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International Stability and Change in Explicit and Implicit Attitudes: An Investigation Spanning 33 Countries, Five Social Groups, and 11 Years (2009–2019)

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Whether and when explicit (self-reported) and implicit (automatically revealed) social group attitudes can change has been a central topic of psychological inquiry over the past decades. Here, we take a novel approach to answering these longstanding questions by leveraging data collected via the Project Implicit International websites from 1.4 million participants across 33 countries, five social group targets (age, body weight, sexuality, skin tone, and race), and 11 years (2009–2019). Bayesian time-series modeling using Integrated Nested Laplace Approximation revealed changes toward less bias in all five explicit attitudes, ranging from a decrease of 18% for body weight to 43% for sexuality. By contrast, implicit attitudes showed more variation in trends: Implicit sexuality attitudes decreased by 36%; implicit race, age, and body weight attitudes remained stable; and implicit skin tone attitudes showed a curvilinear effect, first decreasing and then increasing in bias, with a 20% increase overall. These results suggest that cultural-level explicit attitude change is best explained by domain-general mechanisms (e.g., the adoption of egalitarian norms), whereas implicit attitude change is best explained by mechanisms specific to each social group target. Finally, exploratory analyses involving ecological correlates of change (e.g., population density and temperature) identified consistent patterns for all explicit attitudes, thus underscoring the domain-general nature of underlying mechanisms. Implicit attitudes again showed more variation, with body-related (age and body weight) and sociodemographic (sexuality, race, and skin tone) targets exhibiting opposite patterns. These insights facilitate novel theorizing about processes and mechanisms of cultural-level change in social group attitudes.

Public Significance Statement
How did explicit (self-reported) and implicit (automatic) attitudes toward five social categories (age, body weight, sexuality, skin tone, and race) change across 33 countries between 2009 and 2019? Harnessing advances in statistical techniques and the availability of large-scale international data sets, we show that all five explicit attitudes became less negative toward stigmatized groups. Implicit attitudes showed more variation by target: Implicit sexuality attitudes also decreased in bias, but implicit age, body weight, and race attitudes did not change, and implicit skin tone attitudes even increased in bias favoring light-skinned over dark-skinned people. These findings underscore the possibility of widespread changes in a direction of more positivity toward stigmatized social groups, even at an automatic level. However, increasing bias in certain domains suggests that these changes are far from inevitable. As such, more research will be needed to understand how and why social group attitudes change at the cultural level.

Keywords: cross-cultural comparisons, Integrated Nested Laplace Approximation, social change, social group attitudes, time-series modeling

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Benedek Kurdi and Tessa E. S. Charlesworth contributed equally to this work. Benedek Kurdi is a member of the Scientific Advisory Board at Project Implicit, a 501(c)(3) nonprofit organization and international collaborative of researchers who are interested in implicit social cognition. All data and analysis code are publicly available on the Open Science Framework at https://osf.io/bfqgu/. All preprocessing steps and statistical analyses were performed in the R statistical computing environment (Version 4.2.2; R Core Team, 2021). The analyses were not preregistered.

Benedek Kurdi played a lead role in conceptualization, data curation, formal analysis, investigation, methodology, project administration, software, supervision, visualization, and writing–original draft. Tessa E. S. Charlesworth played a lead role in conceptualization, data curation, formal analysis, investigation, methodology, project administration, software, supervision, visualization, and writing–original draft. Patrick Mair played a lead role in methodology and a supporting role in formal

continued

Humans are arguably the most social species on our planet (Dunbar, 1993). Therefore, maintaining accurate representations of others—both as individuals and as members of social categories—is critical to successfully navigating people's everyday environments. Central to this mundane yet vital task are social group attitudes, or representations of social groups along a positive–negative continuum (Eagly & Chaiken, 1993). From the very inception of scientific psychology, attitudes have been recognized as guiding decisions about whom to approach and whom to avoid, whom to affiliate with and whom to stay away from, and whom to help and whom to harm (Allport, 1935; LaPiere, 1934; Thurstone, 1928).

Critically, social attitudes are not set in stone. Both human minds and social environments are complex and dynamic, and attitudes thus have the potential to shift adaptively in response to new information (Albarracin & Shavitt, 2018; Wood, 2000). A primary endeavor in experimental social psychology has therefore been to document why, when, and how social attitudes change versus remain stable. Indeed, accurately characterizing how social attitudes shift in the moment and over longer periods of time is central to understanding how the human mind represents social information (Lewin, 1935). Moreover, social group attitudes help explain and predict social behavior at both the individual (Kurdi et al., 2019; Talaska et al., 2008) and the collective level (Calanchini et al., 2022). As such, shifting attitudes toward less bias in favor of dominant groups has also been seen as essential to the endeavor of alleviating social group-based inequality (Ferguson et al., 2025; Paluck et al., 2021).

Evidence of Explicit and Implicit Attitude Change: Short-Term, Experimental, and Individual

A key conceptual distinction that has driven much empirical research into processes of attitude malleability and change over the past decades is that between explicit and implicit attitudes. The nature of this distinction and the best way to define it continue to be contested (see, e.g., De Houwer, 2019; Ferguson & Cone, 2021; Gawronski et al., 2022; Greenwald & Banaji, 1995). However, for the present purposes, we define explicit attitudes as reflecting relatively controlled (conscious, controllable, and intentional) aspects of retrieving evaluative information—processes that are most often measured via self-report. By contrast, implicit attitudes reflect relatively automatic (unconscious, uncontrollable, and unintentional) aspects of retrieving evaluative information and are usually measured via indirect assays, such as the Implicit Association Test (IAT; Greenwald et al., 1998), sequential priming (Fazio et al., 1986), or the Affect Misattribution Procedure (Payne et al., 2005).

Most critical for the present purposes, explicit and implicit attitudes are also often thought to differ in their potential for, and mechanisms of, change. For instance, dominant dual-process perspectives in social cognition (McConnell & Rydell, 2014; Smith & DeCoster, 2000; Strack & Deutsch, 2004) have converged on the idea that explicit attitudes are updated via quick and flexible propositional processes (e.g., in response to persuasive appeals). In contrast, according to these theories, implicit attitudes are relatively unlikely to change. If they do, change is assumed to require exposure to vast numbers of stimulus pairings in one's social environment.

Indeed, early experiments (e.g., Olson & Fazio, 2001; Rydell et al., 2006, 2007) seemed to support this dual-process perspective. However, more recent evidence, now consisting of hundreds of studies, suggests that implicit attitudes, much like their explicit counterparts, can be updated rapidly and flexibly (Cone et al., 2017). Moreover, implicit attitudes can reflect relatively complex and sophisticated forms of information and mechanisms of change that go well beyond stimulus pairings experienced in the environment (De Houwer et al., 2020; Kurdi & Dunham, 2020; Mandelbaum, 2016).

Although these studies have been characterized by tight experimental control and, as such, high levels of internal validity in understanding cognitive mechanisms of change, the external validity of their conclusions has been uncertain (Greenwald et al., 2022; Kurdi et al., 2023). In particular, this line of work has focused on (a) novel targets (e.g., fictitious groups or geometric shapes), (b) short-term change, with measurements immediately following the intervention, and (c) the individual as the sole level of analysis. As such, it is unclear whether the results suggesting malleability in explicit (and especially implicit) social group attitudes would extend to (a) real-world targets imbued with lifelong histories of evaluative learning, (b) enduring, rather than ephemeral, shifts (see, e.g., Lai et al., 2014, 2016; Paluck et al., 2021), and (c) emergent processes at the cultural level, such as those associated with changes in legal contexts (Ofosu et al., 2019), media representations (Ravary et al., 2019), and large-scale social movements (Sawyer & Gampa, 2023). To summarize, most existing research on explicit and implicit attitudes has focused on experimental, short-term, and individual-level processes of change, with questionable generalizability to naturally occurring, long-term processes at the cultural level (Kurdi & Charlesworth, 2023).

Evidence of Explicit and Implicit Attitude Change: Long-Term, Naturalistic, and Cultural

Recently, a complementary line of work has started documenting more naturalistic, long-term changes in explicit and implicit social group attitudes, although with an exclusive focus on the United States (Charlesworth & Banaji, 2019, 2021, 2022a). Relying on publicly available data collected via the Project Implicit United States (PI:US) educational website (https://implicit.harvard.edu/), this research showed that explicit attitudes consistently dropped toward less bias: Since 2007, respondents in the United States have been expressing less anti-old/pro-young, anti-fat/pro-thin, anti-gay/pro-straight, anti-dark skin/pro-light skin, and anti-Black/pro-White

analysis, investigation, software, and writing–review and editing.

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attitudes. These findings align with similar, well-documented trends obtained in representative U.S. surveys, such as the General Social Survey (Marsden et al., 2020), and likely reflect changing norms about the acceptability of expressing negativity toward stigmatized groups (Payne et al., 2017).

More importantly, the same line of work has shown that some (but not all) implicit social group attitudes also decreased in bias over the same time span in the United States. Specifically, implicit sexuality attitudes dropped in bias by 65% and are now close to neutrality. Implicit race and skin tone attitudes have also decreased, although at slower but still notable rates of 26% and 25%, respectively. These findings are theoretically noteworthy, because they provide initial evidence that, contrary to dominant dual-process perspectives, but in line with propositional accounts, implicit attitudes can exhibit meaningful, long-term change even in the context of preexisting, consequential social group targets.

However, implicit attitude change did not extend to all social group targets in the United States: Implicit age and body weight attitudes were, and have remained, high in bias. These different trajectories of implicit attitudes across social groups provide an empirical basis for new theorizing about factors that help explain when attitude change does (and does not) occur, as well as whether change will be widespread across people and places (Charlesworth & Banaji, 2021; Charlesworth, Sanjeev, et al., 2023). We return to these ideas in the context of the present project below.

As a final general remark on this line of work, we note that a cultural-level lens on explicit and implicit attitude change bypasses many of the ongoing debates about the validity and reliability of both indirect and direct measures when applied to individual-level cognition and behavior. For instance, whereas direct measures of attitudes have been criticized for their easy fakeability (Fazio et al., 1995), indirect measures, such as the IAT used in the present project, have been in the crosshairs for relatively low predictive validity at the individual level (e.g., Meissner et al., 2019). However, at the cultural level, aggregates of explicit attitudes can be interpreted as valid indicators of widely accepted social norms (Tankard & Paluck, 2016), and aggregates of implicit attitudes have shown moderate-to-strong correlations with consequential outcomes (Calanchini et al., 2022; Hehman et al., 2019). As such, these divergent results reinforce the importance of studying change in these constructs at the cultural level of analysis.

Cultural-Level Explicit and Implicit Attitude Change Beyond the United States

The emerging focus on cultural-level explicit and implicit attitude change has, with few exceptions, remained hampered by an exclusive focus on the United States. However, there is an obvious need to expand psychological inquiry beyond a Western, Educated, Industrialized, Rich, and Democratic perspective (Henrich et al., 2010). Doing so allows not only for more equitable inclusion of previously understudied populations but can also provide important insights into the cross-country correlates and mechanisms of attitudinal processes. That is, moving beyond the United States may help us uncover informative cultural differences in when and how attitudes change.

After all, cultures differ in the very meaning that they ascribe to social groups (e.g., race in the United States vs. Brazil; Daniel, 2006), in their historical contexts (e.g., slavery in colonizing vs. colonized countries), and in their present cultural and ecological settings (e.g., vulnerability to climate devastation, social events). Recent evidence even suggests that, if anything, cultural values—especially emancipatory values, such as pro-gay attitudes—have been diverging across countries (Jackson & Medvedev, 2024). Yet, studies linking long-term changes in social group attitudes to social events—such as the Black Lives Matter movement (Sawyer & Gampa, 2018), the federal legalization of marriage equality (Ofosu et al., 2019), and the Trump presidency (Charlesworth & Banaji, 2022a)—have been largely U.S.-centric. Ultimately, the presence of myriad cultural differences in the meaning, histories, and present ecology surrounding social groups raises the possibility that attitude trends previously observed in the United States may not generalize to other countries.

At the same time, with the rise of mass media and technological access, cultures around the world seem to be becoming increasingly interconnected. Indeed, some provocative perspectives argue that we may eventually reach "the end of history," with all countries becoming liberal democracies (Fukuyama, 1992). As evidence for such collapsing cultural differences, one may consider the growing dominance of English and the loss of most indigenous languages (Krauss, 1992) or the global spread of Christianity (Pew Research Center, 2011). Certain recent events that are potentially relevant to social group attitudes have also transcended cultural boundaries: The Black Lives Matter movement spurred anti-racist protests far beyond the United States (Beaman et al., 2023), and the push for marriage equality spanned many countries (Paternotte, 2015). It is therefore an open question whether and how explicit and implicit social group attitudes will have changed or remained stable beyond the United States.

