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Does alienation (or negative emotionally) contaminate the results of engineering student surveys?

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This is a full research paper in the empirical research category. Team-based learning has become common in engineering schools [1], [2], [3]. When students are placed in teams, students' perceptions of respectful treatment determine their learning outcomes and persistence [4], [5], [6], [7]. Consequently, educators sometimes conduct survey studies to determine the association between disrespectful treatment and negative outcomes [8]. However, spurious correlations between self-reported treatment and self-reported outcome may emerge due to a confounder, which affects both the independent and dependent variable. Alienation, or negative emotionality, is a potential confounder because people high in alienation view themselves as consistently deceived, exploited, and maltreated by other people [9]. Some published correlations may therefore be overestimated. Alternatively, alienation may have an impact on both the independent variable and outcome without having any confounding effect. The current study examines whether alienation is a confounder in a study of justice and inclusion.

Individuals high in alienation tend to experience negative emotions such as fear, anxiety, and depression, and are more likely to interpret ordinary situations as threatening [10]. It is hence also referred to as negative emotionality. However, it is measured with the alienation scale, and hence that label is used here.

Microaggression scholarship is a domain where the impact of alienation as a confound has been recently debated. The issue of confounding was raised by Lilienfeld in a critique of the scientific status of the microaggression concept [9], an article that has now been cited almost 900 times. Lilienfeld noted that microaggressions are, by definition, in the eye of the beholder. The implication is that people high in alienation, which Lilienfeld called negative emotionality, will report both more microaggressions and more negative life outcomes. Even though the engineering education literature has several articles on microaggressions [5], [8], [11], [12], alienation is usually ignored as a possible confound.

Students high in alienation may be predisposed to interpret ambiguous statements as criticisms or insults, leading them to give lower ratings to all targets: professors in course evaluations, teams in team climate evaluations, and peers in peer evaluations. This issue is itself relevant because a professor who has a cluster of alienated students may receive low evaluation scores despite performing the job adequately.

Accordingly, alienated students should also give lower ratings on dimensions like fairness, inclusion, satisfaction, respect, trust, and a number of other teamwork outcomes. This raises an important methodological concern: if alienation influences all perceptions, it could represent a confounding variable that artificially inflates or obscures the true relationship between numerous constructs, even ones unrelated to microaggressions.

To be sure, this assertion of confounding can be a sensitive issue. People who feel victimized by microaggressions want this perceived perpetration of injustice to be taken seriously. Unlike academic researchers, they may not appreciate the putative role that alienation—and they may find it rational to be mistrustful of others given prior discrimination. Indeed, Raihani and Bell have documented why paranoia may have evolved as a functional adaptation in ethnic minorities

[13]. Nevertheless, in a research context, it is essential to avoid using under-specified statistical models [14]. Consequently, researchers should determine whether alienation is a confound in self-report studies.

To be fair, engineering educators are already aware of problems with self-report studies. They often use an objective indicator like GPA as a dependent variable to mitigate this problem. This tactic is common enough to suggest that researchers are aware that traits can confound associations between two self-reported variables, which necessitates the use of a non-self-reported variable. However, in some scenarios, certain subjective phenomena need to be measured through self-report or aggregated through multiple individuals' self-reports. In these cases, it is rational to worry about confounding variables.

The present study examined the reciprocal relationship between perceived peer-justice climate and perceived inclusion in student engineering teams while evaluating the potential confounding role of alienation. Using a longitudinal design with repeated measures in a problem-based learning situation, we employed a random-intercept cross-lagged panel model (RI-CLPM) to disentangle within-person temporal dynamics from stable between-person differences [15]. This analytical approach is described in greater detail later. By clarifying the robustness of the justice-inclusion relationship in the presence of personality-based individual differences, this research contributes to both theory and practice for engineering educators seeking to cultivate inclusive team environments.

Method

Sample

The participants were 235 biomedical-engineering students in a 2000-level course. Participants filled surveys across five weeks in the middle of with a mandatory semester-long team project. Data were cumulatively collected from two semesters to obtain a large sample size.

