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An abstract of
a thesis submitted to the Faculty of Emory College of Arts and Sciences
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Abstract

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Emotion dysregulation is a multifaceted transdiagnostic risk factor for the development and maintenance of psychopathology. Person-centered analyses can be used to identify distinct profiles of emotion dysregulation based on individuals' response patterns, which cannot be investigated using variable-centered analyses. Previous studies have uncovered emotion dysregulation profiles that are differentially associated with psychological outcomes. However, a lack of investigation into predictors, a narrow scope of distal outcomes, and underrepresentation of racial minorities limit the current literature. To address these gaps, we used latent profile analysis to uncover unique patterns of emotion dysregulation, examine the role of childhood maltreatment in predicting profile membership, and examine differences in internalizing and externalizing symptoms in a trauma-exposed community sample (n = 783, 97% Black). Participants were recruited from medical clinics of an urban public hospital and completed a battery of self-report measures assessing emotion dysregulation, trauma exposure, and psychological symptoms. The best-fitting model uncovered four classes: Regulators (42%), Managers (34%), Dwellers (17%), and Dysregulators (6%). Childhood maltreatment history predicted class membership, such that those who experienced more severe maltreatment were more likely to be classified in the Dwellers and Dysregulators profiles. All classes differed in terms of internalizing symptoms (anxiety sensitivity, depression, PTSD), with classes characterized by higher emotion dysregulation reporting greater symptomatology. For externalizing symptoms (food addiction behaviors, alcohol and drug abuse, aggressive behavior), the Regulators were lower than all other profiles. Thus, patterns of emotion dysregulation ought to be assessed and considered as treatment targets for those experiencing internalizing and externalizing psychopathological symptoms.

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Identifying Latent Profiles of Emotion Dysregulation in a Trauma-Exposed Sample

Emotion regulation is a complex psychological process by which individuals attempt to influence their emotional experiences and expressions by consciously or unconsciously engaging in strategies that impact the emotion generation process (Gross, 1998). Difficulties in emotion regulation, or emotion dysregulation, reflects deficits in one or more components of this process, including lack of emotional awareness and acceptance, an inability to engage in goal-directed behavior and withhold impulsive behavior in the context of strong emotions, and the inability to flexibly utilize a range of emotion regulation strategies when distressed (Gratz and Roemer, 2004). Emotion dysregulation is a transdiagnostic risk factor implicated in the development, maintenance, and treatment of a variety of psychopathology including major depressive disorder (MDD; Liu & Thompson, 2017), post-traumatic stress disorder (PSTD; Lanius et al., 2010), substance use disorder (SUD; Kober, 2014), and alcohol use disorder (AUD; Jakubczyk et al., 2018). To date, most studies focus on the direct associations between specific emotion regulation deficits and psychopathological symptoms (Aldao, 2013; Sheppes et al., 2015). Other research has examined how specific disorders are related to certain deficits in emotion regulation (Kneeland et al., 2016; Sheppes et al., 2015). However, less is known about how an individual's constellation of emotion dysregulation relate to overall emotional and behavioral health (Aldao, 2013; Nolen-Hoeksema, 2000; Nolen-Hoeksema & Watkins, 2011).

Early theories conceptualized emotion regulation as a largely conscious process whereby individuals actively modify their emotional states by engaging in strategies in order to say within the "window of tolerance" between hyper- and hypo-arousal (Gross, 1998; Schore, 2003). According to these models, some emotion regulation strategies are more adaptive than others. For instance, cognitive reappraisal, problem solving, and accepting one's emotions are all associated with more positive mental health outcomes (Liu & Thompson, 2017; Aldao et al., 2010), whereas rumination and excessive distraction are associated with more severe psychopathological symptoms, and therefore, are generally considered maladaptive (Aldao et al., 2010; Nolen-Hoeksema, et al., 2008; Hu et al., 2014). However, recent evidence supports a more nuanced view of adaptive versus maladaptive emotion regulation strategies and instead posits that adaptive emotion regulation depends upon the individual's ability to flexibly select and deploy one or more strategies to suit the context (Aldao et al., 2015). There is growing concern that having a limited repertoire of emotion regulation strategies is a risk factor for both internalizing and externalizing psychopathology (Dixon-Gordon et al., 2014). Research focused solely on the direct association between the use of a specific emotion regulation strategy and psychological outcomes may fail to account for the fact that individuals inevitably use strategies to varying degrees (Aldao et al., 2015). Thus, to fully understand individuals' emotion dysregulation capacity, it is necessary to examine their capacity to use different skills simultaneously. Furthermore, because psychopathological disorders are often characterized by rigid response patters to the environment (Morris & Mansell, 2018), further investigation into the variety and flexibility of emotion regulation strategy deployment may shed light on the association between dysregulation and specific disorders (Kashdan & Rottenberg, 2010; Rottenberg, Gross, & Gotlib, 2005, Bonanno & Burton 2014). Thus, investigating within-person patterns of emotion dysregulation may provide insight into the value of variable and flexible emotion regulation skills and the associations between specific emotion dysregulation and psychopathology.

Evaluating patterns of emotion dysregulation within trauma-exposed adults is particularly relevant considering the strong connections between trauma exposure, emotion dysregulation, and trauma-related psychopathology (Messman-Moore & Bhuptani, 2017). Individuals exposed to trauma experience higher levels of emotion dysregulation than their non-exposed peers (Lilly & Lim, 2013; Tull et al., 2007). Emotion dysregulation is also a risk factor for the development of PTSD following acute trauma exposure (Pencea et al., 2020). Furthermore, investigation into the role of emotion dysregulation in the development and maintenance of psychopathology following trauma exposure has revealed that emotion dysregulation contributes to anxiety disorders (Goldsmith et al., 2013; Cisler & Olatunji, 2012), depression (Klemanski et al., 2012), PTSD (Bradley et al., 2011; Powers et al, 2015), alcohol abuse (Radomski & Read, 2016; Dutcher et al., 2017), substance abuse (Mandavia et al., 2016; Tull et al., 2018), emotional eating (Michopoulos et al., 2015) and perpetration of aggression (Besharat et al., 2013; Memedovic et al., 2010).

The association between emotion dysregulation and psychiatric symptoms appears to be most prominent in survivors of repeated interpersonal traumas (Ehring & Quack, 2010; Walsh et al., 2011). Childhood abuse and neglect are especially associated with greater emotion dysregulation in adulthood (Thompson et al., 2019; Powers et al., 2015). Those who experience abuse and neglect in childhood are at risk of developing inadequate emotional and arousal regulatory systems (Cicchettti, Ackerman, & Izard, 1995; Sullivan et al., 2010). For childhood maltreatment survivors, the inability to regulate emotions and arousal during and following a traumatic experience in adulthood exacerbates the development of trauma-related psychopathology, including PTSD, depression, and substance use (Cole & Deater-Deckard, 2009; Crow et al., 2014; Bradley et al., 2011; Pencea et al., 2020; Mandavia et al., 2016). Individuals who develop PTSD and have a history of childhood maltreatment tend to have more internalizing symptoms, including negative emotions, anger, guilt, and shame compared to the adult exposure groups who primarily report fear-related symptoms (Lanius et al., 2001, 2003). Of all maltreatment types, emotional abuse appears to be an especially strong predictor of emotion dysregulation later in life, as caregivers may interfere directly in the acquisition of healthy emotion regulation strategies by punishing efforts to process emotions and develop adaptive responses during childhood (Burns et al., 2010). However, to our knowledge, no study to date has examined how sexual, physical, and emotional abuse and neglect may differentially relate to patterns of emotion dysregulation in adulthood. Although all forms of childhood abuse and neglect are prominent risk factors for emotion dysregulation and psychopathology (Kim & Cicchetti, 2009; Perry, 2008), particularly for those who are later exposed to trauma in adulthood (Clemmons et al., 2007; Lanus, 2010), little is known about the differential risk childhood abuse type may pose for different constellations of emotion dysregulation patterns.

