Looking for social class in all the wrong places:

Differences in interdependence emerge reliably between—but not within—class contexts

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Abstract

Despite theorizing that many cultural phenomena originate in collective processes, psychologists often analyze such phenomena at the individual level. This approach can skew conclusions by obscuring processes that unfold primarily at the level of groups or contexts. To demonstrate the importance of examining cultural effects at the group or contextual level, we examine differences in social interdependence as a function of social class. Across three large datasets (N_{total} = 30,332), full-sample correlations between class proxies (i.e., income and education) and indices of interdependence (i.e., social network structure and reported social support) were weak and inconsistent. However, when latent profile analysis (LPA) is used to model these associations at the level of class-cultural groups, we observe a working-class group that displays reliably higher levels of interdependence relative to a middle/upper-class group. Our work underscores that class-cultural differences often constitute contextual phenomena that are not reducible to individual-level processes.

Keywords*:* social class, culture, culture cycle, latent profile analysis, LPA

Searching for social-class differences in interdependence: Level of analysis matters

Social class "is one of the most consequential social divides of our time" (Stephens et al., 2024, p. 2). As a material context, class influences individuals' access to education (Grusky et al., 2019), healthcare (Chetty et al., 2016), housing (Massey, 2020), and jobs (Charles et al., 2019). As a cultural context that arises in response to such material realities (Carey & Markus, 2017; Nisbett, 2003), class shapes people's trust in government (Kim et al., 2022), sociopolitical views (Schaffner et al., 2018), conceptions of human agency (Stephens et al., 2011), and cognitive styles (Varnum et al., 2010).

Within psychology, social classes are conceptualized as distinct socioeconomic niches that give rise to unique behavioral norms, values, lay theories, and self-construals—that is, *cultures* (Stephens et al., 2024). A class culture can be seen as a "compass" that helps people cope with life's challenges by orienting them to the resources available within their context (Piff et al., 2012). Reflecting this logic, theories of class-as-culture often posit an inverse relationship between people's material resources and their levels of social interdependence (Carey & Markus, 2017; Fiske & Markus, 2012). Because working-class contexts afford relatively few material resources, people within such niches tend to rely on close others in times of need. Wealthier middle- and upper-class contexts, in contrast, enable individuals to rely on financial resources in meeting life's challenges. When sick, a parent from a working-class background might need to call on family or friends to look after their child, whereas a parent from a middle-class background might hire a babysitter or enroll their child in daycare.

Over time, socialization to the utility of social ties within class contexts come to shape individuals' self-construals and cognitive tendencies. Whereas students from middle-class backgrounds are typically motivated to attend college by a need for self-actualization, students from working-class backgrounds are often driven by a desire to help their families and communities (Stephens et al., 2007, 2012). Group-based work emphasizing interdependence and collaboration tends to benefit students and employees from working-class contexts

(Dittmann et al., 2020, 2024; Müller et al., 2023). Class differences extend even to basic social cognition, such that those from working-class contexts display heightened visual attention to other human beings (Dietze & Knowles, 2016), superior perspective-taking and emotion-reading performance (Dietze & Knowles, 2021), and better memory for faces (Dietze et al., 2024) relative to their middle-class counterparts. These and other studies (e.g., Carey & Markus, 2017; Kraus & Keltner, 2009; Stephens et al., 2011; Varnum et al., 2010, 2016) converge on a critical insight: Working-class contexts foster an interdependent orientation in response to material scarcity.

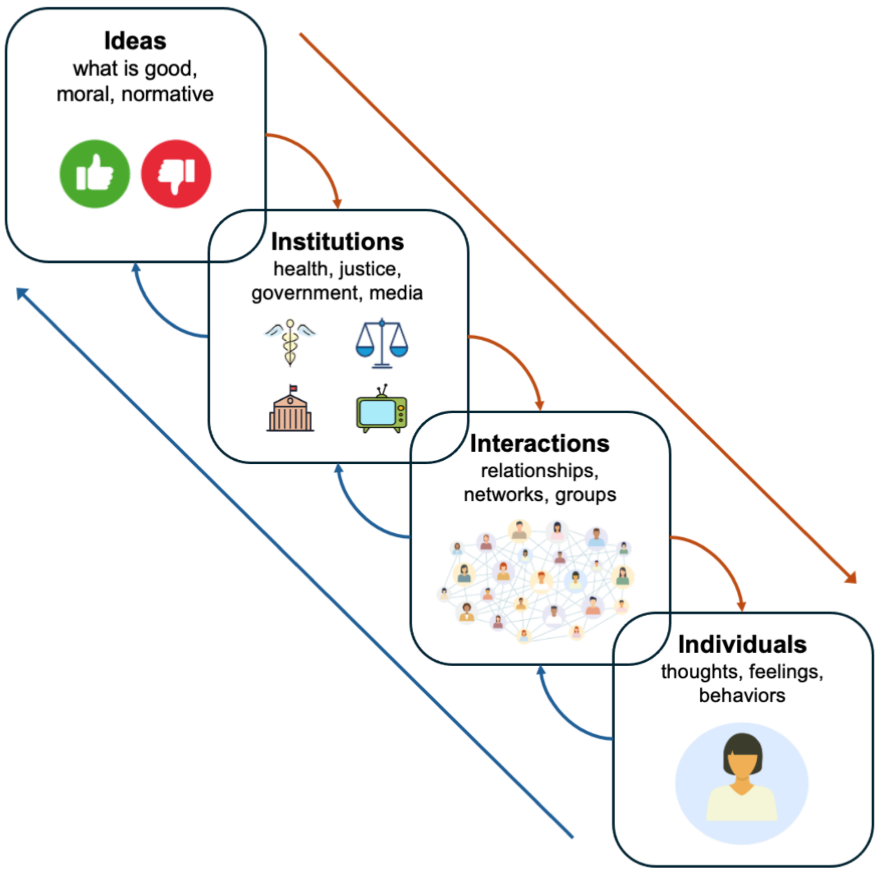
In the present work, we term the inverse relationship between material resources and interdependent social orientation the material–social tradeoff (MST). Despite robust evidence for MSTs, extant research is silent regarding whether they predominantly occur at the individual level, the contextual level, or both levels simultaneously.

Culture Cycles and the Multilevel Nature of Cultural Processes

The different levels at which MSTs might occur can be understood in terms of the culture cycle, a framework delineating the multilayered processes by which culture and mind mutually constitute one another (Figure 1; Markus & Kitayama, 2010; Stephens et al., 2014). The "bottom-up" portion of the culture cycle articulates how people shape their culture. In this portion of the cycle, people's thoughts, feelings, and preferences affect their interactions with the environments, institutions, and the social representations that prevail within the culture. The "top-down" portion of the culture cycle examines the reverse, emphasizing how broader cultural contexts—with their associated institutions, interaction patterns, and ideas—shape individual psychology. This part of the cycle emphasizes that cultural phenomena reflect context- or group-level effects that are not reducible to individual agency or decision-making.

Figure 1

The Culture Cycle



Note. Orange arrows represent “top-down” effects of the cultural context; blue arrows depict “bottom-up” effects of individual agency. Straight arrows stand in for all other links (e.g., ideas to interactions, individuals to institutions) not otherwise depicted. Adapted from Hamedani and Markus (2019).

