Appendices for Intergroup contact fosters more inclusive social identities

April 24, 2020

Appendix A: Additional Measures

We included additional measures to validate the triple crossed-categorization task and to replicate earlier research. We tested to what extent various social identity measures correlated with responses in the triple crossed-categorization task. We also assessed Karmic beliefs to replicate Cotterill et al.'s (2014) finding that Karmic beliefs mediate the relationship between social dominance orientation and support for hierarchy-enhancing policies. We do not report results from this replication here, but make all data available online.

Measures

Group identification was measured with one item per ingroup (Postmes et al., 2013): "I identify with my [nationality/religion/caste group]" (1 = *strongly disagree*, 7 = *strongly agree*).

Social identity complexity (Roccas & Brewer, 2002; Schmid et al., 2009) was operationalized as the extent to which participants perceived their different group memberships as conceptually interrelated (*similarity complexity*) and numerically overlapping (*overlap complexity*). Two items measured similarity complexity for religion/nationality and for nationality/caste: "How similar or different are the typical [Hindu/Indian] and the typical [Indian/person from your caste group] to each other?" (1 = *very different*, 5 = *very similar*, reverse coded), and "Do you think that being [Hindu/Indian] means the same as being [Indian/from your caste group]?" (1 = *means something very similar*, 5 = *means something very different*). Two items measured overlap complexity for religion/nationality: "How many [Indians/ Hindus] do you think are [Hindus/Indian]?" (%, r = .63). Three items measured overlap complexity for nationality and caste: "How many Indians do you think are [GC, OBC, SC/ST]?" (%, $.33 \leq rs \leq .50$). Overlap items were reverse coded, so that higher scores indicated less perceived overlap.

Entitativity (Lickel et al., 2000) was measured with six items: "Being Indian is important to each Indian, no matter their caste or religion", "Indians of all castes and religions interact often with each other.", "Indians of all castes and religions are working towards shared goals", "What happens to one Indian also impacts other Indians", "Indians of all castes and religions depend on one another", and "Indians are similar to one another" (1 = *strongly disagree*, 7 = *strongly agree*, $\alpha = .80$). Participants were encouraged to "take Indian/Indians to mean Indian citizens of all castes and religions" when reading the items of this scale. This scale thus measured an inclusive conception of entitativity.

Karmic beliefs (Cotterill et al., 2014) were measured with three items: "my current caste group position reflects my actions or deeds in my past life", "if I do good deeds in my current life they will positively influence my caste status in my future life", and "the caste group position I was born into reflects the Karma of my past life" (1 = *strongly disagree*, 7 = *strongly agree*).

Correlates of categorization

We explored how participants' responses in the triple crossed-categorization task related to other measures of social identification. To that end, we estimated the correlations between, on the one hand, the proportions of targets that participants had categorized as "us" in each of the six categories, and, on the other hand, the (aggregated) social identification variables described in the *Measures* section. We derived the likelihood of the observed responses from a multivariate normal distribution:

$$\mathbf{Y} \sim \text{MVNormal}(\mu, \mathbf{S})$$

where **Y** is the matrix of observed variable scores (columns) across participants (rows), μ is the vector of all variable means, and **S** is the variance-covariance matrix across variables.

Figure 1 shows the estimated correlations between participants' categorizations in the triple crossed-categorization task (from left to right) and various social identification variables (from top to bottom). Entitativity—the extent to which participants saw Indians of *all* castes and religions as similar to one another, as depending on each other, as sharing a common fate, as working towards shared goals, and as valuing their shared identity—was positively correlated with the proportion of *Indian, Hindu, GM* ($r = .16$, $[.04, .27]$, $\Pr(r > 0|M) > .99$), *Indian, Hindu, OBC* ($r = .21$, $[.09, .31]$, $\Pr(r > 0|M) > .99$), *Indian, Hindu, SC/ST* ($r = .10$, $[-.02, .22]$, $\Pr(r > 0|M) = .97$), and *Indian, Muslim, OBC* ($r = .18$, $[.07, .30]$, $\Pr(r > 0|M) > .99$) targets participants categorized as "us".