To understand the relation between emotion dysregulation and psychological outcomes, it is important to consider how different facets of emotion dysregulation may coexist and interact (Kashdan & Rottenberg, 2010; Dennis, 2007). To date, most research on emotion regulation and dysregulation has used variable-centered statistical approaches, which indicate the magnitude of associations between emotion dysregulation and related constructs. However, variable-centered analyses do not take into account how emotion dysregulation facets vary within the individual. Whereas variable-centered analyses describe the relationship between variables, person-centered approaches classify individuals based their response to multiple continuous variables, assuming heterogeneity in the population (Laursen & Hoff, 2006). Person-centered analyses, such as latent profile analysis (LPA), uncover patterns in the sample of individual's variable responses, which cannot be investigated using variable centered or linear association analyses. In the context of emotion dysregulation, LPA can be used to identify a number of subgroups within a sample that show patterns of variance in their emotion dysregulation tendencies (Bauer & Curran 2004).

There is a growing literature of person-centered analyses that yield unique typologies of emotion regulation that are differentially associated with mental health outcomes. Most prior studies have uncovered a three- to five-class solutions with classes characterized by either overall low/high emotion dysregulation or specific emotion regulation strategy use/deficits (see Supplemental Table 1 for summary). In the majority of these studies, the largest class was characterized by the overall lowest levels of emotion dysregulation and the smallest class was characterized by the most severe emotion dysregulation (Brewer et al., 2016; Chesney et al., 2019; Lougheed & Hollenstein, 2012; Suh et al., 2020; van Eck et al., 2017). All extant studies uncovered at least one class characterized by either specific patterns of emotion regulation (e.g. Accepting with Suppression, Chesney et al., 2019; Worriers/Ruminators, Dixon-Gordon et al., 2015) or moderate levels of emotion dysregulation (e.g. At Risk, Eck et al., 2017; Observant yet Judgemental, Suh et al., 2020). The most frequently studied mental health correlates were depression and anxiety (Chesney et al., 2019; Dixon-Gordon et al., 2015; Eck et al., 2017; Grommish et al., 2019; Lougheed & Hollenstein, 2012). A number of studies also measured some type of social functioning (e.g., social wellbeing, Brewer at al., 2016; hostility, Eck et al., 2017; social anxiety, Lougheed & Hollenstein, 2012; work-family-school conflict, Suh et al., 2020) and externalizing symptoms (e.g., disordered eating, Dixon-Gordon et al., 2015; conduct problems and substance use, Eck et al., 2017; illicit drug use, Wong et al., 2013). The majority of these studies found class differences in mental health outcomes, with lower emotion dysregulation classes reporting less internalizing and externalizing symptomatology than classes characterized by higher levels of emotion dysregulation or overreliance on specific emotion regulation strategies (Dixon-Gordon et al., 2015; van Eck et al., 2017).

Although these studies provide substantial evidence for the existence of distinct emotion dysregulation typologies, the extant literature has notable limitations including a) an overreliance on primarily white and young adult samples, b) a limited range of examined distal outcomes, and c) a failure to evaluate variables that predict class membership, such as childhood maltreatment. First, the majority of person-centered emotion regulation studies utilize primarily white, college student samples. Emotion dysregulation patterns in young adults may differ from other age groups (Zimmermann & Iwanski, 2014). Furthermore, there is evidence to suggest that culture may affect one’s tendency to adopt certain emotion regulations strategies (Matsumoto et al., 2008), and the impact of emotion regulation on health may differ by racial and ethnic groups (Consedine et al., 2005). As such, research examining emotion dysregulation profiles and their mental health correlates using primarily white, college student samples may not be representative of the spectrum of emotion dysregulation tendencies and outcomes. Black adults living in urban, low socioeconomic communities experience extremely high rates of chronic interpersonal trauma, childhood maltreatment, and trauma-related psychopathology (Gillespie et al., 2009; Gluck et al., in press), and thus may be a particularly helpful group to study in relation to emotion dysregulation patterns. Second, despite the relation between childhood maltreatment on emotion dysregulation (Messman-Moore & Bhuptani, 2017), prior LPA studies have not examined the potential of child maltreatment type in predicting emotion dysregulation class membership. Third, patterns of emotion dysregulation are associated with a wide array of both internalizing (e.g. depression, PTSD) and externalizing (e.g. substance abuse, aggression) psychopathology (Aldao et al., 2016). The range of distal outcomes examined in previous person-centered analyses is limited, with most studies examining one or two internalizing problems (e.g., depression, anxiety) and neglecting externalizing psychopathology.

The current study aims to address the limitations of previous person-centered analyses of emotion dysregulation profiles by using LPA to assess emotion dysregulation profiles in a primarily Black community sample with high levels trauma exposure and psychopathology. Profiles will be created using data from the Difficulties in Emotion Regulation Scale (DERS; Gratz & Roemer, 2004) a multidimensional measure of emotion dysregulation, which includes six specific factors: (a) lack of emotional clarity; (b) difficulties engaging in goal-directed cognition and behavior; (c) difficulty regulating impulsive behavior; (d) unwillingness to accept emotional responses; (e) lack of strategies for feeling better when distressed; (f) lack of emotional awareness. To evaluate the role of childhood trauma history in predicting profile membership, a measure of childhood physical, emotional, and sexual abuse, as well as physical and emotional neglect were examined as predictors (Wong et al., 2013; Dixon-Gordon, Aldao, & De Los Reyes, 2015). To examine the relation between emotion dysregulation profiles and a range of both internalizing and externalizing psychopathology, we compared groups on psychiatric symptoms commonly associated with emotion dysregulation including depression, PTSD, anxiety sensitivity, food addiction, alcohol abuse, drug abuse, and frequency of aggressive behavior (Berking & Wupperman, 2012; Weiss et al., 2012). By identifying latent patterns of emotion dysregulation in a trauma-exposed population, our goal is to shed light on the factors that may predispose individuals to engage in such patterns, and potentially show how these distinct groups differ in their psychological and behavioral outcomes. We had three main hypotheses:

a. Distinct profiles will emerge from the LPA analysis, including profiles characterized by overall low and high levels of emotion dysregulation. Given the inconsistent findings in previous person-centered emotion dysregulation analyses, we do not have a priori hypotheses regarding patterns of emotion dysregulation facets that will characterize class membership.
b. Higher overall childhood maltreatment and emotional abuse specifically will predict membership in the profiles characterized by higher levels of emotion dysregulation.
c. Profiles characterized by greater emotion dysregulation will have higher internalizing symptoms (anxiety sensitivity, depression, PTSD) and externalizing symptoms (food addiction, alcohol and substance abuse, interpersonal aggression).

