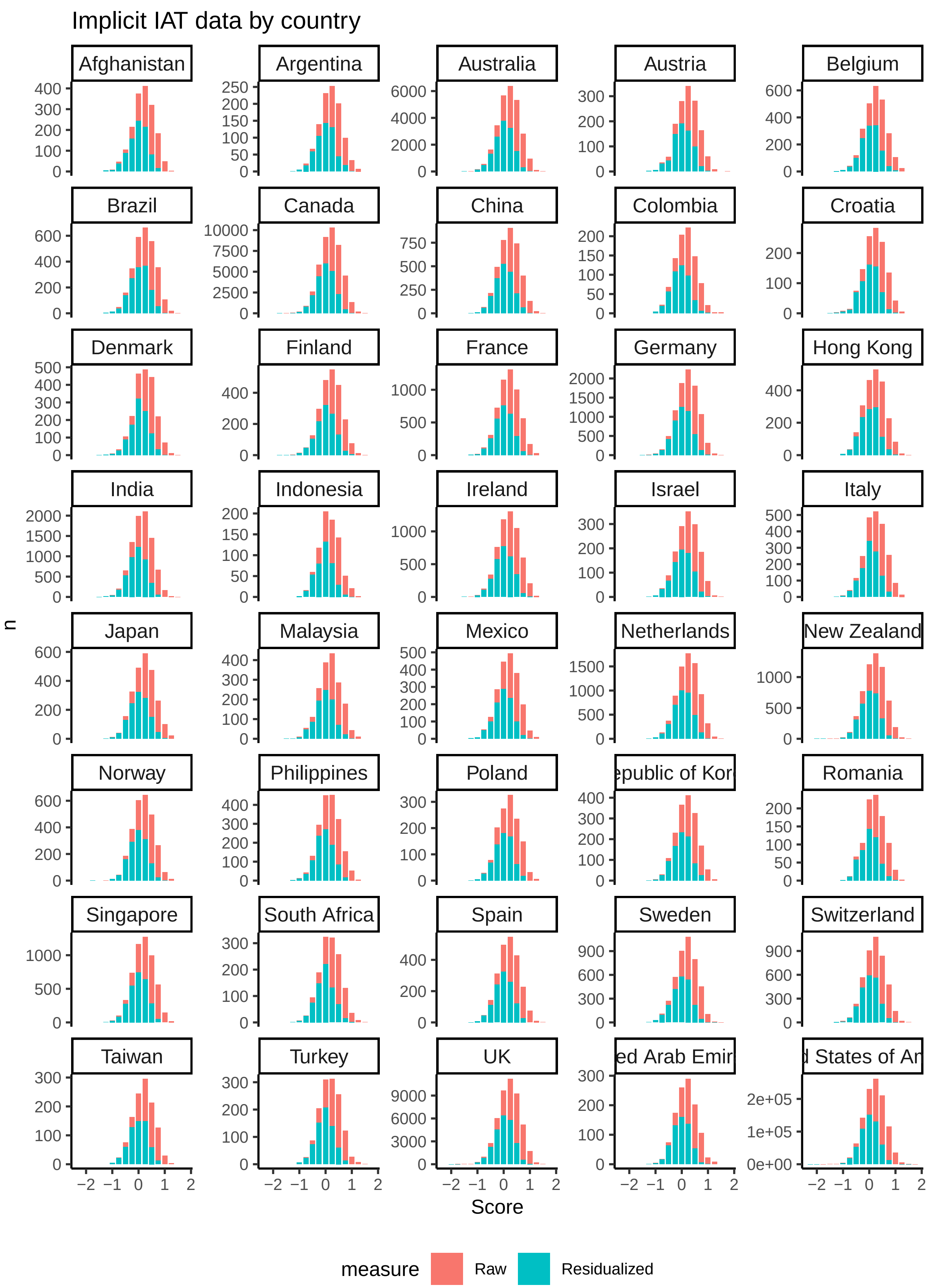
Asterisks correspond to languages that were excluded from our analysis because word embedding models were unavailable.

Dependent Measures

Below are histograms for the implicit and explicit measures in the IAT Project Implicit data presented for each country separately. The implicit raw scores are the D-score values (estimate of career-gender association, with positive values indicating strong bias to associate men with career), and the residualized values are the D-scores with participant age, participant sex and trial order residualized out. For the explicit measure, the raw score is the difference between participants answer to the question, "How strongly do you associate the following with males and females?" for the words "career" and for the word "family". Participants indicated their response on a Likert scale ranging from female (1) to male (7). For each participant, a single explicit score was calculated as the Career response minus the Family response, such that greater values indicate a greater bias to associate males with family. The residualized explicit value is the difference score with participant age, participant sex and trial order residualized out (we had no a priori reason for residualizing out trial order for explicit responses but did so to remain consistent with the residualized implicit measure).

NOTE: See online version for this content (https://mollylewis.shinyapps.io/iatlang_SI/).

Implicit



Implicit IAT data by country
Afghanistan
Argentina
Australia
Austria
Belgium
Brazil
Canada
China
Colombia
Croatia
Denmark
Finland
France
Germany
Hong Kong
India
Indonesia
Ireland
Israel
Italy
Japan
Malaysia
Mexico
Netherlands
New Zealand
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Score
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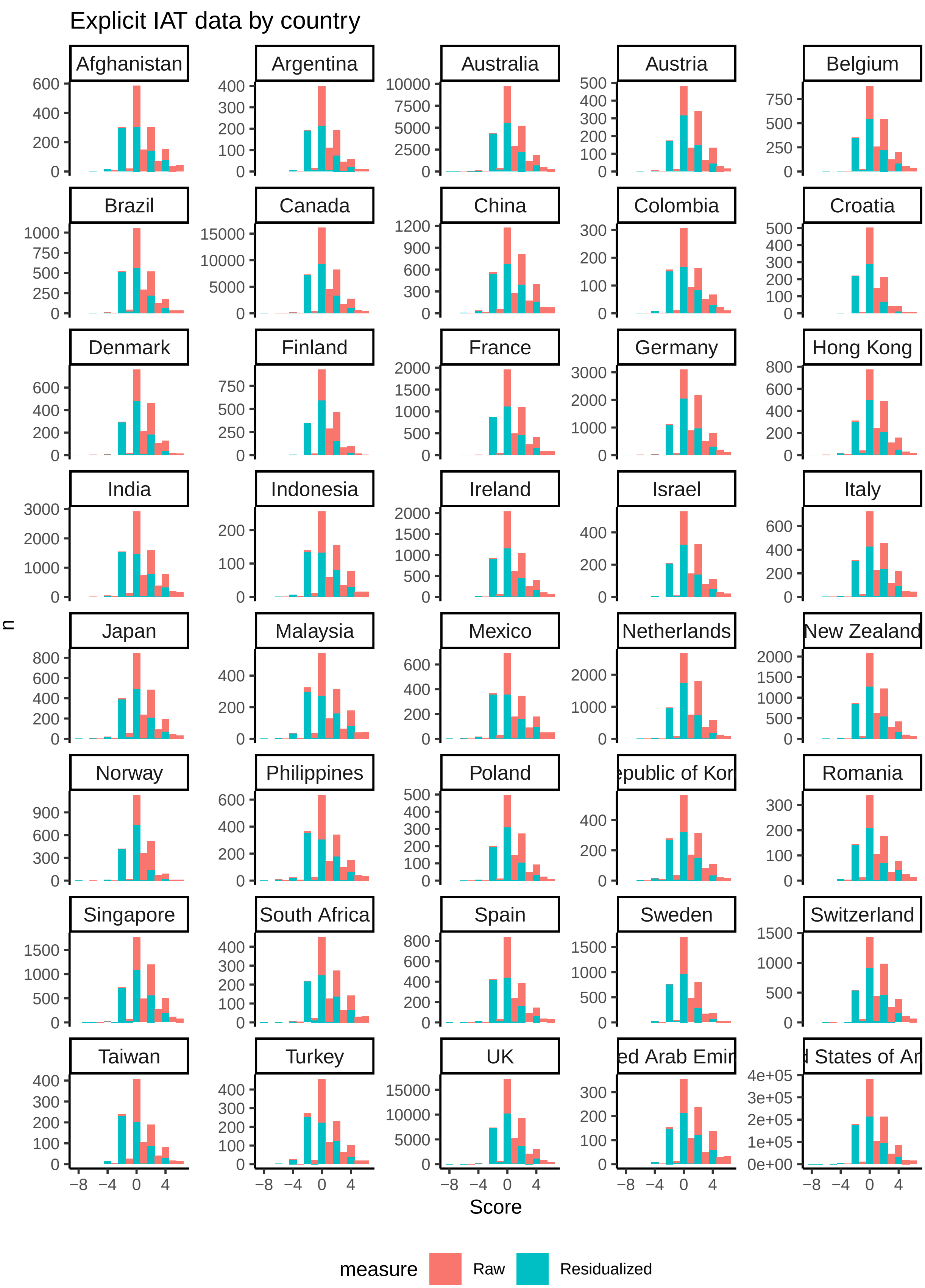
Raw
Residualized