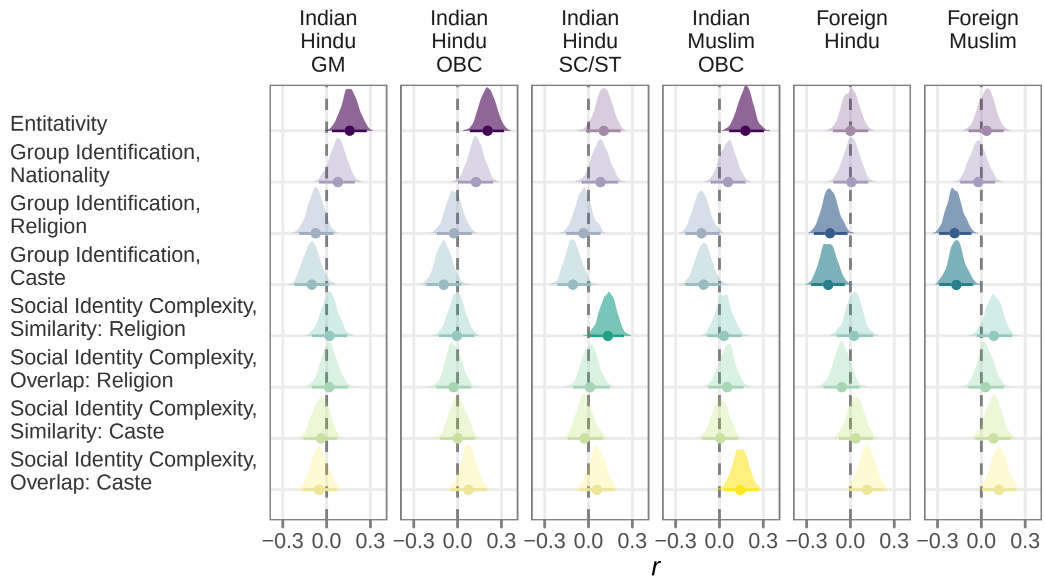

Figure 1. Correlations between various social identity variables (top to bottom) and the proportion of targets that participants had categorized as "us" in each target category (left to right). Points indicate the most likely estimate for a given correlation, while lines encompass the 97% most likely estimates of that correlation. Curves show the density distributions of the posterior probabilities, based on all samples from the posterior probability distribution. Correlations for which $\Pr(r > 0|M) > .99$ or $\Pr(r < 0|M) > .99$ are shown in a darker shade.

Group identification was only associated with participants' categorizations of foreign targets, not their categorizations of Indian targets. The extent to which participants identified with their religion was negatively correlated with how many *foreign, Hindu* ($r = -.14$, $[-.25, -.02]$, $\Pr(r > 0|M) > .99$) and *foreign, Muslim* ($r = -.18$, $[-.29, -.07]$, $\Pr(r > 0|M) > .99$) targets participant categorized as "us". I obtained similar correlations for the extent to which participants identified with their caste group, $r = -.15$, $[-.27, -.04]$, $\Pr(r > 0|M) > .99$ and $r = -.17$, $[-.29, -.06]$, $\Pr(r > 0|M) > .99$, respectively. The extent to which participants identified with their nationality was not associated with participants' categorizations—perhaps because there was a little variation in participants responses, with 81% of participants strongly agreeing with the statement. Other variables were not systematically correlated with participants' responses in the crossed-categorization task (see Figure 1).

Correlations thus confirmed that participants' categorizations were more than a straight-forward reflection of the strength of their group identification, affirming the value of the crossed-categorization task for studying identification in contexts with multiple, cross-cutting group memberships. Furthermore, participants' perceptions of entitativity across caste and religions were associated with more inclusive construals of national identity, providing tentative evidence for its potential for fostering more inclusive identities.

Appendix B: Sample Size

We ran simulations to determine the sample size required to obtain reasonably precise estimates of the model parameters of interest.[1] What made these simulations challenging is that multilevel models have more parameters than simple generalized linear models and that no clear default values exist to narrow down the parameter space for our simulations. We constrained our simulations in several ways:

1. We re-analysed existing data (kindly provided by van Dommelen et al., 2015) from a study of 91 Turkish Australians (46 women, 45 men) completing a version of the triple crossed-categorization task with eight target categories. We ran a model identical to Model 1 (Table 2, in the main text) which estimated participants' categorizations as varying across participants and across target categories. We could not estimate group differences across the participants' ingroup because all participants belonged to the same group.