Method

Procedure

Data was collected as a part of a large, ongoing study investigating genetic and environmental factors associated with the development of PTSD in a primarily Black and highly trauma exposed population with low socioeconomic resources. Potential research participants were approached at random by trained interviewers in the primary care and obstetrical–gynecological clinic waiting rooms of an urban, public hospital in the South-Eastern United States. Eligible participants were between 18-65 years of age and capable of providing informed consent (i.e., no overt active psychosis or severe cognitive impairment). Individuals hospitalized in the last month for psychiatric care were excluded. After completing a written and verbal informed consent, participants completed a battery of self-report measures administered by a trained interviewer. These assessments lasted between 45-75 minutes, depending on the extent of the individual's trauma history. The emotion dysregulation measure used for this study was either administered at the initial screening assessment or during a return visit to the laboratory that included a comprehensive diagnostic assessment with a trained clinician (time duration approximately 2-3 hours). Participants were compensated $15 for the screening assessment and $60 for the follow-up assessment. All study procedures were approved by Emory University's Institutional Review Board and the Grady Health Care System Research Oversight Committee.

Participants

The final sample consisted of 783 individuals, the majority of whom self-identified as Black (96.8%). Participants who began the study but did not complete the key emotion dysregulation measure were excluded from analyses. Participants were mostly women (93.0%) and all adults between the ages of 18-65 (M = 41.0, SD = 12.26). Large proportions of the sample had either graduated high school or obtained their GED (35.0%) or received some level of higher education (46.7%), although graduation was not specified. Monthly household income for participants was as follows: 14.2% of participants reported an income of less than \$249, 7.1% had income between \$250 – 499, 24.8% had income between \$500-999, 30.7% had income between \$1000 – 2000, and 23.1% reported an income of over \$2000. Trauma exposure was high in this sample, with the number of types of Criterion A traumatic events (American Psychiatric Association, 2012) experienced or witnessed ranging from 0-17 (mean = 5.36, *SD* = 3.44). See Table 1 for all demographic details of study sample.

Measures

Demographic information, including age, self-identified race and ethnicity, self-identified gender, education, and monthly household income, was collected using an internally-developed form.

The Difficulties in Emotion Regulation Scale (DERS; Gratz & Roemer, 2004) is a 36-item self-report measure of emotion regulation difficulties. Six aspects of emotion regulation were measured: awareness and understanding of one's emotions (Awareness), emotional clarity (Clarity), acceptance of negative emotions (Acceptance), the ability to successfully engage in goal-directed behavior (Goals) and control impulsive behavior when experiencing negative emotions (Impulse), and the ability to use situationally appropriate emotion regulation strategies (Strategies). Participants were asked to rate their level of agreement on a 5-point Likert scale ranging from 1 (*almost never*) to 5 (*almost always*). The Awareness subscale includes six items that are all reverse-scored to assess lack of emotional awareness (e.g., "I pay attention to how I feel"; α = .73). The Clarity subscale includes five items, with 3 items directly assessing emotional clarity (e.g., "I have no idea how I am feeling") and two reverse-scored items (e.g., "I am clear about my feelings"; α = .77). The Acceptance subscale includes six items (e.g., "When I'm upset, I become angry with myself for feeling that way"; α = .88). The Goals subscale includes five items (e.g., "When I'm upset, I have difficulty getting work done"; α = .83). The Impulse scale includes six items (e.g., “I experience my emotions as overwhelming and out of control”; α = .85). The Strategies subscale includes eight items (e.g., “When I’m upset, it takes me a long time to feel better”; α = .87). Mean subscale scores were calculated by averaging response scores and dividing my number of items, and thus ranged between one and five. Higher scores indicated greater emotion dysregulation for the given subscale. This measure has demonstrated excellent psychometric properties (Gratz & Roemer, 2008) and construct-related validity in a sample of trauma-exposed Black women (Mekawi et al., 2020). Internal consistency of the DERS total score was high in this sample (α = .94).

The Traumatic Events Inventory is an 18-item measure that assesses history of experiencing, witnessing, and being confronted with traumatic stressors over the lifetime (Gillespie et al., 2009). This internally constructed inventory covers a wide variety of interpersonal (e.g., being attacked by a romantic partner, witnessing a friend or family member attacked) and non-interpersonal traumas (e.g., experiencing a serious accident/injury). For each trauma type, participants provide information regarding the number of times exposed and age of first exposure. Consistent with prior research (Gillespie et al., 2009; Power et al., 2019), overall trauma load was measured by summing the total number of types of traumas experienced or witnessed over the lifetime.

The Childhood Trauma Questionnaire (CTQ; Bernstein et al., 1998) is a 25-item self-report measure used to assess sexual abuse (e.g., “Someone tried to touch me in a sexual way or tried to make me touch them”), physical abuse (e.g., “People in my family hit me so hard it left me with bruises or marks”), emotional abuse (e.g., “People in my family said hurtful or insulting things to me”), physical neglect (e.g., “I knew there was someone there to take care of me and protect me”), and emotional neglect (e.g., reverse scored “People in my family looked out for each other”) before the age of 18 (Forde et al., 2012; Paivio & Cramer, 2004). This measure has demonstrated good criterion-related validity in both clinical and community populations (Bernstein et al., 2003), and has been utilized in the current population with high reliability (Cross et al., 2014; Stojek et al., 2020). Items were scored on a 5-point Likert scale ranging from 1 (*never true*) to 5 (*always true*). Severity scores were calculated by averaging response scores in each maltreatment subscale (range = 5 - 25); CTQ total reflects the average total score across all maltreatment types and ranged between 25 and 114. The CTQ showed excellent internal consistency in the current sample (α = .95).

The Anxiety Sensitivity Index (ASI; Peterson & Reiss, 1992) is a 16-item self-report psychometrically validated inventory of anxiety sensitivity, assessing a range of physical, cognitive, and social concerns individuals' have regarding their anxiety (Rodriguez et al., 2004; Sandin et al., 2001). Participants were asked to rate their level of agreement with each item (e.g., "It scares me when I am unable to keep my mind on a task") on a 5-point Likert scale from 0 (*very little*) to 4 (*very much*). A total score was calculated by summing item scores and ranged between 0 and 64. Internal consistency was adequate in this sample (α = .88).

The Beck Depression Inventory - II (BDI-II; Beck et al., 1996) is a 21-item self-report measure of depressive symptoms in the past two weeks. Items are scored on a 4-point scale (Likert Scale ranging from 0 to 3). Total summed score reflects depressive symptom severity (range = 0 - 58), with scores greater than 18 indicating a likely diagnosis of depression (Beck et al.,1996). In terms of concurrent validity, the BDI-II demonstrated high internal consistency and construct validity in racially diverse samples and samples of trauma-exposed civilian (Farhood & Dimassi, 2015; Wang & Gorenstein, 2013). The BDI-II demonstrated excellent internal consistency in the current sample (α = .93).

