SWEATING THE BIG STUFF: AROUSAL AND STRESS AS FUNCTIONS OF SELF-UNCERTAINTY AND IDENTIFICATION

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Sweating the big stuff: Arousal and stress as functions of self-uncertainty and identification

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Abstract

Groups serve a variety of crucial functions, one of which is the provision of an identity and belief system that impart self-referent information, thereby reducing self-uncertainty. Entitative groups are more attractive for highly uncertain participants seeking groups for identification and self-uncertainty reduction than less entitative groups. The purpose of the current study was to explore how self-uncertainty impacts physiological arousal and stress responses. Using a mixed-methods design (N = 123), we found that self-uncertainty increased physiological arousal (measured via skin-conductance level) and stress responses (measured via heart rate). Furthermore, we found that uncertainty-activated physiological arousal and stress responses were decreased through identification with a high entitativity group. Our findings expand upon uncertainty identity theory by identifying physiological mechanisms that motivate uncertainty reduction.

KEYWORDS

HR, identification, piecewise multilevel growth curve modeling, SCL, self-uncertainty

1 | INTRODUCTION

Excessive uncertainty characterizes many distressing events that people experience (e.g., death, divorce, war, natural disaster, etc.). Although some uncertainty is usually exciting, an abundance of uncertainty is potentially aversive (Hogg, 2000, 2007). As such, being uncertain about important things in our lives (e.g., relationships, identity, the future) should increase feelings of distress and activate stress responses that motivate uncertainty reduction (Jetten et al., 2000; Mullin & Hogg, 1998). For example, in the movie *8 Mile* (Hanson et al., 2002), Eminem's wannabe-musician, Rabbit, raps that his "palms are sweaty, knees weak, arms are heavy" before confronting a situation that could make or break his music career. Eminem's uncertainty about himself activates his natural physiological arousal and stress responses, which subsides once he initiates himself among his rapper-peers. Indeed, Hogg and colleagues have, for over two decades, claimed that self-uncertainty is aversive and arouses stress responses (e.g., Hogg, 2000, 2007; Hohman & Hogg, 2015; Jetten et al., 2000; Mullin & Hogg, 1998). However, this central part of uncertainty identity theory has not yet been tested experimentally with proper measures of stress response and/or physiological arousal. We aimed to rectify this shortcoming in the current study. Our central hypothesis was that self-uncertainty would activate increased stress responses and general physiological arousal. Furthermore, we hypothesized that identifying with a group would reduce uncertainty-activated stress responses and general arousal, while groups with greater entitativity would reduce autonomic activation best.

1.1 | Reducing self-uncertainty

Broadly, uncertainty is characterized by a lack of information about a given event (Bar-Anan et al., 2009). Uncertainty reduces predictability, threatens ontological foundations, and is especially uncomfortable vis-à-vis the self (Hogg, 2000;

Hogg et al., 2007). Self-uncertainty has been described as pervasive self-doubt (Doosje et al., 2013), as an identity crisis resulting from unclear self-referent cognitions (McGregor et al., 2001), and as insecurity concerning the self-concept (Hogg, 2007). As such, an especially robust predictor of uncertainty-driven discomfort is the degree to which uncertainty is self-relevant: the more personally significant the uncertainty, the more intense the subsequent distress. This distress motivates behaviors intended to diminish self-uncertainty (Hogg & Mullin, 1999; Mullin & Hogg, 1999).

Generally, individuals strive to reduce self-uncertainty to a subjectively manageable amount, and an expedient way of reducing self-uncertainty is through group identification (Hogg, 2007; Jetten et al., 2000). Indeed, uncertainty-identity theory suggests that one powerful motive behind group identification is the reduction of self-uncertainty (Hogg, 2000). According to uncertainty-identity theory, group identification is underpinned by self-categorization, a social classification process that activates group prototypes (i.e., fuzzy sets of attributes and characteristics) that prescribe social interactions and facilitate group identification (Turner et al., 1987). Self-categorization regulates perceptions, inferences, feelings, behaviors, and interactions, validates the self-concept, and increases predictability, thus serving as an effective vector of reducing self-uncertainty (Hogg, 2006).

With respect to self-uncertainty reduction, not all groups are created equal—some groups are better suited to alleviate self-uncertainty. Groups with higher entitativity—the degree to which a group is perceived as a coherent unit—provide unambiguous, explicit social identity information (Hogg et al., 2007; Lickel et al., 2000). Highly entitative groups are conspicuous and discrete, and provide their members with distinct identities (Blanchard et al., 2020). Jetten and colleagues (2000) showed that more homogenous (i.e., more entitative) groups were more attractive for highly uncertain participants seeking groups for identification than more heterogenous (i.e., less entitative) groups. Lickel and colleagues (2000) showed that entitativity is more than mere ingroup homogeneity: participants in three studies rated more entitative groups as more coherent, more similar, and more valuable than less entitative groups. The prototypes modeled by coherent, homogenous, and discrete (i.e., high-entitativity) groups are unambiguous and therefore more effective at reducing self-uncertainty than the inexplicit prototypes offered by low-entitativity groups (Hogg et al., 2007).

1.2 | Experiencing self-uncertainty

Given the subjective psychological consequences of self-uncertainty, it seems reasonable that a person with high self-uncertainty would exhibit measurable increases in arousal and stress (Bradley et al., 2001; Eisenbarth et al., 2016). Many situations associated with self-uncertainty (e.g., first dates, encountering a new social environment) are characterized by markers of physiological activation (i.e., sweaty palms, elevated heart rate; Cacioppo et al., 2007; Eisenbarth et al., 2016). These markers suggest that the psychological discomfort associated with self-uncertainty is accompanied by autonomic nervous system activity (Eisenbarth et al., 2016).