2. We decided to focus our simulations on two kinds of parameters of interest. First, we considered how participants' categorizations of the eight target categories differed across three participant ingroups. Second, we considered how participants' categorizations varied as a function of a continuous predictor variable. As we could not estimate these parameters from the existing data, we used informative prior distribution to simulate plausible values for the corresponding model parameters.[2]

3. We decided to run our simulations for samples of 3 (groups) x 100 (sample size per group) = 300 participants. This sample size reflects constraints in the number of potential participants available to us.

First, we simulated 4,000 datasets of 300 participants by combining posterior predictive draws from the model fit to the existing data for the varying intercepts across participants and target categories, simulation draws from the informative prior distributions for the varying effects of participant ingroups and the fixed effect of the continuous predictor variable, and simulation draws from a Normal$(0, 1)$ distribution for values of the continuous predictor variables. Second, we randomly selected 10 of these datasets and estimated the relevant model parameters by applying a model akin to Model 4 (Table 2, in the main text).[3] Third, we calculated the

[1] Bayesian data analysis does not usually allow for *analytical* power analyses.

[2] We modeled differences between the three participant ingroups as $\beta_k \sim \text{Normal}(\beta_0, \sigma)$ with the prior distributions $\beta_0 \sim \text{Normal}(0, 1)$ and $\sigma \sim \text{Half-Student-t}(10, 0, 0.2)$, where $1 < k < 8$ was an index for the eight target categories. We modeled the fixed coefficient of the continuous predictor with the prior distribution $\beta_x \sim \text{Normal}(0, 1)$.

[3] We decided to use no more than ten samples as running these models was computationally expensive and as the precision of our estimates did not differ much across samples.

standard deviations of the posterior distributions (equivalent to standard errors in classical statistics) for all model parameters and all samples.

Table 1 shows the results of our simulations. For $N = 300$, our model estimated the (varying) effects of group differences with an average precision of $SD = 0.41$ (0.34–0.50) and the (fixed) effect of a continuous predictor with an average precision of $SD = 0.17$ (0.14–0.21) on the log odds scale. As log odds are difficult to interpret, we translated these values to the change in the proportion of "us" categorizations that results from a $+1SD$ increase in log odds above the average log odds of "us" categorizations. We thus translate the average precision to $\Delta \mathrm{Pr} = .074$ for group differences and $\Delta \mathrm{Pr} = .033$ for the continuous predictor. As we expected group differences to be greater than individual differences in participants' categorizations, we concluded that 100 participants per group would yield reasonably precise estimates of the parameters of interest.

Table 1. Standard deviations of the posterior distributions for 17 parameters across 10 simulations. *SD* is the average standard deviation across the 10 simulations while *Min* is the minimum and *Max* is the maximum. Δ Pr is the change in the proportion of "us" categorizations for a +1*SD* increase in log odds.

Parameter	k	*SD*	*Min*	*Max*	Δ Pr
$\beta_{\text{Group 1 - Group 2}}$	1	0.42	0.33	0.51	.076
$\beta_{\text{Group 1 - Group 2}}$	2	0.41	0.34	0.49	.075
$\beta_{\text{Group 1 - Group 2}}$	3	0.40	0.33	0.48	.073
$\beta_{\text{Group 1 - Group 2}}$	4	0.40	0.33	0.48	.072
$\beta_{\text{Group 1 - Group 2}}$	5	0.40	0.32	0.46	.072
$\beta_{\text{Group 1 - Group 2}}$	6	0.40	0.33	0.46	.072
$\beta_{\text{Group 1 - Group 2}}$	7	0.40	0.33	0.47	.073
$\beta_{\text{Group 1 - Group 2}}$	8	0.39	0.32	0.47	.070
$\beta_{\text{Group 1 - Group 3}}$	1	0.43	0.35	0.52	.077
$\beta_{\text{Group 1 - Group 3}}$	2	0.44	0.36	0.56	.079
$\beta_{\text{Group 1 - Group 3}}$	3	0.42	0.35	0.53	.076
$\beta_{\text{Group 1 - Group 3}}$	4	0.42	0.36	0.53	.075
$\beta_{\text{Group 1 - Group 3}}$	5	0.42	0.35	0.54	.075
$\beta_{\text{Group 1 - Group 3}}$	6	0.42	0.35	0.52	.075
$\beta_{\text{Group 1 - Group 3}}$	7	0.42	0.36	0.52	.075
$\beta_{\text{Group 1 - Group 3}}$	8	0.40	0.34	0.52	.073
β_x		0.17	0.14	0.21	.033