The sample's gender composition was 31% male, 66% female, 0.4% transgender male, and 3% unknown. The racial/ethnic composition was 42% Non-Hispanic White, 8% Hispanic White or Hispanic only, 8% Black, 27% Asian, 5% Asian-White biracial, 4% Middle Eastern, 3% other, and 3% unknown. Data were collected across 38 teams, most of which (75%) had 6-7 members per team (range = 4-8). In Spring 2020, data collection was completed before remote learning was initiated due to the COVID-19 pandemic.

The team project was to develop biomedical sensors for diagnosing gait/balance disorders or stress disorders. Students engage in diagnostic reasoning using limited information as in an entrepreneurial setting, i.e., problem-based learning. Project data were collected using instruments and students developed a prototype. Students were observed by facilitators (third-year students) who provided no direct instruction but sporadically prompted discussion through questioning. In the first phase, students wrote a subject literature review. In the next phase, students assess signal types for diagnostic value. Survey data were collected in this phase.

Procedure

The Institutional Review Board declared the study exempt from full review under Protocol Number H20027. A Canvas announcement notified potential participants about the nature of the study and about upcoming Qualtrics email invitations to participate. Students could get course credit for participation, and an alternate credit assignment was offered to students for the same credit value.

The initial survey began with the consent form. Participants then proceeded to a block of demographic questions and personality trait questions. The next five survey waves, distributed in successive weeks, contained blocks of questions on peer justice climate and inclusion. Wave invitations were distributed on Thursday evenings in consecutive weeks; every team had completed its mandatory weekly meeting by Thursday.

Measures

For justice and inclusion scales, participants were instructed to "rate the accuracy or inaccuracy" of the scale items. A 7-point Likert scale was used with optimized anchors for equal spacing [16]: "1 Very inaccurate," "2 Moderately inaccurate," "3 A little inaccurate," "4 Neutral (neither accurate nor inaccurate)," "5 A little accurate," "6 Moderately accurate", and "7 Very accurate." The verb "agree" was avoided to mitigate acquiescence bias [17].

Inclusion. The inclusion scale was a 6-item version of a 16-item perceived group inclusion scale [18]. In earlier research, we used a four-item scale that produced skewed results. To mitigate skew, we used six items in this study. Examples of items are "In the past seven days, my team has cared about me" and "In the past seven days, my team has encouraged me to be who I am." Table 1 displays internal consistencies.

Justice (Peer Justice Climate). The peer justice climate scale contained 9 items. The first two items were original distributive justice items, e.g., "Some people on the team fail to do their share of the work.". Procedural justice and informational items were from a peer justice scale [19], e.g., "In general, we thoroughly explain the procedures we use to each other." Two interactional items came from an organizational justice scale [20]. The referent was changed from "my boss" to "teammates," e.g., "Teammates refrain from improper remarks and comments." Table 1 displays internal consistencies. This scale did not tap into personally targeted injustice.

Alienation. Alienation was measured using seven items from the alienation subscale of the Multidimensional Personality Questionnaire ($\alpha = .81$). The items are copyright-protected, and the University of Minnesota granted us permission to use it. Items pertain to constructs such as mistrust, perceptions of malevolent intent, and feelings of being exploited. This scale is recommended over alternatives in cases where negative emotionality is expected to be confound, because other negative-affect scales do not tap into perceived victimization and exploitation [9].

Data Modeling

Formerly, the conventional model for causation in longitudinal data was the cross-lagged panel model (CLPM). However, this model is inadequate at decomposing variance. The random intercept cross-lagged panel (RI-CLPM) was proposed as an extension. It is now used in social science, but the CLPM seems to be still the norm in engineering education [21]. The RI-CLPM has three notable features. First, it separates within-person effects and between-person differences, which are conflated in the CLPM. This is critical for zooming into within-person processes, such as whether a *particular* person feels more included after that person perception of justice changes. In contrast, a between-person relationship would indicate that people with a stable high level of perceived justice (possibly due to a personality trait) feel more included than people with a stable low level of perceived justice.