Two markers of autonomic nervous system activity that may be elevated under self-uncertainty are skin conductance level (SCL) and heart rate (HR). SCL and HR are associated with separate divisions of the autonomic nervous system: SCL is indicative of sympathetic activation and is associated with general physiological arousal; HR is indicative of both sympathetic and parasympathetic activation and is associated with stress responses (Berntson et al., 2007; Dawson et al., 2007; Niedbala et al., 2018; Wallin, 1981). Moreover, increased physiological arousal (via increased SCL) and stress (via increased HR) ought to persist until the associated self-uncertainty is reduced (e.g., following identification with a high entitativity group; Hogg, 2007). Indeed, Niedbala and colleagues (2018) found that ingroup members who demonstrated ingroup identification and loyalty were buffered against physiological stress responses in a cold-pressor pain task. The current study tested whether and in what sense self-uncertainty impacts autonomic nervous system activity and how group identification affects the autonomic nervous system activity associated with self-uncertainty.

1.3 | Current study

At the heart of uncertainty, identity theory is the proposition that uncertainty is aversive and that group identification reduces uncertainty. However, research on uncertainty identity theory has yet to establish that uncertainty is aversive using non-self-report measures. Moreover, research has yet to establish that group identification reduces uncertainty. This will be the first work to test these critical predictions and assumptions of uncertainty identity theory. Specifically, the current study explored the physiological consequences of self-uncertainty via SCL and HR (Bradley et al., 2001; Eisenbarth et al., 2016). We used a 2(high/low self-uncertainty) x 2(high/low entitativity) mixed-methods model in which participants underwent a self-uncertainty manipulation (Time 1: T1) followed by an entitativity manipulation (Time 2: T2). We used multilevel modeling (MLM) to account for the inherent nested structure of the data—changes in SCL/HR over time nested within participants. We predicted that participants high in self-uncertainty would show significantly increased physiological activity (via elevated SCL/HR) compared to their low self-uncertainty counterparts over Time 1. Moreover, among participants high in self-uncertainty, we expected a significant decrease in physiological activity (via attenuated SCL/HR) in those exposed to a high-entitativity group over Time 2.

2 | METHOD

2.1 | Participants

The present research was approved by the institutional review board at the authors' university. The study was performed in accordance with ethical standards at federal and local standards, and with the 1964 Helsinki Declaration and its later amendments. Informed consent was obtained electronically and is presented in the supplementary materials available through the Open Science Foundation at osf.io/2yptc. We report measures, manipulations, and exclusions in this study below and in supplementary materials.

2.1.1 | Analysis plan

Originally, our analysis plan was to analyze participants' data using a repeated-measures ANCOVA. An a priori power analysis using *G*Power 3* ($F = 0.25$; $1 - \beta = .80$; Faul et al., 2007) recommended a sample size of 96 participants. One-hundred twenty-three Texas Tech University students (86.9% female, $M_{age} = 18.99$; $SD_{age} = 2.27$) participated for course credit. Participants were randomly assigned to experimental conditions in a 2(self-uncertainty: High vs. Low) × 2(entitativity: High vs. Low) × 2(time: Time 1 vs. Time 2) mixed methods design.

Krisjansson et al. (2007) explicitly recommends growth curve multilevel modeling as a better analysis for psychophysiological data (especially skin conductance) than repeated-measures ANOVA. Kristjansson and colleagues' high praise for multilevel modeling convinced us that our best course of action would be to modify our original analysis plan which would have improperly aggregated participants' physiological data and use multi-level modeling rather than repeated-measure ANOVAs. We made this decision after we collected participants' data but before any data were analyzed.

Because of this modification, we did not conduct an a priori power analysis for multilevel modeling. This is because multilevel models are more robust to issues that reduce power in traditional ANOVA techniques (e.g., missing variables, non-independent variables, heteroscedasticity; see Singer, 1998; Snijders & Bosker, 1993); thus, multilevel models are as effective, if not more so, at detecting hypothesized effects than ANOVA. Our sample size exceeds minimum sufficient sampling estimates as calculated by simulation studies conducted by Maas and Hox (2004, 2005; see also Scherbaum & Ferreter, 2009). In support of our decision, we examined the calculated standard errors for our effects of interest as a post hoc power analysis and found sufficiently small standard errors for the hypothesized effects (see Tables 1 and 2; Snijders & Bosker, 1993).

2.2 | Participant preparation

Upon arrival, participants washed their hands with warm water and soap. After completing the informed consent, participants were asked if they have a history of skin allergies or any sensitivities to lotions or cosmetics. No participants responded that they had a history of skin allergies; thus, all participants' HR and SCL were measured. Participants were asked to remove any arm jewelry or watches before beginning. The experimenter first cleaned the participant's forearms with an alcohol pad for 30 s in the areas where the EL 503 disposable HR electrodes were attached. Next, the experimenter attached two HR sensors to the participant's left forearm and one HR sensor to their right forearm. The HR sensors had a small amount of Signa electrode gel on them to enhance conductivity. The experimenter then asked the participant to attach the BIOPAC recording device to themselves by stretching the long elastic bands around their own waist. Once secured, the experimenter connected the BIOPAC HR recording device to the sensors on the participant's arms. Both HR and SCL were recorded via BIOPAC Systems, Inc. MP150 EDA; data were collected via BIOPAC Systems, Inc. AcqKnowledge 4.4 software (BIOPAC Systems, Inc., 2016; Niedbala et al., 2018). Next, the experimenter cleaned the participant's non-dominant palm skin with distilled water and a sterile gauze pad in the areas where the EL 504 disposable SCL electrodes were attached. Afterward, the experimenter attached two SCL sensors (coated in isotonic gel to aid conductivity) along the bottom of the participant's non-dominant palm. The experimenter then secured the BIOPAC SCL recording device to the participant's non-dominant wrist and connected the recording device to the SCL sensors.