Both portions of the culture cycle occur in tandem. As Markus and Kitayama (2010) note, “people are socioculturally shaped shapers of their environment” (p. 421). Individuals are seldom born into a cultural vacuum and instead begin the lifelong process of socializing to the norms, values, and self-construals of their communities during infancy (Laible et al., 2015). At the same time, human agency can spur cultures to change when people’s appraisals, judgments, and intentions sufficiently alter the interaction patterns, institutions, and social representations that comprise a culture (Hamedani & Markus, 2019; Markus & Hamedani, 2019). Although both portions operate simultaneously, we argue that the relative prominence of individual agency and cultural socialization in a given culture cycle can illuminate important features of the culture under study.

Individual- vs. Context-Level Material–Social Tradeoffs

The culture cycle implies that class-cultural MSTs can take two forms, each with its own empirical signature. First, an individual-level interpretation of MSTs reflects the bottom-up, agentic portion of the culture cycle. On this account, individuals actively calibrate their levels of social interdependence to their personal financial means with little influence from the broader norms and structures of a class context. Within any class community, those with few material resources should display higher levels of interdependence—perhaps by maintaining highly interconnected and supportive networks of social ties as a means of coping with life's challenges. In contrast, more affluent individuals in a class community have the option of leveraging material capital to cope with challenges and may therefore opt to form and maintain fewer or weaker social ties.

An individual-level MST embodies the idea that cultural differences are individual differences “writ large” (Na et al., 2020, p. 908; Smith & Bond, 1999)—with between-class differences in interdependence reflecting the sum total of individuals’ decisions within their respective socioeconomic contexts. Relatively impoverished individuals within a given class context will tend to be more interdependent than their wealthier within-class peers, with group-level differences in social orientation deriving from the fact that people in working-class contexts are on average poorer than those in middle-class contexts.

A context-level interpretation of MSTs, on the other hand, reflects the top-down portion of the culture cycle. This view affirms that human behavior is shaped not only by people’s appraisals of their immediate circumstances but also by the norms, values, and self-construals that predominate within their culture (Carey & Markus, 2017; Markus & Kitayama, 1991). In this way, class cultures communicate which values and self-construals are generally adaptive within one's class milieu—thus allowing individuals to adopt a social orientation tailored to the context without having to calibrate their levels of interdependence to their personal means. A context-level MST implies an inverse relationship between material means and levels of interdependence *between social-class groups*, with average differences existing independently of any within-class relationships between material resources and social orientation.

Our argument echoes that of sociologists and cultural psychologists who emphasize that certain social phenomena are irreducibly contextual in nature. In sociology, this fact is often understood in terms of "neighborhood effects," in which individual outcomes vary independently as a function of person- and group-level characteristics (Diez Roux, 2001). In one famous example, Gelman and colleagues (2005) used the logic of neighborhood effects to rebut claims that the Republican Party had, through its emphasis on cultural wedge issues like gun rights and sexual morality, become the party of low-income Americans (Frank, 2005). The authors showed that although voters in lower-income states were more likely overall to support Republican candidates, the opposite pattern emerged for residents within a state. That is, poorer individuals were *less* likely to vote Republican than their richer within-state peers. Similarly, cultural psychologists have shown that measures of social orientation and cognitive style are correlated as theory would suggest when comparing countries' mean scores—but uncorrelated at the individual level within any given country (Na et al., 2010). Findings such as these demonstrate the separability of individual and contextual phenomena, as well as the importance of appropriately modeling cultural effects at each level.

Distinguishing Individual-Level and Context-Level MSTs

As exemplified by the culture cycle, cultural-psychological theorizing emphasizes the bidirectional, multilevel processes through which culture and individual psychology shape one another (Hamedani & Markus, 2019; Markus & Kitayama, 2010; Stephens et al., 2014). Nevertheless, we know of few empirical attempts to parse the degree to which specific cultural phenomena occur at the individual versus contextual level (but see Na et al., 2010, 2020). Thus, the present research sought to disentangle the extent to which the material–social tradeoff (MST) reflects top-down influences of class cultural contexts or the bottom-up operation of individual agency.

A pervasive, yet underappreciated, ambiguity arises when individual-level markers of social class (e.g., financial assets or educational attainment) are used to predict outcomes of interest (a practice common among class researchers, including the present authors). Provided that one's sample contains respondents from multiple class contexts, any observed relationship will inevitably conflate the effects of person- and context-level variation in the class proxy.

To illustrate, previous research has found that educational attainment predicts the amount of time people spend looking at human beings in still images, such that those without a four-year degree devote more attention to others than do those with a four-year degree (Dietze & Knowles, 2016, Studies 2a and 2b). Although the class proxy (educational attainment) robustly predicted patterns of visual attention, the data provide no information concerning the individual versus contextual nature of the education–attention relationship. Indeed, the observed association may reveal something about individuals (e.g., when a person gets a college degree they start looking less at others) or something about the class context (e.g., contexts that afford few opportunities for higher education foster a tendency to look more at other people). To infer from these data that a college education reduces chronic attention to others risks an "ecological fallacy" wherein group- or context-level effects are mistaken for individual-level effects (Na et al., 2010, 2020; Robinson, 1950).

Whether a cultural process primarily unfolds at the individual or contextual level is more than a matter of theoretical nuance, but also has implications for researchers' ability to detect that process in the first place. As Na and colleagues (2010) demonstrate through mathematical simulation, evidence for cultural phenomena occurring primarily at the context-level may be extremely difficult to document using individual-level analyses alone, even when mean differences between contexts are very large. This can be seen by imagining two cultural groups, A and B, that exhibit a large context-level MST—such that individuals in culture A display a higher mean income level (Cohen's $d = 0.8$) and lower mean level of interdependence (Cohen's $d = -0.8$) than do individuals in culture B. In the absence of any association between income and interdependence within cultures A or B, the correlation between these variables cannot exceed $r = -.14$ in the "full sample" combining individuals from both cultures (Na et al., 2010, p. 6194). In other words, individual-level analytical techniques risk overlooking cultural phenomena that occur primarily at the contextual-level (rather than the individual-level).

Existing analytic approaches enable researchers to model effects at nested levels of analysis (e.g., individuals within contexts). In particular, multilevel modeling (MLM) makes it possible to regress an outcome of interest simultaneously on characteristics of the person and the context. For instance, Gelman and colleagues (2005) regressed voting behavior on respondents' incomes as well as those incomes' within-state means; here, U.S. states were a contextual unit between which varied the intercept of candidate preference and slope of candidate preference on income.

Unfortunately, typical approaches to studying class and its consequences precludes the use of MLM to disentangle contextual vs. individual MSTs. This is because the constructs whose contextual and individual relationships we wish to model—material resources and social orientation—are the same ones that might underpin our contextual units (i.e., social-class cultures). Because MLM does not allow a variable to perform "double duty" as both the predictor or outcome and the nesting variable, we sought a different analytic approach.

The Present Research

As an alternative to MLM, we used latent profile analysis (LPA) to model between- and within-context relationships between material resources and social orientation. A form of mixture modeling, LPA tests the likelihood that a variable of interest samples two or more distributions characterized by different means (Oberski, 2016). Different combinations of means across multiple "indicator variables" reveal distinct subgroups in the population (e.g., a subgroup marked by high means on one variable, low means on a second variable, and a middling mean on a third variable). Like other techniques used to identify groups of similar individuals, such as latent class analysis (LCA) or cluster analysis, LPA is a "person-centered" analytic approach (Pastor et al., 2007). However, unlike other approaches, LPA allows researchers to assess between-profile differences in respondents' indicator means while simultaneously modeling associations between indicator variables within the subgroups that emerge from the analysis.