The Present Project

The present project aims to advance research on long-term explicit and implicit attitude change by taking a more expansive, international approach. Within this general framework, we focus on three empirical and theoretical contributions, along with three methodological contributions.

Empirical and Theoretical Contributions

The first contribution, as already mentioned, is to document international trends of attitude change in a sample of 1.4 million+ participants from 33 different countries, collected continuously between 2009 and 2019 in countries' native languages through the Project Implicit international websites (PI:INT; Charlesworth, Navon, et al., 2023). These international trends are then directly compared to trends from the United States to understand the generality or specificity of past U.S.-focused analyses. Notably, given vast differences in country-level sample sizes, we analyze broader international patterns, along with cross-country variability, and leave the investigation and interpretation of country-specific trajectories to future work.

The second empirical contribution is to compare the rates of change across explicit (controlled) and implicit (automatic) social group attitudes, as well as across five social group targets (age, race, sexuality, skin tone, and body weight). Notably, comparing explicit and implicit trajectories in this way can shed light on possible mechanisms of societal attitude change. For example, previous

U.S.-focused research has found that explicit attitudes change relatively consistently across attitude targets, suggesting that the underlying mechanism is likely to be a domain-general norm prohibiting the expression of negativity toward stigmatized social groups. By contrast, the same research suggests that implicit attitude trajectories are more sensitive to unique cultural events yoked to specific attitude targets (Charlesworth & Banaji, 2019; Payne et al., 2017). However, it is an open question whether the same results would generalize to countries beyond the United States, some of which are characterized by vastly different social norms and societal structures.

Theoretically, comparing trends across social group targets can also contribute to both classic and recent perspectives that draw a distinction between body-related and sociodemographic stigmas[1] (Charlesworth, Sanjeev, et al., 2023; Neel et al., 2013; Sidanius & Pratto, 1999). For instance, because physical and health-related body stigmas (such as age and body weight) are perceived to have objectively negative consequences, they are both more consensually held (Sechrist & Stangor, 2001) and more socially acceptable to express (Crandall et al., 2002) than more sociodemographic stigmas assigned to characteristics such as race or skin tone (Goffman, 1986; Sidanius & Pratto, 1999). Related research on fundamental social motives (Schaller et al., 2017) also suggests that these different categories of stigma will activate different threats, such that body weight stigma primarily activates disease-avoidance motivations, whereas race and skin tone stigma primarily activate safety motivations (Neel et al., 2013).

Although both safety and disease concerns have decreased across human evolutionary history, it is possible that the precipitous drops in homicide and assault rates worldwide (Gurven & Kaplan, 2007) could result in less chronic activation of safety-related stigmas, while the still-present concerns about pandemics and illness could maintain disease-related stigmas. Indeed, recent empirical evidence using 100 years of historical English book text supports the idea that sociodemographic stigmas have changed faster than body-related stigmas (Charlesworth, Sanjeev, et al., 2023). The present project provides an opportunity to test this distinction over a different time frame and across cultures that may also vary in their fundamental social motives (Pick et al., 2022).

Finally, the third and most exploratory contribution is to consider how key ecological correlates may predict international trajectories of explicit and implicit attitudes over time. There is now a large body of research suggesting that features of the environment shape psychological outcomes: Rice-based agriculture involves greater human coordination and thus prompts more collectivism than wheat-based agriculture (Talhelm et al., 2014); hard soil requires ploughing and promotes more gendered division of labor and stronger gender stereotypes (Alesina et al., 2013); and the propensity for disease threats results in more out-group distrust to avoid pathogens (Schaller & Park, 2011). Most relevant for the present purposes, social group attitudes and ecology have long been argued to be fundamentally linked (Sng et al., 2018; Uskul & Oishi, 2020). In fact, Hehman et al. (2021) recently showed a role for some ecological correlates in understanding the variation of explicit and implicit attitudes across space. However, the focus in that work was variation in attitude magnitudes and only within the United States; by contrast, the present exploratory analyses focus on correlates of attitude change across 33 different countries.

Methodological Contributions

In addition to the three substantive contributions outlined above, the current work offers several methodological advances beyond past work. First, we rely on cutting-edge Bayesian time-series modeling using Integrated Nested Laplace Approximation (INLA; Rue et al., 2009), which combines the well-known flexibility and cross-model comparability afforded by Bayesian statistics with much improved speed of estimation, even in the context of large samples and complex models such as those used here. For example, the present Bayesian approach has allowed us to fit models to the same data both at the level of Country × Year aggregates and at the level of individual participants, thus ensuring robust conclusions. Given the open data and analysis code provided, future investigators will have the opportunity to emulate and further improve upon the current analytic strategy.

Second, we compare trends across different subsets of respondents, including addressing the effects of education (comparing those with more vs. less education), key demographics (e.g., straight vs. nonstraight respondents on the sexuality test), and age versus cohort effects on change using age–period–cohort (APC) models (Fosse & Winship, 2019; Yang & Land, 2013). In fact, to our knowledge, the current project is the first to use this advanced statistical modeling approach across multiple attitude targets for both explicit and implicit attitudes, thus providing the first insights into various potential sources of change.

Third, we address common challenges in inferring attitude change from cross-sectional, cultural-level data. Specifically, we rule out concerns of self-selection (and especially that participants may be self-selecting into attitude topics for which they have lower bias) in two supplemental experiments. We find no evidence that self-selection affects participants' explicit or implicit attitudes, once relevant demographic differences are accounted for. Relatedly, following previous work, we use various raking and weighting approaches to rule out concerns of sample change (Charlesworth & Banaji, 2019). We also stress test the robustness of all findings, including refitting the models to citizens of each country (rather than residents), using population weighting (rather than within-sample weighting; see the Method section), and testing for the possibility of country-level response biases (i.e., preferentially using extreme vs. moderate scale values; Hui & Triandis, 1989).

Despite these efforts to address methodological concerns, we nevertheless face the obvious omission of nearly all countries of the Global South, most notably Africa and Latin America. Furthermore, PI:INT relies on samples of online volunteers who may not be broadly representative of population demographics,

[1] The distinction between "body-related" (e.g., body weight, age) and "sociodemographic" (e.g., race, skin tone, sexuality) stigmas is derived from both empirical observations showing that the two sets of stigma tend to differ in stereotype content and trends over time (Charlesworth, Sanjeev, et al., 2023; Pachankis et al., 2018), as well as from theoretical arguments about their evolutionary and contemporary function in society (Goffman, 1986; Neel et al., 2013; Sidanius & Pratto, 1999). Of course, race and skin tone are also visible on the body, but they are not first and foremost about the physical body (its health or its appearance). Rather, race/skin tone are more principally about the cultural meanings that have become attached to those physical cues (e.g., about perceived violence, competence, laziness, etc.). Body-related stigmas thus have the unique feature of being first and foremost about physical appearance and especially about bodily health.

especially for countries with smaller sample sizes and with higher levels of inequality in terms of access to the Internet (Charlesworth, Navon, et al., 2023). Thus, although we see great potential in using the PI:INT data for expanding research on the patterns and correlates of explicit and implicit attitude change to an international scale, we underscore that the current project is only the beginning. We hope that future work will make targeted efforts to ensure truly global representation in data collection of explicit and implicit social group attitudes.

Method

Data Source and Access

All data were accessed from the PI:INT data set archived at https://osf.io/26pkd/ using the osfr package (Wolen et al., 2020), which automates integration with OSF. The PI:INT data (Charlesworth, Navon, et al., 2023) were collected via a set of 34 country-specific websites and contain measures of explicit and implicit attitudes administered in each country's native language or languages (e.g., French in France; French and German in Switzerland). Comprehensive details on measures, procedures, and the archiving process for PI:INT are provided in Charlesworth, Navon, et al. (2023).

Volunteer participants found their respective countries' websites mostly through assignments for work or school or through word-of-mouth. Once on their country's website, participants selected one of seven social group targets. In this project, we use a subset of five of these social group targets (a) for which measures of explicit and implicit attitudes were available (thus excluding the gender stereotype task, which measures associations of women with the arts and men with science) and (b) that were consistently available across all countries (thus excluding the nationality attitude task, which measures evaluations of one's own country relative to the United States, leading to noncomparable estimates across countries). As such, the five social group targets used for the present project include age (old vs. young), body weight (fat vs. thin), race (Black vs. White), sexuality (gay vs. straight), and skin tone (dark skinned vs. light skinned).

Measures and Procedure

All measures were administered in each country's native language(s). Once the participant selected a social group of interest, they completed a measure of implicit attitudes and a measure of explicit attitudes in randomized order. Data were collected over an 11-year period between January 1, 2009, and December 31, 2019. Data collection was continuous in the sense that the website was always available for volunteers to participate, although actual rates of participation varied over time (see Supplemental Materials).

Implicit attitudes were measured using the IAT (Greenwald et al., 1998). The IAT is a computerized response time task in which participants are asked to sort category and attribute stimuli across two critical blocks. For example, on the age attitude IAT, one critical block involved sorting stimuli representing the category of old people and stimuli representing the positive attribute using one response key and stimuli representing the category of young people and negative attributes using a different response key. During the second critical block, the mapping of categories to attributes was reversed. The order of the two critical blocks was randomized.

IAT performance was scored using the improved scoring algorithm (Greenwald et al., 2003). The resulting D score captures the difference in response time between stereotypically congruent pairings (e.g., old–bad/young–good) and stereotypically incongruent pairings (e.g., old–good/young–bad), standardized by dividing the raw response time difference by the inclusive standard deviation of all response latencies. The IAT was scored in such a way that higher scores correspond to higher levels of bias in favor of dominant groups (i.e., young, thin, White, straight, or light-skinned people) over stigmatized groups (i.e., old, fat, Black, gay, or dark-skinned people).

Explicit attitudes were measured using 7-point response scales that asked participants to report which statement best described them, with response options ranging from 1 (corresponding to a strong preference for the stigmatized over the dominant group, e.g., old over young people) to 4 (no preference) and finally to 7 (corresponding to a strong preference for the dominant over the stigmatized group, e.g., young over old people). To ensure that zero represents neutrality (as it does on the IAT), we subtracted four from explicit attitude scores. Furthermore, to place measures of explicit and implicit attitudes on a common scale, both scores were standardized by dividing them by the respective sample standard deviations. Thus, all reported values can be interpreted in terms of standard deviation units. For example, an explicit (implicit) attitude score of 0.50 indicates that explicit (implicit) attitudes deviated from the zero point (neutrality) by half a standard deviation.

A common concern in cross-cultural research is that respondents vary in how they approach self-report scales (Baumgartner & Steenkamp, 2001; Chen et al., 1995; Hui & Triandis, 1989; Johnson et al., 2005). Specifically, some cultures (typically individualist, highly masculine, or high-power-distance countries such as the United States and Canada) tend to use more extreme responses, whereas other cultures (typically collectivist, low masculine, or low-power-distance countries such as Japan, Turkey, or Portugal) tend to use the middle responses. In supplemental analyses, we rule out this concern and show that all cultures have similar distributions of responses (see Supplemental Materials).

Sample Characteristics

The final PI:INT sample for this project consisted of 1,436,782 participants across the five attitude tasks and 33 countries: Argentina, Australia, Austria, Belgium, Brazil, Canada, China, Colombia, the Czech Republic, Denmark, France, Germany, Hungary, India, Ireland, Israel, Italy, Japan, Mexico, Norway, Poland, Portugal, Romania, Russia, Serbia, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Turkey, and the United Kingdom. Data were retained for all participants with complete IAT scores. Most participants (95%) also had data from the corresponding explicit attitude task; however, this was not a criterion for inclusion.

In addition, we retained only participants in the sample who reported the corresponding country as their country of residence. For example, an Indian participant reporting their place of residence as the United States—which is not included in PI:INT—would have been excluded from the data set for India. All participants from the Netherlands were excluded from the analyses on this basis, because, due to a coding error during data collection, residency information was not available for this country. Given that our main goal in the present project is to capture cultural trends, we reasoned that participants completing an IAT and self-report measure of attitudes in the language of their country of residence are sufficiently representative of that country's cultural environment even if they are noncitizens. Nevertheless, in supplemental analyses, we refit the primary models using respondents' country of citizenship (rather than residency) as the criterion for inclusion and found inferentially identical results (see Supplemental Materials).