Explicit



Explicit IAT data by country
Afghanistan
Argentina
Australia
Austria
Belgium
Brazil
Canada
China
Colombia
Croatia
Denmark
Finland
France
Germany
Hong Kong
India
Indonesia
Ireland
Israel
Italy
Japan
Malaysia
Mexico
Netherlands
New Zealand
Norway
Philippines
Poland
epublic of Kor
Romania
Singapore
South Africa
Spain
Sweden
Switzerland
Taiwan
Turkey
UK
ed Arab Emir
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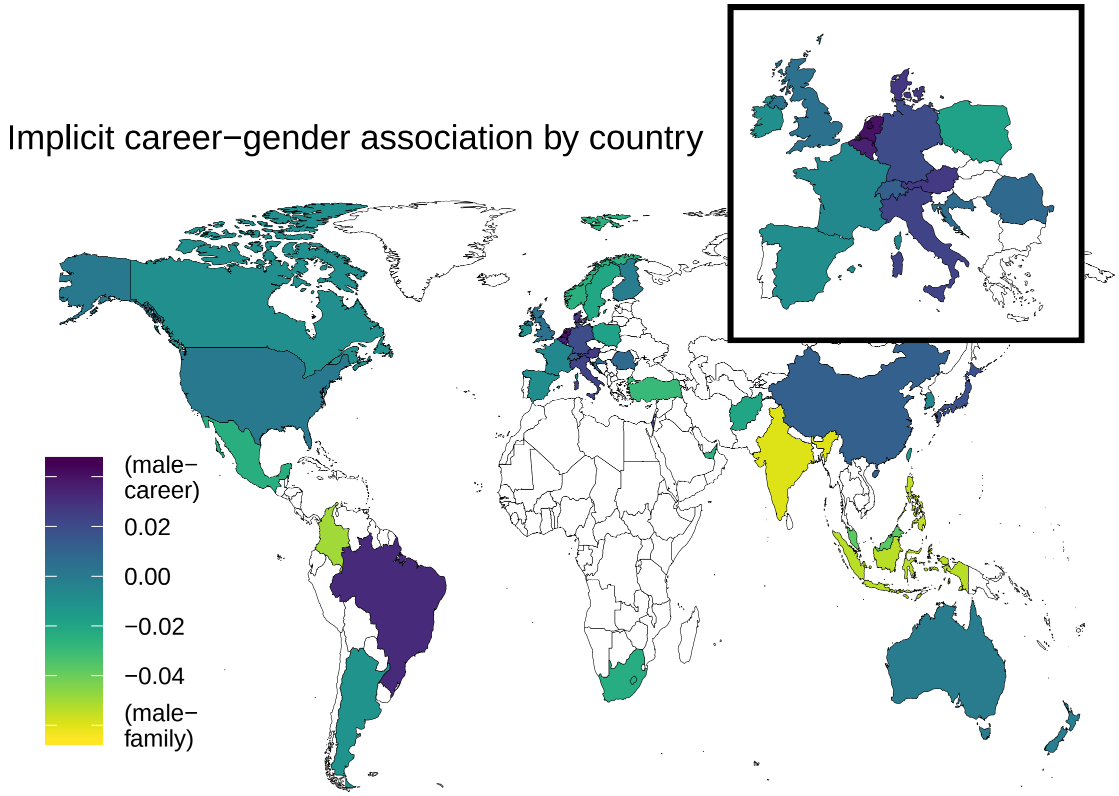
Score
measure
Raw
Residualized

Geographic distribution of IAT scores

Residualized implicit career-gender association (IAT score) shown by country. Larger values (blue) indicate a larger bias to associate men with the concept of career and women with the concept of family. Countries in grey correspond to countries for which there was insufficient data to estimate the country-level career-gender association. Inset shows IAT scores for European countries only.



Note that while Hindi is identified as the most frequently spoken language in India, India is highly multilingual and so Hindi embeddings may be a poor representation of the linguistic statistics for speakers in India as a group.

IAT scores and country age

At the participant level, median country age predicts IAT bias over and above participant age: Countries with older populations tend to have individuals with stronger career-gender associations, even after controlling for participant age. The analysis below presents an additive mixed-effect regression predicting IAT D-score at the participant level with participant age and median country age, controlling for participant sex and trial order. The model includes by-country random intercepts.

	Overall IAT D-score		
Predictors	Estimates	SE	Statistic
(intercept)	-0.03	0.02	-1.53
median country age	0.00	0.00	4.96
sex (M)	-0.10	0.00	-103.14
task order	0.09	0.00	105.67
log age	0.06	0.00	55.05
Random Effects			
s2	0.12		
T00 country code	0.00		
ICC	0.00		
N country code	39		
Observations	657335		
Marginal R2 / Conditional R2	0.036 / 0.038		

The relationship between median country age and IAT bias holds, even after controlling for the percentage women in STEM. The model below presents an additive mixed effect model predicting IAT D-score at the participant level with participant age, median country age and percentage women in STEM in country, controlling for participant sex and trial order. The model includes by-country random intercepts.

	Overall IAT D-score		
Predictors	Estimates	SE	Statistic
(intercept)	-0.00	0.03	-0.05
median country age	0.00	0.00	4.11
% women in STEM	-0.00	0.00	-2.73
task order	0.09	0.00	104.76
sex (M)	-0.10	0.00	-102.78
log age	0.06	0.00	54.56
Random Effects			
s2	0.12		
T00 country_code	0.00		
ICC	0.00		
N country_code	33		
Observations	646271		
Marginal R2 / Conditional R2	0.036 / 0.038		

Study 1b: Career-Gender association across languages

Replication of Caliskan et al. (2017)

Here we replicate the original set of Caliskan, Bryson, and Narayanan (2017; henceforth *CBN*) findings using the models trained on the corpora used in our paper, English Wikipedia (Bojanowski, Grave, Joulin, & Mikolov, 2016) and Subtitles (Lison & Tiedemann, 2016; Van Paridon & Thompson, 2019).