The Modified PTSD Scale (PSS; Falsetti et al., 1993) for DSM-IV was used to assess PTSD symptoms in the past two weeks. This 17-item self-report measure has demonstrated good concurrent validity with clinical assessments of PTSD in civilian trauma survivors (Foa & Tolin, 2005). Items assess intrusive, avoidance/numbing, and hyperarousal symptoms. Responses are given on a 4-point Likert scale ranging from 0 (*not at all*) to 3 (*almost always*). A total PTSD symptom severity score was calculated by summing response scores, which ranged between 0 and 50 in the current sample. The PSS showed excellent internal consistency (α = .91).

The Yale Food Addiction Scale (YFAS; Gearhardt, et al., 2009) is a 25-item self-report measure of addictive eating behaviors that mirror the DSM-IV substance dependence criteria but with regards to high fat/sugar foods. This measure assesses food addiction in two ways: as a continuous variable (symptom count) and as a categorical variable (presence of absence of food addiction). In this study, we use the symptom count scoring, which indicates the number of symptoms experienced over the last 12 months, which ranged between 0 and 7. This scale has demonstrated adequate reliability and construct validity in preliminary psychometric evaluations (Gearhardt, et al., 2009) and in samples of childhood maltreatment survivors (Imperatori et al., 2016; Hardy et al., 2018). Internal consistency in this sample was adequate (α = .72).

The Alcohol Use Disorders Identification Test (AUDIT; Saunders et al., 1993) is a 20-item self-report measure assessing problematic alcohol use in the past year and during the year of heaviest alcohol consumption. Items assess both consumption and consequences, with responses were assessed on a 5-point Likert scale ranging from 0 (*never*) to 4 (*daily or almost daily*). For this study, a total severity score was calculated by summing the past year and lifetime subscales (range = 0 – 36). The AUDIT demonstrated good concurrent validity with clinical interviews assessing Alcohol Use Disorder symptoms in clinical and community samples (Bradley et al., 2003; Rubin et al., 2006) and has demonstrated good internal consistency in previous studies in this sample (α = .89; Mandavia et al., 2016). Internal consistency was adequate in this sample (α = .90).

The Drug Abuse Screening Test (DAST; Skinner, 1982) is a 20-item self-report measure that assesses substance consumption as well as interpersonal and medical consequences in the last year and over the lifetime. Items are coded dichotomously, and total scores ranged between 0 and 10. For this study, a total score was created using both the last year and lifetime subscales. The DAST has demonstrated excellent reliability and construct validity in trauma-exposed civilian samples (Shirinbayan at al., 2020; Wingo et al., 2014) and adequate internal consistency in the current sample (α = .84).

The Behavior Questionnaire - Short (BQ-S) is an internally constructed self-report measure of aggressive behavior frequency (α = .75) based on the Conflicts Tactics Scale (Straus et al., 1996). This measure assesses perpetration of violent acts (e.g. "Punched or hit someone with something that could hurt", "Stabbed or shot at someone"). Responses were measured on a 5-point Likert scale ranging from 0 (*Never*) to 4 (*More times than I can count*), and the sum was computed to attain a total score.

Data Analytic Plan

The research questions proposed in this study require identifying latent profiles of emotion dysregulation tendencies, and examining whether profile membership predicts psychopathological outcomes. To carry out this analysis, we used LPA, a person-centered statistical approach, which allows latent subgroups to emerge based on observed indicators. Several statistical frameworks attempt to elucidate an underlying latent construct by mapping patterns of observable indicators. Latent profile analysis was chosen because this particular method allows for the input of continuous indicators and maps the data onto a latent categorical variable.

We began our analysis by narrowing our dataset from the total sample of participants enrolled in the study to those who had complete data for our main indicator variables (n = 783). Although the full-information maximum likelihood model-based data procedure is capable of handling missing data, participants missing data on emotion dysregulation (DERS) were excluded. This is the case for two conceptual reasons: first, the DERS was included in the screening assessment years after data collection began for this project, and second, due to the time-constrained nature of study recruitment (i.e., in hospital waiting rooms), participants were typically missing data from measures administered towards the end of screening assessments. To test this assumption, we conducted a test of missing completely at random for multivariate data (MCAR; Little, 1988), which revealed that data was not missing at random. Therefore, these cases were excluded to avoid biased results (Collins & Lanza, 2010). Once the dataset was narrowed, we examined sample demographics characteristics and correlations between our variables of interest using SPSS software.

Latent profile analyses were conducted using Version 8.2 of Mplus (Muthén & Muthén, 2018). Our analyses followed the best practices for direct application of LPA described by Masyn (2013) using maximum likelihood estimation with robust standard errors (MLR). This process began by specifying a one-profile solution (k = 1), then increasing the number of profiles by one until the models were no longer well identified (k + 1), meaning the model failed to converge on the same mathematical solution. In accordance with recommendations, we specified 600 sets of random start values for each iteration to ascertain whether the class solution consistently converged on the same maximum likelihood solution (Berlin, Williams, & Parra, 2014; Masyn, 2013).

To begin the process of selecting the best fitting class solution (i.e., class enumeration), we evaluated the absolute fit of each class-solution model to see how well the model represents the data. The model with the optimal number of profiles was determined by evaluating and comparing class solutions based on their absolute and relative fit using several fit indices. First, the absolute fit examines overall model-data consistency by comparing the model's representation of response-pattern frequency to the observed response-pattern frequency (Collins & Lanza, 2010). Specifically, the log likelihood value (LL) and the likelihood-ratio tests describe how well a latent class model fits the observed data

(McCutcheon, 1987). Second, we evaluated relative model fit by using series of likelihood-ratio difference tests and information criteria to compare one model's representation of the data to another model's representation. These values do not indicate how well the model itself fits the data; rather the comparison is used to select the best-fitting class solution between models with adequate absolute fit (Collins & Lanza, 2010). The two likelihood-ratio tests examined are the Vuong-Lo-Mendell-Rubin Likelihood Ratio Test (VLMR-LRT; Lo, Mendell, & Rubin, 2001), which compares fit between two nested latent class models (i.e. a three-class vs. a four-class model), and bootstrapped LRT (BLRT; McLachlan & Peel, 2000), which uses bootstrapped samples to empirically estimate the difference distribution of the log likelihood test statistic between class models. Both likelihood ratio tests provide a *p*-value, which, if statistically significant (i.e., $p < .05$) indicates that adding a class significantly improves model fit (Nylund, Asparouhov, & Muthén, 2007). Information criteria were used to compare the relative balance of model fit and parsimony, with smaller values being more favorable (Collins & Lanza, 2010). Several information criteria were considered, including the Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), Consistent Akaike Information Criterion (CAIC), Sample-Size Adjusted Bayesian Information (SABIC), Schwarz Information Criteria (SIC), and Approximate Weight of Evidence Criterion (AWE). Each information criterion is based in by the maximum log likelihood value and applies a different penalty for sample size and/or the number of model parameters estimates (Nylund et al., 2007). In accordance with the parsimony principle, information criteria favor simpler models that estimate no more parameters than is necessary to represent the data adequately (Collins & Lanza, 2010). Because every information criterion applies different penalties, it is common in LPA for information criteria to point to different class solutions. As such, these values do not generally unambiguously identify the best fitting model, but are useful for ruling out models and, when taken together, narrow down plausible options (Collins & Lanza, 2010). Lastly, the approximate correct model probability (cmP) information-heuristic comparison was used to quantitatively compare models. The cmP value denotes how well Model A compares to the entire set of models under consideration (Masyn, 2013). The sum of cmP values across all models is equal to 1.00, and thus each model's cmP reflects the probability of that model being the correct (Nagin, 1999). When evaluating fit indices, it is important to note that as the number of latent classes increases (and therefore more parameters are estimated), there may come a point when information criteria values will continue to increase even though the log likelihood continues to decrease (Collins & Lanza, 2010). Therefore, it is important to consider all absolute and relative fit indicators together. There is no universally accepted procedure for determining the best-fitting model in LPA (Masyn, 2013). All of the indices described are useful for exploring and evaluating model solutions, but in addition, interpretability and utility must be taken into account.