LPA is well-suited to teasing apart between- and within-group phenomena when the groups in question are "hidden"—that is, unknown independently of one's analytic variables (Oberski, 2016). As such, we assess relationships between material resources and interdependence between and within potential class contexts identifiable only through reference to these same variables. Informed by cultural-psychological theorizing (e.g., Stephens et al., 2024), we had good reason to believe that individuals would cluster into distinct groups delineated by mean levels of material resources and interdependent patterns of being. However, such clustering is by no means guaranteed. Whereas other techniques, such as MLM, presuppose the existence of meaningful higher-level groupings, LPA renders the existence of subgroups a strictly empirical question. Thus, before attempting to document context- and individual-level relationships between material resources and interdependence, we were first required to demonstrate that groups emerge in the first place. Provided that groups do emerge, we can then evaluate whether MSTs occur between them (suggesting a context-level process) or within them (suggesting an individual level process).

To this end, we subjected three publicly available datasets (N_{total} = 30,332) to LPA. Consistent with theory that casts social class as a cultural context (e.g., Carey & Markus, 2017; Fiske & Markus, 2012; Stephens et al., 2024), we expected to identify at least two class-cultural groups displaying a material-social tradeoff: (1) a working-class group exhibiting low levels of material resources but high levels of interdependence and (2) a middle- or upper-class group displaying high levels of material capital (i.e., income and education) but low levels of interdependence. We then examined which level of the culture cycle class-based differences in interdependence likely reflect. To the extent that MSTs are a matter of individual agency (i.e., the bottom-up portion of the culture cycle), we should observe negative full-sample and within-profile correlations. To the degree that MSTs predominantly reflect the manner in which contexts shape individuals (i.e., the top-down portion of the culture cycle), we should see negative material–social associations between—but not within—profiles. Consistent with Na et al.'s (2010) calculations, a context-level effect of this sort may be accompanied by only a small full-sample correlation.

Materials and Methods

Transparency and Openness

Below we describe all datasets, data exclusions, and measures used in the research. Prepared data files, materials, analysis code, and supplemental materials for all studies are posted on the project's Open Science Framework (OSF) page. The methods and analyses used in Study 3 were pre-registered at AsPredicted. Although our Study 3 preregistration includes analyses of physical and mental health outcomes, we focus here on social-class differences in interdependence.

Samples

Study 1

The Study 1 sample was compiled by linking the 2018 Cooperative Congressional Election Study (CCES; Ansolabehere et al., 2018) and the Social Capital Atlas (Chetty et al., 2022a, 2022b). The CCES is a nationally-stratified survey, administered by YouGov, measuring Americans' political attitudes, voting behavior, and demographics. The SCA assesses patterns of online connection among Facebook users in the United States; the resulting indices of social capital (e.g., cohesiveness, economic connectedness, and civic engagement) are aggregated to the ZIP-code and county levels. We restricted our analyses to respondents with valid measures of income and education in the CCES, as well as the ZIP codes necessary to match these data with estimates of social capital in the SCA. Respondents younger than 25 were omitted, thus excluding most current college and university students. Ages ranged from 25–99 (M = 47.38, SD = 16.15). 43% percent of the sample had a college education and the mean income bracket was $50,000–$59,999. The majority of the sample was female (61%) and White (68% White, 12% Black, 11% Hispanic, 4% Asian, 1% Native American, <1% Middle Eastern, 2% more than one race, and 1% "other"). Our final analysis sample after exclusions consisted of 26,985 respondents.

Study 2

The Study 2 data were retrieved from the General Social Survey (GSS; Davern et al., 1972) website. The GSS is an ongoing series of nationally representative surveys in the U.S. detailing trends in social opinions, attitudes, and behaviors. Given that 2018 was the most recent GSS year containing adequate measures of income, educational attainment, and a commonly measured type of interdependent behavior (i.e., social network support), we restricted our analyses to 2018 respondents. Additionally, we limited our analyses to respondents who had viable responses to all three variables of interest. Respondents under 25 were excluded, thus omitting most current college and university students. Ages ranged from 25–89 (M = 50.78, SD = 16.34). 45% of the sample had a college degree or advanced degree (e.g., MBA, PhD, JD, or MD) and respondents' mean income was $35,395 ($SD$ = $32,096). The majority of the sample was White (73% White, 16% Black, 11% Other) and female (52%). After exclusions, our final analysis sample consisted of 939 respondents.

Study 3

The Study 3 sample was obtained through the National Social Life, Health, and Aging Project (NSHAP; Waite et al., 2017) — a nationally representative study of relationships and healthy aging. We restricted our sample to those respondents with viable responses to all three indicator variables in Wave 3 (collected 2015–2016) and the Covid-19 substudy (collected 2020–2021). Ages ranged from 49–94 (M = 67.17, SD = 9.74). 34% of the sample had a college degree or advanced degree, respondents' mean income bracket was \$50,000–\$99,999, and respondents' mean asset bracket was \$100,000–\$499,999. Participants were mostly female (56% female) and mostly White (73% White, 14% Black, 9% Hispanic, 3% Other). Our final analysis sample consisted of 2,408 participants.

Measures

Access to Material Resources

Across each of the three samples, we used respondents' household income and educational attainment (1 = four-year degree or higher, 0 = no four-year degree) as our primary measures of access to material resources. In Study 3, household income was replaced with a composite of income and financial assets. Assets are an important component of material capital (and thus people's class positioning) as they represent wealth that can be marshaled in times of crisis (Oliver & Shapiro, 2006). Similarly, a college degree is a form of "human" capital that can be converted over the lifespan into financial earnings and wealth. In this sense, college education is an indicator of access to material resources in the future (Becker, 2009; Schultz, 1961).

Interdependent Social Orientation

Study 1. In Study 1, interdependence was indexed via the *clusteirng_zip* variable in the SCA dataset. Clustering is defined as the likelihood that any two individuals' Facebook friends are also friends with each other. This measure of clustering is aggregated to the ZIP-code level and serves as an estimate of the tightness of respondents' communities. We surmised that this operationalization of social network clustering would be a valid proxy for interdependence, given that networks rich in mutual ties are theorized to provide "bonding capital" crucial for adapting to material scarcity (Carey & Markus, 2017).

Study 2. In Study 2, interdependence was measured using 10 GSS variables pertaining to support-seeking behavior (Table 1). These items capture whom respondents could turn for help with various everyday tasks and larger life problems. "Everyday task" items were dichotomized such that *No one* (7) equals 0 and any other response equals 1; “life problem” items were dichotomized such that *Private companies* (3) or *No person or organization* (7) equals 0 and any other response equals 1. The items were then averaged to form an index of respondents’ use of social relationships and interpersonal networks to cope with life’s difficulties.

Table 1

General Social Survey (GSS) items measuring support-seeking behavior in Study 2 (α = 0.56)

GSS variable name	Question
	Everyday Tasks
	Who would you turn to first to…
HLPHOME	help you with a household or a garden job that you can't do yourself?
HLPSICK	help you around your home if you were sick and had to stay in bed for a few days?
HLPDOWN	be there for you if you felt a bit down or depressed and wanted to talk about it?
HLPADVCE	give you advice about family problems?
HLPSOCOC	enjoy a pleasant social occasion with?
	Life Problems
	Who would you turn to first to…
HLPLOAN	help you if you needed to borrow a large sum of money?
HLPJOB	help you if you needed to find a job?
HLPPAPER	help you with administrative problems or official paperwork?
HLPRESDE	help you if you needed to find a place to live?
HLPSICKR	look after you if you were seriously ill?