For both the Wikipedia and Subtitle trained models, we calculate an effect size for each of the 10 biases reported in CBN which correspond to behavioral IAT results existing in the literature: flowers/insects–pleasant/unpleasant, instruments/weapons–pleasant/unpleasant, European-American/Afro-American–pleasant/unpleasant, males/females–career/family, math/arts–male/female, science/arts–male/female, mental-disease/physical-disease–permanent/temporary, and young/old–pleasant/unpleasant (labeled as Word-Embedding Association Test (WEAT) 1-10 in CBN). Note that CBN test three versions of race bias. We calculate the bias using the same effect size metric described in CBN, a standardized difference score of the relative similarity of the target words to the target attributes (i.e. relative similarity of male to career vs. relative similarity of female to career). This measure is analogous to the behavioral effect size measure where larger values indicate larger gender bias.

The figure below shows the effect size measures derived from the English Wikipedia corpus and the English Subtitle corpus plotted against effect size estimates reported by CBN from two different models (trained on the Common Crawl and Google News corpora). With the exception of biases related to race and age, effect sizes from our corpora are comparable to those reported by CBN. In particular, for the gender-career IAT—the bias relevant to our current purposes—we estimate the effect size to be 1.78, while CBN estimates it as approximately 1.85.

Wikipedia

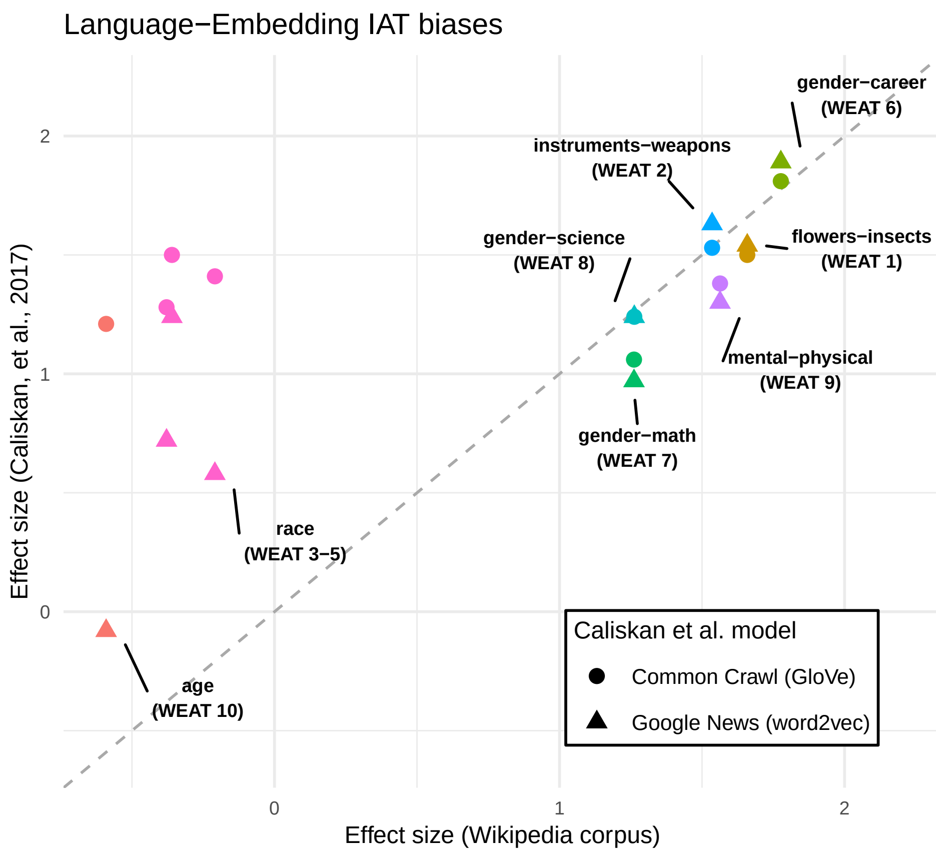


Figure 3: Effect sizes for the 10 IAT biases types (WEAT 1-10) reported in Caliskan et al. (2017; CBN). CBN effect sizes are plotted against effect sizes derived from the Wikipedia (left) and Subtitle (right) corpora. Point color corresponds to bias type, and point shape corresponds to the two CBN models trained on different corpora and with different algorithms.

Subtitles

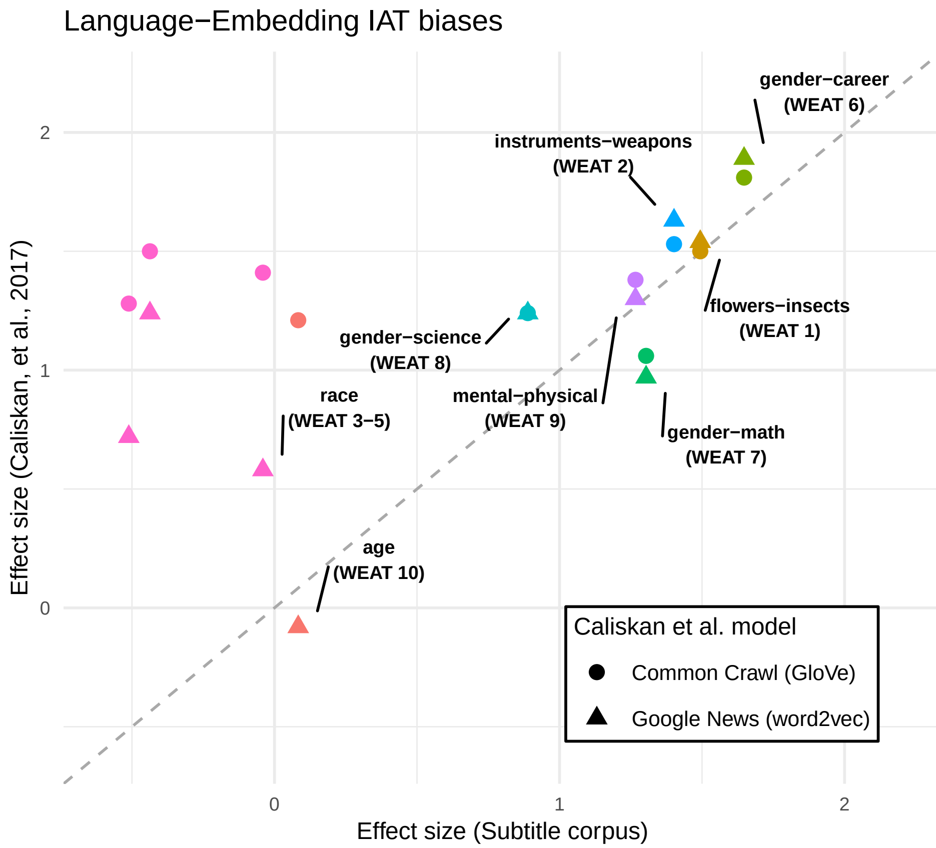


Figure 4: Effect sizes for the 10 IAT biases types (WEAT 1-10) reported in Caliskan et al. (2017; CBN). CBN effect sizes are plotted against effect sizes derived from the Wikipedia (left) and Subtitle (right) corpora. Point color corresponds to bias type, and point shape corresponds to the two CBN models trained on different corpora and with different algorithms.