2.3 | Procedure

Once seated at the computer, following a 5-min calibration period, participants' baseline SCL and HR were measured for 20 s. Participants across all conditions were told that they would be participating in a study about their experiences as university students. Participants were told that they would read statements about university life, while their physiology was measured. Participants were randomly assigned to write about three things that make them feel certain or uncertain about their lives (the self-uncertainty manipulation;

TABLE 1 Fixed/random parameters for final piecewise model of change in SCL (μS) with quadratic fixed and random effect of time (s) over two 20 s time periods, fixed effects of participant-level variables/covariates, and fixed effects of cross-level interactions

Fixed parameter	Coefficient	*SE*	*t* ratio	*df*	*p*
Intercept (γ_{00})	4.168	0.215	19.37	82.54	<.001
Self-uncertainty (γ_{01})	0.243	0.307	0.79	82.37	.431
Entitativity (γ_{02})	−0.016	0.284	−0.06	71.07	.955
Self-uncertainty × entitativity (γ_{03})	−0.260	0.402	−0.65	70.77	.519
Baseline SCL (γ_{04})	0.980	0.030	32.17	70.13	<.001
SCL after uncertainty (γ_{05})	0.970	0.032	30.04	2,125.88	<.001
T1 (γ_{10})	−0.007	0.013	−0.52	802.94	.602
T1 self-uncertainty (γ_{11})	0.004	0.018	0.20	742.08	.842
T1^2 (γ_{20})	0.0004	0.001	0.72	1894.43	.473
T1^2 self-uncertainty ($_{\gamma 21}$)	−0.0003	0.001	−0.36	1814.46	.720
T2 (γ_{30})	0.003	0.009	0.34	150.96	.736
T2 self-uncertainty (γ_{31})	0.005	0.012	0.41	137.53	.680
T2 entitativity (γ_{32})	−0.003	0.009	−0.35	304.17	.728
T2 self-uncertainty × entitativity (γ_{33})	0.003	0.012	0.29	272.41	.775
T2 SCL after uncertainty (γ_{34})	−0.070	0.006	−11.19	2,328.75	<.001
T2^2 (γ_{40})	−0.0007	0.0003	−2.49	103.82	.014
T2^2 self-uncertainty (γ_{41})	0.0004	0.0004	1.01	94.29	.313
T2^2 Entitativity (γ_{42})	0.0008	0.0004	1.98	107.28	.051
T2^2 self-uncertainty × Entitativity (γ_{43})	−0.0012	0.0005	−2.25	98.40	.027
T2^2 SCL after uncertainty (γ_{44})	0.0011	0.0002	6.04	2,335.31	<.001
Random parameter	Variance Component		−2LL χ^2	*df*	*p*
Level 1 error (σ^2)	0.152		161.77	4	<.001
Intercept variance (τ_{00})	0.852				
Time (τ_{11})	0.001				
Time-squared (τ_{22})	0.000001				

Hohman & Hogg, 2015). Participants' HR and SCL were measured concurrently during the writing task (constituting T1). Next, participants were randomly assigned to read about Texas Tech University being high or low in entitativity (the entitativity manipulation; see Appendix and Hohman et al., 2016). Participants in the high entitativity condition read a short essay highlighting the entitative characteristics of Texas Tech University; participants in the low entitativity condition read a short essay highlighting the non-entitative characteristics of Texas Tech University. Participants' HR and SCL were measured concurrently during the reading task (constituting T2). Participants then completed a demographic questionnaire. After completing the study, the experimenter removed the HR and SCL sensors and provided the participant with paper towels to wipe off any excess prepping gel. Participants were then thoroughly debriefed. None of the participants realized a connection between the questions they answered, the statements they read, and the physiological measurements we collected. Participants believed that the research was focused only on their experience as university students.

2.4 | Independent variable: Self-uncertainty writing task (Preceding T1)

To manipulate self-uncertainty, participants completed an autobiographical writing task (e.g., Hohman & Hogg, 2015). Participants were instructed, in accordance with experimental condition, as follows:

2.4.1 | High self-uncertainty

Please list three aspects about yourself that make you feel the most uncertain about yourself, your future, or your place in the world.

2.4.2 | Low self-uncertainty

Please list three aspects about yourself that make you feel the most certain about yourself, your future, or your place in the world.

TABLE 2 Fixed/random parameters for final piecewise model of change in HR (bpm) with quadratic fixed and random effect of time (s) over two 20 s time periods, fixed effects of participant-level variables/covariates, and fixed effects of cross-level interactions

Fixed parameter	Coefficient	*SE*	*t* ratio	*df*	*p*
Intercept (γ_{00})	89.07	1.256	70.94	178.07	<.001
Self-uncertainty (γ_{01})	−5.08	1.768	−2.87	178.41	.005
Entitativity (γ_{02})	−1.81	1.456	−1.24	133.40	.216
Self-uncertainty × entitativity (γ_{03})	1.93	2.038	0.95	132.03	.345
Baseline HR (γ_{04})	0.84	0.032	26.50	115.51	<.001
HR after uncertainty (γ_{05})	0.82	0.019	43.41	4,333.65	<.001
T1 (γ_{10})	−0.08	0.107	−0.75	1,267.96	.451
T1 self-uncertainty (γ_{11})	0.09	0.149	0.60	1,217.64	.546
T1^2 (γ_{20})	0.003	0.005	0.69	3,779.46	.489
T1^2 self-uncertainty(γ_{21})	−0.004	0.006	−0.68	3,727.14	.492
T2 (γ_{30})	−0.03	0.071	−0.45	229.08	.655
T2 self-uncertainty (γ_{31})	0.06	0.098	0.65	218.36	.520
T2 entitativity (γ_{32})	0.02	0.069	0.31	725.92	.755
T2 self-uncertainty × entitativity (γ_{33})	−0.07	0.095	−0.70	698.18	.485
T2 HR after uncertainty (γ_{34})	−0.03	0.004	−8.69	4,375.96	<.001
T2^2 (γ_{40})	−0.004	0.002	−2.11	170.44	.036
T2^2 self-uncertainty (γ_{41})	0.002	0.003	0.72	161.02	.472
T2^2 entitativity (γ_{42})	0.002	0.003	0.67	198.91	.501
T2^2 self-uncertainty × entitativity (γ_{43})	−0.002	0.004	−0.48	189.12	.633
T2^2 HR after uncertainty (γ_{44})	0.0002	0.0001	1.64	4,372.72	.101
Random parameter	Variance Component				
Level 1 error (σ^2)	19.624				
Intercept variance (τ_{00})	53.733				
Time (τ_{11})	0.129				
Time-squared (τ_{22})	0.0001				