Readers interested in country-specific demographic details, including specific country sample sizes, should consult the OSF page for PI:INT (https://osf.io/26pkd/), as well as the initial report of the data (Charlesworth, Navon, et al., 2023). Overall, country sample sizes varied widely and ranged from 2,414 participants from Romania to 402,267 participants from the United Kingdom. The mean age in the overall sample was 30 years ($SD = 12$ years). In terms of gender, 57.32% of the sample identified as female and 41.89% identified as male. No other options to report gender were included. In terms of political orientation, 45.68% identified as liberal, 31.76% identified as neutral, and 16.27% identified as conservative. Other demographic variables (e.g., race) were collected idiosyncratically by country and task, and thus, these variables cannot be summarized at the level of the full sample. However, below, we investigate key demographic differences (e.g., race on the race task) and report the respective demographic sample sizes in Supplemental Materials.

Finally, for the purposes of comparing the average international trends to trends observable in the United States, we used the cleaned PI:US, as reported in Charlesworth and Banaji (2022a) and openly available from OSF (https://osf.io/qywh4/). To ensure a match with the current data, we included U.S. residents who completed one of the five attitude tasks described above (age, body weight, sexuality, skin tone, or race) between 2009 and 2019 on the English-language Project Implicit demonstration website. The final PI:US sample used for this project consisted of 6,746,008 participants. The mean age was 28 years ($SD = 13$ years). In terms of gender, 67.89% of the sample identified as female and 31.24% identified as male. In terms of political orientation, 47.68% identified as liberal, 29.91% identified as neutral, and 22.41% identified as conservative.

Analytic Strategy

Preprocessing: Weighting for Demographic Change

Examining change in aggregate cross-sectional data raises the concern that changes in the sample composition over time could result in spurious patterns of attitude change. For example, given that, on average, female and liberal participants tend to be less biased in favor of dominant groups, if their representation in the sample increases over time, this might lead to the erroneous conclusion that attitudes have decreased in bias. To guard against this issue, we used a within-sample weighting and raking approach implemented through the anesrake package (Pasek, 2022).

Specifically, for each of the five tasks separately, we first set target weights across the whole sample, representing the proportion of the full sample identifying as female or male, falling within four age groups (18–24, 25–34, 35–44, 45–100), and identifying as liberal, neutral, or conservative.[2] Then, for each annual subsample (e.g., the age task in 2009), we reweighted the data to match these overall target weights. For instance, if the sample was relatively less female in 2009 compared to the overall target weights, any female-identifying participant in 2009 would be given a weight greater than one to upweight her contribution to the mean in 2009. In practice, weighting was performed for all intersections of gender, age, and politics (e.g., the proportion of liberal women who are 18–24 years old).

We then used these weight values to compute weighted annual means within each country and task (e.g., the weighted annual mean in 2009 for the age task in Sweden) and to perform model fitting. As part of the robustness checks described below, we refit all models without any demographic weighting. All conclusions were robust across weighted and unweighted models. This result implies that changes in sample demographics did not introduce meaningful confounds into the observed trends. As such, the unweighted models are available in Supplemental Materials but are not discussed further.

Preprocessing: Weighting for Sample Size

Critically, because of the wide variation in country sample sizes (from less than 3,000 in Romania to over 400,000 in the United Kingdom), for the purposes of model fitting, we also used inverse weighting based on country sample size. That is, we multiplied each country's annual estimates by the reciprocal of the sample size ($1/N$) for that country. This approach down-weights the relative contribution to the estimate from the largest countries in PI:INT (e.g., the United Kingdom and Canada) to ensure that the final international estimates are not excessively driven by these large subsamples.

In supplemental analyses, we also address the concern of certain countries being over- (or under-)represented in the data set by reweighting the data according to their real-world population representation. That is, we first collected the population size of all 33 included countries and then calculated the sum of all populations in the data (the 33 included countries had a total real-world population of $N = 4{,}343{,}542{,}431$). Then, for each country, we calculated its relative real-world representation and used those relative representations as the weights in the model (e.g., Argentina had a population of $N = 46{,}556{,}542$, which is ~1% of the total population across the 33 countries, and therefore contributed a weight of 0.01). This approach readjusts the estimates such that countries such as China and India, which have very large real-world populations, contribute more to the final model estimate. All critical conclusions were robust to this modeling strategy, although the estimates became considerably more uncertain (see Supplemental Materials).

Modeling Strategy

Bayesian modeling provides many benefits for inference, including the interpretability of inferential outputs and the ability to estimate models of high complexity (Wagenmakers et al., 2016). However, traditionally, one of the main limitations of a Bayesian approach has been the computational demands of estimating the models using Markov chain Monte Carlo sampling. Addressing this limitation, Rue et al. (2009) have introduced, validated, and implemented the INLA approach to Bayesian estimation (for book-length introductory

[2] Although the meanings of liberal/conservative may differ across countries, we are using this variable only for within-country weighting to ensure that the same proportions of liberal/conservative respondents are maintained across time; we do not use the variable to compare across countries.

treatments, see Gómez-Rubio, 2020; Wang et al., 2018; Zuur et al., 2017). This approach drastically improves the speed of estimation while also allowing for model flexibility in estimating random effects structures, as well as incorporating weighting terms, autoregressive structures, spline terms, and extensive options for modeling spatio-temporal data (Blangiardo & Cameletti, 2015).

Moreover, unlike analytic techniques such as autoregressive integrated moving average models (Box & Jenkins, 1970; Cryer & Chan, 2008), which have been developed specifically for aggregate cross-sectional time-series modeling, INLA allows for model fitting across all model types and classes, thus allowing for easy cross-model comparisons and generalizable inferences. Given these advantages, we used INLA, implemented in the R-INLA package (Rue et al., 2016), to estimate all models for this project, including (a) the model capturing overall international trends, (b) APC models (explained in more detail below), and (c) country-specific models, including all countries represented in PI:INT and the United States.

Analysis I: Modeling the Overall International Trend

The first and most important set of models were designed to capture average international trends in explicit and implicit attitudes between 2009 and 2019. To balance model complexity (and the resulting regularization) with interpretability, we fit separate models for each attitude target–attitude type combination, resulting in a total of 10 models (i.e., one model for implicit age attitudes, a second for explicit age attitudes, etc.), with each of these primary models including data from all 33 countries.

For each attitude target–attitude type combination (e.g., implicit age attitudes), we began with a linear model predicting attitude scores (either IAT D scores or relative preference scores) from the linear effect of time (year). Specifically, the dependent variable was Country × Year average attitude scores, weighted both by demographic composition and country-level sample size, as described above. We also included random intercepts for each of the 33 countries to account for the nested nature of the data. We assumed random effects to be independent and identically distributed. INLA can accommodate more complex random effects specifications (e.g., spatial autocorrelations among the random effects). However, the current sample of countries was relatively small and few countries in the data set shared borders with each other, resulting in a sparse adjacency matrix. As such, we did not explicitly model spatial dependencies in the data.

Given that temporal trends are often nonlinear, we also fit a more complex, nonlinear model to the data. The only difference relative to the model described above was that, instead of a linear effect, the effect of time was modeled using splines. The use of splines results in more flexible models by including multiple low-degree polynomial (i.e., curvilinear) effects across different sections of the independent variable. The number of such sections, and thus the complexity of the model, depends on the number of knots specified. In the models reported below, we used a total of five knots, with two knots used for the start and end points and three internal knots allowing for the modeling of nonlinear trends in attitude trajectories.

Relying on splines rather than a more complex smoothing (random walk) approach improves the parsimony of models and reduces concerns of overfitting. Based on a visual inspection of all tasks (see Figure 1), the choice of five knots provided a reasonable description of all trends and facilitated comparisons across all fitted models. Notably, these nonlinear models consistently provided better fit to the data than the more parsimonious linear models. As such, we retain and interpret only the nonlinear models in the Results section. Model fit statistics are available in the open code.

Analysis II: Age–Period–Cohort Models

Observing change in the overall attitude trends from cross-sectional time-series data could be attributed to any combination of three, interrelated factors (Fosse & Winship, 2019; Yang & Land, 2013): (a) age, that is, the sample getting older and thus producing different attitudes over time because of developmental processes (e.g., maturation or changes in executive function); (b) period, that is, attitudes changing because of widespread changes in the culture affecting most people in similar ways; and/or (c) cohort, that is, attitudes changing because of older generations (e.g., baby boomers) being replaced by younger generations (e.g., millennials). These three factors are linearly dependent on one another, such that age = period − cohort (e.g., for a 30-year-old in 2024, 30 = 2024 − their birth year of 1994). Such dependency makes it computationally difficult to decompose the relative contribution of each factor to an observed overall trend.

Again, innovations implemented with INLA have improved the ability to efficiently estimate Bayesian APC models (Fosse, 2020). As such, we use INLA to capture APC effects in the average international trend across all countries by fitting models to individual-level data. Similar to the overall trend models described above, we fit 5 (Attitude Targets) × 2 (Attitude Type) separate models to ensure computational viability and interpretability. Notably, unlike the models described above, the APC models were not based on Country × Year aggregates but rather used individual-level data as the dependent variable. The reason for this is that APC models require information regarding each individual participant's age-group and birth cohort. This difference offers an important check on the robustness of the results emerging from the present project.

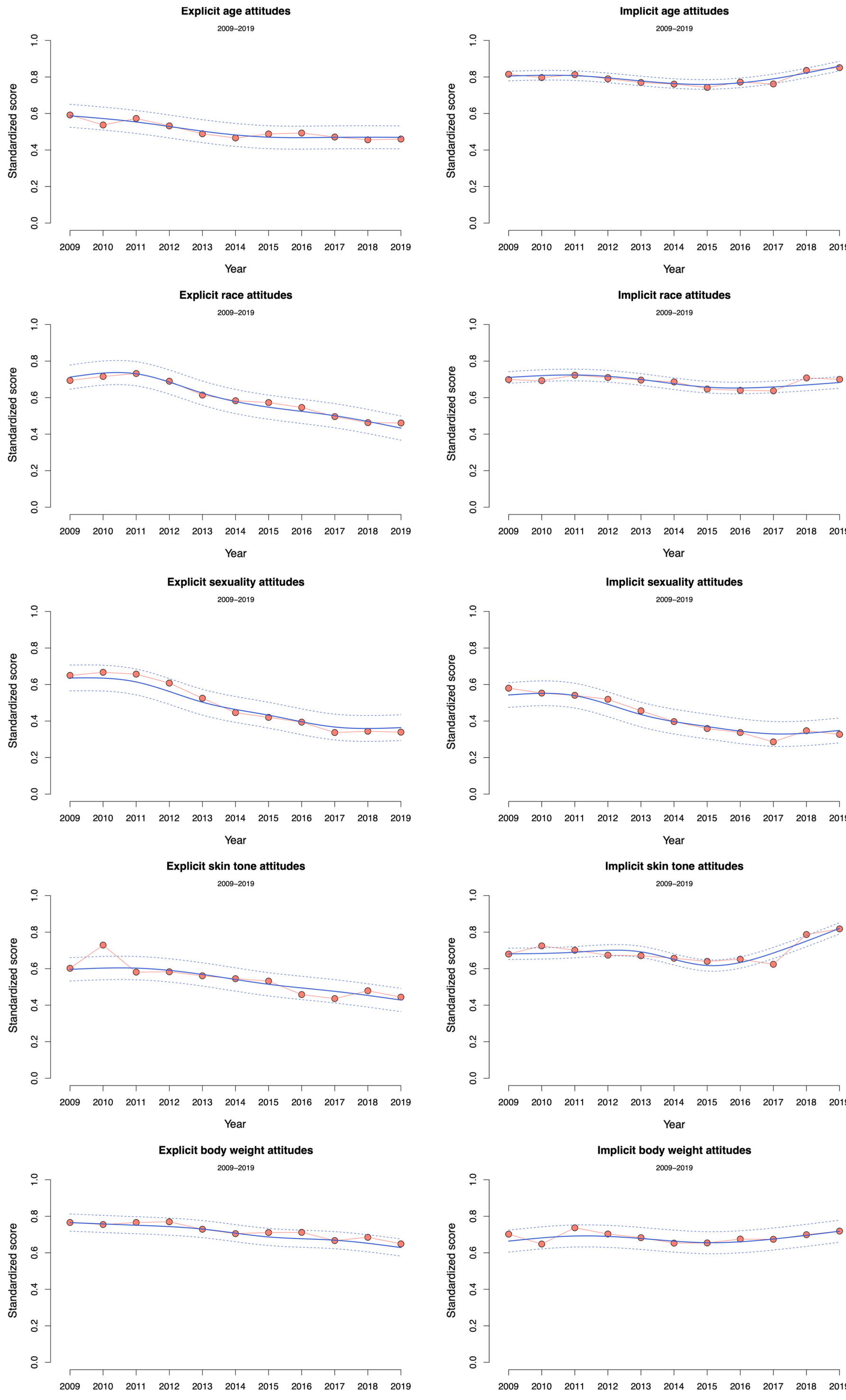
For example, for the age implicit attitudes model, we predicted individual participants' age IAT scores from a fixed effect of year, with nonlinear splines using five knots to ensure comparability with the aggregate-level models. We also included independent and identically distributed random effects for age groups, cohorts, and countries of residence. Cohorts were determined based on standard thresholds (Charlesworth & Banaji, 2019): Generation Z (after 1995), millennials (1980–1995), baby boomers (1960–1979), and silent generation (1945–1959). Age groups were separated, as above, into bins of roughly equivalent sample sizes: 18–24, 25–34, 35–44, and 45+ years. To further optimize estimation, we provided initial values based on frequentist mixed effects models fit using the lme4 package (Bates et al., 2015; Kuznetsova et al., 2017) that predicted attitude scores from a fixed effect of year and additionally included random effects for age, cohort, and country.