Once initial class enumeration was complete, classification diagnostics were used to assess the degree of class separation by using posterior class probabilities to evaluate the precision of latent class assignment for individuals. Posterior class probability values reflect how accurately the class to which an individual is assigned matches their response pattern (Collins & Lanza, 2010). Model quality is reflected by high posterior class probability values, which indicate that classes are highly differentiated and homogenous (Nylund-Gibson & Choi, 2018). Relative entropy is a classification diagnostic that provides a systemic summary of posterior class probabilities across classes and individuals, and thus indicates the overall precision of classification across all latent classes for the entire sample (Masyn, 2013). Relative entropy values are bound between 0 and 1, with 0 indicating that posterior classification is no better than random chance and 1 indicating perfect posterior classification for all individuals in the sample (Masyn, 2013). The average posterior class probability (AvePP) provides a summary of the posterior classification probabilities for a specific class *k* by averaging all of the individuals whose maximum posterior probabilities are for class *k* (Cheung & Beck, 2010). Unlike relative entropy, the AvePP is class-specific classification diagnostic that assesses how well a set of indicators predicts class membership in the sample (Masyn, 2013). Similar to relative entropy, AvePP is measured between 0 and 1, with a value above 0.70 indicating adequate class separation and latent class assignment (Nagin, 2005). The odds of correct classification ratio indicates class-specific classification accuracy, using a scale of 1 to 5 with larger values indicating good latent class separation and assignment accuracy in the model (Nagin, 2005). Overall, these classification diagnostics are useful in that they summarize how well the latent model fits the observed individual response patterns, and thus they are considered after class enumeration to evaluate how well the model fits the observed data.

Once the class solution is reached through this process of enumeration, further analyses were performed to compare classes on auxiliary variables, also known as covariates. Adding auxiliary variables to the models allows researchers to test whether observed variables predict latent profile membership (predictor variables) or are predicted by latent profile membership (distal outcomes; Nylund-Gibson & Choi, 2018). In both cases, this is accomplished by performing latent class regression (LCR), which follows the same process as ordinary logistic regressions, with the only difference being that the outcome is latent rather than directly observed (Collins & Lanza, 2010). In LCR, the measurement model parameterization (the relationship between the observed indicators and the latent class variable) remains the same, but the latent class proportions become conditional on one or more covariates. The resulting regression coefficients are then interpreted as odds ratios and computed in relation to a reference class (Collins & Lanza, 2010). This model-based approach to comparing classes on auxiliary variables derives and summarizes class-dependent density functions of predictors and distal outcomes with categorical and continuous distributions (Lanza et al., 2013).

In LPA, predictor auxiliary variables are introduced in order to identify characteristics that predict latent profile membership. Before introducing predictor auxiliary variables, the latent structure of the model must already be identified and interpreted (Asparouhov & Muthen, 2014). Thus, predictor auxiliary variables do not inform class structure, but rather, are used to test hypotheses regarding what variables influence the likelihood of belonging to one profile or another (Collins & Lanza, 2010). To evaluate whether childhood maltreatment predicted profile membership, we used the three-step approach developed by Vermunt (2010). This method was chosen over the standard one-step approach and pseudoclass draw method because it produces substantially less biased and more accurate estimates of the effect sizes (Collier & Leite, 2017). To begin this method, latent class models are first estimated using the full process of class enumeration, as previously described. Second, a most likely class variable is created using the posterior probability distributions obtained during latent class enumeration. Third, the most likely class is regressed on predictor variables, taking into account misclassification error in the second step to reduce bias (Asparouhov & Muthen, 2014). The yielded regression coefficients are then exponentiated, allowing for intercepts to be interpreted as odds and regression coefficients to be interpreted as odds ratios. In order to compare across profiles using multinomial logistic regression, a reference class is selected, the choice of which does not affect hypothesis testing. LPA allows for the inclusion of interactions between covariates and all the usual guidelines for regression interactions apply (Collins & Lanza, 2010).

Next, latent profile membership was used to predict our distal outcomes: anxiety sensitivity, depressive symptoms, PTSD symptoms, food addiction symptoms, problematic alcohol and drug use, and interpersonal aggression. We used the Lanza, Tan, and Bray method (LTB; Lanza, Tan, & Bray, 2013) of multinomial logistic regression to evaluate the conditional distribution of our distal outcomes across profiles. The LTB method is an adapted 3-step method specific to evaluating distal outcomes. This analysis uses Bayes theorem to represent the distribution of the latent class variable and the distal variable as a regression of the latent class variable conditional on the distal variable (Lanza, Tan, & Bray, 2013). Chi-square tests were used to determine statistical significance in the final step (Asparouhov & Muthén, 2014). Similar to the Vermunt method for predictor variables, the LTB method for distal outcomes yields more accurate coefficient estimates, less relative bias of coefficient estimates, and a lower Type I error rate compared to the standard one-step method and pseudo-class draw methods, and is thus recommended (Collier & Leite, 2017; Asparouhov & Muthen, 2014). Furthermore, this method is applicable for both continuous and count variables, which was particularly important due to the nature of our distal outcomes.

Results

Preliminary Analyses

First, correlations between emotion dysregulation subscales and each predictor and distal outcome variables were conducted (see Table 2). The associations between all forms of childhood maltreatment and emotion dysregulation subscales were positive and significant. Emotional abuse and emotional neglect had the strongest associations with emotion dysregulation, respectively ranging from $r = .15$ (Awareness) to $r = .32$ (Strategies) and $r = .18$ (Awareness) to $r = .31$(Strategies). Sexual abuse was moderately associated with the DERS subscales, with correlation coefficients ranging from $r = .10$ (Awareness) to $r = .29$ (Nonacceptance). Physical abuse and neglect showed the weakest associations, between $r = .11$ (Awareness) to $r = .21$ (Goals) and $r = .10$ (Awareness) to $r = .26$ (Goals), respectively. Likewise, with the exception of the non-significant association between drug abuse and DERS Awareness, all distal outcomes were significantly associated with the each of the DERS subscales. Depressive symptom severity was most strongly associated with emotion dysregulation, ranging from $r = .33$ (Awareness) to $r = .63$ (Strategies). Correlations between then DERS subscales and anxiety sensitivity and PTSD symptoms were small to moderate, with the smallest associations with the Awareness subscale ($r = .18$ and $r = .23$, respectively) and the strongest associations with the Strategies subscale ($r = .46$ and $r = .50$, respectively). Food addiction symptoms and aggressive behavior correlations were weak to moderate, ranging from $r = .18$ (Awareness) to $r = .36$ (Clarity) for food addiction and $r = .09$

(Awareness) to *r* = .34 (Impulse) for aggressive behavior. Alcohol abuse correlations ranged from *r* = .09 (Awareness) to *r* = .26 (Goals) and drug abuse correlations ranged from *r* = .18 (Clarity) to *r* = .25 (Goals, Impulse). Next, we extended these variable-centered analyses by classifying our sample based on the DERS subscales using latent profile analysis.

