Social class and the motivational relevance of other human beings: Evidence from visual attention

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Abstract

We theorize that social class affects people's appraisals of others' "motivational relevance"—the degree to which others are seen as potentially rewarding, threatening, or otherwise worth attending to. Supporting this account, three studies indicate that classes differ in the amount of attention they direct toward other human beings. In Study 1, wearable technology was used to film the visual fields of pedestrians on city streets; higher-class participants looked less at other people than did lower-class participants. In Studies 2A and 2B, participants' eye movements were tracked while viewing street scenes; higher class was associated with reduced attention to people in the images. In Study 3, a change-detection procedure assessed the degree to which human faces spontaneously attract visual attention; faces proved less effective at drawing the attention of participants high (vs. low) in class, implying that class affects spontaneous relevance appraisals. The measurement and conceptualization of social class are discussed. [150 words]

Despite a surge of interest in the psychology of social class (see Kraus, Piff, Mendoza-Denton, Rheinschmidt, & Keltner, 2012), there is little consensus as to how class itself should be conceptualized and measured (APA Task Force on Socioeconomic Status, 2007; Diemer, Mistry, Wadsworth, López, & Reimers, 2013). Recently, however, researchers have unified around a *cultural* conception of social class, according to which classes are groups characterized by distinct norms, values, and self-construals (Grossmann & Varnum, 2011; Kraus, Piff, & Keltner, 2011; Stephens, Markus, & Townsend, 2007). A cultural analysis of social class implies that membership in a class group can shape cognitive processes in fundamental ways (Bourdieu, 1986; Kitayama & Uskul, 2011; Markus & Kitayama, 1991).

The present research explores the influence of social class on individuals' social-cognitive functioning. We posit that class affects people's appraisals of others' "motivational relevance"—the degree to which others are seen as potentially rewarding, threatening, or otherwise worth paying attention to (Lang, Bradley, & Cuthbert, 1997). Supporting this account, we demonstrate that lower-class perceivers devote more visual attention to other people than do higher-class perceivers (Studies 1 and 2). Consistent with the notion that culture affects cognition at the most basic levels (Nisbett, 2003), we show that class predicts spontaneous processes of attentional selection (Study 3). As a secondary goal, we seek to promote clarity in the measurement of social class cultures, arguing that individuals' class-group category (e.g., working class) predicts attention better than do other constructs (e.g., subjective social status).

Culture, Cognition, and Social Class

Interdependent cultures emphasize harmony and connection, whereas independent cultures emphasize self-expression and autonomy (Markus & Kitayama, 1991). Moreover, interdependent and independent values lead to distinct cognitive styles (Varnum, Grossmann, Kitayama, & Nisbett, 2010). Members of Western cultures tend to process information analytically (e.g., disregarding context and focusing on a single aspect of a stimulus), while East Asians tend to process information holistically (e.g., attending to context and focusing on relational information). Applying a cultural analysis to social class, researchers have found that classes, too, differ in terms of social orientation and, correspondingly, cognitive style. Whereas working-class individuals tend to construe themselves in interdependent terms and exhibit a more holistic cognitive style, members of the middle class tend to have an independent self-concept and analytic cognitive style (Grossmann & Varnum, 2011; Stephens et al., 2007).

Given the existence of class differences in domain-general cognitive processes, we surmised that social class might affect *social* cognition in ways at least as striking. Specifically, we propose that individuals from higher (and thus more independent) classes regard other people as less motivationally relevant (Lang et al., 1997) than do members of lower classes. Consistent with this idea, social class has been found to predict perceivers' social attunement and sensitivity. Members of lower (vs. higher) classes feel more compassion for others' suffering (Stellar, Manzo, Kraus, & Keltner, 2012), respond to perceptions of chaos by prioritizing community (Piff, Stancato, Martinez, Kraus, & Keltner, 2012), and display more engagement cues during interactions (Kraus & Keltner, 2009). These findings may reflect, not just the momentary activation of relevant values and norms, but rather overlearned cultural defaults in the appraisal of others' motivational relevance. Thus, we propose that social classes differ in their relevance appraisals even at early stages of social information processing. Our arena for testing these claims is one closely tied to the construct of motivational relevance: visual attention.

Motivational Relevance and Visual Attention

Organisms must engage in selective attention to successfully navigate the environment. Attentional selection, in turn, is informed by appraisals of nearby objects' motivational relevance, or their assumed potential to advance or thwart the perceiver's goals (Brosch & Van Bavel, 2012; Lang et al., 1997). If we are correct that members of lower social classes regard other people as more relevant than do higher-class perceivers, then lower-class individuals should spend more time looking at other people in the immediate environment. Studies 1, 2A, and 2B tested this hypothesis.

The proposed class difference in visual attention need not reflect perceivers' conscious appraisals of relevance or deliberate attempts to focus on (or ignore) other people. Indeed, the human visual system rapidly and preconsciously distinguishes between inanimate objects and social stimuli, such as human faces and bodies (Fletcher-Watson, Findlay, Leekam, & Benson, 2008). The brain's capacity to quickly and effortlessly distinguish social from nonsocial stimuli opens the door for culture to influence social-cognitive responses that occur outside of conscious control (e.g., neural signals indicative of empathy; Varnum, Blais, Hampton, & Brewer, 2015). We therefore sought to test the notion that social classes differ in the extent to which other human beings act as attentional cues (Pashler & Sutherland, 1998) that spontaneously summon visual attention. Study 3 tested this hypothesis.

Measuring Social Class

Although individuals' class-group membership can, in principle, be assessed using any number of indicators, such as income (e.g., Duncan & Petersen, 2001), education (e.g., Stephens et al., 2007), occupational prestige (e.g., Nakao & Treas, 1994), and self-perceived socioeconomic status (e.g., subjective SES; Piff, Stancato, Côté, et al., 2012), Americans regard an array of class *categories* as meaningful and can tell researchers which they belong to (Jackman & Jackman, 1983). We venture that, if class is culture, and culture is a group phenomenon, then group-based self-report measures of social class are a particularly promising tool for research. We further suspect that popular measures of social class (such as the subjective SES ladder; Adler, Epel, Castellazzo, & Ickovics, 2000) are at best distant proxies for class culture—just as hair length is a distant proxy for gender—and may be tainted by within-group individual differences. Indeed, variables that distinguish cultural groups often lack analogous psychological correlates within cultures (Na et al., 2010); thus, researchers may lose statistical power when they forgo group-level measures (like self-reported social class) in favor of measures that mix between- and within-group variance. Because we measured multiple class indicators across studies, we can empirically assess our expectation that a group-based measure of social class will best predict patterns of visual attention.

Study 1

Participants

Seventy-one pedestrians were recruited from two locations in New York City. An *a priori* decision was made not to analyze data from participants unfamiliar with the U.S. class system; thus, we excluded non-U.S. citizens who had lived in New York for less than two years (7 participants). Three additional participants' were excluded—1 due to a technical malfunction, 1 for leaving the primary measure of social class blank, and 1 for failing to follow the experimenter's instructions. (The results remain substantively unchanged if all the initially-recruited participants are included in the analyses.) The final sample consisted of 61 people (53 males, 8 females), aged 18 to 50 ($M = 26.66$, $SD = 6.94$). Thirty-two participants identified as White, 9 as Black or African American, 8 as Latino/a, and 4 as Asian American, with 8 participants specifying another ethnicity or declining to answer the question. Participants received no compensation for taking part in the study. The sample size was determined by the number of participants that could be run before the end of the academic term.