2.4.3 | Uncertainty manipulation check

To verify that the uncertainty manipulation increased self-uncertainty, we measured self-reported self-uncertainty after the uncertainty writing task. Participants completed a validated 6-item self-uncertainty scale (Hohman et al., 2017), for example, “my beliefs about myself often conflict with one another” (7-point scale from “strongly disagree” to “strongly agree”), $M = 3.03$, $SD = 1.08$, $\alpha = .87$.

2.5 | Independent variable: Entitativity (Preceding T2)

To manipulate entitativity, participants completed an entitativity reading task adapted for the current study based on previous entitativity manipulations (Crawford et al., 2002; Hogg et al., 2007; Crump et al., 2010; see Appendix for full manipulation). Participants read, in accordance with experimental condition, passages advocating the following:

2.5.1 | High entitativity

Strong Leadership (e.g., Texas Tech students adhere to a tightly organized leadership system, in which there is a clear hierarchy within the Student Government Association (SGA)); *Unified Student Body* (e.g., Texas Tech University's student body is highly unified on many dimensions); *Common Goals for Action* (e.g., Texas Tech students have a clear vision for their university and actively demonstrate what it means to be a Red Raider).

2.5.2 | Low entitativity

Open Leadership (e.g., Texas Tech students have adopted an open leadership system, in which there is a loose hierarchy within the Student Government Association (SGA)); *Diverse Student Body* (e.g., Texas Tech University's student body is highly dissimilar on many dimensions); *Distinct Goals for Action* (e.g., Texas Tech students do not have a clear vision for their university and actively change what it means to be a Red Raider).

2.5.3 | Entitativity manipulation check

To verify that the entitativity manipulation increased perceptions of entitativity, we measure self-reported entitativity after the entitativity manipulation. Participants completed a validated 8-item entitativity scale (Hohman et al., 2016), for example, "how organized is the group?" (7-point scale from "not at all" to "very much"), $M = 4.69$, $SD = .81$, $\alpha = .76$.

2.6 | Covariate: Baseline SCL/HR

The average of the first 20 s of SCL (μS) or HR (bpm)—recorded following a 5-min calibration period to allow participants to return to baseline SCL/HR before any manipulations—determined participants' baseline SCL/HR. We followed recommendations from Kristjansson et al. (2007), which suggests methods to control for baseline physiological measures (especially SCL). Our fixed parameter of Baseline SCL/HR (γ_{04}) is grand-mean centered average baseline SCL/HR and was included as covariate predictors separate from linear and quadratic effects specified in our multilevel models (see 2.7). Following Kristjansson et al. and's (2007, pp. 732–734) guidelines, we included Baseline SCL/HR (γ_{04}) nested within our Level 1 β_{0i} predictors so as to control for baseline SCL/HR before accounting for change effects from our manipulations. Once baseline covariance was controlled for, all other Level 1 predictors only accounted for variance associated with within-subjects trial variance nested within the manipulated Level 2 predictors over the Time periods of interest (T1 and T2; see Appendix). Including baseline SCL/HR covariance parameters in our models helps ensure that all reported effects are free from error associated with participants' individual physiological differences (Chou et al., 2004; Kristjansson et al., 2007).

2.7 | Piecewise multilevel growth curve modeling data analysis

Given the longitudinal nature of our data, we used multilevel modeling to examine the relationship between self-uncertainty, group entitativity, and autonomic stress responses, nesting repeated measurements of SCL or HR (Level 1) within participants (Level 2; Singer, 1998; Hernandez-Lloreda et al., 2004; Kristjansson et al., 2007). As mentioned in 2.1.1, we considered using repeated-measures ANOVAs to analyze data, but when we compared model fit for a totally fixed repeated-measures ANCOVA model versus a basic SCL multi-level model (with only within-subjects change in SCL over time modeled as a Level 1 random parameter) using −2 Log-likelihood deviance change tests, we found that including even one multilevel parameter to account for individual differences in change over time significantly and substantially improved model fit (−2LL χ^2 (13) = 9,614.52; $p < .001$). Furthermore, multilevel models provide important information about hypothesized cross-level effects (such as our hypothesized cross-level interaction effect showing how participants' average reactions to one manipulation can impact their rate of reaction toward a subsequent manipulation) that cannot be easily accounted for using other analytic techniques. We have included results from repeated-measures ANCOVAs in our supplementary online materials for interested readers.

Because this study was the first of its kind to test the psychophysiological effects of self-uncertainty and identification, we used a strategy wherein we conducted exploratory analyses followed by confirmatory analyses (Krisjansson et al., 2007; Snijders & Bosker, 2012). We used a portion of our data set (N = 70) to build exploratory models for SCL and HR then analyzed the full data set (N = 123) against our final exploratory models (see Tables 1 and 2 and Appendix Tables 1–4; Snijders & Bosker, 2012). All confirmatory analyses confirmed the final models we determined from exploratory analyses and are reported in this manuscript.

The current study uses 60 s of systematic data collection modeled as a piecewise multilevel growth curve (Chou et al., 2004; Hernandez-Lloreda et al., 2004; Krisjansson et al., 2007; Vos et al., 2012). The average of the first 20 s of SCL (μS) or HR (bpm) recorded following a 5-min calibration period before any manipulations determined participants' baseline SCL/HR (see 2.6 and Kristjansson et al., 2007); the second 20 s (i.e., Time 1: T1) followed the self-uncertainty manipulation; the final 20 s (i.e., Time 2: T2) followed the entitativity manipulation with T1 measurements hypothesized to affect T2 measurements.