Appendix C: Descriptive Statistics

Table 2 reports means and standard deviations for all variables. Tables 3 to 6 report correlations between all variables for various ingroups and outgroups.

Table 2. Means and standard deviations (in brackets) for all measured combinations of outgroups (rows) and ingroups (columns).

Variable	Outgroup	GM	OBC	SC/ST
Contact quantity	GM	-	4.21 (0.96)	3.84 (1.02)
Contact quantity	OBC	3.74 (1.12)	-	4.04 (0.94)
Contact quantity	SC/ST	3.76 (1.10)	3.92 (0.98)	-
Contact quantity	Muslims	3.49 (1.30)	3.54 (1.17)	3.49 (1.19)
Positive contact	GM	-	4.03 (1.01)	3.91 (1.05)
Positive contact	OBC	3.83 (1.01)	-	3.84 (1.13)
Positive contact	SC/ST	3.68 (0.98)	3.70 (1.19)	-
Positive contact	Muslims	3.40 (1.21)	3.64 (1.13)	3.53 (1.29)
Negative contact	GM	-	2.17 (1.30)	2.27 (1.30)
Negative contact	OBC	1.96 (1.19)	-	2.38 (1.32)
Negative contact	SC/ST	1.99 (1.13)	1.88 (1.13)	-
Negative contact	Muslims	2.44 (1.30)	2.20 (1.20)	2.28 (1.23)
Friendship	GM	-	4.21 (0.84)	3.95 (0.85)
Friendship	OBC	3.58 (1.00)	-	4.03 (0.85)
Friendship	SC/ST	3.43 (0.96)	3.66 (1.00)	-
Friendship	Muslims	3.20 (1.12)	3.37 (0.95)	3.30 (0.93)
(Dis-)advantage	GM	2.83 (2.13)	2.86 (2.02)	4.08 (1.96)
(Dis-)advantage	OBC	4.89 (1.68)	3.90 (1.81)	4.11 (1.70)
(Dis-)advantage	SC/ST	5.44 (1.65)	5.40 (1.79)	4.30 (2.01)
(Dis-)advantage	Muslims	4.26 (1.83)	4.34 (1.77)	3.84 (1.96)
Policy support	OBC	2.66 (1.35)	3.79 (1.03)	3.54 (0.94)
Policy support	SC/ST	1.91 (1.15)	2.28 (1.18)	4.22 (0.88)
Policy support	Muslims	2.62 (1.23)	2.82 (1.17)	3.28 (1.30)
Realistic threat	SC/ST	3.79 (1.16)	3.48 (1.06)	-
Realistic threat	Muslims	3.39 (1.09)	3.06 (1.00)	3.24 (1.10)
Symbolic threat	SC/ST	3.28 (1.07)	3.18 (1.06)	-
Symbolic threat	Muslims	3.60 (1.17)	3.37 (1.12)	3.53 (1.27)
SDO-D		0.02 (0.71)	-0.04 (0.74)	0.05 (0.78)
SDO-E		0.14 (0.72)	-0.06 (0.68)	-0.07 (0.82)

Table 3. Correlations between variables for GM (above the diagonal) and SC/ST (below the diagonal) participants with people from other backward classes (OBCs) as the relevant outgroup.

#	Variable	1	2	3	4	5	6	7	8
1	Contact quantity		.63	.01	.67	.22	-.12	-.06	-.02
2	Positive contact			-.12	.55	.04	.02	-.08	-.03
3	Negative contact	-.28			.01	.01	.11	.13	.10
4	Friendship	.41	.49			.16	-.06	-.10	-.06
5	(Dis-)advantage	.14	.12	-.05			-.22	-.09	-.03
6	Policy support	.11	.12	-.19	.13			.14	.15
7	SDO-D	.11	.06	.15	.13	.14			.43
8	SDO-E	-.05	.17	-.03	.03	.14	.15		

Table 4. Correlations between variables for OBC (above the diagonal) and SC/ST (below the diagonal) participants with people from general castes (GM) as the relevant outgroup.