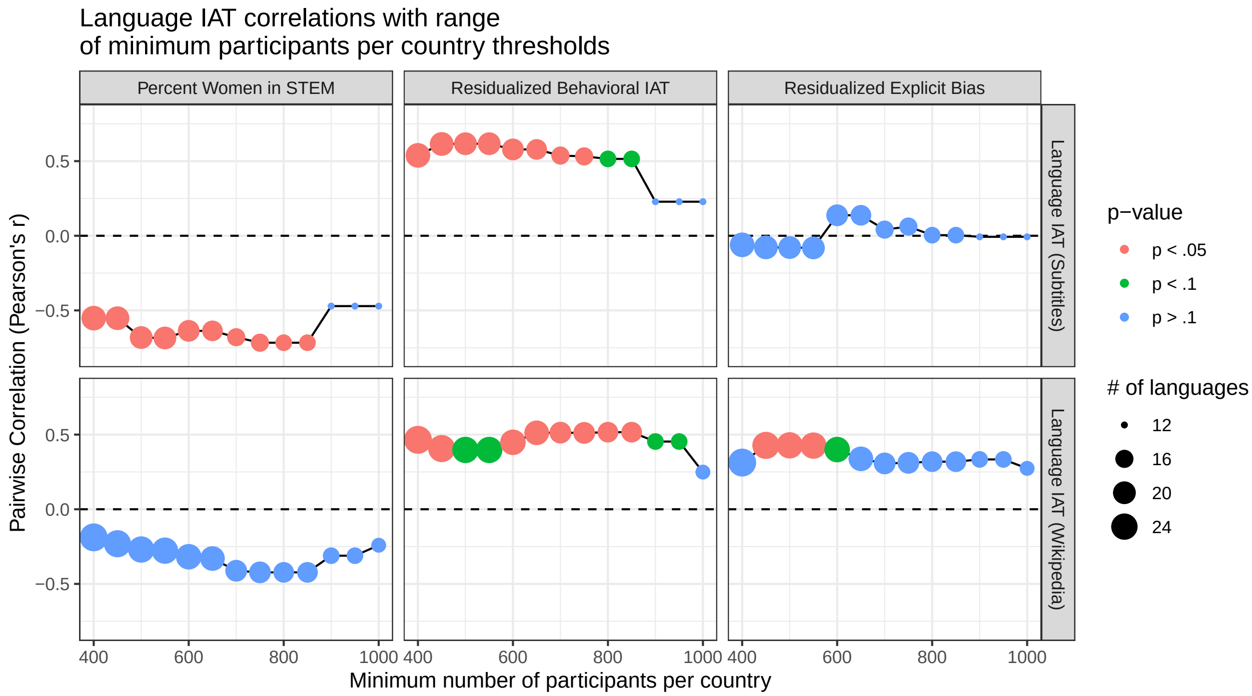
Descriptive statistics for all language-level measures

Below are the mean and standard deviation estimates for all measures presented in Table 1 of the Main Text.

Measure	Mean	SD
Explicit Male-Career Assoc.	-0.018	0.175
Implicit Male-Career Assoc. (IAT)	-0.008	0.028
Percent Women in STEM	14.954	4.550
Male-Career Assoc. (Subtitle)	0.423	0.398
Male-Career Assoc. (Wikipedia)	0.385	0.300
Prop. Gendered Occup. Terms	0.355	0.358
Lang. Occup. Genderness (Subtitle)	0.044	0.016
Lang. Occup. Genderness (Wikipedia)	0.051	0.028
Median Country Age	36.567	7.458

Correlations by language exclusion threshold

In the Main Text, we report psychological IAT data for participants who came from countries with at least 400 participants. This cutoff was largely arbitrary, but was selected to allow for a relatively large number of languages to be included in our analysis while also excluding languages with small sample sizes (and therefore less reliable estimates). Nevertheless, the pattern of findings we report in the Main Text remains broadly the same when larger thresholds of minimum number of participants per country are used. The plot below shows pairwise correlations between the language bias measures and three psychological/objective measures described in Study 1: Residualized behavioral IAT, residualized explicit IAT, and percent women in STEM. As in the main text, the residualized values are participant age, participant sex, and trial order. Point size corresponds to the number of languages included in the analysis at that threshold, and point color corresponds to the p-value of the pairwise Pearson's r coefficient.



Partial correlations controlling for median country age

Partial correlation (Pearson's r) for all measures in Study 1 and 2 at the level of languages, controlling for median country age. Single asterisks indicate $p < .05$ and double asterisks indicate $p < .01$. The + symbol indicates a marginally significant p-value, $p < .1$.

	Explicit Male-Career Assoc.	Implicit Male-Career Assoc. (IAT)	Percent Women in STEM	Male-Career Assoc. (Subtitle)	Male-Career Assoc. (Wikipedia)	Prop. Gendered Occup. Terms	Lang. Occup. Genderness (Subtitle)
Explicit Male-Career Assoc.		.28	.16	-.06	.38+	.14	.21
Implicit Male-Career Assoc. (IAT)	.28		-.38+	.42*	.43*	.48*	.31
Percent Women in STEM	.16	-.38+		-.49*	-.09	-.23	-.10
Male-Career Assoc. (Subtitle)	-.06	.42*	-.49*		.47*	.20	.28
Male-Career Assoc. (Wikipedia)	.38+	.43*	-.09	.47*		.11	.46*
Prop. Gendered Occup. Terms	.14	.48*	-.23	.20	.11		.53**
Lang. Occup. Genderness (Subtitle)	.21	.31	-.10	.28	.46*	.53**	
Lang. Occup. Genderness (Wikipedia)	.22	.37+	-.46*	.35+	.49*	.73**	.79**

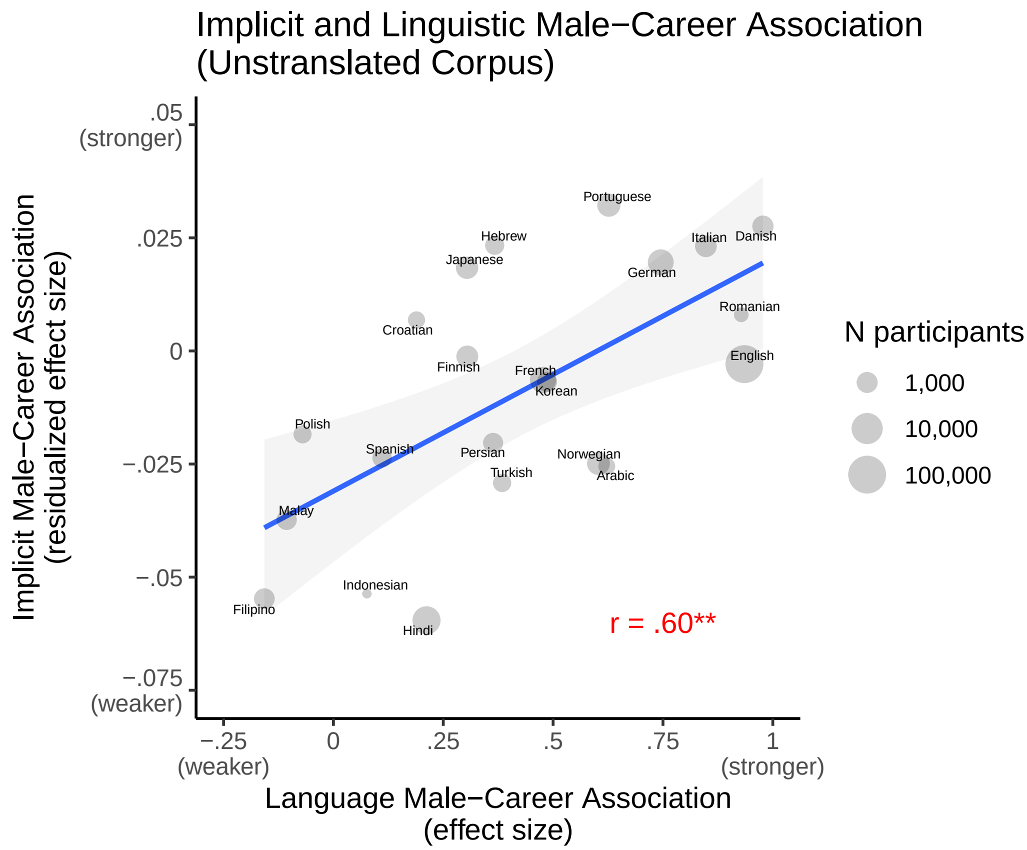
Replication on untranslated corpus

Both the Subtitle and Wikipedia corpora likely contain some documents that are translated from other languages (e.g., the Wikipedia article on "Paris" is written in French and then translated into English). The parallel content across languages allows us to estimate the gender bias in language statistics, while holding content constant across languages. Nevertheless, content may itself be a driver of gender bias (e.g. one language may have more articles about male politicians relative to another).