Analysis III: Modeling Country-Level Variability

Although cross-country comparisons are not the focus of the present work, it is nevertheless meaningful to ask to what extent countries differed in their explicit and implicit attitude trajectories over time, for several reasons. First, if country trajectories are

Figure 1

Overall Trends of Explicit and Implicit Attitudes Across 33 Countries



Note. The solid blue lines indicate the fitted trajectories from the aggregate Integrated Nested Laplace Approximation (INLA) model; the dashed blue lines indicate the 95% highest density intervals. The red dots and red line show the raw annual means, using weights for sample change. See the online article for the color version of this figure.

uncorrelated with each other, then the combined analyses described above are arguably challenging if not impossible to interpret. Second, a comparison of average cross-country correlations across explicit and implicit attitudes and the five attitude targets can provide meaningful mechanistic insights into the drivers of attitude stability and change. Finally, comparing country-level standard deviations at the beginning versus the end of the time series can reveal whether cultures are generally converging with or diverging from each other.

To explore how trends varied across countries, we repeated the model fitting steps described above for each of the 5 (Attitude Targets) × 2 (Attitude Type) × 33 (Country) combinations separately. This approach removed country-level dependencies from the data; as such, no country-specific (or other) random effects were included. We note that each of these country-specific models was fit to a small set of 11 weighted annual means. As such, we use the model outputs exclusively to understand the range and variability of trends across countries, and we refrain from making inferences about any one country in particular.

To ensure robust conclusions, for each set of models, we removed any country from the analyses that had missing values for any year. For example, Colombia had missing data on the age task in 2009; therefore, Colombia was not included in any models involving age attitudes as the dependent variable. This step was necessary to ensure that no predicted values were out of the range of the predictor (years), thus resulting in noisy estimates. In addition, in a simulation study reported in Supplemental Materials, we show that the annual increase in sample sizes observed in the PI:INT data may result in spurious estimates of convergence in attitudes over time; as such, we urge readers to interpret the results of these analyses with caution.

Analysis IV: Modeling Comparison With the United States

We applied the same modeling steps reported under Analysis III above to the data from the United States to ensure direct comparability with the international data. As such, the U.S. models reported below differ from those previously published (Charlesworth & Banaji, 2019, 2021, 2022a, 2022b), which used an autoregressive integrated moving average time-series approach (Box & Jenkins, 1970; Cryer & Chan, 2008). Thus, the current modeling of the PI:US data provides an important test of robustness across two fundamentally different modeling techniques.

Analysis V: Modeling Key Demographic Differences

The current work aims to provide a survey of the overall international trends in explicit and implicit attitudes; thus, a comprehensive review of all demographic differences in trends is beyond the scope of this project. However, because of the central role of social group identities in attitude formation and change (Nosek et al., 2007; Ratliff et al., 2020), we conducted five key demographic difference comparisons. Specifically, we assess the difference in trends for (a) relatively older versus younger respondents on the age task; (b) White versus non-White respondents on the race task; (c) straight versus nonstraight respondents on the sexuality task; (d) relatively lighter skinned versus darker skinned respondents (based on self-reported relative skin tone) on the skin tone task; and (e) relatively heavier versus thinner respondents (based on self-reported relative weight) on the body weight task.

For the key demographic difference models, we fit separate INLA models for the two groups of respondents (e.g., straight vs. nonstraight), using the same specifications as in the primary models, with inverse weights for country frequencies, and weighted yearly means according to demographic representation on gender, age, and political orientation. Given potential concerns about the overrepresentation of highly educated participants in the PI:INT data, we also fit separate models to more versus less highly educated participants in a similar fashion for all five tasks and found highly robust results across the two subgroups of respondents (see Supplemental Materials).

Analysis VI: Exploratory Representational Similarity Analysis of Ecological Correlates

Because the PI:INT data set exhibits variability not only across a relatively long time span of 11 years but also across a large sample of 33 countries, it provides a unique opportunity to explore how explicit and implicit attitude change may be coupled with spatiotemporal variation in ecology. We draw on data from the Ecology–Culture Dataset (Wormley et al., 2022), which contains nine time-varying ecological variables (e.g., gross domestic product and life expectancy) and 72 static cultural variables (e.g., tightness–looseness, gender inequality, and personality) across 220 countries. Because temporal trends are the primary focus of the present work, we narrow our focus to those nine ecological variables from the Ecology–Culture Dataset that have time-stamped data. After detrending and normalizing the data to avoid spurious time-series correlations, we then use representational similarity analysis (Kriegeskorte et al., 2008) to establish links between spatiotemporal variation in (a) ecological indicators and (b) attitudinal indicators. The details of these analyses, including the detrending and normalization of the data, are reported in Supplemental Materials.

Transparency and Openness

All data and analysis code are publicly available on the Open Science Framework (OSF) at https://osf.io/bfqgu/. All preprocessing steps and statistical analyses were performed in the R statistical computing environment (Version 4.2.2; R Core Team, 2021). The analyses were not preregistered.

Results

First, we report the average international trends between 2009 and 2019, derived from the aggregate INLA models fit to data from all 33 countries, for each attitude target (age, race, sexuality, skin tone, and body weight) and attitude type (explicit vs. implicit). Second, we test the robustness of our conclusions using individual-level models that decompose potential sources of change into age, period, and cohort effects. Third, we explore variability around the overall trends via country-specific models. Fourth, we contextualize the average international trends by comparing them to trajectories of explicit and implicit attitude change observed in the United States. Fifth, we examine key demographic differences in the average international trends for each individual test (e.g., race differences on the race test). Sixth, we explore correlations between trajectories of ecological variables (e.g., population density) and explicit and implicit attitudes.

Analysis I: Overall International Trends

Explicit Attitudes

Aggregating across all 33 countries, explicit attitudes consistently shifted toward neutrality between 2009 and 2019 for every attitude target (see Table 1). The largest drops are seen in explicit sexuality attitudes, which decreased in bias by 43% (based on fitted estimates from the INLA model), and in explicit race attitudes, which decreased in bias by 39%. The smallest changes toward neutrality are observed in explicit body weight and age attitudes, which decreased in bias by 18% and 20%, respectively. The change in explicit skin tone attitudes fell between these two extremes, with a 28% decrease in bias.

Visual inspection of the overall trends (see Figure 1) suggests that decreases in explicit attitudes were mostly linear. However, explicit race attitudes showed some suggestion of an inflection point around 2012, with consistent evidence for change toward less bias since then (but not before). Explicit sexuality attitudes also showed some suggestion of an inflection point around 2012, with increasing rates of change toward less bias up until 2012 and an indication that change toward neutrality has decelerated since 2012. These observations based on visual inspection were further supported by supplemental analyses (provided in the open code) that calculate the first derivative of the fitted time series.

Implicit Attitudes

Implicit attitudes showed more variation in long-term trends, with the rate and even the direction of change depending on the social group target. Specifically, only implicit sexuality attitudes were found to have decreased in bias between 2009 and 2019, with a considerable overall drop of 36%. Notably, implicit sexuality attitudes exhibited the lowest level of bias both at the beginning and the end of the time series. By contrast, with only a small 4% drop in magnitude, implicit race attitudes barely changed over the same period. Implicit age and body weight attitudes also remained largely stable, with slight increases of 7% and 8% in bias, respectively. On the other end of the spectrum, implicit skin tone attitudes exhibited a unique and sizable increase of 20% in bias between 2009 and 2019. As a result, implicit skin tone attitudes became the second most biased by the end of the time series (behind age).

Visual inspection of the overall trends (see Figure 1) reveals that the change in implicit sexuality attitudes was largely linear, although—similar to explicit sexuality attitudes—the pace of change has been decelerating since 2012, again supported by supplemental analyses. By contrast, the increase in bias in implicit skin tone attitudes was due to a marked inflection point observed in 2015. Before this inflection point, implicit skin tone attitudes had been largely stable (and even showed some signs of dropping in bias between 2012 and 2014).

Analysis II: Age–Period–Cohort Models

Explicit Attitudes

To better understand the sources of change observed in the relevant attitude trajectories, we fit APC models to the PI:INT data, separately for each attitude target (age, race, sexuality, skin tone, and body weight) and attitude type (explicit vs. implicit). As described above, these models included random effects for both cohort and age, allowing us to better isolate the focal period effects of interest (i.e., the effects of large-scale cultural changes affecting entire societies at any given time). If the APC models yield similar conclusions to those reported in the main analyses involving aggregate-level models, then we can infer that any observed changes are likely due to period effects. Moreover, given that APC models were fit to the data of individual participants (rather than to Country × Year aggregates), a convergence between the two sets of models would also provide some reassurance that the main results reported above were not an artifact of aggregation.

Indeed, we find that the predicted time-series trajectories for explicit attitudes were highly correlated with each other across the main aggregate models reported above and the APC models (Spearman's ρs > .95; see Table 2 and Figure 2). The reason for this convergence is that both the main aggregate models and the APC models were characterized by a robust and similar decrease of explicit attitudes in bias. Such consistency across the main aggregate and the APC models strongly suggests that the most likely source of change in explicit attitudes was a period effect (affecting most or even all segments of society) rather than cohort replacement or aging of the sample.

Table 1

Sample Characteristics and Summary Statistics of Overall Trends by Task (From Fitted Model Estimates)

	Sample size			Explicit attitude			Implicit attitude		
Task	N	N_{min}	N_{max}	Start	End	% change	Start	End	% change
Age	194,856	460	35,433	0.59	0.47	−20.06	0.81	0.86	6.78
Race	528,286	432	263,408	0.71	0.43	−39.23	0.71	0.68	−3.90
Sexuality	317,766	669	41,603	0.64	0.36	−42.76	0.54	0.35	−35.80
Skin tone	183,421	332	30,145	0.60	0.43	−28.17	0.68	0.82	20.49
Body weight	212,453	467	35,852	0.77	0.63	−17.85	0.66	0.72	8.15

Note. All values are computed from standardized scores weighted by sample composition and country sample size. The start and end values represent the first and last of 100 predicted values between 2009 and 2019, derived from the aggregate Integrated Nested Laplace Approximation (INLA) models. Percent change values indicate the amount of change between the predicted start and end values. N = total sample size; N_{min} = smallest country-specific sample size; N_{max} = largest country-specific sample size.

Table 2
Trends From APC Models and Similarities Across Modeling Approaches (From Fitted Model Estimates)

	Explicit attitude (APC model)					Implicit attitudes (APC model)				
Task	Start	End	% change	Correlation with aggregate model (ρ)	Percentage in aggregate model	Start	End	% change	Correlation with aggregate model (ρ)	Percentage in aggregate model
Age	0.58	0.41	−29.28	.95	100%	0.83	0.87	5.09	.90	75.25%
Race	0.82	0.51	−37.71	.98	32.67%	0.74	0.68	−8.07	.94	100%
Sexuality	0.73	0.45	−38.06	>.99	58.42%	0.63	0.43	−31.05	.98	59.41%
Skin tone	0.61	0.46	−24.18	.98	100%	0.69	0.83	20.05	.91	71.29%
Body weight	0.76	0.63	−17.11	>.99	100%	0.67	0.72	7.22	.94	100%

Note. All values are computed from standardized scores. The start and end values represent the first and last of 100 predicted values between 2009 and 2019, derived from the APC models. Percent change values indicate the amount of change between the predicted start and end values. Correlations indicate the Spearman's ρ correlation across the predicted trajectories derived from the APC and aggregate models. Percent of APC in aggregate model refers to the percentage of the estimated APC trajectories that fall within the 95% highest density intervals of the aggregate model trajectories. APC = Age–Period–Cohort.