All analyses used MIXED in IBM SPSS version 22 and employed maximum likelihood (ML) approximation with unstructured covariance matrices. The intra-class correlation coefficient (ICC) of the empty SCL model (.856) indicated 85.6 percent of the variance in SCL was attributable to differences between participants. The ICC of the empty HR model (.794) indicated 79.4 percent of the variance in HR was attributable to differences between participants.

For model building, we used a "bottom-up" approach which follows recommendations for growth curve multilevel modeling suggested by Kristjansson et al., (2007; see also Chou et al., 2004). The model-building process from Kristjansson et al., (2007, pp. 732–734) suggests building the Level 1 model first (i.e., our Time model), then adding Level 2 effects after the initial model is specified, and finally adding hypothesized cross-level interactions. This "bottom-up" approach ensures that every additional parameter is considered via parsimony such that only parameters that increase model fit are kept and is a common strategy used in model building (Chou et al., 2004; Hernandez-Lloreda et al., 2004; Kristjansson et al., 2007). First, we determined the Level 1 fixed and random structures of SCL and HR across measurement conditions prior to specifying Level 2 participant variables. Once we established a Level 1 within-participant structure for SCL and HR, we tested three Level 2 participant-level variables (self-uncertainty condition, entitativity condition, and grand-mean centered average SCL/HR following the self-uncertainty manipulation) and one Level 2 participant-level covariate (baseline SCL/HR) for the improvement of model fit. We then added hypothesized two-way and three-way cross-level interactions before incorporating the piecewise nature of the data into our SCL and HR models. We compared −2 Log-likelihood deviance change tests to guide model selection and determined the significance of fixed effects through Wald tests (Snijders & Bosker, 2012).

2.7.1 | Building the models for SCL/HR

We first built the SCL model then used the SCL model as a guide to build the HR model. The first step of our model-building approach for SCL indicated that including a linear representation of measurement occasion as a Level 1 fixed parameter substantially improved model fit (−2LL $\chi^2(1) = 96.62$, $p < .001$), and the coefficient parameter itself was significant, $t(2{,}556.09) = -9.92$, $p < .001$. Including a quadratic representation of measurement occasion as a Level 1 fixed parameter substantially improved model fit; the coefficient parameter for the quadratic representation of measurement occasion was significant, while the coefficient parameter for the linear representation of measurement occasion was no longer significant (see Appendix Table 1). Specifying the linear and quadratic representations of measurement occasion as Level 1 random effects substantially improved model fit (see Appendix Table 2), suggesting that the change in SCL over each 1 s occasion varied across participants. As such, all future models specify linear and quadratic representations of measurement occasion as random effects.

Next, we tested the joint effect of three Level 2 participant-level variables (self-uncertainty condition, entitativity condition, and grand-mean centered average SCL following self-uncertainty manipulation), one Level 2 participant-level covariate (baseline SCL), and the hypothesized Level 2 interaction between experimental manipulation conditions (self-uncertainty and entitativity conditions); results indicated the addition of these Level 2 variables and interaction further improved model fit (see Appendix Table 3). Wald tests for coefficients of Level 2 fixed effects suggested only effects for baseline SCL and grand-mean centered average SCL following self-uncertainty manipulation were significant (see Appendix Table 3). We retained all these Level 2 participant-level variables to test for cross-level interaction effects in later models.

We next tested for cross-level interaction effects between Level 1 representations of measurement occurrence, Level 2 self-uncertainty condition, Level 2 entitativity condition, and Level 2 grand-mean centered average SCL following self-uncertainty manipulation; results indicated the addition of these cross-level interactions further improved model fit (see Appendix Table 4). Additionally, Wald tests for coefficients of cross-level interactions suggested there were significant effects for the hypothesized three-way cross-level interaction between the Level 1 quadratic representation of time, Level 2 self-uncertainty condition, and Level 2 entitativity condition along with lower order interactions and fixed effects (see Appendix Table 4). We retained all these cross-level interaction effects to test for the piecewise nature of the final model.

The final step of model specification involved testing a piecewise multilevel growth curve model for SCL, the incorporation of which significantly improved model fit (see Table 1). Furthermore, Wald tests for fixed effect coefficients showed significant effects for the three-way cross-level interaction between the Level 1 quadratic representation of measurement occasion, Level 2 self-uncertainty condition, and Level 2 entitativity condition during T2, along with the cross-level interaction between the Level 1 quadratic representation of measurement occasion and Level 2 grand-mean centered average SCL following self-uncertainty manipulation during T2 (see Table 1 and Section 3.2 SCL).

Due to problems with model convergence, which were likely due to the inclusion of time as a Level 1 random effect, we did not specify a piecewise structure for random effects across time (see Howell & Sweeny, 2020). Consequently, our final model for SCL comprised fixed effects for Level 1 linear and quadratic representations of measurement occasion during T1 and T2, Level 2 self-uncertainty condition, Level 2 entitativity condition, a Level 2 baseline SCL covariate, Level 2 grand-mean centered average SCL following self-uncertainty manipulation, the Level 2 interaction between self-uncertainty and entitativity conditions, the cross-level interaction between Level 1 linear and quadratic representations of measurement occasion and Level 2 self-uncertainty condition during T1 and T2, the cross-level interaction between Level 1 linear and quadratic representations of measurement occasion and Level 2 entitativity condition during T2, the cross-level interaction between Level 1 linear and quadratic representations of measurement occasion and Level 2 grand-mean centered average SCL following self-uncertainty manipulation during T2, and the three-way cross-level interaction between Level 1 linear and quadratic representations of measurement occasion, Level 2 self-uncertainty condition, and Level 2 entitativity condition during T2 with Level 1 random effects for linear and quadratic measurement occasions.