Latent Profile Analyses

We completed multiple latent profile analyses using Mplus Version 8.2 (Muthén & Muthén, 2018), following the guidelines outlined by Masyn (2013). We began our analyses by specifying a one profile solution (*k* = 1) and added classes until loglikelihood tests indicated that the *k* + 1 model was an inferior fit. The VLMR-LRT p-value was no longer significant after the 4-class solution, indicating that the non-significant VLMR-LRT p-value indicates that the relative model fit did not improve significantly with additional classes (Masyn, 2013). However, because the models continued to converge on a single solution, and BLRT p-value was significant for all models, as is common for applied LPA, and the information criteria continued to decrease, we continued running profile solutions up to *k* = 7. In order to select the best-fitting profile solution, we compared models on a number of absolute and relative fit indices (see Table 3). We found that the AIC, BIC, CAIC, and SABIC information criteria consistently decreased with the addition of profiles. However, the AWE decreased from *k* = 1 to *k* = 4 then increased when *k* = 5 and continued to increase until *k* = 7. Similarly, the *cm*P value, which reflects the probability of a given model being correct compared to the other calculated models, continued to increase with the addition of profiles. Because the information criteria did not point to a definitive best-fitting class solution, we considered the conceptual meaningfulness of the 4- to 7-class models. We found that in the *k* = 5, *k* = 6, and *k* = 7 models, each contained two classes characterized by high levels of emotion dysregulation comprising <5% of the sample. Such small class sizes raised concerns about the stability and separation of the classes (Nylund-Gibson & Choi, 2018).

To examine whether small classes were justified in our sample, we used average latent class probabilities and to evaluate model quality. Average latent class probabilities close to one indicate that an individual is highly likely to be classified in one profile compared to the others given their response pattern, and thus reflect class homogeneity, separation, and quality of latent class assignment (Nagin, 2005). We found similarly high average probabilities for the most likely latent class membership and low average probabilities for the other classes in both the 4-class and 5-class solutions. For the 4-class solution, the average probabilities were Class 1 = .88, Class 2 = .89, Class 3 = .94, Class 4 = .95, and for the 5-class follows were Class 1 = .93, Class 2 = .93, Class 3 = .89, Class 4 = .87, and Class 5 = .92. Next, we calculated the Odds of Correct Classification, which likewise indicated a high degree of accuracy in class assignment for both the 4- and 5-class solutions (OCC > 5). Because the indicators examined did not point to a clear best solution, we considered the interpretability and utility of the model solutions. The two smallest classes in the 5-class solution both demonstrated high overall dysregulation, but varied slightly in which subscale were most severe. These individuals were grouped together in the 4-class solution to create a single class with the most severe emotion dysregulation on all subscales. We concluded that the 4-class model offered a more parsimonious and potentially generalizable solution. Therefore, based on the absolute and relative fit indices, classification quality, and overall meaningfulness of the classes, we selected the k = 4 model (Figure 1).

The largest emergent class (42.4%, *n* = 332) was characterized by relatively low levels of emotion dysregulation on all subscales. Given their low levels of emotion dysregulation, we named this class the *Regulators.*

The second largest class (34.4%, *n* = 269) was characterized by low-to-moderate levels of emotion dysregulation. Individuals in this class had relatively higher scores on the Goals, Awareness, and Clarity subscales, and lower scores on Impulse, Strategies, and Non-acceptance subscales. Due to their relatively high Goals and Clarity scores in combination with low Strategies and Impulse scores, we concluded that this class may have relatively less difficulty managing their behavior when upset compared to the regulators, and named this class the *Managers*.

The third largest class (16.6%, n = 132) was characterized by overall moderate-to-high levels of emotion dysregulation with a particularly high Goals score and fairly consistent mean scores for Awareness, Clarity, Impulse, Strategies, and Non-acceptance. We named this class the *Dwellers* because their relatively elevated Goals and Impulse scores may reflect a greater propensity to have negative emotions adversely affect subsequent behaviors.

The smallest class (6.4%, n = 50) was characterized by higher scores on all emotion dysregulation subscales except Awareness, which did not seem to differ from the *Managers* and *Dwellers*. This class' most elevated scores were on the Strategies, Non-Acceptance, and Goals' subscales, while the Clarity, Impulse, and Awareness subscales were comparatively lower. Given the overall higher scores, we named this class the *Dysregulators.*

Predictors and Distal Outcomes

As shown in Table 4, we then examined the descriptive statistics of our predictor variables and distal outcomes by class. Next, R3step, a multinomial logistic regression analysis (Asparouhov & Muthén, 2014), was used to assess whether higher childhood maltreatment scores increased the likelihood of an individual belonging to one profile versus another (Gabriel et al., 2018). To ease interpretation, regression coefficients were converted to odds ratios (ORs). Each pair of profiles were compared on both overall childhood maltreatment severity (CTQ Total) and severity of each type of maltreatment: sexual abuse, emotional abuse, physical abuse, emotional neglect, and physical neglect (see Table 5).

We found that overall high levels of maltreatment made individuals 1.07 times more likely to be placed in the Dysregulators profile compared to the Regulators profile ($p < .05$), and 1.02 times more likely to be placed in the Dysregulators profile compared to the Managers profile ($p < .05$). Overall low levels of maltreatment made individuals 1.05 times more likely to be placed in the Regulators profile compared to the Managers profile ($p < .05$), and 1.06 times more likely to be placed in the Regulators profile compared to the Dwellers profile ($p < .05$). All other comparisons were not significant (p = ns).

More severe sexual abuse made individuals 1.17 times more likely to be placed in the Dysregulators profile compared to the Regulators profile ($p < .05$), and 1.08 times more likely to be placed in the Dysregulators profile compared to the Managers profile ($p < .05$). Lower levels of sexual abuse made individuals 1.08 times more likely to be placed in the Regulators profile compared to the Managers profile ($p < .05$), and 1.14 times more likely to be placed in the Regulators profile compared to the Dwellers profile ($p < .05$). All other comparisons were not significant (p = ns).

More severe emotional abuse made individuals 1.25 times more likely to be placed in the Dysregulators profile compared to the Regulators profile ($p < .05$), and 1.07 times more likely to be placed in the Dysregulators profile compared to the Managers profile ($p < .05$). Lower levels of emotional abuse made individuals 1.17 times more likely to be placed in the Regulators profile compared to the Managers profile ($p < .05$), and 1.22 times more likely to be placed in the Regulators profile compared to the Dwellers profile ($p < .05$). All other comparisons were not significant (p = ns).