At the same time, one small difference between the two sets of models emerged: APC models showed slightly more biased baselines for explicit race and sexuality attitudes than the main aggregate models (but notably not for the three other tasks, which were entirely contained within the 95% highest density intervals [HDIs]). This difference is likely due to the fact that earlier cohorts (e.g., baby boomers) tend to have more biased attitudes toward race and sexuality but are also smaller in sample size than later cohorts (e.g., millennials) are. APC models, unlike the aggregate models reported above, weight the contributions of different cohorts equally. As such, early cohorts' more biased attitudes will have a stronger influence on the overall estimates in the APC models than in the aggregate models. These small differences notwithstanding, the key takeaway of this robustness check is that trends of change over time were highly consistent across modeling approaches.

Implicit Attitudes

As above, the APC models and aggregate models showed similar patterns of decreasing trajectories (for implicit sexuality attitudes), stable trajectories (for implicit race, age, and body weight attitudes), or recently increasing trajectories (for implicit skin tone attitudes). In fact, correlations between predicted values across the modeling approaches were consistently high (Spearman's ρs > .90), and the majority of the fitted trends from the APC models were contained within the 95% HDIs of the aggregate models. Similar to explicit attitudes, we observed a slight difference in baseline implicit sexuality attitudes, such that the APC models showed higher levels of bias at the beginning of the time series, likely due to the increased contribution from early cohorts. Nevertheless, like for explicit attitudes, the comparison across modeling approaches underscores the general conclusion that the most likely source of change (or stability) in implicit attitudes are period effects that influenced all cohorts and age groups to similar degrees.

Analysis III: Country-Level Variability

Explicit Attitudes

The country-level variability in starting points, end points, and trajectories of explicit and implicit attitude change between 2009 and 2019 is shown in Table 3 and Figure 3. Most important, country-level intercorrelations across explicit attitude trajectories were consistently positive and statistically significant. This result suggests a substantive amount of international overlap in processes of change, which makes the aggregate analyses reported above meaningful. Interestingly, intercorrelations differed substantially across tasks, ranging from ρ = .26 for explicit age attitudes to ρ = .68 for explicit sexuality attitudes, with body weight, skin tone, and race falling between these two extremes. These results may reflect the fact that sexuality and race are more prominently present in public discourse than other social group distinctions (Charlesworth & Banaji, 2019), with greater international discussion perhaps enabling more cross-country consensus and similarity in trends.

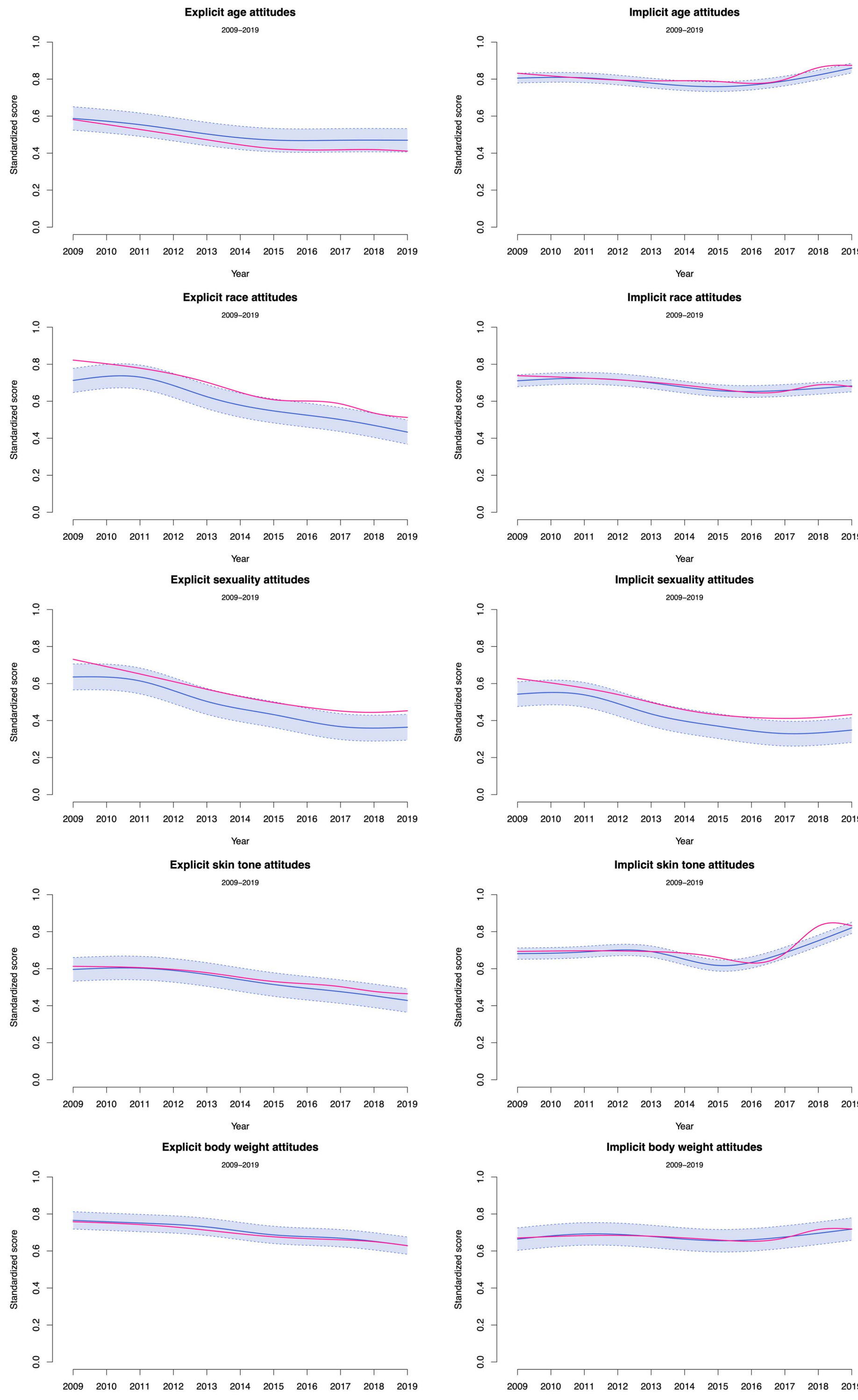
Notably, with the exception of explicit body weight attitudes, cross-country variability decreased for all tasks between 2009 and 2019. The decrease in variability was especially pronounced for explicit sexuality attitudes (30%), which also exhibited the highest level of cross-country intercorrelations. With the methodological caveat involving a potential spurious effect of sample size change over time (see the Method section), this pattern of results may suggest especially strong attitudinal convergence for sexuality attitudes across countries, potentially via processes of cultural globalization, as discussed in the Introduction.

Implicit Attitudes

Similar to explicit attitudes, implicit attitudes consistently showed positive cross-country intercorrelations in their trajectories over time, thus making the collapsed analyses reported above meaningful. Also similar to explicit attitudes, the intercorrelations varied substantially across tasks, ranging from ρ = .14 for implicit body weight attitudes to ρ = .69 for implicit sexuality attitudes. Interestingly, sexuality attitudes exhibited the highest amount of cross-country similarity in trajectories on both tasks, perhaps reflecting the increased and cross-culturally consistent attention to this social group distinction as a result of a globalizing marriage equality and gay rights movement (Paternotte, 2015). Also similar to explicit attitudes, implicit attitudes seemed less variable across countries at the end than at the beginning of the time series, potentially in response to globalizing influences (Steger, 2012). However, given the possible confound stemming

Figure 2

Trends of Explicit and Implicit Attitudes: APC Models Versus Aggregate Models



Note. The solid blue lines indicate the fitted trajectories from the aggregate Integrated Nested Laplace Approximation (INLA) models for the Project Implicit international (PI:INT) data, with the shaded blue areas showing the corresponding 95% highest density intervals. The pink lines show the fitted trajectories from the Age–Period–Cohort (APC) models. See the online article for the color version of this figure.

Table 3
Country-Level Variability in Trends by Task (From Fitted Model Estimates)

	Explicit attitude			Implicit attitude		
Task	*SD* start	*SD* end	Intercorrelation (ρ)	*SD* start	*SD* end	Intercorrelation (ρ)
Age	0.23	0.21	0.26	0.13	0.09	0.29
Race	0.28	0.25	0.56	0.14	0.11	0.21
Sexuality	0.26	0.20	0.68	0.20	0.20	0.69
Skin tone	0.27	0.23	0.37	0.14	0.14	0.52
Body weight	0.16	0.17	0.31	0.22	0.20	0.14

Note. All values are computed from standardized scores weighted by sample composition. The standard deviations are derived from the start and end values calculated from each country's individual Integrated Nested Laplace Approximation (INLA) models. The start and end values represent the first and last of 100 predicted values between 2009 and 2019. The intercorrelations indicate the average pairwise Spearman's correlation across all country-level (predicted) trajectories; higher values indicate that countries show more similar trajectories overall, whereas lower values indicate more variability across country-specific trajectories.

from sample size change over time, this result should be interpreted with caution.

Analysis IV: Comparison With the United States

Explicit Attitudes

Comparing the explicit attitude trajectories in the present international data to previously published results from the United States (see Table 4 and Figure 4) yields two key conclusions.

First, explicit attitudes were considerably higher in bias internationally than in the United States, for all five attitude targets. This was especially true for explicit race attitudes whose starting point in 2009 was over twice as high internationally (0.71) as in the United States (0.31). In fact, none of the PI:US trajectories were contained within the 95% HDIs of the corresponding PI:INT trajectories for explicit race, sexuality, skin tone, or age attitudes. Only explicit body weight attitudes showed similar magnitudes across the PI:US and PI:INT data, with approximately 65% of the PI:US time series contained within the 95% HDI of the PI:INT time series. Such large baseline differences in explicit attitudes reinforce that the United States—or at least broad segments of it—may be unique in norms against expressing social group-related negativity (with a possible exception of body weight bias).

Second, despite differences in the magnitudes of bias, both the PI:US and PI:INT trajectories exhibited similar decreases across all explicit attitudes. Indeed, Spearman's correlations between the trajectories of PI:US and PI:INT data showed strong relationships for all tasks, ranging from ρ = .76 for explicit skin tone attitudes to ρ = .99 for explicit sexuality attitudes. Changes in U.S. explicit attitudes were not an anomaly but, instead, seem to generalize across the 33 countries included in the present investigation.

Implicit Attitudes

Implicit attitudes showed more similar baseline magnitudes across the PI:US and PI:INT data: Whereas the intercepts in explicit attitudes differed, on average, by 0.22 standard deviation units, the mean difference in implicit attitude intercepts was only 0.04 standard deviation units. Moreover, the PI:US trajectories for some attitudes (sexuality and body weight) were, at least partially, contained in the 95% HDIs of PI:INT trajectories.

Critically, correlations between the PI:US and PI:INT implicit attitude time series were generally more modest and, in fact, often showed differing trajectories across samples. First, whereas implicit race attitudes decreased in bias by 14% in PI:US between 2009 and 2019, the international trend showed only a 4% drop over the same time period. Thus, although the U.S. and international time series correlated at ρ = .81, likely as a result of similar decreases between 2011 and 2014, the magnitude of change suggests U.S.-specific processes have led to a marked decrease in bias on race attitudes.

Even more notable were the diverging trends for skin tone attitudes. Whereas implicit skin tone attitudes decreased by 18% in PI:US, internationally they were largely stable until 2016, then increased in bias. Accordingly, the trends of skin tone attitudes in the PI:INT and PI:US samples were entirely uncorrelated with each other (ρ = −.09). Implicit age (ρ = .33) and body weight (ρ = .05) attitude trajectories also showed modest correlations across PI:US and PI:INT trends, likely explained by the fact that neither age nor body weight attitudes changed significantly in either sample, thus leading to a restriction in range.