#	Variable	1	2	3	4	5	6	7
1	Contact quantity		.64	-.31	.60	-.00	-.10	-.03
2	Positive contact			-.27	.63	-.12	-.07	-.11
3	Negative contact	-.03			-.27	-.04	.00	-.05
4	Friendship	.17	.42			-.07	-.08	-.12
5	(Dis-)advantage	.06	-.02	-.04			.09	.01
6	SDO-D	.15	.08	.14	.14			.46
7	SDO-E	.06	-.02	.15	-.06	.10		

Table 5. Correlations between variables for GM (above the diagonal) and OBC (below the diagonal) participants with Dalits (SC/ST) as the relevant outgroup.

#	Variable	1	2	3	4	5	6	7	8	9	10
1	Contact quantity		.47	-.14	.41	.28	-.20	.25	.09	-.03	-.06
2	Positive contact			-.30	.18	.31	.02	-.08	-.08	-.03	-.09
3	Negative contact	.05			-.01	-.15	.03	.16	.22	.13	-.10
4	Friendship	.31	.40			.06	-.10	.07	-.05	-.12	-.10
5	(Dis-)advantage	-.03	-.02	-.23			-.21	.24	-.06	.06	.14
6	Policy support	.13	.21	.12	-.03			-.33	.06	.30	.04
7	Realistic threat	.04	.10	.03	-.03	.08			.39	-.03	.02
8	Symbolic threat	-.12	.02	.16	-.08	-.04	-.05			.35	-.03
9	SDO-D	-.11	.01	.18	.09	.11	.07	.14			.43
10	SDO-E	-.08	.11	.02	.04	.13	.15	.13	.10		

Table 6. Correlations between variables for all non-Muslims participants with Muslims as the relevant outgroup.

#	Variable	1	2	3	4	5	6	7	8	9	10
1	Contact quantity		.64	-.11	.61	.17	.10	-.11	-.18	-.04	-.01
2	Positive contact	.64		-.18	.65	.14	.15	-.19	-.22	-.04	-.06
3	Negative contact	-.11	-.18		-.12	-.01	-.08	.14	.22	.17	.02
4	Friendship	.61	.65	-.12		.03	.11	-.21	-.25	.01	-.03
5	(Dis-)advantage	.17	.14	-.01	.03		-.16	.11	.06	.02	.00
6	Policy support	.10	.15	-.08	.11	-.16		-.17	-.14	.05	-.01
7	Realistic threat	-.11	-.19	.14	-.21	.11	-.17		.51	.10	.08
8	Symbolic threat	-.18	-.22	.22	-.25	.06	-.14	.51		.13	.07
9	SDO-D	-.04	-.04	.17	.01	.02	.05	.10	.13		.46
10	SDO-E	-.01	-.06	.02	-.03	.00	-.01	.08	.07	.46	

Appendix D: Pilot Study

Informed by local knowledge, we intended to rely on last names to unobtrusively communicate caste membership in the triple crossed-categorization task. To find the most prototypical stimuli, we compiled an initial set of 50 surnames, drawing on local knowledge, databases on naming preferences, and publicly available archives of Facebook usernames. We selected 10 surnames for each of five combinations of nationality, religion, and caste: (1) Indian Hindus of upper-caste backgrounds, (2) Indian Hindus of lower-caste backgrounds (Dalits), (3) Indian Muslims, (4) foreign Hindus, and (5) foreign Muslims. From these 50 names, we created 100 stimuli resembling identity cards, 50 with female first names and 50 with male first names. Each card had the target's first and last name, age (21–26 years), and religion (Hindu, Muslim) printed on them, as well as a flag corresponding to the target's nationality (Indian, Nepali, Sri Lankan, Bangladeshi) and a silhouette corresponding to the target's gender (adapted from Ma et al., 2015). Cards for female and male targets were identical in all attributes except first name and silhouette.