2.7.2 | Interpreting multilevel coefficients

The Level 2 between-persons fixed effects are dummy coded or grand-mean centered and can be interpreted as the relationship between each manipulation controlling for baseline with average levels of autonomic arousal outcomes across measurement occasions. A positive coefficient suggests that participants in the "high" condition, in general, reported higher levels of autonomic arousal, in general. A negative coefficient suggests that participants in the "high" condition, in general, reported lower levels of autonomic arousal, in general. The Level 1 within-person effects can be interpreted as the change in autonomic arousal for a person over time, with Time-squared representing changes in arousal rates. Cross-level interactions between Level 1 within-person fixed effects and Level 2 between-person fixed effects can be interpreted as how manipulations affect arousal over time.

2.7.3 | HR

We used the model building process for SCL to guide our model building for HR. Our final model for HR (see Table 2) comprised Level 1 fixed effects for linear and quadratic representations of measurement occasion during T1 and T2, Level 2 self-uncertainty condition, Level 2 entitativity condition, a Level 2 baseline HR covariate, Level 2 grand-mean centered average HR following self-uncertainty manipulation, the Level 2 interaction between self-uncertainty and entitativity conditions, the cross-level interaction between Level 1 linear and quadratic representations of measurement occasion and Level 2 self-uncertainty condition during T1 and T2, the cross-level interaction between Level 1 linear and quadratic representations of measurement occasion and Level 2 entitativity condition during T2, the cross-level interaction between Level 1 linear and quadratic representations of measurement occasion and Level 2 grand-mean centered average HR following self-uncertainty manipulation during T2, and the three-way cross-level interaction between Level 1 linear and quadratic representations of measurement occasion, Level 2 self-uncertainty condition, and Level 2 entitativity condition during T2 with Level 1 random effects for linear and quadratic measurement occasions (discussed in 2.7.1).

3 | RESULTS

All data, code, and supplementary materials are available through the Open Science Foundation at osf.io/2yptc.

3.1 | Manipulation checks

3.1.1 | Self-uncertainty manipulation check

A 2 (entitativity: high vs. low) × 2 (uncertainty: high vs. low) analysis of variance (ANOVA) on measured self-uncertainty showed that there was a significant main effect for uncertainty, $F(1, 119) = 4.31$, $p = .040$, $\eta_p^2 = .034$. Participants in the high uncertainty condition reported more self-uncertainty ($M = 3.23$, $SE = .14$) compared to those in the low uncertainty condition ($M = 2.83$, $SE = .14$). There was no main effect for entitativity on participants' reported uncertainty, $F(1, 119) = 1.39$, $p = .241$, $\eta_p^2 = .011$, and no interaction between entitativity and uncertainty, $F(1, 119) = .20$, $p = .653$, $\eta_p^2 = .002$. The uncertainty manipulation significantly increased self-uncertainty.

3.1.2 | Entitativity manipulation check

A 2 (entitativity: high vs. low) × 2 (uncertainty: high vs. low) ANOVA on measured entitativity showed that there was a significant main effect for entitativity, $F(1, 119) = 7.52$, $p = .007$, $\eta_p^2 = .058$. Participants who read the high entitativity description reported significantly more entitativity ($M = 4.88$, $SE = .10$) compared to those who read the low entitativity description ($M = 4.49$, $SE = .10$). There was no main effect for uncertainty on participants' perceptions of entitativity, $F(1, 119) = .01$, $p = .941$, $\eta_p^2 < .001$, and no interaction between entitativity and uncertainty, $F(1, 119) = .56$, $p = .455$, $\eta_p^2 = .005$. The entitativity manipulation significantly increased perceptions of entitativity.

3.2 | SCL

A single univariate outlier was detected at 13.91 SDs below the mean for baseline skin conductance and was listwise deleted from the final data set prior to analyses. Descriptive statistics for continuous control variables included in the SCL model are in Table 3. The pseudo-R^2 for our final SCL model was .91, indicating that the final model produced a 91 percent reduction in prediction error from the null model. The multi-level and extended regression equations for the final SCL model are reported in Appendix.

We found support for our hypothesized interaction effects, including the proposed three-way cross-level interaction between

TABLE 3 Descriptive statistics for continuous control variables

Variable	*M*	*SD*	Minimum	Maximum	*N*
SCL	3.02	3.74	−10.48	21.04	4,740
Baseline SCL	2.48	3.38	−3.34	13.38	123
Grand-mean centered SCL after uncertainty	0.00	0.43	−4.00	2.00	123
HR	84.31	14.09	8.79	166.51	4,740
Baseline HR	83.10	13.99	36.62	118.37	123
Grand-mean centered HR after uncertainty	0.00	5.03	35	63	123

Note: All SCL data are in μS units. All HR data are in bpm units.

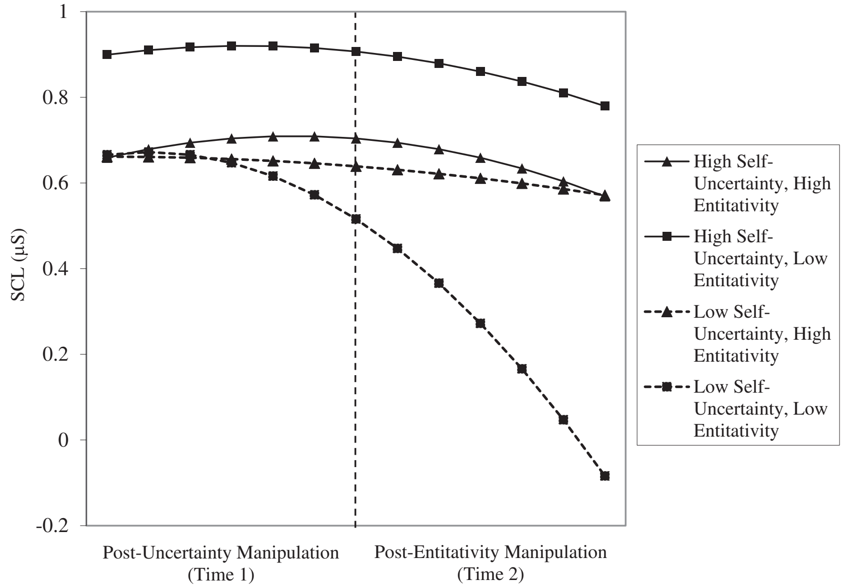

FIGURE 1 Change in SCL (μS) over the 20 s following the uncertainty manipulation and 20 s following the entitativity manipulation—a significant interaction between time, self-uncertainty condition, and entitativity condition, $t(71.67) = -2.65$, $p = .010$