Everyday task response options: 1 = *Family members or close friends*, 2 = *More distant family members*, 3 = *Close friend*, 4 = *Neighbor*, 5 = *Someone I work work*, 6 = *Someone else,* 7 = *No one*. Life problem response options: 1 = *Family members or close friends*, 2 = *Other persons*, 3 = *Private companies*, 4 = *Public services*, 5 = *Nonprofit or religious organizations*, 6 = *Other organization,* 7 = *No person or organization*.

Study 3. In Study 3, interdependence was measured using four NSHAP variables relevant to perceived social support (Table 2). These items assess the degree to which respondents feel they can rely on family members and friends in times of need. Scores were averaged to form a composite reflecting the degree to which respondents rely on their interpersonal relationships for social support.[1]

Table 2

National Social Life, Health, and Aging Project (NSHAP) items assessing perceived social support in Study 3 ($\alpha = 0.65$)

NSHAP variable name	Question
FAMRELY2	How often can you rely on members of your family for help if you have a problem?
FAMFEEL	How often do members of your family really understand the way you feel about things?
FROPEN2	How often can you open up to your friends if you need to talk about your worries?
FRRELY2	How often can you rely on your friends for help if you have a problem?

Item options: 0 = *never*; 1 = *hardly ever or rarely*; 2 = *some of the time*; 3 = *often*.

Results

Full-Sample Correlations

Having identified measures of material resources and social interdependence, we proceeded to test relationships between these variables using an individual-level analytic

[1]We note that our measure of interdependence differs from our pre-registration. Initially, we intended to include three additional items assessing participants' perceptions of their neighbor and community (e.g., "Are people in this area willing to help?"). However, given that these items are not directly tied to individuals' interpersonal relationships and would likely be confounded with neighborhood affluence, we ultimately excluded them from our analyses.

approach: by computing their correlations in the full samples. In Study 1, the index of interdependence (i.e., network clustering) was negatively correlated with household income (r = -.13; Cohen's d = -.27, p < .001) and educational attainment (r = -.16; Cohen's d = -.33, p < .001). These effects are small but consistent with the material–social tradeoff (MST). In Study 2, however, interdependence (i.e., supportive relationships) was uncorrelated with household income (r = -0.02; d = -0.03, p = .632) and education (r = -0.02; d = -0.03, p = .644)—and in Study 3, interdependence (i.e., perceived support) was *positively* correlated with income and assets (r = .13; d = 0.27, p <.001) and education (r = .10; d = 0.21, p < .001). These weak and inconsistent individual-level associations might be taken as evidence against MSTs, thus calling into question a core tenet of cultural-psychological theorizing.

However, group-level cultural processes may be extremely difficult to document using only the full-sample correlations between individual-level measures which conflate group- and individual-level effects (Na et al., 2010). Thus, to ascertain whether MSTs emerge more reliably at a higher level of analysis, we subjected each dataset to latent profile analysis (LPA). In doing so, we first sought to confirm the presence of "hidden" social-class clusters in the data—a prerequisite for the existence of interpretable group-level effects. We then proceed to quantify the degree to which MSTs occur at the group vs. individual level.

Latent Profile Analysis

Mplus 8.5 software (Muthen & Muthen, 2017) was used to test LPA solutions across each of our three studies, treating the three variables of interest—income, educational attainment, and interdependent behavior—as profile indicators. Prior to the LPA, income and interdependence were scaled from 0 to 1, with 0 representing the lowest observed score and 1 representing the highest observed score. Educational attainment was coded such that 0 = no four-year college degree and 1 = four-year college degree. Restricted maximum likelihood estimation was specified. Many sets of random starting values (10,000) were tested for each model, increasing our confidence that the estimation algorithm found global (rather than local) log-likelihood maxima and thus the most probable latent groups (Lewis-Beck et al., 2004).

In line with Pastor and colleagues' (Pastor et al., 2007) guidance, we tested models specifying different numbers of profiles and alternative variance–covariance structures for the continuous profile indicators (i.e., income and clustering). Our models specified from 1 to 10 profiles. For each number of profiles, we tested a simple model constraining the variance of the continuous indicators (material resources and interdependence) to equality across profiles and constraining the covariance between these indicators to zero (A models). More complex sets of models were then fitted: B models, which retained the A models' single variance estimates but freed the continuous indicators to covary equally across profiles; and C models, which retained the A models' zero-covariance constraint but freed the continuous indicators' variances to differ between profiles. Finally, two progressively more complex models were fitted: D models, which freely estimated variances in each profile and allowed a single covariance across profiles; and E models, which freely estimated both the continuous indicators' variances and their covariance in each profile.

Selection of Preferred Solutions

Across the three studies, we selected our preferred LPA solutions with the following principles in mind. For a full description of how we implemented these principles and selected solutions in Studies 1–3, see pp. 3–6 of the supplemental materials.

The primary goal of LPA is to identify subgroups within a population on the basis of shared attributes (Spurk et al., 2020). The analyst attempts to identify a well-fitting, theoretically useful, and parsimonious statistical solution—that is, one that accurately reflects contours in the data without "overfitting" them by estimating more model parameters than necessary (Pastor et al., 2007; Spurk et al., 2020; Weller et al., 2020). To this end, researchers estimate a range of models specifying different numbers of profiles and alternative variance-covariance structures for the continuous indicators (Pastor et al., 2007). Choosing an optimal solution involves quantitative, theoretical, and subjective considerations (although the use of rigorous model-selection criteria makes LPA less subjective than other clustering techniques; Pastor et al., 2007, p. 14). As such, it is important that researchers make explicit their rationale for selecting a model so that other researchers can evaluate this choice (Spurk et al., 2020).

In a first cut, candidate models can often be ruled out on the basis of model-estimation issues. A common problem occurs when the estimation algorithm is unable to replicate the log likelihood of the best-fitting solution, even with many sets of random starting values. Nonreplication reduces confidence that the algorithm has identified a global (rather than local) log-likelihood maximum and suggests that the model is poorly defined for the data (Geiser, 2013). Another issue arises when the algorithm resorts to “boundary estimates” (i.e., values at the theoretical minimum or maximum for a profile indicator) in order to avoid a singular information matrix. Boundary estimates can indicate that the model is nonidentified or that too many profiles have been requested (Geiser, 2013). Finally, the estimation algorithm may yield untrustworthy standard errors, or fail completely, due to matrix problems.

Once LPA solutions have been screened for estimation problems, the overall fit of the remaining models may be assessed using an array of indices—most commonly the Bayesian information criterion (BIC), sample-size adjusted BIC (SABIC), and Akaike information criterion (AIC; Spurk et al., 2020). Moreover, the effect of specific parameterizations on fit can be assessed using various model-improvement tests. χ^2-difference tests are useful in comparing alternatives that specify different variance–covariance structures but the same number of profiles; conversely, the adjusted Lo-Mendell-Rubin likelihood ratio test (LMR-LRT; Lo, 2001; Pastor et al., 2007) or parametric bootstrapped likelihood ratio test (BLRT; McLaughlin et al., 2003) is used to compare models with different numbers of profiles but the same variance–covariance specification.

Unfortunately, comparison of overall fit and use of model-improvement tests cannot always be relied on to prevent overfitting. As profiles are added, BIC may continually decrease and model-improvement tests (e.g., the BLRT) may never reach nonsignificance, tempting the analyst to extract more profiles than are generalizable, theoretically interpretable, or practically useful (Ferguson et al., 2020; Masyn, 2013). In such cases, one can plot the decrease in model BIC (Masyn, 2013) or increase in log likelihood (Ferguson et al., 2020) as profiles are added, inspecting the trend for an inflection point ("elbow") after which the rate of model improvement diminishes (elbow test; Masyn, 2013). Similar to the use of scree tests in selecting factor-analytic solutions, the researcher may opt to reject LPA models beyond this point.