We asked 26 students (19 women, 7 men) of diverse caste groups (*SC/ST*: 8, *GM*: 10, *OBC*: 8) and religious backgrounds (*Hinduism*: 16, *Islam*: 4, *Christianity*: 5, *Jainism*: 1) to review 25 of the 50 stimuli corresponding to their gender. For each stimulus, we asked participants which caste they thought the target most likely belonged to (*SC/ST*, *GM*, *OBC*, *GM or OBC*, *Can't tell/Don't know*), how typical or unusual they considered the target's name for someone of that particular nationality, religion, and (if applicable) caste (1 = *very typical*, 6 = *very unusual*), and whether the target's name reminded them of anyone in particular (*yes*, *no*) and, if so, of whom.

Participants' responses had important implications for designing the triple crossed-categorization task. On average, participants regarded all targets' names as at least "somewhat typical" ($1.42 \leq Ms \leq 3.50$). Names, however, were not enough to reliably cue caste membership—only 55% to 83% of participants identified even the most distinctive Dalit targets as Scheduled Caste / Scheduled Tribe (see Figure 2). Further, participants consistently categorized Muslim targets as Other Backward Class (see Figure 3), introducing a potential confound when comparing Muslim (OBC) and Hindu (GM) targets. Considering these findings, we decided to explicitly state caste membership (as reservation categories: GM, OBC, SC/ST) for Indian targets, and to add *Indian, Hindu, OBC* targets as a sixth category.

For the final set of stimuli, we chose the four most prototypical targets for each of the six categories under study. We ranked Indian targets by the proportion of "correct" categorizations (e.g., $\Pr(OBC)$ for *Muslim, OBC* targets) weighted by the inversed proportions of "incorrect" categorizations (e.g., $1 - \Pr(SCST)$ and $1 - \Pr(GM)$ for *Muslim, OBC* targets). We selected the four highest-ranked (Category 1) *Hindu, GM*, (2) *Hindu, OBC*, (3) *Hindu, SC/ST*, and (4) *Muslim, OBC* targets (see

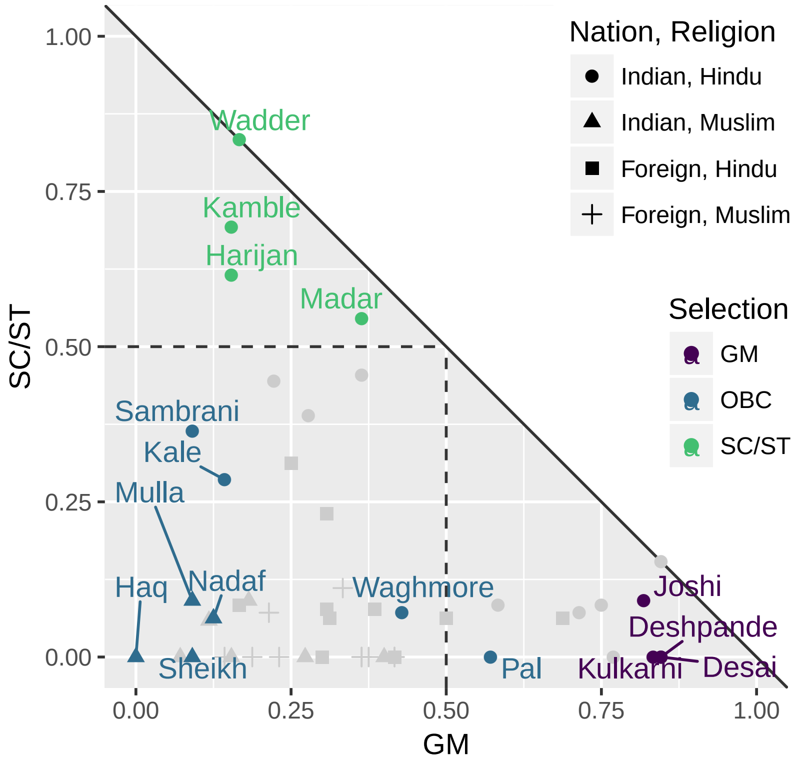

Figure 2. Proportion of SC/ST vs GM classifications per target stimulus. Targets in the upper-left quadrant were most often classified as SC/ST, while targets in the lower-right quadrant were most often classified as GM. Targets in the lower-left quadrant were more often classified as GM or OBC, or OBC than as SC/ST or GM, or could not be classified reliably. Colours highlight Indian targets selected as GM, OBC, and SC/ST stimuli, respectively, based on participants' categorizations in the pilot study. GM = General Merit, OBC = Other Backward Class, SC/ST = Scheduled Caste / Scheduled Tribe