In fact, the only clear similarity on implicit attitudes consisted in the parallel trajectories observed for implicit sexuality attitudes, where PI:US and PI:INT trends were correlated at ρ = .96. This result aligns with the earlier finding that implicit sexuality attitudes also had the highest cross-country intercorrelations within the PI:INT sample. Implicit sexuality attitudes therefore appear to have the most consistent trajectories across all types of country-level comparisons.

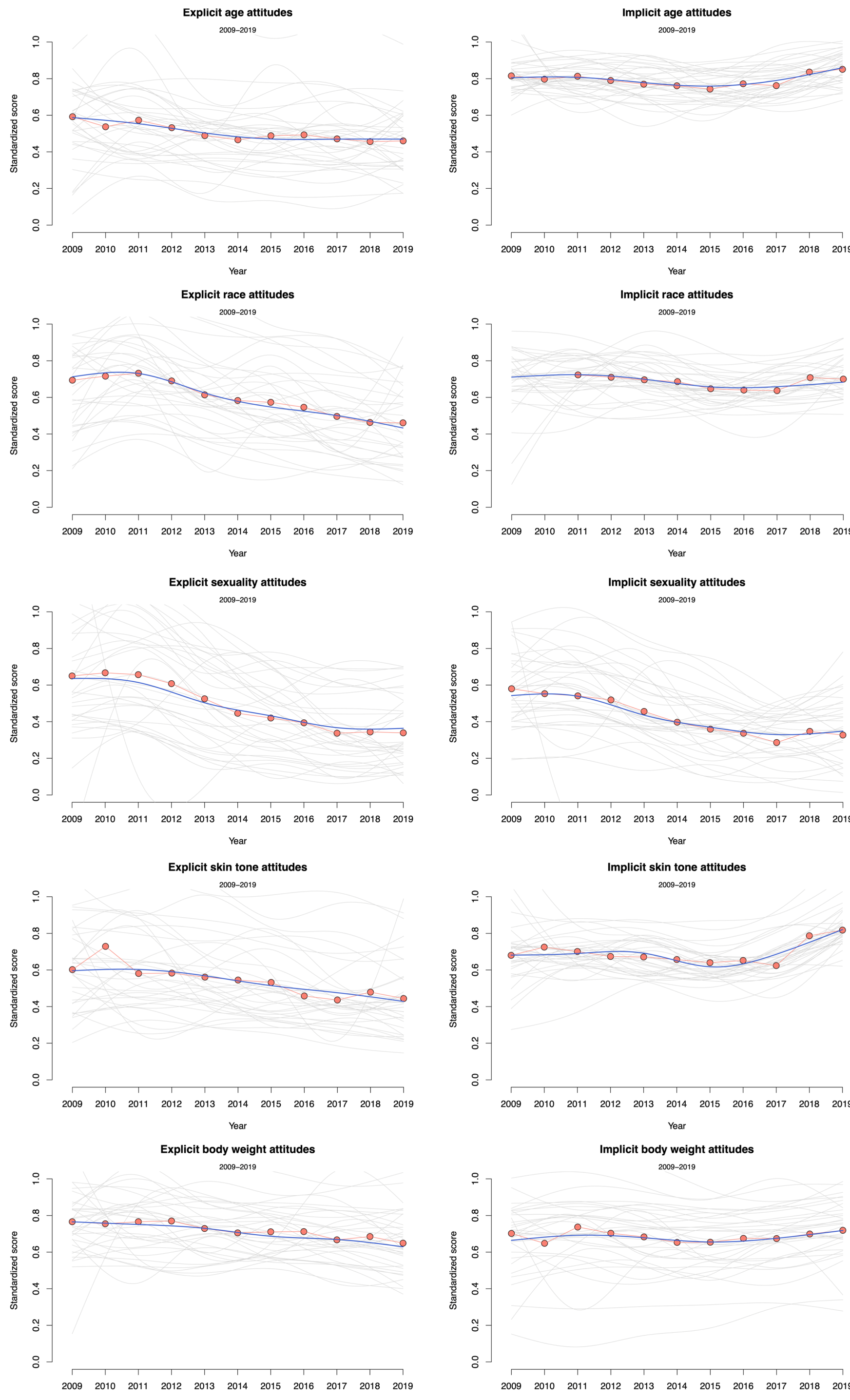
Analysis V: Key Demographic Differences

Explicit Attitudes

Key demographic differences on explicit and implicit attitudes are shown in Table 5. As expected from decades of relevant work, explicit attitudes showed evidence of known-groups validity such that members of dominant groups (younger, White, straight, light-skinned, and thinner respondents) showed more evidence of explicit preference for dominant groups than members of stigmatized groups (older, non-White, nonstraight, dark-skinned, and

Figure 3

Country-Level Variability in Trends of Explicit and Implicit Attitudes Across 33 Countries



Note. The gray lines indicate the individual fitted country trajectories from the country-specific Integrated Nested Laplace Approximation (INLA) models. The solid blue lines indicate the fitted means from the overall INLA model. The red dots and red line show the raw annual means, using weights for sample change. See the online article for the color version of this figure.

Table 4
Trends in PI:US Data and Similarities Across PI:INT and PI:US Data (From Fitted Model Estimates)

Task	Explicit attitude (PI:US)					Implicit attitude (PI:US)				
	Start	End	% change	Correlation with PI:INT (ρ)	% in PI:INT	Start	End	% change	Correlation with PI:INT (ρ)	% in PI:INT
Age	0.43	0.34	−21.46	0.82	0.00%	0.75	0.72	−3.91	0.33	0.00%
Race	0.31	0.04	−88.13	0.98	0.00%	0.59	0.51	−14.07	0.81	0.00%
Sexuality	0.48	0.19	−60.12	0.99	0.00%	0.57	0.26	−53.83	0.96	68.32%
Skin tone	0.29	0.09	−68.01	0.76	0.00%	0.61	0.50	−17.84	−0.09	0.00%
Body weight	0.72	0.52	−28.24	0.78	65.35%	0.68	0.76	12.28	0.05	28.71%

Note. All values are computed from standardized scores weighted by sample composition. The start and end values represent the first and last of 100 predicted values between 2009 and 2019, derived from the U.S.-specific Integrated Nested Laplace Approximation (INLA) models. Percent change values indicate the amount of change between the predicted start and end values. Correlations indicate the Spearman's correlation across the predicted trajectories of PI:INT and PI:US data. Percent of PI:US in PI:INT refers to the percentage of the estimated PI:US trajectories that fall within the 95% highest density intervals of the PI:INT trajectories. PI:INT = Project Implicit international; PI:US = Project Implicit United States.

heavier respondents) did. This difference was consistently present at both the beginning and the end of the time-series trajectories. Interestingly, among members of stigmatized groups, only non-straight respondents exhibited in-group preference; members of other stigmatized groups merely showed attenuated out-group preference relative to members of dominant groups.

Critically, however, when it came to patterns of change, both dominant and stigmatized group members tended to change in parallel, with correlations in trajectories over time ranging from $\rho =$ .75 for the sexuality task to $\rho > .99$ for the race task. These findings reinforce the widespread nature of explicit attitude change, not only across countries but also across key demographic groups even within countries. Further details are reported and discussed in Supplemental Materials.

Implicit Attitudes

Similar results were also found for implicit attitudes: For nearly all tasks, we observed large differences in the magnitudes of implicit attitudes among members of dominant versus stigmatized groups, both at the beginning and the end of the time-series trajectory. The sole exception was implicit age attitudes, which showed similar baseline magnitudes for both relatively older and younger respondents, aligning with previous findings on the widespread nature of implicit anti-old/pro-young attitudes, which are internalized even by older populations (Levy & Banaji, 2002).

Critically, similar to explicit attitudes, the time-series trajectories were highly correlated across key demographics, ranging from $\rho =$ .75 for the race task to $\rho = .95$ for the sexuality task, again suggesting widespread influences cutting across critical social group boundaries. Of note, despite the similarity in overall trajectories, White respondents' implicit race attitudes increased in bias by about 15%, whereas non-White respondents' implicit race attitudes decreased in bias by about the same magnitude. These results combined may provide interesting additional insight into the apparent stability observed in the sample as a whole.

These small differences notwithstanding, the most important result emerging from analyses of both explicit and implicit attitudes is that of highly similar trajectories over time, even despite the (often sizable) baseline differences across key demographics.

Analysis VI: Ecological Correlates

Explicit Attitudes

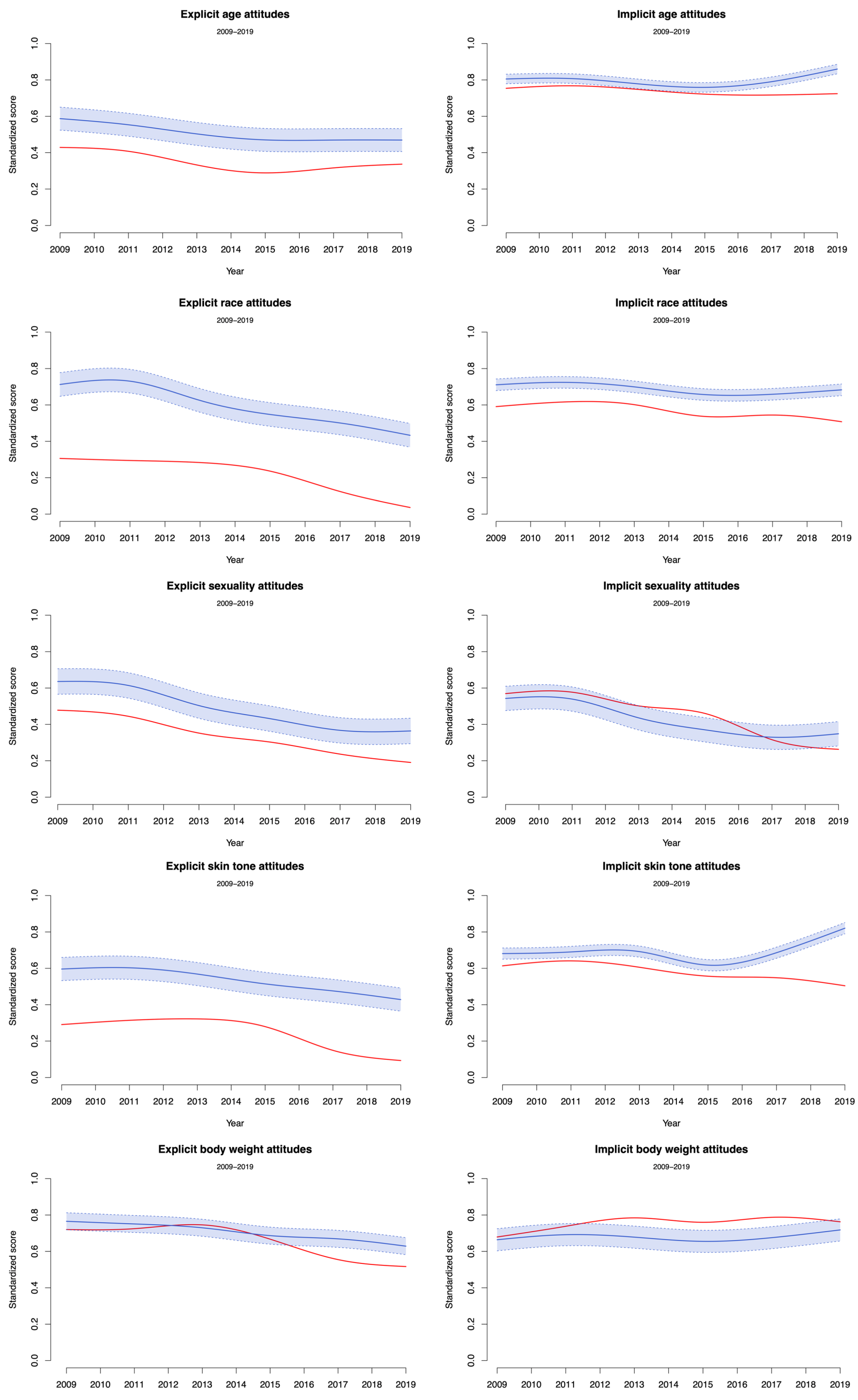
The relationships between the cross-country trajectories of ecological correlates and cross-country trajectories of attitudinal variables are shown in Figure 5, with positive correlations displayed in blue and negative correlations displayed in red. All methodological details and further discussion are available in Supplemental Materials. Here, we highlight two aspects of the data: First, each square in the heatmap represents the average correlation between two vectorized correlation matrices. For example, the square in the top row of the first column shows the correlation between Country × Year values of population density and explicit race attitudes across the 33 countries of interest between 2009 and 2019. Second, these correlations were detrended via columnwise standardization to ensure that the analysis captures true cross-country variation rather than general trends over time. For example, given that temperature has generally been increasing due to global warming and explicit attitudes have generally been decreasing in bias, using raw correlations would have resulted in a spurious relationship between the two. Detrending eliminates confounds of this kind.