Materials and Procedure

The study was introduced to participants as a test of Google Glass—an electronic device that positions a small video camera and head-up display near the wearer's right eye (http://en.wikipedia.org/wiki/Google_Glass). Participants were asked to walk approximately one block while the Glass recorded video from their perspective, for a mean walk duration of 58.50 seconds (SD = 11.59 seconds). During the session, participants were instructed to focus on whatever captured their attention or interest, and to do so by turning their heads in the direction of their gaze. A special application (http://glass-apps.org/videoblack-google-glass-app) recorded video without displaying anything on the head-up display. The experimenter remained silent and several paces behind participants as they walked.

After recording their video, participants filled out a questionnaire containing a group-based measure of social class that has been shown to capture intuitively meaningful class distinctions in the United States (Jackman & Jackman, 1983). The question read as follows: "People talk about social classes such as the poor, the working class, the middle class, the upper-middle class, and the upper class. Which of these classes would you say you belong to?" (Jackman & Jackman, 1983). Participants' selections were converted to an ordinal variable ranging from 1 (poor) to 5 (upper class). Participants also specified their current annual income and highest level of educational attainment, and completed a "ladder" measure of subjective socioeconomic status (Adler et al., 2000). Several other items were included for exploratory purposes and will not be discussed here; the full questionnaire is found in Figure S1. For the theoretical reasons discussed above, our analyses centered on the group-based measure of social class.

Results

Three participants identified as poor, 16 as working class, 19 as middle class, 21 as upper-middle class, and 2 as upper class. Participant gender did not moderate any observed effects and is therefore omitted from the reported analyses.

Six independent coders were trained to identify participants' "social gazes"—glances toward other people—in the Google Glass videos. All coders were blind to participants' social class, ethnicity, and other demographics. Coders were instructed to pinpoint gross movements in which participants turned their heads or bodies to follow people they passed, and to record the duration of each such gaze in seconds. Inter-rater reliability for participants' total number of social gazes and mean gaze length were adequate, with average intraclass correlations of .86 and .72, respectively (Cicchetti, 1994). Raw means for social gaze duration are found in Figure S2.

Because participants' social class was confounded with their ethnicity, with all ethnicities except Asian reporting lower social class than Whites, we adjusted for ethnicity in our analyses. Negative binomial regression, appropriate for count variables, yielded no significant relationship between participants' social-class self-categorization and their total number of social gazes ($B = 0.129$, $SE\ B = 0.086$, $z = 1.50$, $p = .133$, 95% CI [-0.039, 0.297]). However, ordinary least squares (OLS) regression revealed that self-categorization into a higher social class was associated with significantly *shorter* social gazes ($B = -0.113$, $SE\ B = 0.046$, $\beta = -.332$, $t = -2.45$, $p = .018$, 95% CI [-0.205, -0.020]). (Full regression results are shown in Table S1 and S2.) Thus, while higher- and lower-class participants did not differ in their total number of social gazes—perhaps because navigating the street required all participants, regardless of class, to monitor the location of other people—higher-class participants' gazes were reliably shorter.

Discussion

Study 1 provides preliminary evidence that lower social class is associated with increased visual attention to people in everyday contexts and, by extension, that lower-class individuals find other people more motivationally relevant than do their higher-class counterparts. While informative, the use of Google Glass to track individuals' head movements provides an inexact measure of visual attention. Therefore, Studies 2A and 2B utilized a more precise index of individuals' attentional habits when observing everyday scenes. In these studies, participants viewed photographs of city streets in private while their looking behavior was recorded using an eye-tracking system.

Study 2

Participants

Seventy-seven undergraduates at New York University were recruited for Study 2A. One participant was excluded from analysis due to missing eye-tracking data, yielding a final sample of 76 (18 males, 58 females), aged 18 to 22 (M = 19.43, SD = 1.25); 19 participants identified as White, 3 as African American, 17 as Latino/a, and 26 as Asian Americans, with 11 participants specifying another ethnicity or declining to answer the question. Eighty-six undergraduates were originally recruited for Study 2B, but four of these individuals correctly guessed our hypothesis in debriefing and were excluded from analysis. (These exclusions do not substantively change our results.) Thus, the final sample in Study 2B consisted of 82 participants (24 males, 58 females), aged 18 to 22 (M = 19.41, SD = 1.00); 33 participants identified as White, 4 as African American, 10 as Latino/a, and 27 as Asian Americans, with 8 participants specifying another ethnicity or declining to answer the question. In both studies, participants received course credit for completing the study, and sample sizes were determined by the number of participants that could be run before the end of the academic term.

Materials and Procedure

Participants were seated at a desk containing a computer monitor and an SR Research EyeLink 1000 eye-tracking system. Participants placed their heads on a chinrest and, after a short calibration procedure, viewed a series of street scenes. Each scene remained on the screen for 7 seconds. Studies 2A and 2B differed only in terms of the range of street scenes participants viewed. In Study 2A, the stimuli consisted of 41 randomly-ordered photographs of New York City. Study 2B used these photographs, as well as 41 images of San Francisco and 41 images of London; stimuli were grouped into blocks containing randomly-ordered images from one city, and these blocks were presented in random order. See Figures S3–S5 for sample images. The photos, taken from Google Street View, were chosen to provide a broad sampling of environments, and included a diverse set of *people* (e.g., construction workers, business people, and homeless people) and *things* (e.g., cars, trees, and stores). These regions were marked as "interest areas," fixations on which were recorded and timed by the eye-tracking software; other, more diffuse features of the images, such as asphalt and the sky, were not isolated for analysis. Participants were instructed to imagine that they were walking down the street, observing their surroundings, and to look at whatever captured their attention.

After viewing the street scenes, participants completed the group-based measure of social class used in Study 1 (Jackman & Jackman, 1983), questions concerning their own and their parents' educational attainment and income, the subjective SES ladder (Adler et al., 2000), and scale measures of their current and childhood SES (Mittal & Griskevicius, 2014). A number of additional measures, included for exploratory purposes, were administered after our primary predictors and will not be discussed here. As in the previous study, our analyses centered on the first of these measures.