To understand the contribution of language-specific content on gender bias, we constructed a corpus of Wikipedia articles in each language that were originally written in the target language (i.e., untranslated). We identified untranslated articles by examining the interlanguage links on a Wikipedia article page. These links are pointers to the same article content in other languages (e.g. the "Paris" article in French contains a link to the "Paris" article in English). Since the original source language of an article could not be inferred, we excluded all articles that contained one or more interlanguage links. This ensured that all remaining articles contained only text originally written in the target language.

We constructed a corpus for each language containing all untranslated articles. There were a median of 168,326 articles per language (range: 10,307-14,676,484). We trained fastText (Joulin, et al. 2016) on each language corpus with default parameters and a dimension size of 200. We then used these models trained on native text to calculate by-language IAT bias scores and by-language occupation bias scores, using the same procedure as with the models described in the Main Text (Studies 1b and 2). One language was excluded following the same exclusion criteria as in the main analyses (>= 20% missing words in model; Mandarin), but the results remain the same when this language is included.

Using models trained on the untranslated corpora, we replicate the key finding from Study 1b showing a positive correlation between the bias measured behaviorally with the IAT and measured in language (r = .60; p = .002; fig below). Notably, the effect size is somewhat larger relative to the other two corpora types, presumably because additional bias is introduced by allowing the corpus content to vary across languages.



The table below shows the correlation (Pearson's r) for all measures in Study 1 and 2 at the level of languages, including estimates of language bias obtained from models trained on the untranslated Wikipedia corpus.

	Explicit Male-Career Assoc.	Implicit Male-Career Assoc. (IAT)	Percent Women in STEM	Male-Career Assoc. (Subtitle)	Male-Career Assoc. (Wikipedia)	Male-Career Assoc. (Wikipedia, untranslated)	Prop. Gendered Occup. Terms	Lang. Occup. Genderness (Subtitle)	Lang. Occup. Genderness (Wikipedia)	Lang. Occup. Genderness (Wikipedia, untranslated)	Median Country Age
Explicit Male-Career Assoc.		.18	.18	-.08	.34+	.21	.11	.16	.18	.27	-.07
Implicit Male-Career Assoc. (IAT)	.18		-.53*	.50*	.48*	.60**	.57**	.49*	.49*	.60**	.61**
Percent Women in STEM	.18	-.53*		-.55*	-.19	-.39+	-.35	-.26	-.53*	-.44*	-.42+
Male-Career Assoc. (Subtitle)	-.08	.50*	-.55*		.51*	.49*	.28	.38	.41+	.45*	.31
Male-Career Assoc. (Wikipedia)	.34+	.48*	-.19	.51*		.90**	.18	.51*	.53**	.47*	.25
Male-Career Assoc. (Wikipedia, untranslated)	.21	.60**	-.39+	.49*	.90**		.23	.35	.52**	.46*	.48*
Prop. Gendered Occup. Terms	.11	.57**	-.35	.28	.18	.23		.60**	.77**	.75**	.35+
Lang. Occup. Genderness (Subtitle)	.16	.49*	-.26	.38	.51*	.35	.60**		.81**	.74**	.44+
Lang. Occup. Genderness (Wikipedia)	.18	.49*	-.53*	.41+	.53**	.52**	.77**	.81**		.83**	.34+
Lang. Occup. Genderness (Wikipedia, untranslated)	.27	.60**	-.44*	.45*	.47*	.46*	.75**	.74**	.83**		.48*
Median Country Age	-.07	.61**	-.42+	.31	.25	.48*	.35+	.44+	.34+	.48*	

Single asterisks indicate $p < .05$ and double asterisks indicate $p < .01$. The + symbol indicates a marginally significant p-value, $p < .1$

Study 1c: Pre-registered Analysis of British vs. American English

The pre-registration to this study can be found here: https://osf.io/3f9ed.

IAT Target Words

Presented below are the target words for each of the 31 IATs used in our analyses. Each IAT has two target categories (e.g. "money" and "love") and two attribute categories (e.g. negative and positive).

IAT	items
Athletic People - Intelligent People	CATEGORY 1: fit, active, nimble, energetic, muscular CATEGORY 2: clever, bright, smart, brilliant, intellectual, academic ATTRIBUTE 1: animosity, dirty, evil, gross, neglected, rotten ATTRIBUTE 2: appealing, delight, excitement, glee, laughing, splendid
Avoiding - Approaching	CATEGORY 1: back, withdraw, retreat, away CATEGORY 2: toward, closer, advance, forward, near ATTRIBUTE 1: failure, horrendous, nasty, repulsive ATTRIBUTE 2: adore, cheerful, friendship, joyful, smiling
Career - Family	CATEGORY 1: work, business, job, profession, office CATEGORY 2: home, household, children, domestic, kitchen ATTRIBUTE 1: failure, horrendous, nasty, repulsive ATTRIBUTE 2: adore, cheerful, friendship, joyful, smiling
Chaos - Order	CATEGORY 1: anarchy, scattered, disarray, random CATEGORY 2: control, predictable, discipline, structure ATTRIBUTE 1: annoy, disaster, grotesque, horrific ATTRIBUTE 2: attractive, delightful, fabulous, glorious, pleasing
Cold - Hot	CATEGORY 1: cool, freeze, frozen, ice, chill CATEGORY 2: warm, boil, heat, steam, burn ATTRIBUTE 1: abuse, bomb, grief, pain, poison, sadness ATTRIBUTE 2: cheer, friend, love, paradise, pleasure, splendid
Determinism - Free Will	CATEGORY 1: arranged, destined, fixed CATEGORY 2: choice, intention, freedom ATTRIBUTE 1: annoy, disaster, grotesque, horrific ATTRIBUTE 2: attractive, delightful, fabulous, glorious, pleasing
Friends - Family	CATEGORY 1: chum, buddy, pal, peers, companion CATEGORY 2: mother, father, siblings, child ATTRIBUTE 1: awful, disgust, hate, selfish, tragic ATTRIBUTE 2: beautiful, fantastic, happy, lovely, pleasure, terrific
Helpers - Leaders	CATEGORY 1: assistant, worker, attendant, employee CATEGORY 2: president, boss, manage, senator ATTRIBUTE 1: hatred, hurtful, sickening ATTRIBUTE 2: celebrate, enjoy, favorable, gorgeous, magnificent, triumph
Innocence - Wisdom	CATEGORY 1: simple, pure, naive, inexperience, youthful CATEGORY 2: mature, knowledge, enlightened, sophisticated ATTRIBUTE 1: awful, disgust, hate, selfish, tragic ATTRIBUTE 2: beautiful, fantastic, happy, lovely, pleasure, terrific
Jocks - Nerds	CATEGORY 1: sports, strong, athletic, exercise, football, muscles CATEGORY 2: intelligent, smart, study, calculator, brains ATTRIBUTE 1: failure, horrendous, nasty, repulsive ATTRIBUTE 2: adore, cheerful, friendship, joyful, smiling
Lawyers - Politicians	CATEGORY 1: attorney, counsel, prosecution CATEGORY 2: mayor, senator, governor, representative ATTRIBUTE 1: hatred, hurtful, sickening ATTRIBUTE 2: celebrate, enjoy, favorable, gorgeous, magnificent, triumph
Money - Love	CATEGORY 1: wealth, investments, cash CATEGORY 2: affection, heart, relationship, romance ATTRIBUTE 1: failure, horrendous, nasty, repulsive ATTRIBUTE 2: adore, cheerful, friendship, joyful, smiling
National Defense - Education	CATEGORY 1: military, soldiers, combat, army, navy, marines CATEGORY 2: educate, schools, teachers, books, teach, students ATTRIBUTE 1: annoy, disaster, grotesque, horrific ATTRIBUTE 2: attractive, delightful, fabulous, glorious, pleasing
Organized Labor - Management	CATEGORY 1: union, workers, employees, staff CATEGORY 2: supervisors, boss, administration, employer, managers ATTRIBUTE 1: hatred, hurtful, sickening ATTRIBUTE 2: celebrate, enjoy, favorable, gorgeous, magnificent, triumph
Poor People - Rich People	CATEGORY 1: poor, impoverished, broke, bankrupt CATEGORY 2: wealthy, affluent, prosperous ATTRIBUTE 1: animosity, dirty, evil, gross, neglected, rotten ATTRIBUTE 2: appealing, delight, excitement, glee, laughing, splendid
Private - Public	CATEGORY 1: personal, confidential, secret, secluded CATEGORY 2: communal, accessible, open ATTRIBUTE 1: awful, disgust, hate, selfish, tragic ATTRIBUTE 2: beautiful, fantastic, happy, lovely, pleasure, terrific