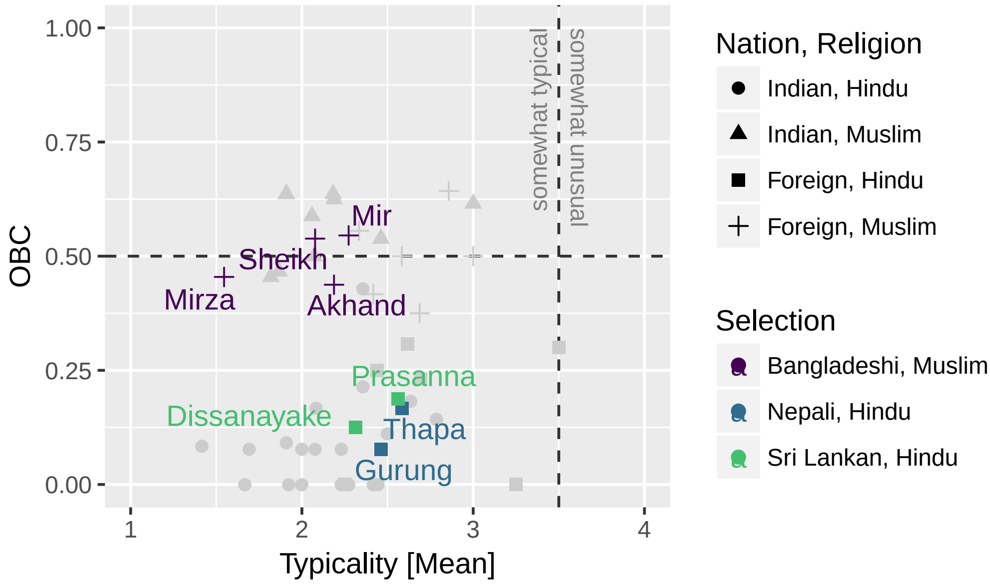

Figure 3. Foreign targets selected as Sri Lankan, Hindu (2), Nepali, Hindu (2), and Bangladeshi, Muslim (4) stimuli, respectively, based on participants' average typicality ratings.

Figure 2). We ranked foreign targets by their average typicality rating, and excluded targets who were categorized as General Merit or Scheduled Caste / Scheduled Tribe by ≥ 50% of participants (to avoid obvious caste associations). We selected the two most typical (Category 5) *Nepali, Hindu* and *Sri Lankan, Hindu* targets, and the four most typical (6) *Bangladeshi, Muslim* targets (see Figure 3). Based on the pilot study, we thus used 6 (categories) × 4 (targets) = 24 stimuli in the final study. Between 0% and 44% of participants (*Mdn* = 10%) recognised each selected name as familiar—in most cases, participants reported that targets reminded them of fellow students, former classmates, or co-workers.

Appendix E: Intergroup Threat

We tested whether participants' perceptions of *realistic* and *symbolic threat* differed depending on the inclusiveness of their ingroup construals. Specifically, we examined whether participants reported feeling less threatened by Muslims and Dalits if they categorized more targets from these outgroups as "us" versus "not us". We excluded responses from Scheduled Caste/Scheduled Tribe participants to Scheduled Caste/Scheduled Tribe targets as we were interested in perceptions of *inter*group threat. Models 0 to 7 estimated participants' mean responses, between 1 = *strongly disagree* and 5 = *strongly agree*, to each of the $5(\text{items}) \times 2(\text{outgroups}) = 10$ items. Models derived the likelihood of the observed responses from the normal likelihood distribution:

$$y_{ij} \sim \text{Normal}(\mu_{ij}, \sigma)$$

where y is the vector of participants' responses to each item, and μ_{ij} is the estimated mean response to item i by participant j, σ is the estimated residual variance (expressed as standard deviation).