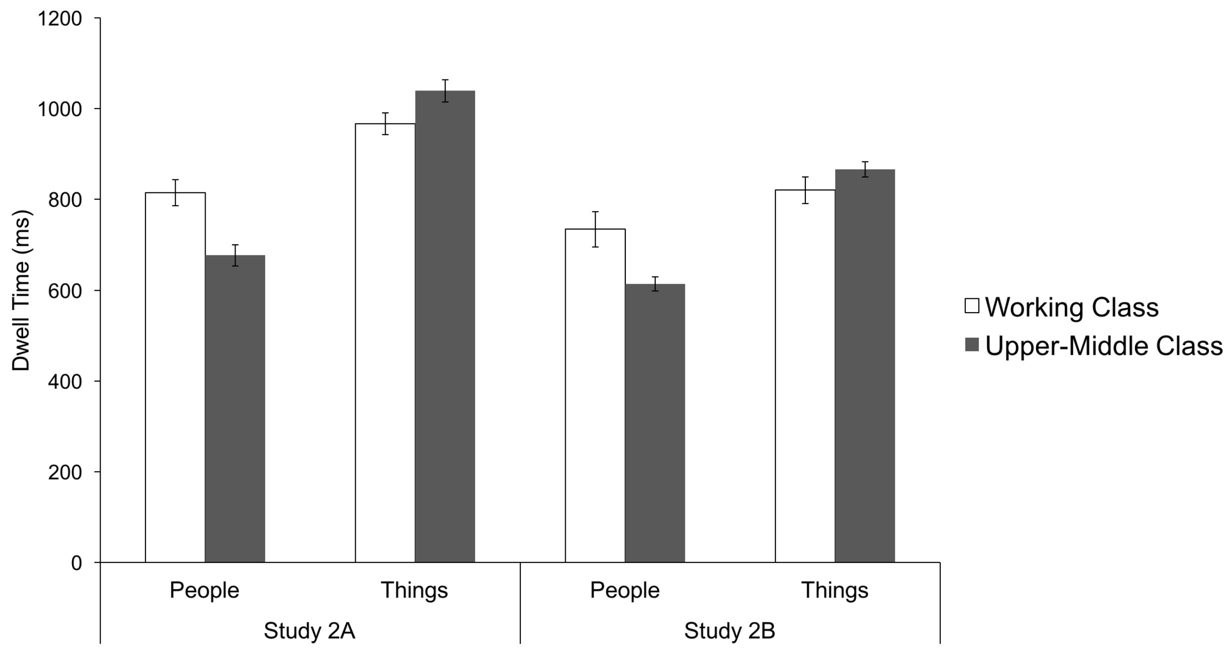
Results

In Study 2A, 19 participants identified as working class, 27 as middle class, 27 as upper-middle class, and 3 as upper class on our group-based class measure (Jackman & Jackman, 1983). In Study 2B, 1 participant identified as poor, 10 as working class, 32 as middle class, 37 as upper-middle class, and 2 as upper class. Participant gender did not moderate the observed effects in either study, and is therefore omitted from the reported analyses.

The dependent measure in Study 2 was visual dwell time—the total time in milliseconds that a participant looked at a given interest area. Because dwell times of zero are psychologically ambiguous—potentially reflecting participants' disinterest in a region of the image *or* lack of awareness of its content—we retained only non-zero dwell times in our analysis. This approach ensures that dwell times reflect the degree of attention paid to content whose status as a person or thing is known to participants. Dwell times were log-transformed to normalize their highly right-skewed distribution (Ratcliff, 1993). Raw dwell time means for Studies 2A and 2B are found in Figures S6 and S7, respectively.

For the purposes of regression analysis, object type was coded such that 0 refers to interest areas classified as things and 1 to those classified as people. Because multiple observations were obtained from each participant, we specified a multilevel model that included a random intercept for dwell time, a random slope for object type, an unstructured covariance matrix, and robust standard errors. Dwell times were regressed on participants' social class (*z*-scored), object type, and the Social Class × Object Type interaction. Because social class and ethnicity were confounded, with all non-White ethnic groups reporting significantly lower class than Whites, we adjusted for participants' ethnicity and all Ethnicity × Object Type interactions (Yzerbyt, Muller, & Judd, 2004) in this model. Interest area size (i.e., total area in pixels) was also entered as a control variable due to its obvious influence on dwell times.

Significant interactions between social class and object type were observed in both Study 2A (B = -0.129, SE B = 0.038, $z = -3.41$, $p = .001$, 95% CI [-0.203, -0.055]) and Study 2B (B = -0.116, SE B = 0.05, $z = -2.34$, $p = .019$, 95% CI [-0.214, -0.019]). These interactions are plotted in Figure 1. (See Tables S3 and S4 for full regression results.) Analysis of simple slopes revealed that, compared to their lower-class counterparts, higher-class participants spent significantly less time looking at people in both Study 2A (B = -0.093, SE B = 0.028, $z = -3.27$, $p = .001$, 95% CI [-0.149, -0.037]) and Study 2B (B = -0.090, SE B = 0.034, $z = -2.63$, $p = .009$, 95% CI [-0.156, -0.023]). No significant class differences were observed for regions coded as things in either Study 2A (B = 0.036, SE B = 0.019, $z = 1.87$, $p = .062$, 95% CI [-0.002, 0.074]) or Study 2B (B = 0.027, SE B = 0.023, $z = 1.18$, $p = .236$, 95% CI [-0.018, 0.071]).[1] (Note that, because not all parts of the images were included in interest areas, less attention to regions coded as people does not entail more attention to regions coded as things.)



Note. Bars represent marginal regression predictions for working and upper-middle classes. Log-transformed dwell times were converted back to milliseconds for graphing purposes. Error bars correspond to 1 standard error above and below the point estimates.

Figure 1. Total dwell time as a function of social class and object type in Studies 2A and 2B.

Discussion

The results of Studies 2A and 2B further support the idea that lower-class perceivers appraise other human beings as more motivationally relevant than do higher-class perceivers. Nonetheless, the results are ambiguous as to the cognitive "depth" of this phenomenon. It may be that class affects only deliberate aspects of attention—such that higher-class individuals consciously *choose* to devote less attention to other people. Or, consistent with the idea that people's sociocultural backgrounds shape even their most basic cognitive tendencies, social class may also influence spontaneous attentional processes that occur independently voluntary control.

Study 3 tested whether human faces have a greater capacity to rapidly and spontaneously summon visual attention among members of lower (vs. higher) social classes. We explored this question using a "flicker paradigm" (Masuda & Nisbett, 2006; Ro, Russell, & Lavie, 2001; Simons, 2000), in which perceivers attempt to identify differences between alternating pairs of visual images. Objects high in motivational relevance spontaneously attract visual attention, and should therefore benefit from a detection advantage in the flicker paradigm (Ro et al., 2001). If, as we have theorized, human targets possess greater motivational relevance for members of lower (vs. higher) social classes, then lower-class perceivers should be better than higher-class perceivers at detecting changes to faces in their visual environment.

Study 3

Participants

Participants were 396 workers (208 males, 188 females), aged 18 to 70 (*M* = 35.8, *SD* = 11.2), on Amazon's Mechanical Turk crowdsourcing platform (Buhrmeister, Kwang, & Gosling, 2011). Three hundred participants identified as White, 36 as Black or African American, 17 as Latino/a, 27 as Asian American, 6 as Native American, and 6 as multiracial, with 4 participants specifying another ethnicity or declining to answer the question. Each participant received $.51 in compensation. The final sample size was determined based on a power analysis of the first 80 participants' data.

Materials and Procedure

Inquisit software (2014) was used to administer the change detection task online. Upon linking to the study, participants read that they would be shown alternating pairs of images that might or might not be identical, and were instructed to press the space bar as soon as they were certain whether or not a change occurred. Participants were told that, upon pressing the space bar, they would be asked to identify any change from a list of possibilities.

Participants completed 10 practice trials with error feedback and 36 test trials without error feedback. At the beginning of each trial, participants were shown an array of pictures arranged radially around a fixation point. This array (*A*) always included one face and 5 inanimate objects (i.e., a fruit or vegetable, a houseplant, an item of clothing, an appliance, and a musical instrument). Each picture category consisted of 6 exemplars (i.e., 6 different faces, 6 different fruits/vegetables, 6 different appliances, etc.) and exemplars of each category were randomly selected from this subset. The screen position of each picture was randomly determined. After 533 milliseconds, Array *A* was replaced by a blank screen lasting for 83 milliseconds. A second object array (A') then appeared. On most trials, A' differed from *A* such that a randomly-selected picture was replaced with another exemplar of the same category; 3 no-change trials were randomly interspersed throughout the experimental session. After remaining on the screen for 533 milliseconds, array A' was replaced by another blank screen lasting 83 milliseconds. This sequence—*A*, blank screen, A', blank screen—was repeated until participants pressed the space bar to indicate that they had detected which picture in the stimulus array, if any, had changed (Figure 2). After pressing the space bar, participants were shown three pictures from array *A* and an icon that read “no change”; in change trials, one of the displayed objects differed between arrays *A* and A' and the other two were randomly-selected decoys. Participants were instructed to select the picture they believed had changed or to click the no-change icon.