In general, as shown on the left-hand side of Figure 5, ecological correlates of explicit attitude change showed similar patterns of positive and negative correlations, regardless of the test. For instance, explicit attitude change was consistently positively correlated with changes in population density, rainfall, and life expectancy, but consistently negatively correlated with changes in temperature, unemployment, and inequality. Combined with the findings from Analyses I–V, these results suggest that explicit attitude change likely reflects domain-general mechanisms.

Although we emphasize again that these results are exploratory and not designed to test specific ecological theories, we can offer some initial interpretation of the most consistent ecological correlates. As one example, the most consistent positive correlate of explicit attitude change was population density, whereby an increase in population density within a year and country corresponded to an increase in bias on explicit attitudes within that year and country. This was true for all explicit attitude domains, with Spearman's correlations ranging from $\rho = .20$ to $\rho = .40$ (all ps < .001). Notably, the strongest effects were obtained for explicit skin tone and race attitudes, with correlations of $\rho = .40$, $p < .001$, and $\rho = .34$, $p <$ .001, respectively.

Figure 4

Trends of Explicit and Implicit Attitudes Internationally Versus in the United States



Note. The solid blue lines indicate the fitted trajectories from the overall Integrated Nested Laplace Approximation (INLA) model for the Project Implicit international (PI:INT) data, with blue shaded areas showing the corresponding 95% highest density intervals (HDIs). The solid red lines indicate the fitted trajectories from the INLA model for the Project Implicit United States (PI:US) data, with red shaded areas showing the corresponding 95% HDIs. Given the exceedingly large sample size and the resulting highly precise estimates, the 95% HDIs are invisible. See the online article for the color version of this figure.

Table 5

Similarities and Differences in Start Values, End Values, Percentage Change, and Correlation of Fitted Model Trajectories Across Key Demographics for Explicit and Implicit Attitudes

Task	Key demographic difference	Explicit attitude Start	End	% change	Correlation across demographic (ρ)	Implicit attitude Start	End	% change	Correlation across demographic (ρ)
Age	Younger (<25)	0.70	0.56	−19.43	.78	0.80	0.79	−0.96	.87
	Older (>35)	0.48	0.37	−22.71		0.80	0.91	14.18	
Race	White	0.64	0.51	−20.70	>.99	0.65	0.75	14.90	.76
	Non-White	0.37	0.16	−57.32		0.58	0.48	−16.45	
Sexuality	Straight	0.94	0.57	−39.46	.75	0.74	0.52	−30.62	.95
	Nonstraight	−0.23	−0.28	−22.80		−0.02	−0.22	−1,126.44	
Skin tone	Light-skinned	0.72	0.53	−26.40	.83	0.76	0.87	14.56	.91
	Dark-skinned	0.38	0.23	−38.45		0.57	0.69	20.38	
Body weight	Thinner	0.93	0.93	−0.15	.93	0.71	0.74	3.46	.93
	Heavier	0.59	0.58	−2.02		0.56	0.57	1.58	

Note. All values represent standardized scores. The start and end values represent the first and last of observed values between 2009 and 2019. Percent change values indicate the amount of change between the observed start and end values. The correlations are derived from model-predicted trajectories.

Some perspectives might have predicted that population density (and the greater opportunity for contact) may have corresponded to lower levels of intergroup negativity (Allport, 1954). However, the current results are more in line with perspectives suggesting that demographic changes might exacerbate intergroup conflict around scarce resources (Goldstone, 2002). This may be especially true if the recent movers are from a minority racial group, thus activating threats of minority demographic "takeovers" among dominant group members (Craig & Richeson, 2014a, 2014b, 2018), an interpretation underscored by the finding that explicit race and skin tone attitudes had the descriptively strongest correlation with population density.

Implicit Attitudes

Ecological correlates of implicit attitude change showed more test-specific variation, with the patterns of correlations tracing a distinction between body-related and sociodemographic stigmas (Charlesworth, Sanjeev, et al., 2023). That is, the body-related tests (age and body weight) tended to have similar ecological correlates with one another, whereas patterns of sociodemographic tests (race, skin tone, and sexuality) tended to have similar ecological correlates with one another. Importantly, these clusters of body-related versus sociodemographic implicit attitudes showed opposing results.

For instance, population density was a positive correlate for implicit race attitudes, $\rho = .22$, $p < .001$, and implicit skin tone attitudes, $\rho = .14$, $p = .001$, but a negative correlate for implicit age attitudes, $\rho = -.19$, $p < .001$, and implicit body weight attitudes, $\rho = -.18$, $p = .001$. That is, increasing population density was associated with increasing levels of bias in implicit race and skin tone attitudes but decreasing levels of bias in implicit age and body weight attitudes. Also notable: The patterns for sociodemographic implicit attitudes were highly similar to the patterns of explicit attitudes (e.g., positive correlations with population density and negative correlations with temperature), whereas the patterns for body-related implicit attitudes were not only different from but an almost perfect mirror image of explicit attitudes. Although a detailed interpretation of this pattern is beyond the scope of the present work, we note that this result dovetails with previous findings showing that sociodemographic attitude targets are characterized by higher explicit–implicit correlations than body-related targets (Nosek et al., 2007; Ratliff et al., 2020).

Additional discussion and visualizations involving both explicit and implicit attitudes are provided in the Supplemental Materials. For the present purposes, we emphasize the high-level conclusion from the analyses of ecological correlates for both explicit and implicit attitude change: Whereas explicit attitudes had consistent effects across attitude targets, reinforcing the conclusion of domain-general mechanisms, implicit attitudes showed a more variable pattern specific to each social group target, and specifically related to the distinction between sociodemographic and body-related stigmas.

Discussion

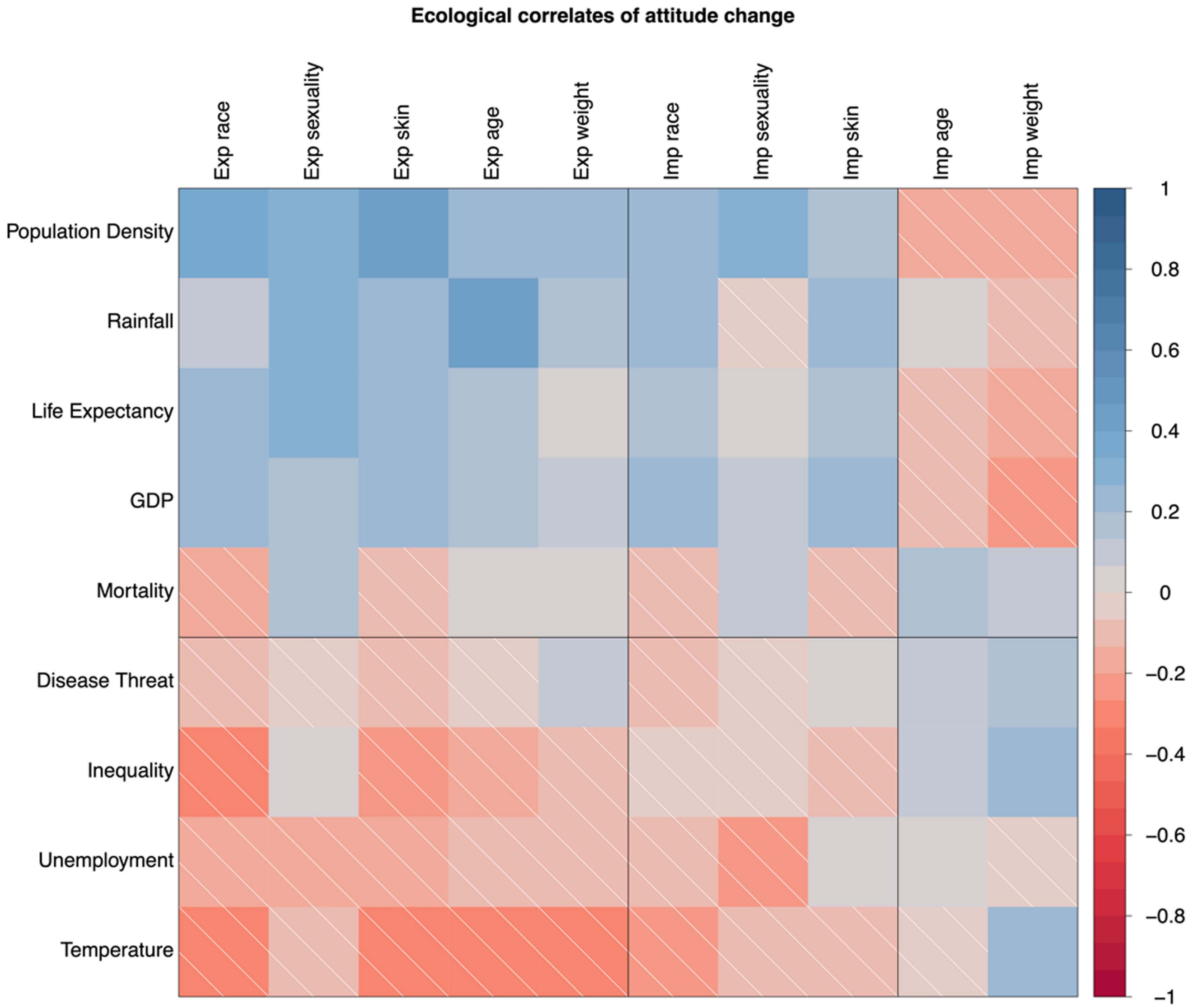
With the rise in availability of large amounts of data encompassing dozens of countries, along with efficient computational methods to analyze them, we stand at a unique moment to advance our understanding of explicit and implicit attitude change beyond Western, Educated, Industrialized, Rich, and Democratic perspectives. Here, we brought together cutting-edge Bayesian estimation techniques with data on five explicit (controlled) and implicit (automatically revealed) social group attitudes from over 1.4 million participants collected across 33 countries between 2009 and 2019 to provide initial insights into processes of attitude stability and change at the cultural level beyond the United States.

At the broadest level, the results shed new light on the different patterns and possible sources of cultural-level change in explicit and implicit attitudes. Specifically, trajectories of explicit attitude change were characterized by consistent decreases in bias (a) for all five tasks, (b) among all key demographic groups, and (c) both internationally and in the United States. Furthermore, explicit attitude change showed (d) consistent patterns of correlations with ecological variables, regardless of the attitude target.

In contrast, implicit attitudes showed considerably more variability, including (a) different trends depending on the attitude target, and both (b) some demographic variation in trends and (c) differences between the international and U.S. trends, at least for some tasks. Implicit attitudes also exhibited (d) varying correlations with ecological variables, with age and body weight attitudes versus race, skin tone, and sexuality attitudes characterized by opposite patterns.

Figure 5

Z-Scored (Within-Year Scaled) Representational Similarity in the Temporal and Spatial Variation of Attitudes (X-Axis) and Ecological Correlates (Y-Axis)



Note. All values are scored such that blue colors indicate positive correlations (i.e., the trends are similar across the variables), while red colors indicate negative correlations (i.e., the trends are opposite across the variables). Darker colors (red or blue) indicate stronger correlations. Ecological predictors (*y*-axis) are ordered from those variables that have the most negative average correlation (on the bottom of the plot; i.e., temperature and unemployment), to those variables that have the most positive average correlation (on the top of the plot, i.e., population density and rainfall). Variables showing similar patterns are surrounded by black boxes. exp = explicit; emp = implicit; GDP = gross domestic product. See the online article for the color version of this figure.

Below, we discuss the implications of such consistency versus variability both for expanding on past perspectives and for generating new theories of cultural-level social group attitude change.

Consistency in Explicit Attitude Change Suggests a Domain-General Mechanism

International explicit attitude change was notably consistent, with all five social group attitudes—including age, race, sexuality, skin tone, and body weight—decreasing meaningfully toward less bias. The decrease in explicit attitudes was also highly consistent across countries within the PI:INT data set, as well as between the international and U.S. trends. Moreover, explicit attitudes decreased consistently in bias across both members of dominant and stigmatized groups (e.g., both straight and lesbian, gay, and bisexual respondents) within the PI:INT data set. Although exploratory and speculative, even the results involving ecological correlations can be interpreted in line with a domain-general mechanism related to norms about expressing negativity toward stigmatized groups. Specifically, in those analyses, we found that all five explicit attitudes showed similar patterns of correlations across variables, including that all were positively correlated with population density and negatively correlated with temperature.