IAT	items
Protein - Carbohydrates	CATEGORY 1: beef, chicken, eggs, fish, meat CATEGORY 2: pasta, bread, starch, cereal, grains, rice ATTRIBUTE 1: awful, disgust, hate, selfish, tragic ATTRIBUTE 2: beautiful, fantastic, happy, lovely, pleasure, terrific
Punishment - Forgiveness	CATEGORY 1: penalty, retribution, discipline, punitive, sanction CATEGORY 2: pardon, reprieve, amnesty, mercy ATTRIBUTE 1: hatred, hurtful, sickening ATTRIBUTE 2: celebrate, enjoy, favorable, gorgeous, magnificent, triumph
Rebellious - Conforming	CATEGORY 1: question, challenge, defy, resist CATEGORY 2: follow, obey, yield, comply, abide ATTRIBUTE 1: angry, ghastly, horrible, negative, ugly ATTRIBUTE 2: cherish, excellent, glad, spectacular
Rich People - Beautiful People	CATEGORY 1: wealthy, prosperous, affluent CATEGORY 2: handsome, gorgeous, stunning, attractive ATTRIBUTE 1: angry, ghastly, horrible, negative, ugly ATTRIBUTE 2: cherish, excellent, glad, spectacular
Security - Freedom	CATEGORY 1: safe, secure, controlled, protected CATEGORY 2: free, liberty, independent ATTRIBUTE 1: angry, ghastly, horrible, negative, ugly ATTRIBUTE 2: cherish, excellent, glad, spectacular
Skeptical - Trusting	CATEGORY 1: questioning, hesitant, wary, doubtful CATEGORY 2: convinced, confident, accepting, believing ATTRIBUTE 1: animosity, dirty, evil, gross, neglected, rotten ATTRIBUTE 2: appealing, delight, excitement, glee, laughing, splendid
Speed - Accuracy	CATEGORY 1: fast, swift, rapid, quick, speedy CATEGORY 2: correct, accurate, precise, valid, exact ATTRIBUTE 1: abuse, bomb, grief, pain, poison, sadness ATTRIBUTE 2: cheer, friend, love, paradise, pleasure, splendid
Stable - Flexible	CATEGORY 1: same, familiar, steady, fixed, enduring, permanent CATEGORY 2: shifting, new, different, variable, changing, novelty, fluctuate ATTRIBUTE 1: awful, disgust, hate, selfish, tragic ATTRIBUTE 2: beautiful, fantastic, happy, lovely, pleasure, terrific
State - Church	CATEGORY 1: government, republic, nation, constitution CATEGORY 2: religion, spirituality, faith, scripture ATTRIBUTE 1: animosity, dirty, evil, gross, neglected, rotten ATTRIBUTE 2: appealing, delight, excitement, glee, laughing, splendid
Tall People - Short People	CATEGORY 1: big, large, gigantic, towering CATEGORY 2: small, tiny, little, slight, petite ATTRIBUTE 1: awful, disgust, hate, selfish, tragic ATTRIBUTE 2: beautiful, fantastic, happy, lovely, pleasure, terrific
Team - Individual	CATEGORY 1: squad, players, group, bunch CATEGORY 2: person, autonomous, solo, one ATTRIBUTE 1: awful, disgust, hate, selfish, tragic ATTRIBUTE 2: beautiful, fantastic, happy, lovely, pleasure, terrific
Technology - Nature	CATEGORY 1: machines, innovation, devices, invention CATEGORY 2: animals, natural, plants, living ATTRIBUTE 1: annoy, disaster, grotesque, horrific ATTRIBUTE 2: attractive, delightful, fabulous, glorious, pleasing
Tradition - Progress	CATEGORY 1: ritual, custom, convention, stability CATEGORY 2: development, advancement, innovation, change ATTRIBUTE 1: angry, ghastly, horrible, negative, ugly ATTRIBUTE 2: cherish, excellent, glad, spectacular
Urban - Rural	CATEGORY 1: city, busy, noise, buildings CATEGORY 2: country, farm, slow, quiet, fields ATTRIBUTE 1: annoy, disaster, grotesque, horrific ATTRIBUTE 2: attractive, delightful, fabulous, glorious, pleasing
Winter - Summer	CATEGORY 1: january, cold, february, december CATEGORY 2: june, hot, july, august ATTRIBUTE 1: annoy, disaster, grotesque, horrific ATTRIBUTE 2: attractive, delightful, fabulous, glorious, pleasing

Behavioral data exclusion criteria

We excluded participants using the pre-defined criteria in the AIID dataset, described below. Participants were excluded if any one of the seven criteria were not satisfied.