To fit an RI-CLPM, the observed scores are decomposed into three components: grand means, trait-like between-person components (stable), and within-person components (time-varying) [15]. This decomposition is represented in Fig. 1 where the "within" components at the left and right periphery (in squares) represent observations at time for a given person, i.e., survey data. The between components are at the bottom—the random intercepts. They capture a person's *time-invariant* deviations from the sample (grand) means. Thus, they represent the stable point around which upper and lower deviations occur in given weeks. This description of the model is necessarily brief as this is a conference paper. Further details can be found in advanced articles [15], [22]. Interested readers may also refer to articles using the RI-CLPM to investigate bidirectional paths between sleep problems and anxiety [23], and family functioning and self-compassion. If a stable trait is hypothesized to exert a between-person effect, e.g., alienation on justice, that can be modeled as shown in Fig. 2.

The key element for engineering educators to consider is that RI-CLPMs are useful when *multiple* waves of data are collected from the same sample. Measurement across multiple occasions reduces measurement error, which may motivate such panel data collection. However, researchers may be interested in how traits, such as empathy or interpersonal skills, explain between-person differences in two other factors that have a bidirectional association, such as weekly satisfaction and weekly engagement. In such cases, the RI-CLPM is useful. Our example includes a bidirectional association between inclusion and justice, but this finding was thoroughly discussed in a previous article [24]. The current focus is on alienation.

Results

Table 1. Descriptive statistics and internal consistency values.

	α	M	SD
Justice 1	.78	5.9	0.8
Justice 2	.84	5.8	0.9
Justice 3	.83	5.8	0.9
Justice 4	.83	5.8	0.9
Justice 5	.85	5.9	0.9
Inclusion 1	.92	6.3	0.9
Inclusion 2	.94	6.2	1.0
Inclusion 3	.95	6.2	0.9
Inclusion 4	.96	6.2	1.1
Inclusion 5	.96	6.4	1.0