More severe physical abuse made individuals 1.22 times more likely to be placed in the Dysregulators profile compared to the Regulators profile ($p < .05$). Lower levels of physical abuse made individuals 1.20 times more likely to be placed in the Regulators profile compared to the Managers profile ($p < .05$), and 1.21 times more likely to be placed in the Regulators profile compared to the Dwellers profile ($p < .05$). All other comparisons were not significant (p = ns).

More severe emotional neglect made individuals 1.23 times more likely to be placed in the Dysregulators profile compared to the Regulators profile (p < .05), and 1.07 times more likely to be placed in the Dysregulators profile compared to the Managers profile (p < .05). Lower levels of emotional neglect made individuals 1.15 times more likely to be placed in the Regulators profile compared to the Managers profile (p < .05), and 1.19 times more likely to be placed in the Regulators profile compared to the Dwellers profile (p < .05). All other comparisons were not significant (*p* = ns).

More severe physical neglect made individuals 1.30 times more likely to be placed in the Dysregulators profile compared to the Regulators profile (p < .05). Lower levels of physical neglect made individuals 1.20 times more likely to be placed in the Regulators profile compared to the Managers profile (p < .05), and 1.23 times more likely to be placed in the Regulators profile compared to the Dwellers profile (p < .05). All other comparisons were not significant (*p* = ns).

Next, we examined anxiety sensitivity, depressive symptoms, PTSD symptoms, food addiction symptoms, alcohol use disorder symptoms, drug use disorder symptoms, and aggressive behavior across classes (see Table 6). Anxiety sensitivity differed significantly by class membership, x^2 (3, n = 658) = 346.87, $p < .05$ (Figure 2a). The Dysregulators had the highest mean scores, followed by the Dwellers, then the Managers, and the Regulators. The mean anxiety sensitivity scores were significantly different between all classes ($p < .05$).

Depressive symptom distribution also differed by class membership, x^2 (3, n = 765) = 631.87, $p < .05$ (Figure 2b). Consistent with anxiety sensitivity, the Dysregulators had the highest depressive symptom scores, followed by the Dwellers, then the Managers, and the Regulators. The depressive symptom scores were significantly different between all classes ($p < .05$).

The distribution of PTSD symptoms differed by class membership, x^2 (3, n = 694) = 248.49, $p < .05$ (Figure 2c). Consistent with anxiety sensitivity and depressive symptoms, the Dysregulators had the highest PTSD symptom scores, followed by the Dwellers, then the Managers, and the Regulators. All classes had significantly different mean PTSD symptom scores ($p < .05$).

Food addiction symptom distribution differed by class membership, x^2 (3, n = 471) = 93.33, $p < .05$ (Figure 2d). The Dysregulators reported the most food addiction symptoms and differed from all other classes ($p < .05$). The Regulators endorsed significantly fewer food addiction symptoms than all other classes. Mean food addiction scores did not differ significantly between the Managers and Dwellers.

Class membership differed in terms of the distribution of alcohol abuse symptoms, x^2 (3, n = 724) = 60.50, $p < .05$ (Figure 2e) and drug abuse symptoms x^2 (3, n = 721) = 66.83, $p < .05$ (Figure 2f). For both alcohol and substance abuse symptoms, the Managers, Dwellers, and Dysregulators had higher scores than the Regulators ($p < .05$), but did not differ significantly from each other.

Lastly, the distribution of mean scores for aggressive behavior was contingent on class membership, x^2 (3, n = 715) = 71.15, $p < .05$ (Figure 2g). Consistent with alcohol and drug abuse, the Managers, Dwellers, and Dysregulators had higher aggressive behavior scores than the Regulators ($p < .05$), but did not differ significantly from each other.

Discussion

The purpose of the current study was to advance the emotion dysregulation literature by applying person-centered analyses to a) identify patterns of emotion dysregulation in a primarily low-socioeconomic status, trauma-exposed, Black community sample with low socioeconomic resources, b) examine whether childhood maltreatment predicted profile membership, and c) determine whether members of the distinct emotion dysregulation profiles differed significantly in terms of internalizing and externalizing symptoms. In line with our hypothesis, our analyses indeed uncovered four distinct profiles, which were labeled as 1) Regulators, 2) Managers, 3) Dwellers, 4) Dysregulators. These classes were distinguished by their overall levels of emotion dysregulation and differed in important ways with regard to childhood maltreatment exposure and psychological symptoms.

Consistent with previous studies (Chesney et al., 2019; Eck et al., 2017; Suh et al., 2020), the largest class uncovered was characterized by overall low levels of emotion dysregulation and the smallest class was characterized by the highest levels of emotion dysregulation across subscales. However, where previous studies found one or more profiles distinguished by specific emotion regulation deficits (Chesney et al., 2019; Dixon-Gordon et al., 2015; Grommish et al., 2019; Lougheed & Hollenstein, 2012), our analyses uncovered two classes characterized by moderate levels of emotion dysregulation that differed from each other. One potential reason for this discrepancy is that these studies include a variety of emotion regulation strategies (e.g. situation selection, distraction, reappraisal) as indicators (Chesney et al., 2019; Dixon-Gordon et al., 2015; Grommish et al., 2019; Lougheed & Hollenstein, 2012), whereas our analysis was conducted using a broader measure of emotion dysregulation (e.g. the inability to engage in goal-directed behavior or to control impulsive behavior when experiencing negative emotions) as the indicator. Likewise, several person-centered analyses of emotion dysregulation also included additional psychological constructs as indicators to inform class membership (i.e., Distress tolerance, Eck et al., 2017; Mindfulness, Suh et al., 2020; Coping strategies, Wong et al., 2013) which may impact the factors that emerge. These factors may, in part, help explain the observed differences between our class solution and prior studies, but more research is necessary to clarify how race, trauma exposure, and age impact patterns of emotion dysregulation. Taken together, this pattern of results suggest there are distinct profiles of emotion dysregulation.

In support of our hypothesis, we found that all childhood maltreatment factors predicted profile membership. Specifically, overall levels of maltreatment and sexual abuse were higher in Dwellers and

Dysregulators, compared with Regulators and Managers. Levels of emotional abuse and neglect were lowest in Regulators, but did not differ between Managers and Dwellers or Dwellers and Dysregulators. Similarly, Regulators experienced the lowest levels of physical abuse and neglect were lowest in Regulators, but Managers, Dwellers, and Dysregulators did not differ from each other on these dimensions. These results suggest that childhood maltreatment type is a salient factor in patterns of emotion dysregulation found in adulthood. It may be the case that abuse and neglect in childhood, especially in the context of an unstable or disadvantaged home, disrupts the development of normative regulatory processes, making it more difficult for maltreatment victims to engage in healthy emotion regulation later in life (Brown & Ackerman, 2011; Teicher & Samson, 2016). Children who experience trauma at a young age may subsequently struggle to develop adequate emotional and arousal regulatory systems, making them more vulnerable to problems regulating anger, guilt, sadness, and numbing later in life (Lanius et al., 2010). Those who cannot effectively down-regulate negative emotions may be more susceptible to psychological problems in adulthood (Gotlib & Joormann, 2010). Differences in maltreatment types predicting class membership in the current study suggest that some forms of abuse and neglect may be more deleterious to emotion regulation development than others. Our findings are aligned with research that suggests emotional abuse is a strong predictor of emotion regulation difficulties in adulthood (Burns et al., 2010), but more research is necessary to clarify and distinguish the pathways between various forms of childhood maltreatment and profiles of emotion dysregulation.