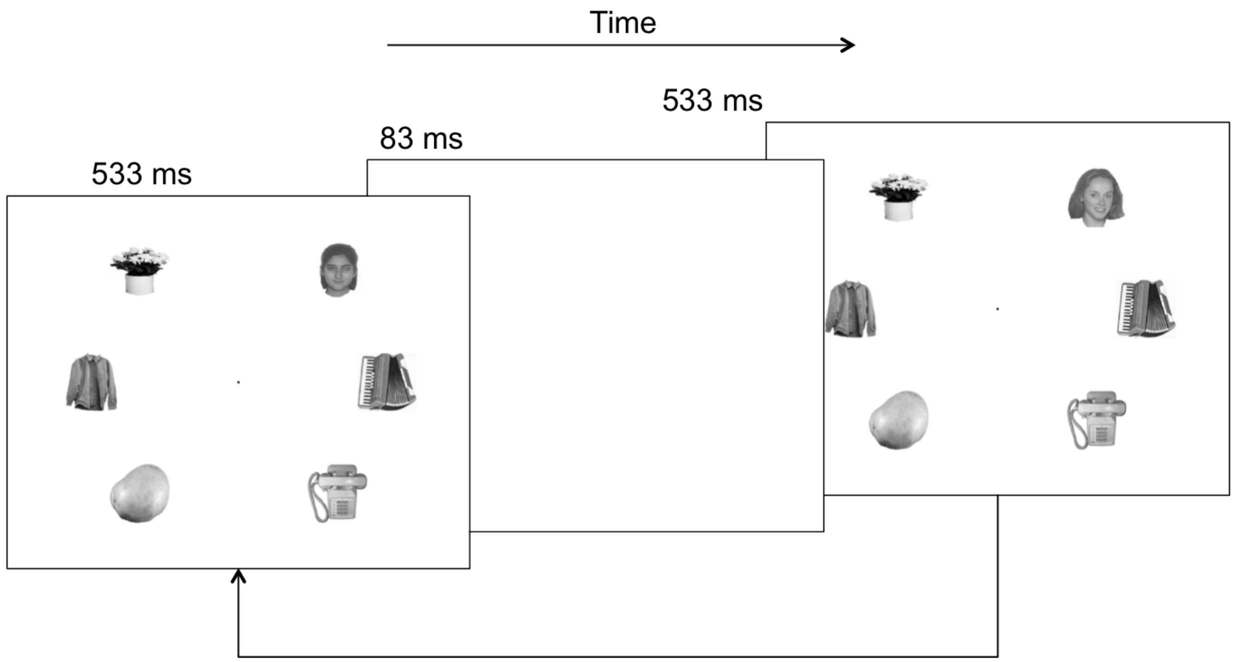


Figure 2. Sequence of screens face-change trials in Study 3.

After completing the change detection task, participants were administered the group-based social class probe used in Studies 1 and 2 (Jackman & Jackman, 1983), questions concerning their own and their parents' educational attainment and income, the subjective SES ladder (Adler et al., 2000), and scale measures of their current and childhood SES (Mittal & Griskevicius, 2014). Measures of political ideology and religiosity were also administered for exploratory purposes and will not be discussed here. As in the previous studies, our analyses centered on the group-based measure of social class.

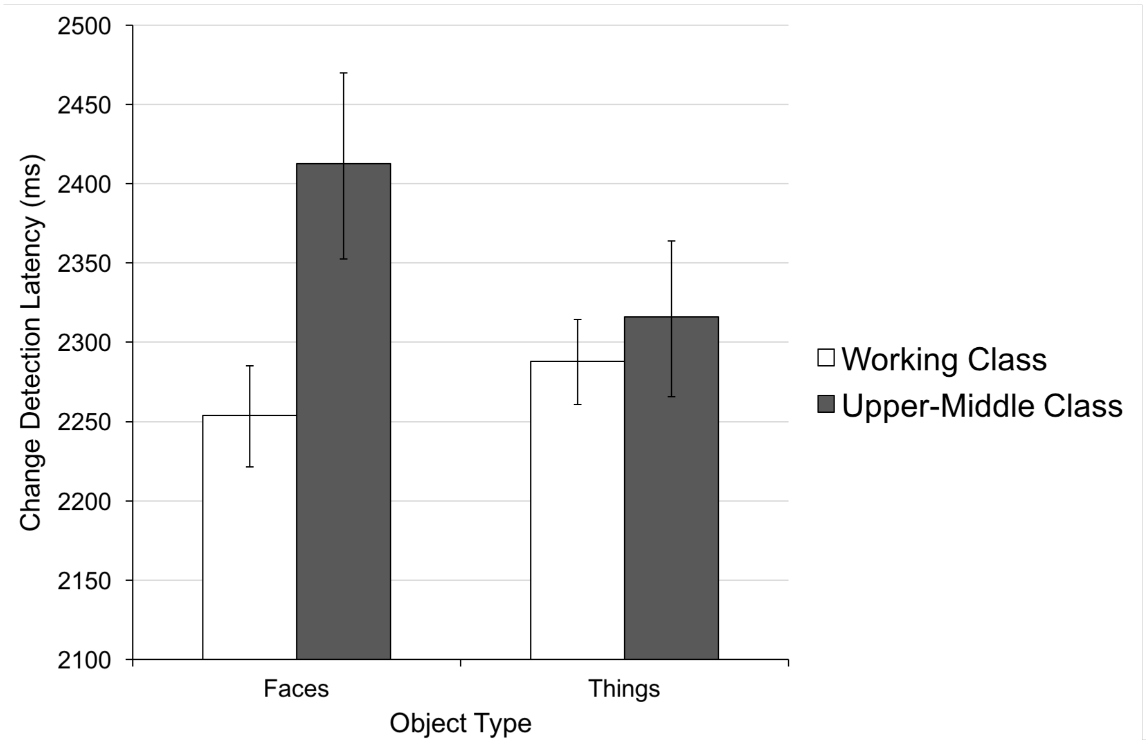
Results

Thirty-six participants identified as poor, 146 as working class, 173 as middle class, 40 as upper-middle class, and 1 as upper class on our group-based class measure (Jackman & Jackman, 1983). Participant gender did not moderate any observed effects and is therefore omitted from the reported analyses.

Practice and no-change trials were excluded from analysis. Participants were no better than chance at correctly identifying changes after fewer than 1350 milliseconds; thus, latencies below 1350 milliseconds were excluded from analysis (6.22% of observations). Of the remaining trials, only those in which participants correctly identified the change were retained (leading to the exclusion of an additional 5.93% of observations). Because the response latency data contained a number of extreme values, a two-step outlier treatment was applied. First, responses more than 2.5 standard deviations above the grand mean latency were excluded (1.25% of the previously-retained observations; Ratcliff, 1993). Second, because the resulting distribution was still highly skewed and kurtotic, we submitted the remaining data to a reciprocal transformation (thus converting response latencies into speeds; Ratcliff, 1993). Raw means for change detection latencies are found in Figure S8.