Models 0 to 3 tested whether participants' responses differed across the two subscales (realistic vs symbolic threat) and across the two outgroups (Muslims vs Dalits). Model 0 estimated item responses as varying between participants but fixed across all items:

$$\mu_{ij} = \beta_0 + \beta_j$$

where μ_{ij}, the estimated mean response to item i by participant j, equals β_0, the fixed intercept across items and participants, plus β_j, the varying intercept for participant j. Instead of assigning the same mean to all items, Model 1 included distinct intercepts for the two subscales:

$$\mu_{ij} = \beta_k + \beta_j$$

where β_k is the fixed intercept for all items i in subscale k, with $k = 1$ for realistic threat and $k = 2$ for symbolic threat. Model 2 instead estimated distinct intercepts for items concerning the two outgroups:

$$\mu_{ij} = \beta_l + \beta_j$$

where β_l is the fixed intercept for all items i for outgroup l, with $l = 1$ for Dalits and $l = 2$ for Muslims as the relevant outgroup. Model 3 tested the interaction of the two factors, and estimated distinct intercepts for all four combinations of subscales and outgroups:

$$\mu_{ij} = \beta_m + \beta_j$$

where β_m is the fixed intercept for realistic threat from Dalits (when $m = 1$), for symbolic threat from Dalits (when $m = 2$), for realistic threat from Muslims (when $m = 3$), and for symbolic threat from Muslims (when $m = 4$).

Table 7. Comparison of models estimating participants' intergroup threat.

#	Description	R^2	*ELPD*	*SE*	$\Delta ELPD$	*SE*	$\frac{\Delta ELPD}{SE}$
0	*Varying intercept*	.31	-3368.1	32.9	-	-	-
1 vs 0	*Subscales*	.31	-3368.9	32.9	-0.8	0.6	-1.3
2 vs 0	*Outgroups*	.32	-3363.7	33.0	4.4	3.3	1.3
3 vs 0	*Subscales × Outgroups*	.33	-3335.1	34.0	33.0	8.4	3.9
4 vs 3	*Categorizations*	.33	-3335.5	34.0	-0.3	0.6	-0.5
5 vs 3	*Categorizations*	.34	-3330.5	34.0	4.7	3.6	1.3
6 vs 3	*Categorizations*	.33	-3336.7	34.0	-1.5	0.7	-2.1
7 vs 3	*Categorizations*	.34	-3332.8	34.0	2.3	3.6	0.6

Model 3, but not Models 1 and 2, improved upon the predictions of Model 0 (Table 7), showing that participants' perceptions of symbolic and realistic threat depended on whether the relevant outgroup was Muslims or Dalits. Specifically, participants reported more realistic ($\beta_1 = 3.62$, $[3.49, 3.75]$) than symbolic ($\beta_2 = 3.21$, $[3.09, 3.33]$) threat from (same-religion) Dalits, $\Pr(\beta_1 > \beta_2 | M3) > .99$, but less realistic ($\beta_3 = 3.23$, $[3.06, 3.38]$) than symbolic ($\beta_4 = 3.47$, $[3.34, 3.61]$) threat from (different-religion) Muslims, $\Pr(\beta_3 < \beta_4 | M3) > .99$.

Models 4 to 7 tested whether the proportion of *Indian, Muslim, OBC* and *Indian, Hindu, SC/ST* targets participants had categorized as "us" was associated with less perceived threat from, respectively, Muslims and Dalits. Model 4 estimated this relationship as constant across outgroups and subscales:

$$\mu_{ij} = \beta_m + \beta_j + \beta_{Q1} x_{Q1,jl}$$

where $x_{Q1,jl}$ is the proportion [0–1] of targets belonging to outgroup l that participant j categorized as "us", and β_{Q1} estimates the difference in threat perceptions between participants who categorized all four targets of outgroup l as "us" and participants who categorized all targets of outgroup l as "not us". Models 5 to 7 instead estimated distinct coefficients $\beta_{Q1,k}$ for each of the two subscales (M5), $\beta_{Q1,l}$ for each of the two outgroups (M6), or $\beta_{Q1,m}$ for each of the four combinations of subscales and outgroups (M7). Other than expected, Models 4 to 7 did not make better out-of-sample predictions than Model 3, indicating that whom participants considered "us" and "not us" was not associated with their perceptions of intergroup threat.

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