Alienation	.81	1.8	0.6

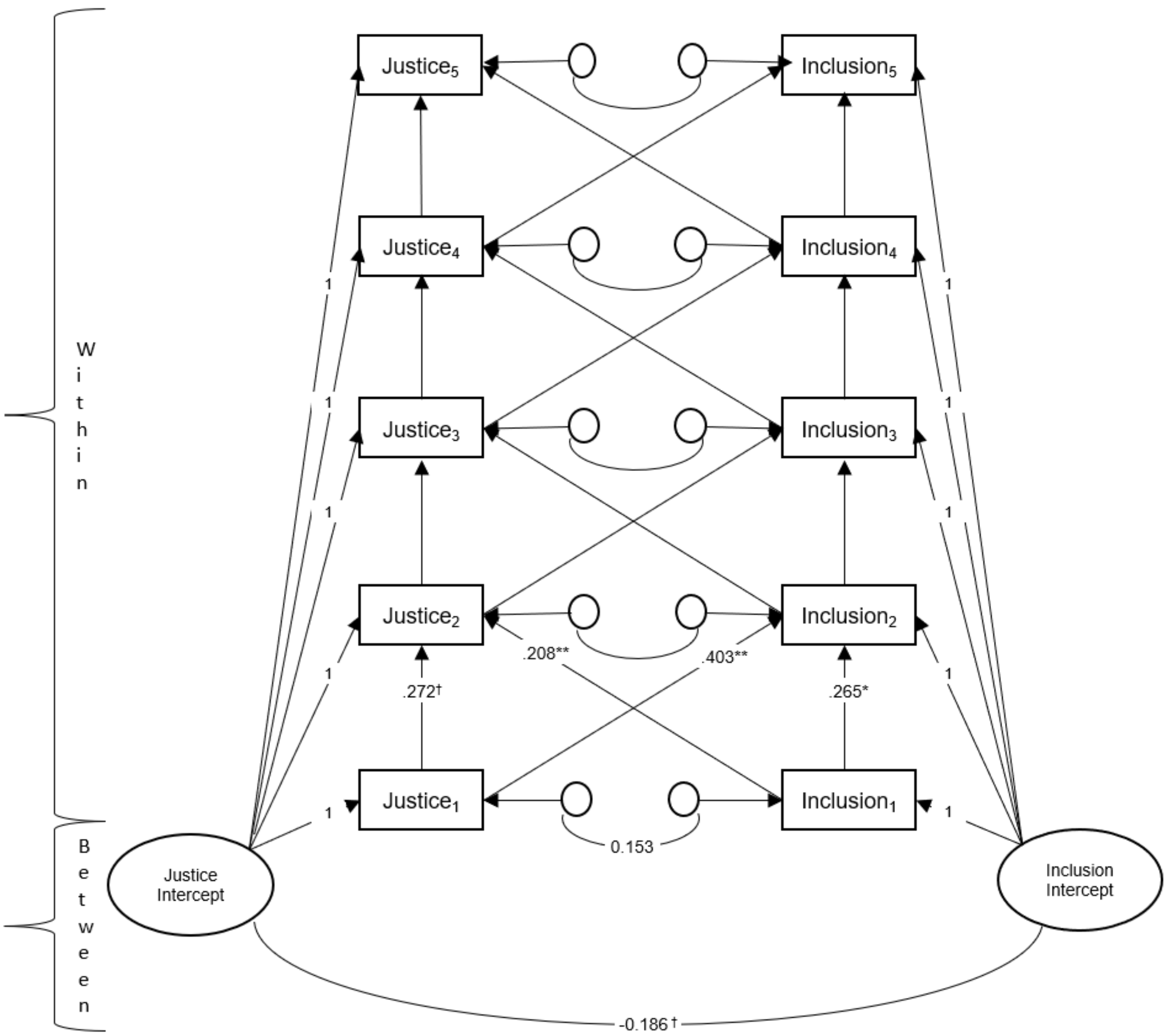

Figure1. RI-CLPM with bidirectional associations between justice and fairness

Descriptive statistics for all variables are in Table 1. Both justice and inclusion scores were well above the scale midpoint. This ceiling effect is natural when individuals know they are being observed and their grade may suffer if they behave disrespectfully. At the person level, inclusion and justice were averaged across all weeks to compute correlations between inclusion, justice, and alienation. Inclusion and justice were strongly correlated, $r(234) = .71$, $p < .001$. alienation was weakly correlated with inclusion, $r(226) = -.16$, $p = .016$, and weakly correlated with justice, $r(227) = -.17$, $p = .007$.

A baseline model without alienation was modeled first. This provided us with fit coefficients for later comparison with the model containing alienation. The baseline model is illustrated in Fig. 1 and it had acceptable fit, $\chi^2(33) = 70.648$, $p = .0001$, RMSEA = .070, CFI =. 927, TLI = .927, BIC = 4623.197. For fit statistics on minor variations of this model, see this earlier paper [24], where fit statistics for a different type of model, the general cross-lagged panel model, are also presented .