For the purposes of regression analysis, object type was coded such that 0 refers to things and 1 to faces. Because multiple observations were obtained from each participant, we specified a multilevel model that included a random intercept for dwell time, a random slope for object type, an unstructured covariance matrix, and robust standard errors. Change detection speeds were regressed on participants' social class (*z*-scored), object type, and the Social Class × Object Type interaction. Because social class and ethnicity were confounded, with Asians reporting significantly higher class than all other groups, we adjusted for participants' ethnicity and all Ethnicity × Object Type interactions in this model. A significant interaction between social class and object type was observed (B = -0.012, SE B = 0.005, z = -2.42, p = .015, 95% CI [-0.022, -0.002]). This interaction is plotted in Figure 3. (See Table S6 for full regression results.) Analysis of simple slopes revealed that higher-class participants were significantly slower to detect face changes than were lower-class participants (B = -0.014, SE B = 0.006, z = -2.27, p =

.023, 95% CI [-0.026, -0.002]). However, lower- and higher-class participants did not differ in their speed to detect changes to things (B = -0.003, SE B = 0.005, z = -0.46, p = .645, 95% CI [-0.013, 0.008]).



Note. Bars represent marginal regression predictions for working and upper-middle classes. Log-transformed dwell times were converted back to milliseconds for graphing purposes. Error bars correspond to 1 standard error above and below the point estimates.

Figure 3. Change detection latencies as a function of social class and object type in Study 3

Discussion

Study 3 suggests that social classes differ in terms of spontaneous processes of attentional selection. In this study, human faces were more effective at cueing lower- vs. higher-class participants' attention, whereas social class did not moderate the degree to which inanimate objects spontaneously summoned visual attention. In keeping with the notion that the ability of stimuli to summon visual attention outside of voluntary control reflects their motivational relevance (Ro et al., 2001), the current results imply that lower-class individuals find other human beings more motivationally relevant than do higher-class individuals. More broadly, this finding suggests that social class, like other forms of culture (see, e.g., Nisbett, 2003), can shape human cognitive functioning at a deep level.

General Discussion

In naturalistic (Study 1) and laboratory (Studies 2A and 2B) settings, lower-class perceivers devoted more visual attention to other human beings than did their higher-class counterparts. Study 3 suggests that divergent relevance appraisals occur early in social information processing: Human targets are more capable of spontaneously drawing lower-class perceivers' visual attention than that of higher-class individuals. Alternative interpretations of the findings are possible—for instance, it may be that members of lower social classes are simply more curious about other people than are higher-class individuals. However, given the tight connection between spontaneous visual attention and motivational-relevance appraisals (Brosch & Van Bavel, 2012; Lang et al., 1997), our data make a compelling case that social classes differ in their judgments of other people's significance.

Broader Implications

Because attention determines the content of much subsequent cognitive processing, class differences in visual attention have a wide range of potential implications for social judgments and behaviors. Our findings may suggest a reconsideration of empirical findings in the class literature—for instance, the finding that members of higher social classes show reduced accuracy when retrospectively judging the emotions of interaction partners (Kraus & Keltner, 2009) may reflect attentional neglect, rather than reduced empathic ability. Future research must distinguish between “upstream” (i.e., attentional) and “downstream” (i.e., interpretive) effects of social class on people’s judgments and behaviors.

Measures of Social Class Revisited

Does a group-based proxy for social class perform better than other measures in terms of its ability to predict visual attention? To answer this question, we reproduced the analyses in Studies 1–3 using each of the available measures of social class. Participants’ class group was the most consistent predictor of visual attention to other human beings (Table 1). The bottom row of Table 1 shows the results of an “integrative data analysis” (IDA; Curran & Hussong, 2009) of the data across studies. (For methodological details of the IDA, please refer to the supplemental online information.) In this analysis, all of the individual class indicators except for the scale measure of SES (Mittal & Griskevicius, 2014) proved significant predictors of visual attention. However, when the indicators were forced to compete in the same regression model, only the group-based class measure and educational attainment were independently associated with attention. These results in part reflect the fact that different research contexts benefit from different class indicators (Diemer et al., 2013). They also, however, vindicate our *a priori* reliance on the group-based operationalization of social class—and by extension the notion that group-based phenomena are best explored using group-based measures (Na et al., 2010).

Table 1. Effects of various social-class indicators on visual attention to human targets.

		Social Class Measure				
Sample	Focal Effect	Class Group	Income	Education	SES Ladder	SES Scale
Study 1	Class on gaze length	**−0.113** **−0.148**	−0.023 0.012	−0.051 −0.087	−0.001 0.036	—
Study 2A	Class × Object Type on dwell time	**−0.129** −0.099	−0.060 0.022	**−0.102** **−0.067**	**−0.077** 0.017	**−0.075** −0.010
Study 2B	Class × Object Type on dwell time	**−0.116** −0.003	**−0.120** **−0.099**	**−0.098** −0.061	**−0.091** 0.030	**−0.090** −0.020
Study 3	Class × Object Type on detection speed	**−0.012** −0.011	−0.004 −0.002	**−0.010** −0.008	**−0.009** −0.004	−0.002 0.005
IDA	Class on “social attention”	**−0.202** **−0.191**	**−0.057** −0.008	**−0.194** **−0.147**	**−0.064** 0.028	−0.039 0.033

Note. IDA = integrative data analysis. Numbers represent unstandardized regression coefficients. For each sample, the top row shows the effect of each predictor when it is the only social-class measure in the model; the bottom row reflects the independent effect of each predictor when it and all other social-class measures are tested simultaneously. In Studies 2A & 2B, which use student samples, “income” refers to parents’ income, “education” refers to the average of mother and father’s highest attainment, and “SES scale” refers to SES during childhood. Boldface indicates statistically a significant effect ($p < .05$); underlines indicate a marginally significant effect ($.05 < p \leq .10$).

Conclusion

Like other forms of culture, social class appears to have a pervasive impact on individuals’ cognitive—and social-cognitive—functioning. As a cultural analysis would predict, this influence occurs not only at the level of norms and values, but also rote attentional processes that occur spontaneously (i.e., independently of voluntary control). Finally, our analysis of different class measures’ predictive efficacy suggests that the best way to study a group-level phenomenon like social-class culture is to employ group-level measures.

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Endnote

[1]We re-ran our analyses using number of fixations to an interest area as the outcome variable. The results remained substantively unchanged: Higher-class participants fixated significantly less often on people than did lower-class participants, no class difference was observed for things.

Supplemental Tables

Table S1. Analysis of number of social gazes in Study 1.

Predictor	B	SE B	*z*	*p*	95% CI LB	95% CI UB
Social Class	0.129	0.086	1.50	0.133	-0.039	0.297
Black	0.134	0.227	0.59	0.556	-0.311	0.578
Latino	0.439	0.218	2.01	0.044	0.012	0.867
Asian	-0.101	0.319	-0.32	0.751	-0.727	0.524
Other	0.154	0.236	0.65	0.515	-0.309	0.616

Table S2. Analysis of length of social gazes in Study 1.

Predictor	B	SE B	β	*t*	*p*	95% CI LB	95% CI UB
Social Class	-0.113	0.046	-0.332	-2.45	0.018	-0.205	-0.020
Black	-0.013	0.122	-0.014	-0.11	0.915	-0.258	0.232
Latino	-0.128	0.126	-0.133	-1.01	0.317	-0.381	0.126
Asian	0.392	0.189	0.261	2.08	0.043	0.014	0.771
Other	0.168	0.126	0.175	1.33	0.188	-0.085	0.422

Table S3. Analysis of visual dwell times in Study 2A.