Level 1 time, Level 2 self-uncertainty condition, and Level 2 entitativity condition. There was a significant interaction between time, self-uncertainty condition, and entitativity condition, such that high self-uncertainty participants exposed to the high entitativity manipulation showed a significantly steeper rate of decline in SCL over the study than high self-uncertainty participants exposed to the low entitativity manipulation, $t(71.67) = -2.65$, $p = .010$ (see Table 1 and Figure 1). The significant interaction between the high self-uncertainty and high entitativity conditions over the 20 s following the entitativity manipulation was shown to be driving this effect according to the piecewise model, $t(98.40) = -2.25$, $p = .027$ (see Table 1).

There was also a significant interaction between time and grand-mean centered average SCL during the 20 s following the self-uncertainty manipulation, such that participants with a higher average SCL following the self-uncertainty manipulation showed a significantly steeper rate of decline in SCL over the 20 s following the entitativity manipulation, $t(4{,}357.253) = 5.62$, $p < .001$ (see Figure 2). In conjunction with the confirmed three-way interaction for SCL, this significant interaction provides support that self-uncertainty-activated aversive arousal is best reduced by association with a high entitativity group.

3.3 | HR

Descriptive statistics for continuous control variables included in the HR model are in Table 3. The pseudo-R^2 for our final HR model was .65, indicating that the final model produced a 65 percent reduction in prediction error from the null model. The multi-level and extended regression equations for the final HR model are reported in Appendix.

There was a significant interaction between time and grand-mean centered average HR during the 20 s following the self-uncertainty manipulation, such that participants with a higher average HR following the self-uncertainty manipulation showed a significantly steeper rate of decline in HR over the 20 s following the entitativity manipulation, $t(4{,}357.96) = -8.69$, $p < .001$ (see Figure 3). In conjunction with both confirmed cross-level interactions for SCL (see 3.2), this significant interaction provides support that

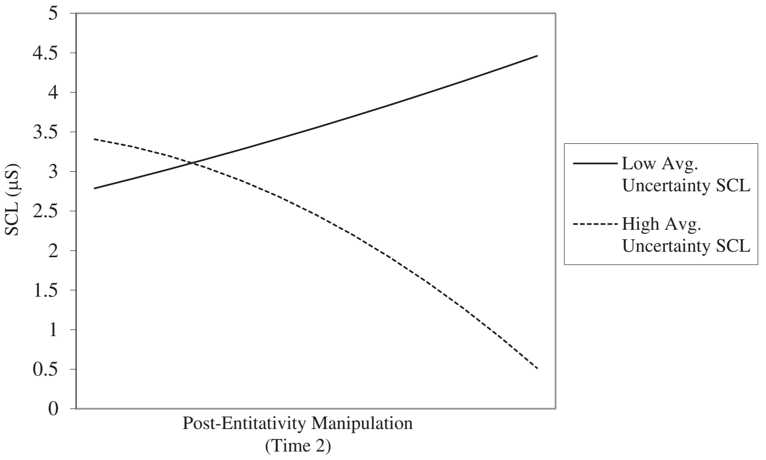

FIGURE 2 Change in SCL (µS) over the 20 s following the entitativity manipulation. Participants with higher average SCL after the self-uncertainty manipulation had a significantly greater negative quadratic decline in SCL than participants with lower average SCL, $t(4{,}357.253) = 5.62$, $p < .001$

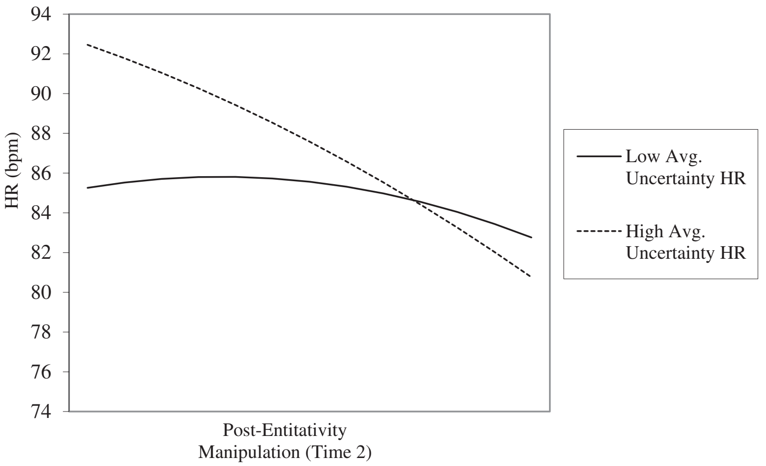

FIGURE 3 Change in HR (bpm) over the 20 s following the entitativity manipulation. Participants with higher average HR after the self-uncertainty manipulation had a significantly greater negative quadratic decline in HR than participants with lower average HR, $t(4{,}357.96) = -8.69$, $p < .001$

self-uncertainty-activated stress responses are best reduced by association with a high entitativity group.