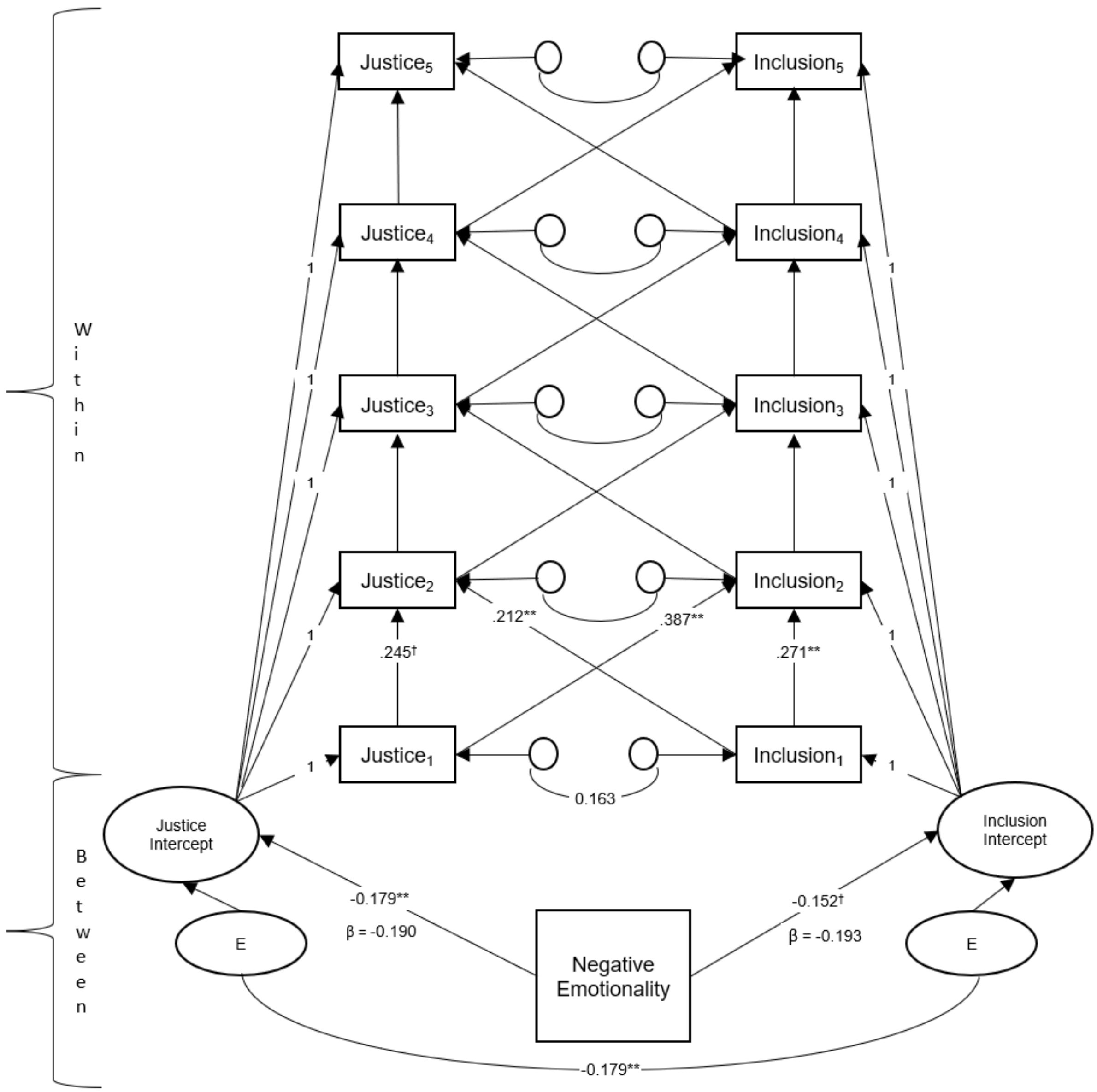

Figure 2. RI-CLPM with bidirectional associations between justice and fairness, and alienation as a time-invariant predictor of random intercepts

The RI-CLPM with alienation is illustrated in Fig. 2. The paths from alienation to the justice intercept, B = -0.179, p < 01, and to the inclusion intercept, B = -0.152, p < .10, were negative as expected. The overall model fit was still acceptable, $\chi^2(41)$ = 82.321, p = .0001, RMSEA = 0.067, CFI = .928, TLI = .904, BIC = 4564.405. BIC change suggested that the negative-emotionality model was better fitting than the baseline. However, the chi-square difference test was ambiguous: it did not indicate the superiority of the second, $\chi^2(8)= 8.8377$, $p = .356$. Note that the Satorra-Bentler correction was used for all models and tests.

Did alienation have a confounding role? A model comparison showed no evidence of confounding or contamination. The strength of the cross-lagged bidirectional paths from justice to inclusion (0.403 vs. 0.387), and inclusion to justice (0.208 vs. 0.212) were roughly equivalent across models. This equivalence suggests that alienation does not confound the primary association, even though it influences both justice and inclusion ratings.