Predictor	B	SE B	*z*	*p*	95% CI LB	95% CI UB
Social Class (SC)	0.036	0.019	1.87	0.062	-0.002	0.074
Object Type (OT)	-0.166	0.072	-2.29	0.022	-0.308	-0.024
SC × OT	-0.129	0.038	-3.41	0.001	-0.203	-0.055
Interest Area Size	0.414	0.009	47.62	0.000	0.397	0.431
Black	0.002	0.040	0.04	0.964	-0.076	0.080
Latino	0.098	0.053	1.86	0.063	-0.005	0.202
Asian	0.003	0.042	0.07	0.943	-0.080	0.086
Other	0.005	0.045	0.12	0.904	-0.082	0.093
Black × OT	-0.154	0.112	-1.37	0.171	-0.374	0.067
Latino × OT	-0.219	0.101	-2.17	0.030	-0.417	-0.021
Asian × OT	-0.201	0.088	-2.28	0.022	-0.374	-0.029
Other × OT	-0.074	0.097	-0.76	0.445	-0.265	0.116

Note. Object Type was coded such that 0 = things and 1 = people.

Table S4. Analysis of visual dwell times in Study 2B.

Predictor	B	SE B	*z*	*p*	95% CI LB	95% CI UB
Social Class (SC)	0.027	0.023	1.18	0.236	-0.018	0.071
Object Type (OT)	-0.226	0.044	-5.19	0.000	-0.311	-0.141
SC × OT	-0.116	0.050	-2.34	0.019	-0.214	-0.019
Interest Area Size	0.426	0.008	51.47	0.000	0.409	0.442
Black	-0.014	0.112	-0.12	0.901	-0.234	0.206
Latino	-0.016	0.055	-0.29	0.769	-0.125	0.092
Asian	-0.016	0.032	-0.48	0.630	-0.079	0.048
Other	0.022	0.050	0.43	0.665	-0.076	0.120
Black × OT	0.131	0.223	0.59	0.556	-0.306	0.569
Latino × OT	-0.037	0.101	-0.36	0.716	-0.236	0.162
Asian × OT	-0.020	0.056	-0.36	0.719	-0.130	0.089
Other × OT	0.035	0.118	0.30	0.768	-0.197	0.267

Note. Object Type was coded such that 0 = things and 1 = people.

Table S5. City-by-city analysis of visual dwell times in Study 2B.

City	Predictor	B	SE B	*z*	*p*	95% CI LB	95% CI UB
New York	Social Class (SC)	0.054	0.032	1.67	0.094	-0.009	0.117
	Object Type (OT)	-0.340	0.058	-5.87	0.000	-0.454	-0.227
	SC × OT	-0.144	0.064	-2.26	0.024	-0.269	-0.019
	Interest Area Size	0.410	0.008	48.55	0.000	0.393	0.426
	Black	-0.073	0.124	-0.59	0.553	-0.316	0.169
	Latino	-0.026	0.064	-0.41	0.683	-0.152	0.100
	Asian	-0.002	0.043	-0.04	0.965	-0.087	0.083
	Other	0.080	0.073	1.10	0.272	-0.063	0.223
	Black × OT	0.221	0.273	0.81	0.417	-0.313	0.756
	Latino × OT	-0.079	0.135	-0.58	0.560	-0.344	0.186
	Asian × OT	-0.055	0.070	-0.78	0.433	-0.193	0.082
	Other × OT	-0.046	0.173	-0.26	0.791	-0.385	0.294
San Francisco	Social Class (SC)	0.012	0.025	0.49	0.627	-0.037	0.062
	Object Type (OT)	-0.113	0.052	-2.17	0.030	-0.214	-0.011
	SC × OT	-0.098	0.055	-1.77	0.076	-0.206	0.010
	Interest Area Size	0.454	0.010	43.90	0.000	0.433	0.474
	Black	-0.070	0.130	-0.54	0.591	-0.326	0.186
	Latino	0.000	0.062	0.01	0.994	-0.121	0.122
	Asian	0.012	0.033	0.37	0.715	-0.053	0.077
	Other	0.015	0.044	0.34	0.737	-0.072	0.102
	Black × OT	0.199	0.274	0.73	0.467	-0.337	0.736
	Latino × OT	-0.026	0.115	-0.23	0.821	-0.251	0.199
	Asian × OT	-0.012	0.065	-0.19	0.850	-0.140	0.115
	Other × OT	0.127	0.104	1.21	0.224	-0.078	0.332
London	Social Class (SC)	0.028	0.023	1.21	0.227	-0.017	0.072
	Object Type (OT)	-0.303	0.047	-6.48	0.000	-0.395	-0.211
	SC × OT	-0.136	0.046	-2.94	0.003	-0.226	-0.045
	Interest Area Size	0.381	0.011	33.88	0.000	0.359	0.403
	Black	0.083	0.120	0.69	0.489	-0.152	0.319
	Latino	-0.025	0.057	-0.43	0.666	-0.137	0.088
	Asian	-0.051	0.042	-1.22	0.223	-0.132	0.031
	Other	0.009	0.054	0.16	0.871	-0.097	0.114
	Black × OT	-0.014	0.183	-0.08	0.939	-0.373	0.344
	Latino × OT	-0.009	0.108	-0.08	0.935	-0.220	0.202
	Asian × OT	-0.006	0.067	-0.09	0.930	-0.137	0.125
	Other × OT	-0.006	0.119	-0.05	0.961	-0.238	0.227

Note. Object Type was coded such that 0 = things and 1 = people.

Table S6. Analysis of speed to detect face changes in Study 3.

					95% CI	
Predictor	B	SE B	*z*	*p*	LB	UB
Social Class (SC)	-0.003	0.005	-0.48	0.629	-0.013	0.008
Object Type (OT)	-0.007	0.005	-1.53	0.125	-0.016	0.002
SC × OT	-0.012	0.005	-2.42	0.015	-0.022	-0.002
Interest Area Size	-0.008	0.017	-0.47	0.637	-0.043	0.026
Black	0.013	0.015	0.86	0.389	-0.016	0.042
Latino	0.024	0.017	1.40	0.160	-0.010	0.058
Asian	-0.024	0.020	-1.18	0.238	-0.063	0.016
Other	0.006	0.012	0.48	0.629	-0.018	0.030
Black × OT	-0.022	0.025	-0.90	0.366	-0.071	0.026
Latino × OT	0.020	0.014	1.40	0.162	-0.008	0.047
Asian × OT	0.018	0.016	1.13	0.258	-0.013	0.050
Other × OT	-0.003	0.005	-0.48	0.629	-0.013	0.008

Note. Object Type was coded such that 0 = things and 1 = faces.

Supplemental Figures

Age (in years) ______ Gender: O male O female O other (please specify): _______ US Citizen or Resident: O Yes O No

Native English speaker: O Yes O No How long have you lived in NYC: ____________ years

Please enter the category that best represents your ethnic background:

- O European/ European American
- O African/ African American
- O Latino
- O East Asian/ Asian American
- O Native American
- O Other (please specifiy): _______________

Please enter the ZIP code of the area where you spent most of your time growing up: __________ Your current ZIP code: ______________

People talk about social classes such as the poor, the working class, the middle class, the upper-middle class and the upper class. Which of these classes would you say you belong to?