Inspection of fit indices, model-improvement tests, and BIC or log likelihood plots may still leave the analyst with an overly complex model. Thus, researchers should carefully examine sample statistics associated with each candidate model. A model that produces one or more extremely small profiles may be rejected, with researchers suggesting cutoffs of 3% or 1% of the overall sample (Spurk et al., 2020) or fewer than 25 cases (Lubke & Neale, 2006). Candidate LPA models should also be examined for evidence of misspecification (Pastor et al., 2007). For instance, if a model fixes the covariances of continuous indicators to zero, but the outputted profiles contain many significant correlations, then the model may be misspecified. Likewise, if a model constrains the variance of an indicator to equality across profiles, and yet the indicator's variance differs significantly between profiles, then the model's parameterization is called into question.

Interpreting the Emergent Profiles

Across each of our three studies, we find that respondents form into profiles marked by different mean levels of access to material resources and mean levels of interdependence. For a visualization of each group's profile means, see Figures 2–4. Before examining the clusters' relative levels of interdependence, we first interpret the profiles in light of their distinct material contexts. In doing so, we sought to give these profiles social-class labels that researchers from a broad range of theoretical perspectives would find appropriate.

Four groups were extracted in Studies 1 and 3, while three profiles emerged in Study 2.

We chose labels for the emergent profiles based on the groups' access to material resources, theory from cultural psychology that treats the possession of a four-year college degree as a marker of middle-class status (Stephens et al., 2024), and additional demographic information (e.g., common occupations, class self-identification) available in the datasets. For a summary of the demographic of the profiles[2], see Tables 3-5.

Middle/Upper Class

In each of the three studies, we observe a group characterized by relatively abundant material capital and the possession of a college degree; we termed this group the "middle/upper class." Demographic information available in Studies 1 and 2 supports this classification: Respondents in the middle/upper-class cluster are relatively likely to own a home, to reside in a city, to have avoided unemployment, to work in the management, business, or financial sectors, and to self-identity as "middle class" (see Tables 3 and 4). We therefore expect that researchers from a range of perspectives would regard this cluster as an amalgam of middle, upper-middle, and upper class individuals.

Secure Workers

Another group emerged in Studies 1 and 3. This cluster tends to have high levels of material capital but *lack* a college degree. Due to their lack of a college or university education, we regard these respondents as members of the working class. At the same time, these individuals enjoy substantial income and assets, including high levels of home ownership (Tables 3–5), likely providing some protection from unexpected financial shocks. We therefore termed this group the "secure workers."

Vulnerable Workers

A third group emerged in each of the three studies. This profile was marked by the lack

[2] To obtain estimates of the profile characteristics, we regressed variables of interest simultaneously on the profiles' posterior probabilities while constraining the intercept term to zero (Pastor et al., 2007). The resulting regression coefficients represent predicted means for each profile, weighted by the accuracy with which individuals can be classified.

of a college degree and modest levels of material capital (i.e., income and assets). These respondents tend to work in service occupations and reside outside of urban centers, and display the second highest rates of recent unemployment of any profile. About half of those in this group own their own homes—substantially fewer that secure workers or the middle/upper class. Like secure works, this profile bears hallmarks of the working class. However, their relative material precarity leads us to label them "vulnerable workers," as they are likely one financial shock away from falling out of the working class altogether.

The Underclass

A fourth and final group emerged in all studies. Members of this cluster have very low incomes and few assets, are highly unlikely to hold a college degree, experience the highest levels of unemployment of any profile, and rarely own a home. Given this pattern of material deprivation, this group likely experiences poverty, stigmatization, and exclusion from mainstream society (McLaughlin et al., 2003). While members of this group prefer to self-identify as "working class," they are also the most likely of any profile to call themselves "poor." We therefore termed this cluster "the underclass."