4 | DISCUSSION

The purpose of the current study was to assess physiological reactions to self-uncertainty, and self-uncertainty reduction through identification with an entitative group. We hypothesized that self-uncertainty and its reduction would impact autonomic nervous system activity. Specifically, we predicted that high self-uncertainty would lead to increased general arousal and increased stress responses compared to low self-uncertainty. We further predicted that increased activation due to high self-uncertainty would be alleviated through exposure to a high-entitativity group versus a low-entitativity group. In support of our first hypothesis, we found that high self-uncertainty participants showed increased arousal via SCL compared to low self-uncertainty participants (see Figure 1). In support of our second hypothesis, we found that exposure to a high-entitativity group was associated with a significantly steeper decrease in arousal via SCL for high self-uncertainty participants compared to high self-uncertainty participants exposed to a low-entitativity group (see Figure 1). Furthermore, participants with higher arousal via SCL and higher stress response via HR following the self-uncertainty manipulation saw greater decreases in arousal and stress responses after the entitativity manipulation (see Figures 2 and 3). These interactions, in conjunction with the significant three-way interaction, suggest that self-uncertainty-activated arousal and stress responses are best reduced by association with a high-entitativity group. These findings expand upon previous research showing that self-uncertain people are motivated to identify with highly entitative groups (see Hogg & Mullin, 1999; Hogg et al., 2007; Jetten et al., 2000).

The current study demonstrates an important aspect predicted by uncertainty identity theory (Hogg, 2007): self-uncertainty increases general physiological arousal, and that uncertainty-activated arousal is best alleviated through exposure to a high-entitativity group. Furthermore, participants who experienced the greatest activation of both sympathetic and parasympathetic systems saw the greatest decreases in physiological arousal via SCL and stress responses via HR following exposure to a familiar group (see Figures 2 and 3). Taken together, these patterns suggest that there is increased autonomic activation when people are highly uncertain about themselves and that this activation is decreased through group identification in general and exposure to high entitativity groups in particular. Our findings expand upon previous uncertainty identity theory research by identifying physiological mechanisms (i.e., increased stress and arousal) that could motivate uncertainty reduction and make entitative groups more appealing than non-entitative groups for uncertainty reduction (see Hogg, 2000; Hogg et al., 2007).

An implication of this work is the possibility of detecting and predicting identification using psychophysiological measures. High self-uncertainty is known to motivate identification with a group (Hogg, 2007), so our models could be used to detect and differentiate events that activate high self-uncertainty to predict subsequent social identification without relying exclusively on self-report measures. Furthermore, our models show that some groups are better than others at reducing increased activation associated with high self-uncertainty. This allows us to detect how people conceptualize a crucial component of group structure—entitativity—on a group-member-by-group-member basis. Future researchers could use our models to gather more precise data about how people conceptualize naturally occurring and pre-existing groups outside the laboratory. Social psychological research is often critiqued due to the lack of precision in both hypotheses and measurements (e.g., Strauss & Smith, 2009; Borsboom, 2006). The precision offered by models generated from physiological measurements can be used to generate more precise hypotheses and improve construct validation for group processes and identity researchers. We hope that more social psychology researchers attempt to incorporate psychophysiological measurements into their hypothesis testing and generate hypotheses about the aversiveness of social phenomenon via psychophysiological changes. Future researchers should make certain to abide by best practices for measuring psychophysiological data, including collecting adequate physiological baselines and using proper analytic strategies for psychophysiological data.

A method of gaining even more precision in future research would be to use a more direct measure of stress via stress hormones associated with the hypothalamus-pituitary-adrenal (HPA) axis, for example, salivary cortisol (Cacioppo et al., 2007). One model presented in this study uses HR as a physiological marker of stress responses (see 2.7.3 and 3.3). The procedures by which we collected physiological data from participants prevented us from collecting cortisol levels, but future self-uncertainty researchers should consider collecting salivary cortisol from participants at multiple time points in conjunction with measuring HR as a more accurate marker for participants' stress responses to self-uncertainty and identification (see Niedbala et al., 2018).

Another limitation concerns the population from which we collected our data. The undergraduate population at our research university is moderately identified with their shared student social identity, whereas other groups have both more socially identified members (e.g., soldiers) and less socially identified members (e.g., minimal groups). Because our participants were moderately socially identified with their group, our results likely demonstrate middle-of-the-road effects, such that minimum and maximum arousal and stress responses to uncertainty and identification are not clearly depicted in our results. Future researchers should investigate how high identification with groups and minimal identification affects arousal and stress responses using procedures from this study for highly identified group members (e.g., religious fanatics) and through the minimal group paradigm (Tajfel et al., 1971). These findings would provide information about important boundary conditions for the physiological effects of uncertainty and identification.

5 | CONCLUSION

These results are among the first to detail the relationship between self-uncertainty, physiological activation via arousal and stress responses, and the mitigating role of entitativity. High self-uncertainty increases arousal (via SCL) and stress responses (via HR). High entitativity reduces the increased arousal and stress responses activated by high self-uncertainty. Our findings help identify physiological mechanisms (i.e., increased stress and arousal) that could motivate uncertainty reduction and indicate why entitative groups are more appealing for identification to highly uncertain people. The current study makes a novel contribution to the existing social identity literature by divulging the physiological consequences of self-uncertainty and rectification thereof.

CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

AUTHOR CONTRIBUTIONS

Joshua Brown: Data curation; Formal analysis; Investigation; Methodology; Project administration; Software; Supervision; Validation; Visualization; Writing-original draft; Writing-review & editing. **Zachary P Hohman:** Conceptualization; Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Project administration; Resources; Software; Supervision; Validation; Visualization; Writing-original draft; Writing-review & editing. **Elizabeth Niedbala:** Data curation; Investigation; Methodology; Project administration; Resources; Software; Supervision; Writing-review & editing. **Alec Stinnett:** Formal analysis; Validation; Writing-original draft; Writing-review & editing.

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SUPPORTING INFORMATION

Additional Supporting Information may be found online in the Supporting Information section.

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