Taken together, we interpret this pattern of consistent trajectories as suggesting a domain-general mechanism accounting for explicit attitude change. We believe that this shared mechanism is most likely the strengthening of norms against the expression of negativity toward stigmatized social groups (Payne et al., 2017; Plant & Devine, 1998). The novel contribution of the present work is to demonstrate that these social norms do not uniquely characterize some groups of respondents (such as liberals or young people) and/or only the United States (as shown by Charlesworth & Banaji, 2019, 2022b). Rather, this mechanism appears to be generalizable across a relatively diverse set of countries and demographic groups within those countries. Of course, whether these processes reflect genuine internalization of egalitarian norms or compliance with external pressures (Norris, 2023; Plant & Devine, 1998) remains a major open question to be answered.

This interpretation of the potential mechanisms driving explicit attitude change across cultures also suggests new predictions for future work. Since 2019 (the end date of the current data), the international political climate has, across many countries, moved toward more authoritarian or even fascist approaches to social group-based distinctions (Zafirovski, 2024). Diversity, equity, and inclusion initiatives have also faced broad-based backlash within companies, politics, and public opinion (Gündemir et al., 2024). If explicit attitude change is indeed driven by the domain-general mechanism of perceived egalitarian norms, then this recent backlash may have led to the perception that it is not only permissible but even encouraged to disparage stigmatized groups. As such, we encourage future data collection on perceived norms for, and against, the expression of prejudice across people and countries to more directly test this proposed mechanism.

Variability in Implicit Attitude Change Suggests Group-Specific Mechanisms

In stark contrast to the consistency and domain-generality of explicit attitude change, we found considerably more variability in patterns of long-term change in implicit attitudes. Most notably, implicit attitudes showed all possible patterns of change depending on the attitude target: decreasing in bias (sexuality), increasing in bias (skin tone), or remaining stable (race, age, body weight). Immediately, this result suggests that implicit attitudes are more likely to change via social group-specific mechanisms, such that sociocultural events specifically involving a particular group (e.g., protests in favor marriage equality) result in cultural changes around that topic (e.g., in the legalization of marriage equality) and changes in the attitude toward the particular social group. Critically, these changes do not appear to "bleed over" into other attitude domains.

Given the unique trajectories of implicit sexuality attitudes decreasing and implicit skin tone attitudes increasing in bias, we elaborate on these two attitude targets illustratively. Consider, first, that the legalization of marriage equality has not only affected the United States but has also occurred worldwide (Paternotte, 2015). For example, the legal environment for lesbian, gay, and bisexual individuals in Europe has become progressively more accommodating over the past decades (ILGA–Europe, 2023), with potential downstream effects for intergroup attitudes. Furthermore, the change of implicit sexuality attitudes toward less bias worldwide may also have been driven by the increasing visibility of lesbian and gay individuals in people's media environments and immediate social environments (Kumar et al., 2023). Together, this interpersonal and institutional source of change is likely to create a positive feedback loop, resulting in a tipping point of change that affects sexuality attitudes alone.

At the other end of the spectrum, the international trajectory of implicit skin tone attitudes revealed a unique and sizable increase in bias after 2016. Despite widespread narratives about the inevitability of social progress (Kraus et al., 2019), this result reinforces the conclusion that implicit social group attitudes have the potential of moving in a direction of stronger bias even within relatively short periods of time. In line with the group-specific explanation offered above, changes in skin tone attitudes may correspond to the strengthening of xenophobic rhetoric in response to the increased immigration of (stereotypically) dark-skinned individuals (Mészáros, 2016). Indeed, a relevant search using Google Trends (https://trends.google.com/) reveals a sharp uptick in interest in the terms "refugee crisis" and "migrant crisis" around late 2015 and early 2016, which coincides with the temporal pattern of change in skin tone attitudes toward more negativity observed in the present data.

Finally, we turn to the three attitude targets showing no change over the 11-year time span between 2009 and 2019: implicit race, age, and body weight attitudes. When it comes to race attitudes, the deviation from the United States—which showed a sizable decrease in bias over the same period—may be explained by the cultural specificity of the increased public attention to anti-Black racism and the social movements aiming to alleviate it (Sawyer & Gampa, 2018). Specifically, although the recent Black Lives Matter movement had some reverberations internationally (Beaman et al., 2023), a Google Trends search suggests that, even at its height, interest was highly concentrated in the United States, with attention in other parts of the world remaining meaningfully lower.

Potentially less surprising is the stability in the international trajectories of implicit age and body weight attitudes. As mentioned in the introduction, both of these social group targets are subject to highly consensual negativity (Sechrist & Stangor, 2001) whose expression is not prohibited, or may even be encouraged, by relevant social norms (Crandall et al., 2002). Moreover, the fact that both of these attitudes are characterized by health-related stigmas (Pachankis et al., 2018) provides a veneer of perceived objectivity. At the same time, implicit anti-fat attitudes, at least, are capable of showing temporary modulations in response to cultural inputs, such as fat-shaming social media messages (Ravary et al., 2023). As such, an important priority for future work will be to investigate whether and how such potential for temporary modulations from cultural events could be harnessed to decrease body weight bias in a more enduring way.

An Emerging Distinction of Body-Related Versus Sociodemographic Attitude Change

In addition to the broad contrast in patterns of change across explicit versus implicit attitudes, the present data also dovetail with both classic and contemporary perspectives classifying social group-based negativity into different subcategories. For example, Goffman (1986) distinguished between more seemingly inherent body-related stigmas such as body weight and age and "tribal" social group affiliations such as race or ethnicity. Similarly, Sidanius and Pratto (1999) separated more evolutionarily relevant stigmas that relate to reproduction and health (e.g., age) from those that are more cultural and arbitrarily defined across history (e.g., race). In fact, this distinction has already been shown to help predict differences in trajectories of stigma representations, with sociodemographic stigmas changing significantly faster than body-related stigmas over the past 100 years of English text (Charlesworth, Sanjeev, et al., 2023).

The current data suggest that this distinction may be relevant not only to predicting the extent of change over time but also to clustering the ecological correlates associated with implicit attitude trajectories: Sociodemographic implicit attitudes (race, skin tone, and sexuality) exhibited the same pattern of correlations as all five explicit attitudes (e.g., a positive correlation with population density and negative correlation with temperature), potentially hinting at shared antecedents of change. By contrast, body-related implicit attitudes (age and body weight), showed the opposite pattern, including negative correlations with population density and positive correlations with temperature. Indeed, it is intriguing that implicit age and body weight attitudes are the only ones positively correlated with ecological disease threat or mortality in spatiotemporal variability. This finding suggests, again, that body-related implicit attitudes might be particularly resistant to change, because they are tied into purportedly more objective physical concerns around disease and health (Park et al., 2007).

Methodological Contributions to Understanding Cross-Sectional Attitude Change

Finally, the methodological advances introduced in this project also support more robust inferences for understanding long-term processes of explicit and implicit attitude change. For one, a common concern when interpreting cross-sectional (cultural-level) attitude change is that the data may conflate change arising from age, cohort, and period effects (Fosse & Winship, 2019). Our interpretations above are mostly in line with period effects, such that change is affecting multiple age groups and multiple cohorts, rather than change arising only from cohort replacement over time.

Although past work has supported this interpretation indirectly (Charlesworth & Banaji, 2019, 2021), here we were able to more directly test these possibilities using APC modeling. Specifically, we showed that the observed trends persisted after accounting for sample aging and cohort replacement. This result reinforces the conclusion that attitude change at the cultural level is most likely due to period effects, or macrolevel inputs that simultaneously affect many individuals in society. In this way, the results echo a wealth of recent experimental findings inspired by a propositional perspective (De Houwer et al., 2020; Kurdi & Dunham, 2020; Mandelbaum, 2016) by suggesting that, much like their explicit counterparts, implicit attitudes can change flexibly in response to a wide range of inputs. However, critically, the present findings provide evidence for enduring change in implicit attitudes toward consequential social group targets, rather than for short-term malleability in the context of novel groups.

Notably, we also systematically rule out various critiques of cross-sectional convenience samples that have previously only been tested indirectly, including (a) providing new experimental tests of participant self-selection, suggesting that self-selection alone cannot explain movements toward neutrality; (b) modeling sample size changes over time, showing that changing sample size over time alone cannot explain the observed trends; (c) addressing education differences, showing that both more and less educated respondents show similar trends; and (d) addressing country-level response styles, showing that countries have similar response styles on the current measures. In addition to many other robustness checks (e.g., refitting models to citizens rather than residents, and using population weights rather than within-sample weights), these results should increase confidence in the present findings.

Limitations and Future Directions

As noted in the introduction, the present work is not sufficiently representative of the international population of countries, with countries of the Global South—especially Latin America and Africa—constituting the most important omission. Given their unique histories and cultures, these regions of the world may exhibit patterns of explicit and implicit attitude change different from the ones observed here. For example, the history of the transatlantic slave trade produced differences in levels of mistrust that are still visible in cross-country differences in Africa today (Nunn & Wantchekon, 2011). Similarly, regressive legal regimes enforced by colonial powers in the Global South often criminalized same-sex relationships (Han & O'Mahoney, 2014), which has had enduring consequences for legal systems and individual-level attitudes reverberating to the present day. These and other cultural and historical features of countries of the Global South may, in turn, have produced unique patterns in explicit and implicit social group attitudes both at baseline and in terms of their potential for long-term change.

Another limitation stems from the use of the IAT as the sole measure of implicit attitudes in this project. Although the cultural-level focus in the present work bypasses typical critiques about the predictive validity and reliability of the IAT at the individual level (Payne et al., 2017), the test still faces several limitations in allowing for fully nuanced inferences about social group-related negativity. For example, the IATs used here have not been designed to inform about attitudes toward intersectional targets (e.g., Race × Gender), despite the unique experiences of prejudice and discrimination faced by these groups (Cole, 2009; Crenshaw, 1991; Hester et al., 2020). New tools drawing on natural language processing (e.g., Charlesworth et al., 2024) can help open the door to future research on patterns of change in collective representations of intersectional social targets. Relatedly, the IAT is a binary measure that forces contrasts between two polar categories (such as old/young or White/Black), thus not capturing negativity toward social targets without polar comparison groups (such as teen parents; Pachankis et al., 2018). Finally, the IATs used in this work index only positive–negative valence and thus may miss important additional content, such as specific emotions associated with different social groups (Cottrell & Neuberg, 2005), thus likely limiting their ability to predict real-world behavior.

Additionally, although the present work has started to uncover potential antecedents of explicit and implicit attitude trajectories, the relevant results are exploratory and highly speculative. Well-designed experimental studies could be helpful in testing potential mechanisms. As such, we hope that future work will integrate observational and experimental approaches to conduct studies with the dual benefits of high external and internal validity (for a recent early example, see Ravary et al., 2023). Mezzo-level experimental studies, implemented at the level of, for example, organizations or municipalities, could be particularly instructive in this regard by combining experimental control with the understanding of dynamics that can unfold in complex systems but are not visible when individuals are studied in isolation (Garcia et al., 2024; Schaller & Muthukrishna, 2021).

Finally, at least some of impetus for studying attitude change is that it can help us understand consequential outcomes both at the individual (Kurdi et al., 2019; Talaska et al., 2008) and at the collective level of analysis (Calanchini et al., 2022). As such, we hope that future work will probe whether, and to what extent, meaningful cultural-level outcomes in domains such as law, education, employment, and housing have followed the long-term trajectories of explicit and implicit attitude change uncovered here.

Conclusion

The questions of whether, when, how, and why social group attitudes can change have animated much theorizing and empirical research since the very inception of scientific psychology. Here, we demonstrate that attitudes toward social groups can change at the level of cultures (not merely at the level of individuals), enduringly (not merely in the moment), and in response to cultural inputs (not merely as a result of controlled experimental interventions). At the same time, the patterns of change were nuanced. Explicit (controlled) attitudes exhibited consistent changes in the direction of less bias toward all stigmatized social groups investigated. By contrast, implicit (automatic) attitudes changed or remained stable in more variable ways depending on the attitude domain. We hope that the present findings will spur new theoretical and empirical approaches toward understanding the inputs, processes, and downstream consequences of attitude change beyond the United States and encompassing multiple levels of analysis.

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