Figure 2

The Four Social-Class Profiles Found in Study 1

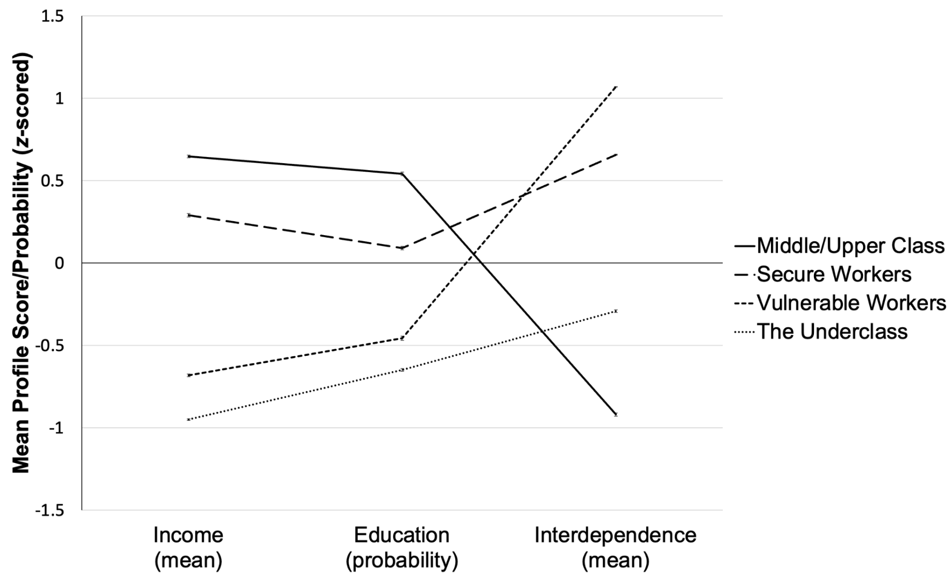


Figure 3

Three Social Class Profiles Found in Study 2

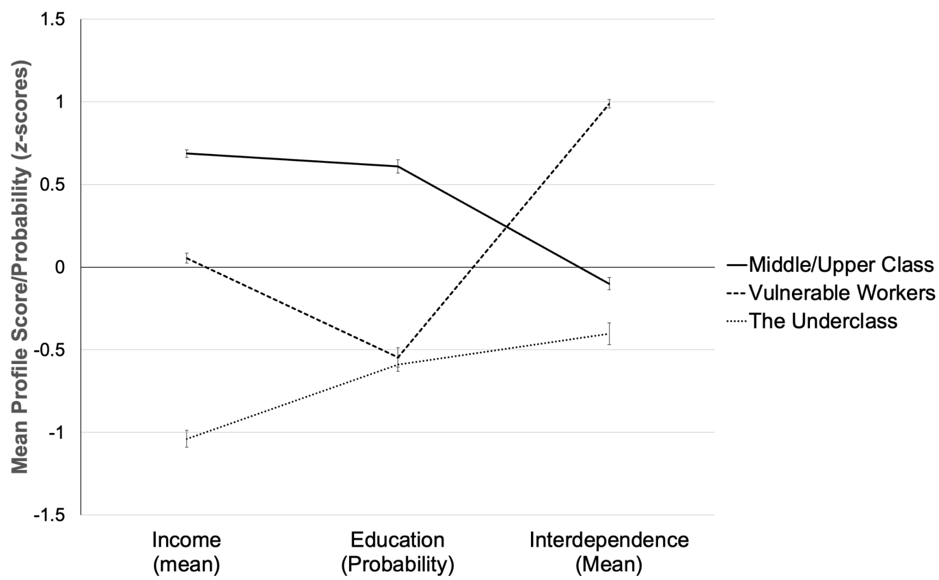


Figure 4

Four Social Class Profiles Found in Study 3

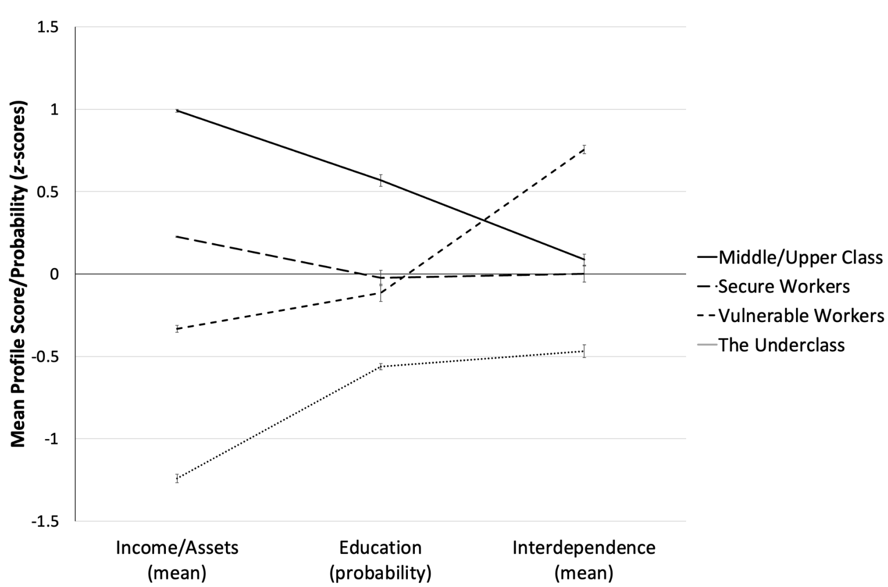


Table 3

Prevalence and Predicted Characteristics of Class Groups Found in Study 1

	The Underclass	Vulnerable Workers	Secure Workers	Middle/Upper Class
n (% of sample)	5,714 (21%)	3,995 (15%)	8,434 (31%)	8,842 (33%)
Age (years)	48.47	48.26	48.88	45.29
% female	65%	66%	60%	56%
% White	62%	80%	75%	61%
Probability of degree	0.16	0.19	0.43	0.67
Income bracket	< $10,000	$20,000–$29,999	$70,000–$79,999	$80,000–$89,999
Mean interdependence	0.86	0.99	0.94	0.81
Probability own home	0.21	0.52	0.76	0.62
Probability live in city	0.48	0.14	0.09	0.47
Probability unemployed in last 5 years	0.58	0.56	0.45	0.43

Table 4

Prevalence and Predicted Characteristics of Class Groups Found in Study 2

	The Underclass	Vulnerable Workers	Middle/Upper Class
n (% of sample)	310 (33%)	173 (18%)	456 (49%)
Age	52.34	45.53	51.37
% female	56%	53%	48%
% White	62%	72%	82%
Probability has degree	0.18	0.26	0.72
Mean income	$5,190	$15,222	$65,583
Mean interdependence	0.75	0.96	0.79
Probability own home	0.37	0.60	0.88
Probability unemployed in last 10 years	0.46	0.32	0.26
Most common occupations	Production, transportation, and material moving	Service occupations	Management, business, and financial
Preferred social class label	“working class”	“working class”	“middle class”

Table 5

Prevalence and Predicted Characteristics of Class Groups Found in Study 3

	The Underclass	Vulnerable Workers	Secure Workers	Middle/Upper Class
n (% of sample)	772 (32%)	338 (14%)	448 (19%)	850 (35%)
Age	67.07	71.52	66.26	65.47
% female	61%	67%	54%	47%
% White	56%	77%	76%	86%
Probability has degree	0.07	0.28	0.32	0.60
Income	< $25,000	$25,000–$49,999	$50,000–$99,999	$100k or greater
Assets	$10,000–$49,999	$100,000–$499,999	$100,000–$499,999	$500k or greater
Mean interdependence	0.65	0.88	0.74	0.75

MSTs at the Group and Individual Level

Having found that the data contain distinct subgroups, and that these subgroups resemble familiar social classes, we next sought to determine whether MSTs occur at the level of class groups, the level of individuals, or at both levels simultaneously. Recall that contextual MSTs imply negative associations *between* classes' mean levels of material capital and interdependence, whereas individual-level MSTs imply negative correlations between material resources and interdependence *within* the emergent class groups.

In testing for group-level MSTs, we focus on the middle/upper class and vulnerable workers. We do so for two reasons. First, unlike secure workers, the middle/upper and vulnerable-worker groups were observed in all of our studies. Second, the theoretical logic of MSTs is most clearly applicable to these groups: The material security of the middle/upper class likely fosters the development of independent norms, while vulnerable workers' material precarity likely fuels the emergence of interdependent norms. While the underclass is even more precarious than the vulnerable workers, existing theory and data suggest that the cultural processes behind MSTs might not operate within groups exposed to extreme deprivation. Indeed, people in poverty often adopt high levels of *in*dependence to cope with chaotic environments—including interpersonal relationships and social networks that are transitory, unpredictable, or nonexistent (Steele & Sherman, 1999).

We see clear and consistent evidence for a group-level MST between the vulnerable workers and middle/upper class, with effect sizes of the difference between these groups ranging from d = –0.80 to d = –2.59 across the three datasets (Table 6). For this pair of groups, the class with greater access to material resources (the middle/upper class) displays, on average, substantially lower levels of interdependence than the class with less access to material resources (the vulnerable workers). Thus, material–social tradeoffs (MSTs)—phenomena central to the cultural psychology of social class—better exemplifies the top-down rather than the bottom-up portion of the cultural cycle (see Figure 1). At least in the case of vulnerable workers and the middle/upper class, prevailing cultural norms, rather than individual decision-making, shape behavioral interdependence.

In contrast to this clear context-level MST, we see less evidence for individual-level MSTs in the data. Indeed, of the 22 within-profile correlations depicted in Table 6, only six (27%) represent negative associations between markers of materials resources (i.e., income or education) and interdependence — the predicted pattern for MSTs. On the other hand, 13 (59%) of the correlations run *opposite* to the predicted pattern for MSTs, such that material resources and interdependence are positively associated with one another. Thus, within the class groupings we see in the present datasets, it is most often the case that individuals with more income and assets have more interconnected and supportive social networks than those with fewer material resources. This is true even in the class profiles that display clear evidence for a group-level MST—that is, vulnerable workers and the middle/upper class. In two of the three studies, the association between material resources and interdependence is positive within these class groupings.

We see little evidence that the underclass or secure workers participate in group-level MSTs. Although secure workers' levels of interdependence fell midway between those of the middle/upper class and vulnerable workers in Study 1, the former group displayed slightly less interdependence than their middle/upper-class counterparts in Study 3. The underclass exhibited the second-lowest and lowest levels of interdependence in Studies 1 and 3, respectively—despite being the least affluent group in any study. Moreover, the underclass was the only group across studies to display consistent evidence for individual-level MSTs across studies (Table 6). We discuss potential implications of these patterns in the Discussion.

Taken together, these findings echo those of Na and colleagues (2010) showing that variables' within-group correlations may run counter to those variables' mean-level differences at the contextual level. Such patterns indicate that within-group correlations and between-group mean differences are analytically independent and thus likely to be governed by distinct cultural processes. In our case, despite clear evidence that class-cultural norms shape the minds of individuals within particular social-class contexts, there is little evidence that this process is paralleled by idiosyncratic material–social calculations among individuals.