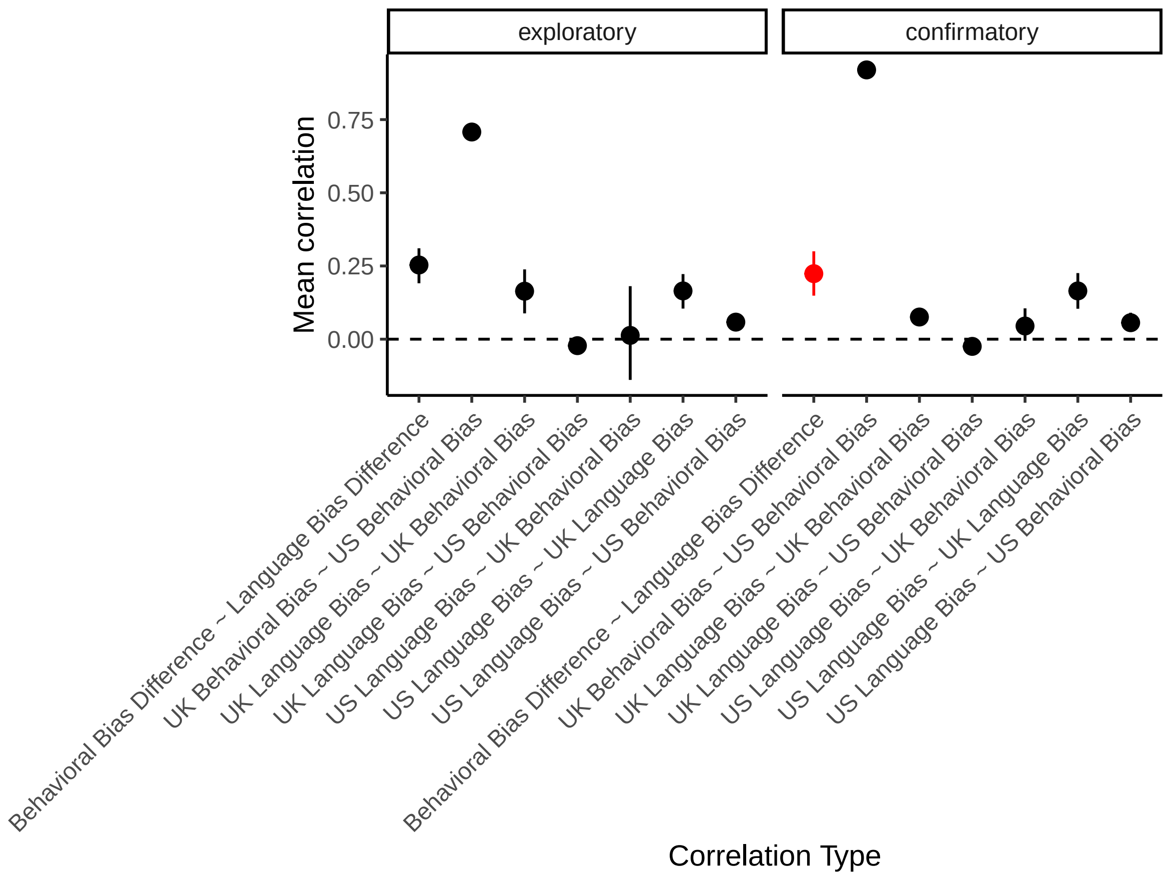
1. >= 35% responses < 300ms responses in any one practice block.
2. >= 25% responses < 300ms responses in any one critical block.

3. >= 10% responses < 300ms in critical blocks.
4. >= 50% error rate in any one practice block.
5. >= 40% error rate in practice blocks.
6. >= 40% error rate in any one critical block.
7. >= 30% error rate in critical blocks.

Pre-registered model

The exact pre-registered analysis (https://osf.io/3f9ed/) of Study 1c is presented below. Pairwise correlations between all variables (language bias, behavioral bias, and UK-US difference measures) are shown, averaging across estimates of language bias from the 5 model runs. Error bars are 95% CIs. As stated in the pre-registration, the key test of our hypothesis is that the correlation between the UK - US linguistic difference ("Language Bias Difference") and the UK - US behavioral difference ("Behavioral Bias Difference") is greater than 0 (shown in red below). That data are consistent with this prediction.

The confirmatory dataset is shown on the right, along with the smaller exploratory dataset on the left for reference.



Mixed-effect model

The full results to the mixed-effect model described in the paper are presented below:

	Behavioral Effect Resid		
Predictors	Estimates	SE	Statistic
(intercept)	-0.00	0.05	-0.09
country (uk)	0.02	0.01	1.74
language bias difference (uk - us)	-0.03	0.07	-0.42
country:language bias difference	0.05	0.02	2.88
Random Effects			
s2	0.20		
T00 user id	0.01		
T00 domain	0.07		
ICC	0.27		
N user id	22059		
N domain	31		
Observations	27045		
Marginal R2 / Conditional R2	0.001 / 0.273		

Study 2: Gender association and lexicalized gender

NOTE: See online version for this content (https://mollylewis.shinyapps.io/iatlang_SI/).

Grammatical gender coding

Below is the binary coding (gender vs. no gender) of each language for a sex-based grammatical gender system, based on WALS (Dryer & Haspelmath, 2013) and other sources when information was not available from WALS.

Show 10 entries

Search:

	Language	Sex-based Grammatical Gender Coding
1	Arabic	Gender
2	Dutch	No Gender
3	Portuguese	Gender
4	Danish	No Gender
5	Italian	Gender
6	Japanese	No Gender
7	Korean	No Gender
8	Malay	No Gender
9	Norwegian	No Gender
10	Polish	Gender

Showing 1 to 10 of 25 entries

Previous 1 2 3 Next

Occupation Items

In Study 2, we selected 20 occupation labels from the set of items used in Misersky, et al. (2014). Listed below are the 20 items along with their perceived gender bias as reported in Misersky, et al. (2014; larger values indicate occupation is perceived to be more closely associated with women).

Show 10 entries

Search:

	Occupation	Perceived Gender Bias (Misersky, et al., 2014)
1	hunter	0.2
2	mechanic	0.2
3	firefighter	0.21
4	postman/postwoman	0.25
5	sailor	0.27
6	governor	0.33
7	judge	0.34
8	doctor/physician	0.37
9	professor	0.38
10	lawyer	0.41

Showing 1 to 10 of 20 entries

Previous 1 2 Next

Occupation Translations

Below are the translations of the 20 occupation words for each of the 25 target languages. "Translation ID" identifies the translation when multiple translations were provided for a given occupation/language.

Show 10 entries

Search:

	Language	Occupation	Gender	Translation ID	Translation
1	Arabic	athlete	F	t1	رياضي
2	Arabic	athlete	M	t1	رياضي
3	Arabic	author	F	t1	مؤلف
4	Arabic	author	M	t1	مؤلف
5	Arabic	baker	F	t1	خباز
6	Arabic	baker	M	t1	خباز
7	Arabic	cleaner	F	t1	منظف
8	Arabic	cleaner	M	t1	منظف
9	Arabic	dancer	F	t1	راقصة
10	Arabic	dancer	M	t1	راقصة

Showing 1 to 10 of 1,177 entries

Previous 1 2 3 4 5 … 118 Next

Predicting career-gender association with both language measures

In this analysis, we predict the magnitude of implicit career-gender association by language with an additive linear model. As predictors, we include proportion gender distinct labels and linguistic career-gender association (as measured by word embeddings of the IAT words). Model coefficients are shown below for models based on the Subtitle (top) and Wikipedia (bottom) corpora.

Subtitle Corpus:

term	estimate	std.error	statistic	p.value
(Intercept)	0.108	0.157	0.691	0.498
Prop. Gendered Occupation Terms	0.388	0.164	2.364	0.029
Lang. Male-Career Assoc (Subtitle)	0.332	0.165	2.011	0.059

This model accounts for 40.63% variance.

Wikipedia Corpus:

term	estimate	std.error	statistic	p.value
(Intercept)	0.000	0.154	0.000	1.000
Prop. Gendered Occupation Terms	0.520	0.159	3.270	0.004
Lang. Male-Career Assoc (Wikipedia)	0.363	0.159	2.282	0.033

This model accounts for 45.32% variance.

Presented below are models that include median country age as an additional predictor.

Subtitle Corpus:

term	estimate	std.error	statistic	p.value
(Intercept)	0.078	0.150	0.521	0.609
Prop. Gendered Occupation Terms	0.328	0.159	2.063	0.054
Lang. Male-Career Assoc (Subtitle)	0.270	0.160	1.681	0.110
Median Country Age	0.298	0.168	1.776	0.093

This model accounts for 49.48% variance.