Discussion

The current study examined whether alienation is a confound in models of justice and inclusion. Our findings showed that alienation was a "third variable" but not a confounder. It was a "third variable" inasmuch as it negatively affected self-ratings of both peer justice climate and inclusion. This suggests that if alienation is measured, it is worth including in a statistical model. However, confounding only occurs when a coefficient's magnitude decreases after the third variable is added. In this case, confounding can be ruled out.

The statistically significant path from alienation to peer justice climate can be interpreted as combining both subjective and objective truths. A person high in alienation may experience a particular setting as unjust due to hypersensitivity to cues [25], even while their peers consider the setting to be just. In addition, a person high in alienation may induce negative behavior due to their alienation-induced reluctance to be generous and make contributions. The path from alienation to inclusion can be interpreted through the same lens: people high in alienation are likely to over-interpret cues as exclusionary but also elicit exclusionary behavior by being withdrawn or mistrustful.

A skeptic would highlight the fact that only two focal variables, justice and inclusion, were studied. If a wider array of inputs and outcomes had been measured, this study may have uncovered cases of true confounding. Thus, replications of this study with other focal variables would be productive. Nevertheless, this study informs the field of engineering education by revealing a case of non-confounding, which implies that we do not need to cast retrospective skepticism toward all self-report studies.

Nevertheless, alienation is problematic in that it colors perceptions of inclusion and justice. Just as anxiety can inadvertently be raised rather than lowered by the use of trigger warnings, albeit to a small degree [26], educators may inadvertently prompt negative emotionality by prompting ethnic-minority students to expect discrimination. Indeed, verbal statements that could be perceived as benign tend to be perceived as harmful by individuals primed to be temporarily high in alienation [25].

On the methodological side, however, researchers can be somewhat confident that alienation does not create a spurious association between actually unrelated factors. A study by Kanter et al. shows similar results, documenting a correlation between Black participants' assessment of the (micro)aggressiveness of statements and the degree of racist attitudes in Whites willing to make such statements [27]. Another study also purportedly found that alienation plays no confounding role, but used a suboptimal measure of alienation, containing no items about perceived victimization or exploitation [28]. The current findings are striking because there was not even slight evidence of confounding (Fig. 1), which starkly contrasts with a finding from the management literature, where certain paths were markedly reduced after alienation was added into the model [29]. In this case, the association was between job stress and work-related outcomes such as job satisfaction.

Should alienation be added as a covariate in regression models? Adding covariates to randomized controlled trials typically increases design sensitivity [30], [31], [32]. If a researcher is conducting a randomized trial and predicts an imbalance in control vs. experimental groups in alienation, the researcher should therefore include alienation in the model. Even outside experimental research, adding a justified covariate can explain more variance in the dependent variable and minimize omitted variable bias [14]. Furthermore, when testing interactions, the inclusion of covariates and the covariate interaction term is essential [33]. However, adding a measure of alienation will length a survey, possibly inducing survey fatigue. Because the alienation subscale is brief, it appears statistically advisable to include it.

Even though the current study did not address team formation, instructors may wonder if alienation in one member of a team has a spillover effect on all other members. Although research is limited here, one empirical study of engineering-student teams showed no evidence of a spillover effect [34]. This non-effect may emerge because alienation involves feelings of being victimized but not an impulse to victimize others. Antisocial personality traits, which do involve victimizing others—along with being selfish and entitled—probably have spillover effects [35], [36], [37], but that is a different issue. As of this writing, CATME, the leading tool for team formation in engineering schools, does not enable measurement of personality traits. However, alternatives like Gruepr [38] can be used by instructors who want to experiment with trait-based team formation to further study the impact or non-impact of alienation and antisocial traits.

Educators are encouraged to conduct conceptual replications by measuring the same putative confounder, alienation, but using different focal variables. If the replications are successful, the consistency of findings would strengthen the credibility of our results, not only informing the engineering education community but also the social psychology and management communities.

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