To visualize the split between group-level and individual-level MSTs in our data, Figure 5 provides visualizations of the distinct between- and within-class relationships between material resources and interdependence in Study 1–3. Each emergent social-class profile is positioned according to its mean level of material resources on the *x*-axis and mean interdependence on *y*-axis, with income and education collapsed into a single indicator for ease of depiction. An ellipse circumscribes 50% of respondents in the class. Overlaid on each ellipse, and passing through the profile mean, is a correlation line representing the within-class relationship between material resources. As can be seen, within-class relationships are generally weak and inconsistent despite large and consistent differences in material resources and interdependence between the vulnerable worker and the middle/upper class groups.

Table 6

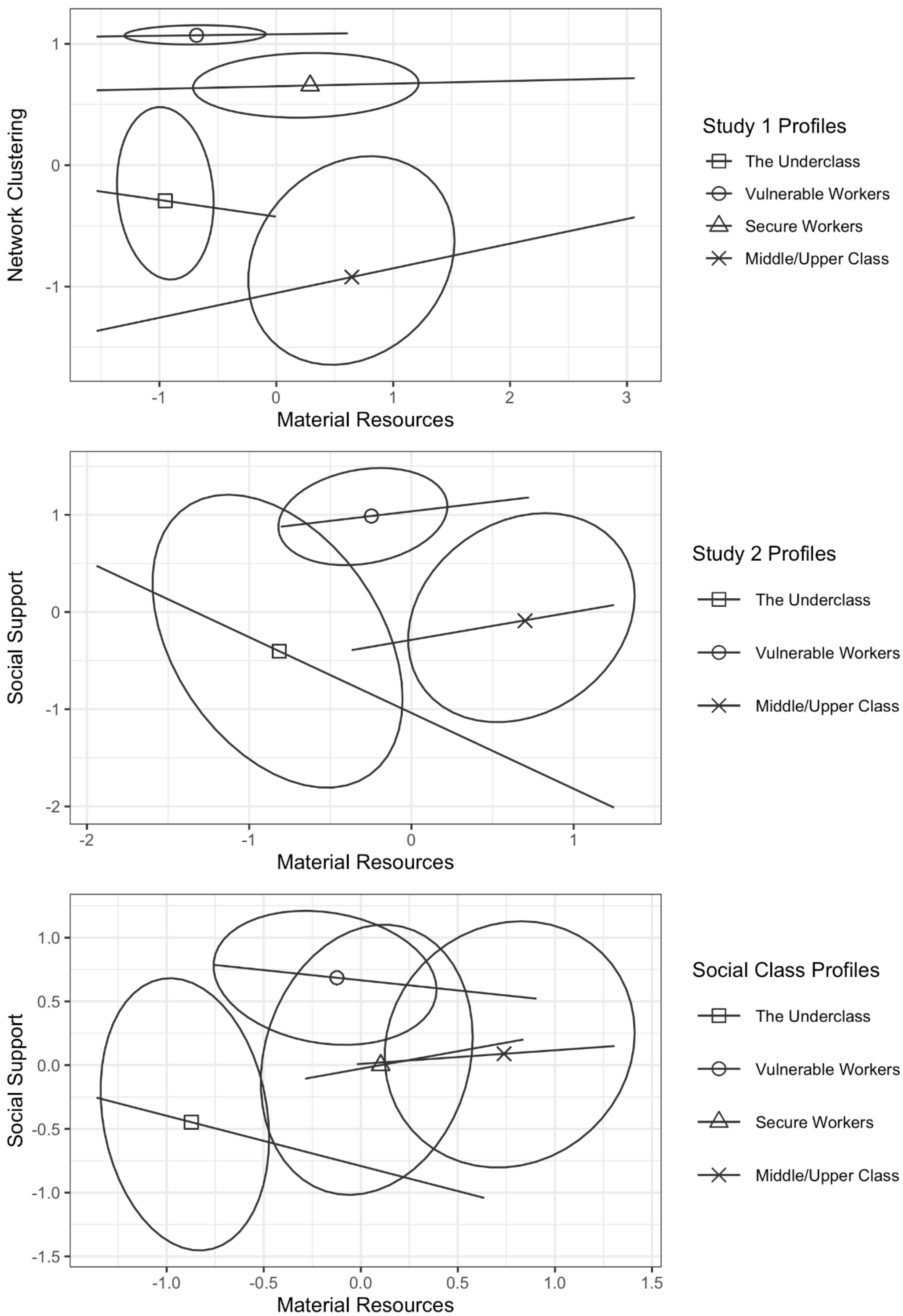
Magnitude and Direction (Cohen's d) *of Associations Between Material Resources and Interdependence at the Individual and Group Levels (Studies 1–3)*

	Full Sample	Within-Profile				Group Difference in Interdependence (VW vs. MU)
		UC	VW	SW	MU	
Study 1 (*N* = 26,985)	−0.27 | −0.33	−0.16 | *−0.05*	0.19 | 0.19	0.16 | 0.09	0.38 | 0.08	−2.59
Study 2 (*N* = 939)	*−0.03* | *−0.03*	–0.97 | −0.16	*0.13* | 0.47		0.22 | 0.29	−1.60
Study 3 (*N* = 2,408)	0.27 | 0.21	–0.37 | *−0.09*	*–0.17* | -0.43	*–0.09* | 0.28	0.16 | *0.09*	−0.80

Note. Income and education associations are located on the left and right sides of the | symbol. All effect sizes are significant (*p*<.05) unless indicated with italics. UC = the underclass, VW = vulnerable workers, SW = secure workers, and MU = middle/upper class.

Figure 5

Social-Class Profile Means and Within-Profile Associations between Material Resources and Interdependence in Studies 1–3



Discussion

Social classes are cultural contexts that shape individuals’ outcomes across a host of important domains, including academics (Müller et al., 2023; Stephens et al., 2012), the workplace (Dittmann et al., 2024), and health (Chetty et al., 2016). Class cultures are theorized to orient individuals toward the resources most abundant within their context (Piff et al., 2012). Working-class contexts, in which material resources are relatively scarce, tend to foster social interdependence, emphasizing the utility of social ties in times of need (Carey & Markus, 2017; Fiske & Markus, 2012). More affluent middle- and upper-class contexts, in contrast, tend to foster independence, autonomy, and self-direction—values compatible with the use of material means to cope with life’s challenges.

Such *material–social tradeoffs* (MSTs) are evident in people’s reasons for attending college (Stephens et al., 2007, 2012), performance on academic tasks (Dittmann et al., 2020; Müller et al., 2023), workplace experiences (Dittmann et al., 2024), and basic patterns of social cognition (Dietze & Knowles, 2016, 2021; Kraus & Keltner, 2009; Varnum et al., 2016). Across these domains, markers of social class (e.g, income and education) have been seen to correlate negatively with diverse indices of social interdependence. Nonetheless, typical approaches to studying social class leave an important question unaddressed: Do class-cultural differences in interdependence reveal the “fingerprint” of culture on individuals’ values—or do they reflect the aggregate of individuals' personal choices regarding reliance on others?

The present research articulates this question in terms of the *culture cycle* (Hamedani & Markus, 2019; Markus & Kitayama, 2010), a framework specifying the “top-down” and “bottom-up” pathways through which culture and mind constitute one another (see Figure 1). The culture cycle frames the manner in which individuals become socialized to the orientations, traits, and behaviors that predominate within a cultural context or group, while also acknowledging that individuals can change their culture by choosing to embrace new norms, values, and selfways. Although both portions of the cycle occur in tandem, we believe that researchers can learn much about specific cultures by examining whether particular phenomena primarily unfold at the level of the individual or the context. As such, the present research sought to empirically distinguish context-level MSTs and individual-level MSTs. To do so, we leveraged latent profile analysis (LPA), a form of mixture modeling well-suited to assessing multilevel relationships of this sort.