O	O	O	O	O
The poor	The working class	The middle class	The upper middle class	The upper class

Using the social class that you marked above (poor, working, middle, upper middle, or upper class), please indicate how much you agree with each of the following statements:

	O	O	O	O	O	O	O
I often think about the fact that I am _______ (poor, working, middle, upper middle, or upper class).	Strongly agree	Agree	Somewhat agree	ither agree r disagree	Somewhat disagree	Disagree	Strongly disagree
The fact that I am _____ (poor, working, middle, upper middle, or upper class) is an important part of my identity.	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
Being _____ (poor, working, middle, upper middle, or upper class) is an important part of how I see myself.	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

Please provide information about your education history

	Did not finish high school	High school grad, general ed. diploma, or some college	College graduate	Postgraduate degrees (e.g. Masters, PhD., MD.)
Your highest level of education	O	O	O	O

Please provide information about your annual income (before taxes). Please provide your best estimates.

	< $15,000	$15,001 - $25,000	$25,001- $35,000	$35,001- $50,000	$50,001- $75,000	$75,001- 100,000	$100,001- $150,000	> $150,000
Current annual salary	O	O	O	O	O	O	O	O

The government should implement more policies to fight social inequality in my country.

O	O	O	O	O	O	O
Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree

Think of a ladder with 10 rungs representing where people stand IN THE UNITED STATES. At the top of the ladder are the people who are the best off, those who have the MOST money, MOST education and BEST jobs. At the bottom are the people who are the WORST off, those who have the LEAST money, LEAST education, and worst jobs or no job. Between 1 (bottom) and 10 (top), where do you think you stand on the ladder IN GENERAL?

O	O	O	O	O	O	O	O	O	O
1 Bottom rung	2	3	4	5	6	7	8	9	10 Top rung

Please list 5 things/people that you saw while you were walking down the street (e.g.: blue car, woman talking on the phone):

________________ ________________ ________________ ________________ ________________

To what extent did wearing Google Glass make you feel self-conscious while you were walking down the street?

O	O	O	O	O	O	O
Not at all self-conscious	Not very self-conscious	Somewhat self-conscious	Moderately self-conscious	Somewhat self-conscious	Very Self-conscious	Extremely self-conscious

Figure S1. Questionnaire administered in Study 1.

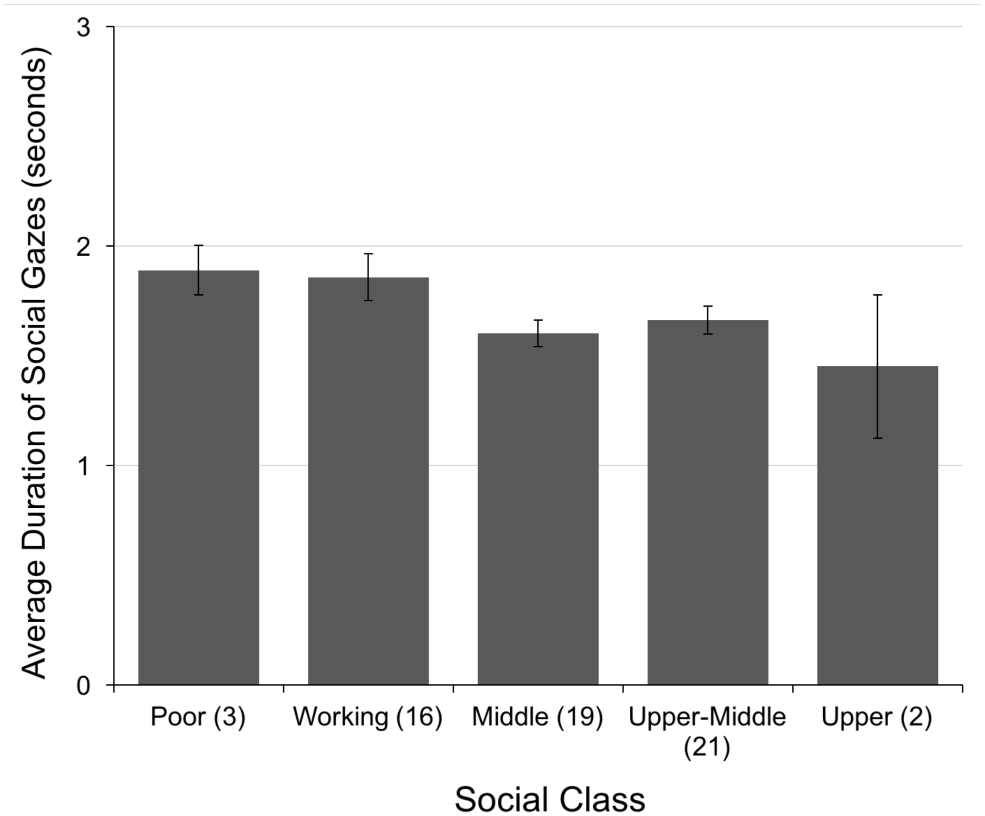

Figure S2. Observed means in Study 1. Error bars represent ±1 standard error. Means are not adjusted for participant race.

Figure S3. Example New York City scene used in Studies 2A and 2B.

Figure S4. Example San Francisco scene used in Study 2B.

Figure S5. Example London scene used in Study 2B.

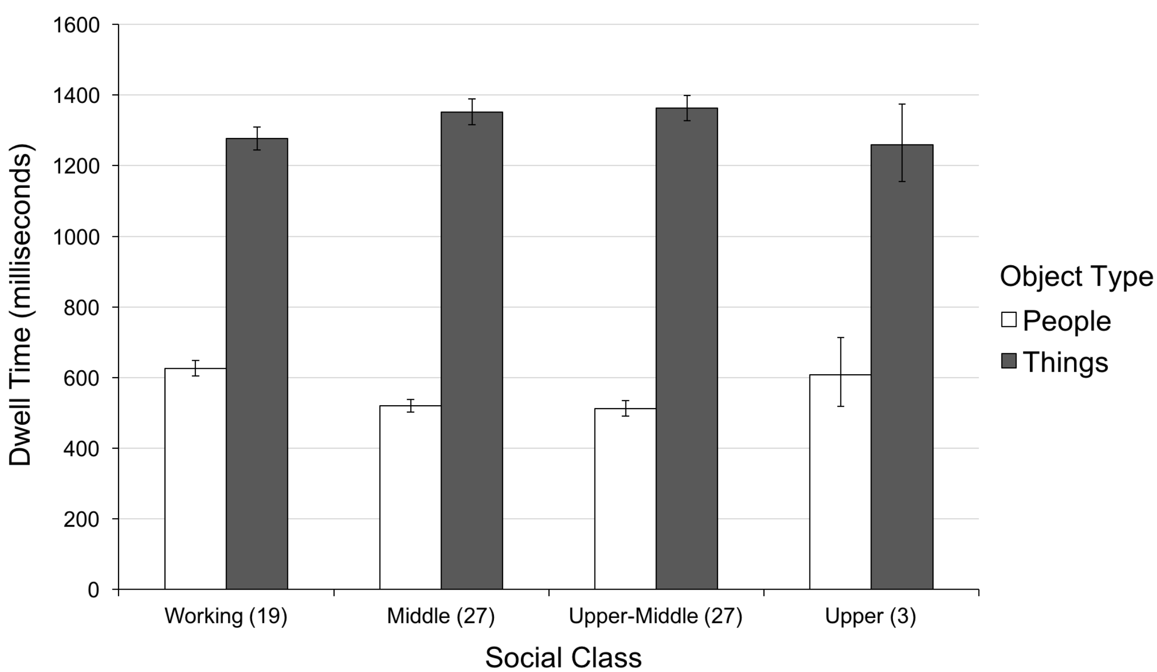

Figure S6. Observed means in Study 2A. Error bars represent ±1 standard error. Means are not adjusted for interest area size or participant race.