Wikipedia Corpus:

term	estimate	std.error	statistic	p.value
(Intercept)	0.000	0.135	0.000	1.000
Prop. Gendered Occupation Terms	0.385	0.148	2.606	0.017
Lang. Male-Career Assoc (Wikipedia)	0.297	0.142	2.095	0.049
Median Country Age	0.413	0.150	2.758	0.012

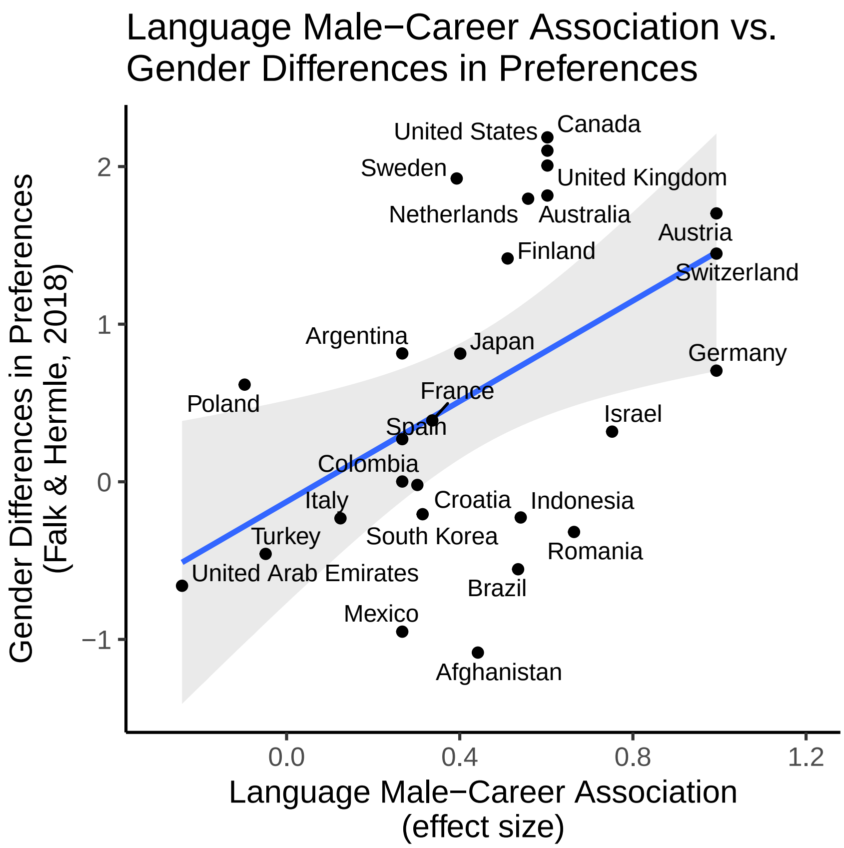
This model accounts for 59.85% variance.

Gender associations in language and other psychological measures

Several recent studies (Falk & Hermle, 2018; Stoet & Geary, 2018) have presented novel theories to account for cases of structural inequality related to gender. Both of these papers argue that psychological differences play a causal role in the emergence of structural inequality. Here, we show that degree of gender bias in language is correlated with these psychological differences at the country level, consistent with the idea that language experience could be playing a causal role in the emergence of psychological differences.

Falk and Hermle (2018)

Gender differences in preferences (Falk & Hermle, 2018; composite score of "six fundamental preferences with regard to social and nonsocial domains: willingness to take risks; patience, which captures preferences over the intertemporal timing of rewards; altruism; trust; and positive and negative reciprocity, which capture the costly willingness to reward kind actions or to punish unkind actions, respectively.") as a function of linguistic gender bias measured in the Subtitle corpus. These two measures are correlated ($r(25) = 0.48$ [0.12, 0.73], $p = 0.01$): Countries with greater differences in gender preferences also have greater gender bias present in their languages.



We also find that per capita GDP (World Bank database; 2017 GDP per capita (current US$ indicator) is correlated with linguistic gender bias measured in both corpora (Wikipedia: $r(35) = 0.64$ [0.4, 0.8], $p < .0001$; Subtitle: $r(31) = 0.58$ [0.29, 0.77], $p < .001$). Futher, the magnitude of the male-career association in the language spoken in a country predicts the magnitude of that bias measured via the behavioral IAT, controlling for both national GDP and median country age. Results are presented below for mixed-effect models predicting behavioral IAT at the country level with median country age, GDP, and Language IAT as fixed effects, and random intercepts by language.

Wikipedia Corpus:

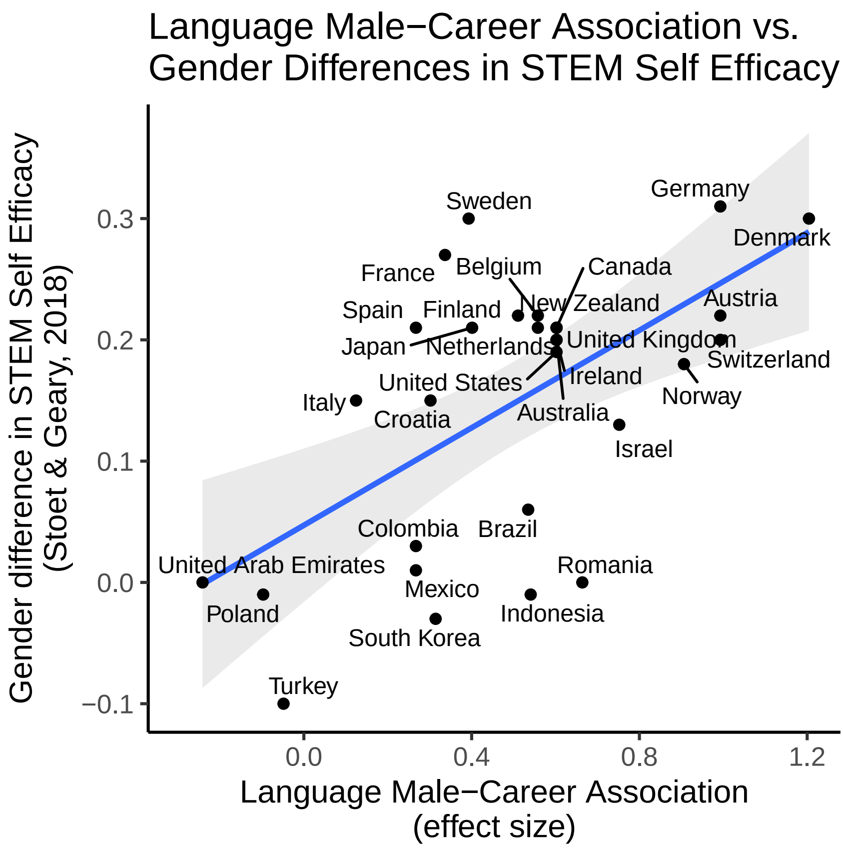
term	estimate	std.error	statistic
(Intercept)	-0.02	0.01	-2.11
Lang. Male-Career Assoc (Wikipedia)	0.04	0.01	2.42
GDP	0.00	0.00	-1.07
Median Country Age	0.02	0.00	3.66

Subtitle Corpus:

term	estimate	std.error	statistic
(Intercept)	-0.01	0.01	-1.72
Lang. Male-Career Assoc (Subtitle)	0.03	0.01	1.97
GDP	0.00	0.00	-0.32
Median Country Age	0.01	0.01	2.10

Stoet and Geary (2018)

Gender difference in STEM Self Efficacy (Stoet & Geary, 20178; "The sex difference in self efficacy (boys – girls)") as a function of linguistic gender bias measured in the Subtitle corpus. These two measures are correlated ($r(28) = 0.59$ [0.3, 0.79], $p < .001$): Countries with greater gender differences in self-efficacy also have greater gender bias present in their languages. Futher, self-efficacy mediated the effect of language statistics on percentage of women in stem (path-ab = -0.33; p = 0.01), suggesting that language statistics could be critical causal factor underlying gender differences in STEM participation.



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