In three publicly-available datasets (N_{total} = 30,332), we found that respondents consistently clustered into three social-class categories: a *middle/upper class* defined by high levels of material resources, a group of *vulnerable workers* characterized by middling levels of material resources, and an *underclass* marked by meager material resources. Comparison of vulnerable workers' and the middle/upper class's mean levels of interdependence reveals a strong context-level MST—such that vulnerable workers displayed much higher levels of the social-network clustering (Study 1) and perceived social support (Studies 2 and 3) than the middle/upper class. This suggests that cultural norms and values promoted within working-class contexts, and passed down to individuals within those contexts, stress the maintenance of social networks rich in supportive ties (Fiske & Markus, 2012; Stephens et al., 2024).

Conversely, we see little evidence for individual-level MSTs among either the vulnerable workers or middle/upper class. In fact, we see *positive* (though weak) relationships between material resources and interdependence among respondents within these class groups. Interestingly, these within-group patterns comport well with models of status hierarchy, such that those highest in material capital tend also to be those highest in social capital (e.g., Bourdieu, 1986). Regardless of their origins, these within-class correlations provide no evidence that individual actors calibrate their levels of sociality to their personal means. The presence of negative group-level relationships between material and social resources, coupled with the absence of such effects at the individual level, indicates that MSTs are primarily context-level processes that are irreducible to individual-level effects. In the language of the culture cycle, MSTs reflect the top-down influence of cultural norms and values on individual minds.

As a practical matter, the present findings highlight how difficult it can be to detect group-level phenomena without modeling effects at multiple levels. Indeed, in the present studies, a purely individual-level analytic approach yields little evidence for MSTs. Examining the full-sample correlations between markers of material resources and interdependence, we find a small negative correlation between income (or education) and social-network clustering (Study 1), a null relationship between income and access to social support (Study 2), and a positive association between a composite of income and assets and perceived social support in (Study 3). The discrepancy between this lack of evidence for MSTs and the robust evidence afforded by our LPAs presents no contradiction. Simple correlations between class markers and measures of interdependence conflate group- and individual-level effects—and therefore obscure MSTs that may occur at one of these levels but not the other (Na et al., 2010, 2020). These data emphasize the importance of contending with the multilevel nature of cultural phenomena, because analyzing these phenomena at one level (but not the other) may overlook or discount them entirely.

The present work is rooted in theories that cast social class as a form of culture. According to cultural-psychological analyses of social class, working-class cultural contexts tend to promote interdependent norms, values and selfways as means of coping with economic scarcity, whereas middle- and upper-class contexts afford greater access to material resources and thus foster independent cultural orientations (Stephens et al., 2024). Grounding social class cultures in resource affordances at the supra-individual level (i.e., context or group) stresses the need to adopt analytic methods capable of distinguishing these higher-order processes from individual-level effects—even when, as in the present research, a single set of analytic variables is used to identify the groups and test relationships between and within them. In this vein, we see LPA as an approach that does justice to the idea of *context in people*—the degree to which everyday contexts and the social realities within them come to shape personal behavior (Adams, 2012; Carey & Markus, 2017).

Although both portions of the culture cycle occur simultaneously (Markus & Kitayama, 2010), we find consistent evidence that MSTs constitute group-level effects that cannot be reduced to individual agency. We believe this illuminates a critical feature of class contexts in the United States. Specifically, class inequality in the U.S. is relatively “sticky”—characterized by low economic mobility (Chancel et al., 2022; OECD, 2010), high geographic segregation as a function of income (Grusky et al., 2019), and differential access to educational opportunities (Grusky et al., 2019; Mazumder, 2005; Reeves, 2017). Because inequalities between classes reflect longstanding patterns of stratification, social classes in the United States can be thought of as “mature” cultures whose characteristic norms, values, and selfways have had ample time to develop. In this sense, the top-down influence of class cultures on individuals exerts a greater influence relative to the bottom-up influences of individual preferences regarding social interdependence.

Rigorously parsing the extent to which cultural phenomena are driven by contexts or the individuals may also shed light on the dynamics of cultural formation and change. In societies characterized by high levels of economic mobility, mature class cultures may have yet to form. In such cases, individual-level class phenomena (including MSTs) would likely be more pronounced than their context-level counterparts. Individuals in high-mobility contexts would still have to contend with their economic positioning and make adaptive decisions concerning their levels of sociality. But to the extent that this positioning is temporary, social representations regarding the “right” norms, values, and selfways may not fully coalesce. If class mobility were to decrease, such that successive generations are now largely consigned to the same material contexts, the countless individual decisions that constitute the bottom-up portion of the culture cycle might gradually be abstracted into stable cultural ideals. Although more work will be required to model cultural change and formation in terms of these pathways' relative magnitudes, we believe such a project is theoretically and empirically tractable.

Although we regard LPA as a promising means of capturing context-level cultural phenomena, we acknowledge that it will not always be feasible for researchers to analyze their data using this approach. In accordance with prior theory that casts social class as a form of context (Carey & Markus, 2017; Stephens et al., 2024), our data highlight that—when LPA is unavailable to identify class contexts—educational attainment might serve as a reliable proxy for individuals' class contexts, given that this variable was often the dividing line between the identified working and middle/upper class cultural groups. Moreover, as Study 2 highlights, individuals reliably self-report their class-cultural contexts when prompted to identify with the working or middle classes. Comparing individuals' LPA classifications with individuals' preferred class labels, we find that if the LPA identified an individual as a member of one of the working class groups, there were roughly 2-to-1 odds that the individual self-identified with the working class. On the other hand, if the LPA identified an individual as a member of the middle/upper-class cultural group, there was almost 2-to-1 odds that the individual self-identified with the middle class. With this in mind, we view educational attainment (dummy-coded as having a four-year degree vs. not), and class-self identification as being two of the more reliable approximations of individuals' class-cultural groups.

Utilizing LPA to study class phenomena can also interrogate linear and monotonic assumptions of social class and its consequences. Class comparisons often assume linear class-based differences in psychology and behavior, such that each gradational increase or decrease in class is expected to yield a congruent difference in some outcome (Stephens et al., 2024). Measuring effects at the group- or context-level, however, interrogates this assumption. In the present work, for instance, we identified one social class — "the underclass" — which displayed the lowest levels of material resources. Taking a linear approach, past theory might suggest that the individuals with the fewest material resources would behave the most interdependently. However, our results show that the underclass often displayed the lowest levels of interdependence—suggesting that a linear understanding of class is not wholly accurate. These results corroborate similar findings that people experiencing extreme poverty could experience severe forms of stigmatization and exclusion by mainstream society and have a unique psychological profile (McLaughlin et al., 2003). For example, women on welfare described themselves as less trusting and more independent from others than women from working- and middle-class contexts (Steele & Sherman, 1999; Stephens et al., 2014). Adopting a group-based conceptualization of social class helps us make sense of the fact that material deprivation does not always lead to greater interdependence.

In sum, our results point towards a contextual understanding of class and its consequences. Rather than reflecting "individual differences write large", our results highlight that social class is a dynamic context individuals move through and are shaped by in consequential ways. Given that past work often measures class phenomena at the individual level, our results also raise the broader possibility that past work has *underestimated* effects attributable to class contexts. We close by emphasizing that approaches such as LPA provide researchers with the ability to understand the magnitude of cultural effects at multiple levels of analysis.

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