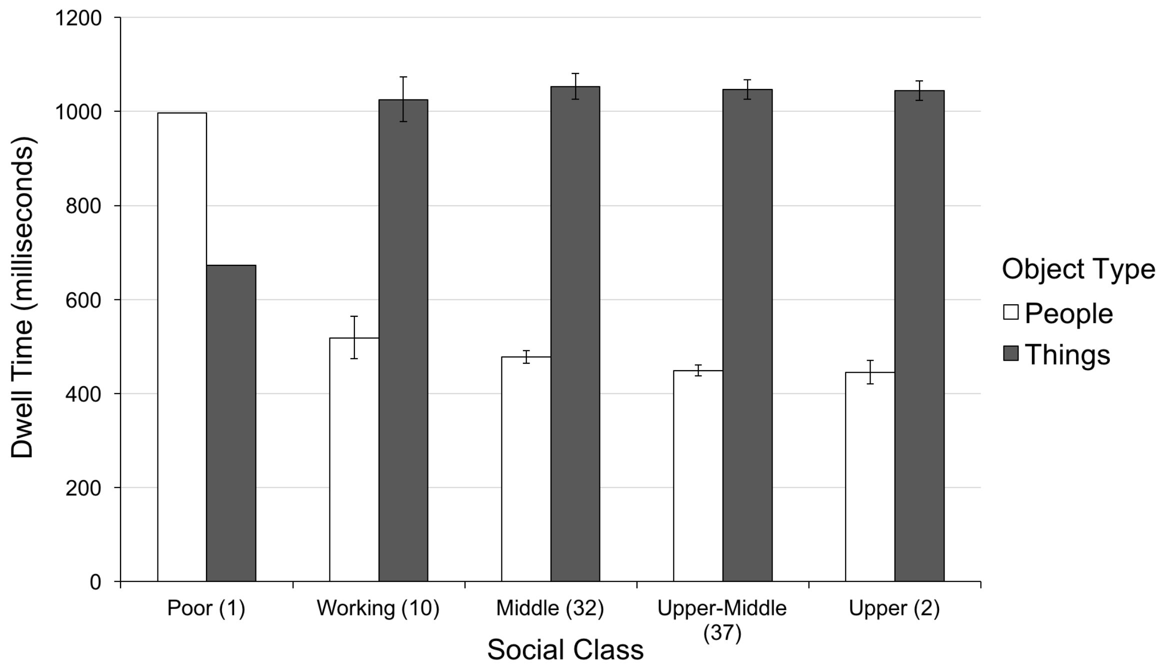

Figure S7. Observed means in Study 2B. Error bars represent ±1 standard error. Means are not adjusted for interest area size or participant race.

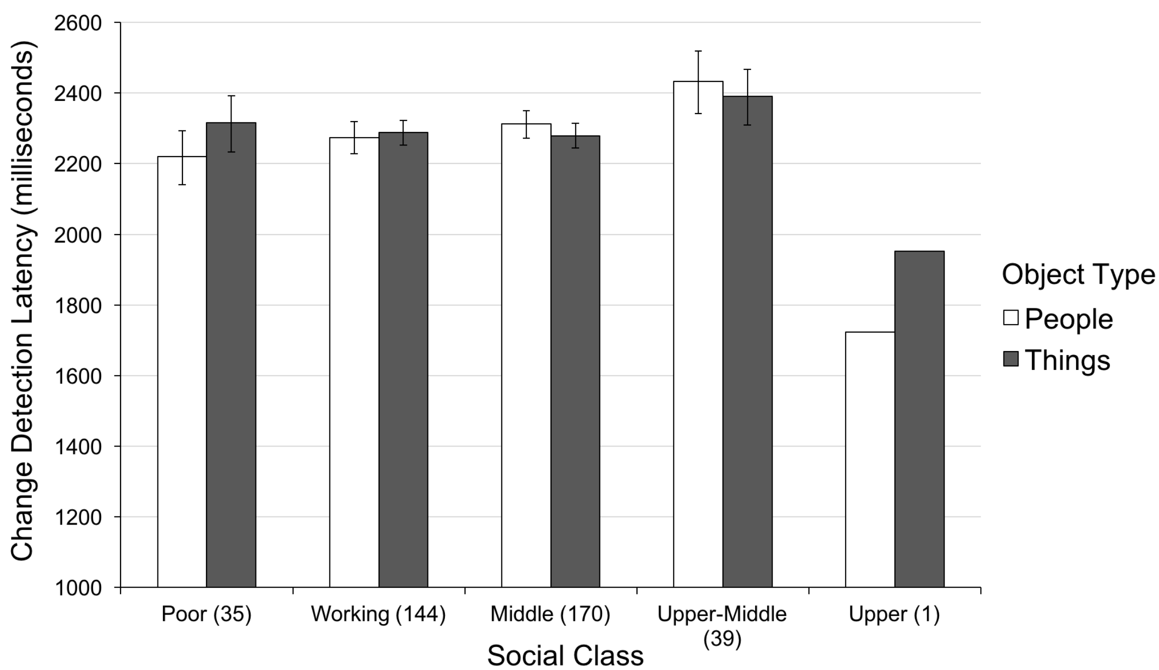

Figure S8. Observed means in Study 3. Error bars represent ±1 standard error. Means are not adjusted for participant race.

City-by-City Analysis

We sought to determine whether, in Study 2B, images' city of origin qualified the crucial interaction between social class and object type. To this end, we ran the previous model separately for scenes of New York, San Francisco, and London. The Social Class × Object Type interaction was significant for both New York and London scenes, and marginally significant for San Francisco scenes. (See Table S5 for full results of these analyses.) Moreover, for all three cities, the simple effect of social class on human-directed attention was significant and in the hypothesized direction—indicating that the tendency of higher-class participants to attend less to human targets held across the different stimulus sets.

Notes on the Integrative Data Analysis

Like meta-analysis, integrative data analysis (IDA) is a method of synthesizing the results of multiple studies that use conceptually related independent and/or dependent variables (Curran & Hussong, 2009). Unlike meta-analysis, which leverages summary statistics from published and unpublished research reports, IDA utilizes the complete data from each integrated study. Curran and Hussong (2009) enumerate a number of advantages of IDA over meta-analysis, including increased statistical power, more precise examination of replicability, and broader psychometric assessment of relevant constructs. Because we have access to the original data for each study reported here, we chose IDA as a means of synthesizing our results and comparing the relative predictive power of various operationalizations of social class.

The IDA was conducted using simplified versions of our datasets. First, since all of the significant effects concerned visual attention to people, and not to things, we excluded any trials involving things before combining the datasets. We also collapsed across repeated trials in the relevant studies (Studies 2A, 2B, and 3), such that each observation reflected the mean level of human-directed attention. Thus, each participant represented a single case in the combined dataset. Finally, since our indices of attention differed substantially across studies, we standardized the various indices within study to render them comparable across datasets. The resulting variable is termed “social attention.”

Because we had only four datasets—too few to reliably estimate study-level variation in our effects—a “fixed-effects” approach to IDA was called for (Curran & Hussong, 2009). Thus, we created three dummy variables specifying the study, with Study 1 as the reference category. We then regressed the social attention variable simultaneously on participants’ class category, income (or, in the student sample, their parents’ income), educational attainment (or, in the student samples, the average educational attainment of their mother and father). Race contrasts were also included as controls in the analysis.