In support of our hypothesis and in line with prior research (e.g., Brewer et al., 2016; Grommisch et al., 2019; van Eck et al., 2017), our four emotion dysregulation profiles differed in in terms of psychological symptoms. For anxiety sensitivity, depressive symptoms, and PTSD symptoms, Regulators reported the lowest symptom levels, followed by Managers, then Dwellers, and Dysregulators reported the most severe symptoms. Food addiction symptoms followed a similar pattern, with the Regulators endorsing the fewest symptoms and the Dysregulators reporting the most symptoms, however the Managers and Dwellers were not significantly different than each other. The Regulators were lower than all classes on alcohol abuse, drug abuse, and aggressive behaviors, but the Managers, Dwellers, and Dysregulators showed similar patterns of symptoms. Overall, differences in psychological and behavioral outcomes across profiles suggest that patterns of emotion dysregulation may be relevant to the etiology and treatment of these symptoms.

In terms of implications for etiology, the pattern of results with regard to emotion dysregulation profiles and psychological symptoms were consistent with hierarchical models of psychopathology, such as the Hierarchical Taxonomy of Psychopathology (HiTOP; Kotov et al., 2017). In the HiTOP model, disorders are first organized under spectra, which are broad dimensions of common mental disorders identified by factor research, then further subdivided into subfactors, which group similar disorders based on rates of comorbidity and likely a degree of shared etiology (Kotov et al., 2017; Perkins et al., 2020). Our distal outcome analyses revealed that all classes were significantly different than each other in anxiety sensitivity, depression, and PTSD symptoms, which are all classified under Internalizing Distress. Similarly, alcohol abuse, drug abuse, and aggressive behaviors all fall under the Disinhibited Externalizing category and follow the same pattern of significance, with Regulators having significantly fewer symptoms than all other classes. Food addiction symptoms, which differ between all classes except the Managers and Dwellers, would likely be classified under Internalizing Eating Pathology, but to our knowledge has not been addressed directly in the HiTOP model. In sum, our distal outcome findings support a hierarchical model of psychopathology by suggesting that increasing levels of emotion dysregulation may be a more salient risk factor for Internalizing Distress disorders than Disinhibited Externalizing disorders, and thus support the existence of these distinct classifications. While our results cannot provide insight into the specific mechanism underlying the association between emotion dysregulation patterns and psychological symptoms, one implication of these findings is that emotion dysregulation ought to be examined in future studies that aim to establish etiological pathways of the HiTOP spectra.

These findings bear substantial clinical implications. The association between emotion dysregulation and a range of internalizing and externalizing symptoms suggest that emotion regulation skills training for psychopathology could be an effective treatment for a variety of disorders in the context of trauma exposure. One such therapeutic method is Dialectic Behavioral Therapy (DBT), which aims to decrease emotion dysregulation and promote adaptive emotion regulation skills (Dimeff & Linehan, 2001). Numerous treatment studies support the use of DBT skills training transdiagnostically to address emotion dysregulation (Neacsiu et al., 2014; Ritschel et al., 2015). Notably, because our analysis utilizes self-report measures of psychiatric symptoms in a non-clinical sample, these results suggest that improving emotion regulation may also benefit those who are not diagnosed with psychiatric disorders. Further, these findings suggest that survivors of childhood abuse and neglect are at risk of more problematic emotion dysregulation patterns in adulthood. As such, early interventions that aim to improve emotion regulation may improve mental health outcomes in this population. Another promising avenue is mindfulness-based interventions, which target emotion dysregulation and could be implemented in diverse settings (behavioral health clinics, schools, primary care clinics) and across development through the lifespan (Gratz & Tull, 2010; Guendelman et al., 2017; Sibinga et al., 2011; Gawande et al., 2019). In sum, assessing and targeting emotion dysregulation may improve treatment for a range of psychopathological symptoms.

There are a number of limitations that ought to be considered given the nature of our data and analytic methods. First, this study was retrospective and cross-sectional in design. As such, we are unable to determine whether there are any causal relations between childhood maltreatment and emotion dysregulation or between emotion dysregulation and distal outcomes. Furthermore, this study utilized self-report measures rather than in-depth clinical interviews, meaning the results show differences in reported psychological symptoms between classes but whether or not these profiles experience different rates of psychological disorders remain unknown. While the current study suggests a relation between these variables, future studies may consider utilizing longitudinal data collection methods and clinical interviews in order to examine the pathway underlying the association between childhood trauma, emotion dysregulation profiles, and psychopathology. Second, the data-driven nature of LPA lends itself to model overfitting, which may limit the generalizability of our findings (Lanza & Rhoades, 2013; Nylund et al., 2007). Although our data is from a group underrepresented in clinical psychology research (e.g., Black women, lower socioeconomic status), the demographic composition may limit generalizability. While our findings are generally aligned with previous LPA studies, more research in diverse, trauma-exposed adult samples is necessary to corroborate our four-class solution characterized primarily by emotion dysregulation severity. Third, our analyses examine each distal outcome independently and does not take into account the frequent co-morbidity between psychiatric symptoms. There are high rates of comorbidity across psychiatric disorders, which suggest that psychopathological symptoms may be underlaid by a common etiology (Capsi et al., 2020; Kelly & Dalley, 2013). Novel classifications that use dimensional structures to model the relationship between symptom profiles may benefit from research using person-centered to uncover transdiagnostic risk factors (Cowan & Mittal, 2020). However, due to the nature of LPA, which examines each distal outcome separately, patterns of comorbidity were not examined in the current study. Thus, the relationship between patterns of emotion dysregulation and symptom profiles remains to be known.

Despite these limitations, our findings contribute to the current emotion dysregulation literature by identifying distinct profiles that are predicted by experiences of childhood maltreatment and that differ in terms of psychological symptomatology. By using person-centered analyses to examine several dimensions of emotion dysregulation in a sample of trauma exposed, primarily Black women, we were able to identify profiles characterized mainly by dysregulation severity. Given that these groups varied in terms of psychological symptoms, and that the patterns of significance were largely aligned with the HiTOP models of psychopathology, our results suggest that emotion dysregulation profiles may be important risk and resilience factors for a variety of psychological disorders. Moreover, exposure to childhood maltreatment, especially sexual and emotional abuse, predicted profile membership, with profiles characterized by greater dysregulation reporting more severe maltreatment. Taken together, our analyses aim to advance the emotion dysregulation literature towards a more complete understanding of how emotion dysregulation facets co-occur within individuals and relate to mental health outcomes, and how childhood maltreatment may inform these patterns. In order to improve treatment outcomes for internalizing and externalizing symptoms, patterns of emotion dysregulation ought to be considered, thoroughly assessed, and included as a target for treatment.

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Table 1

Demographics by Sample and Classs

	Total Sample	Regulators	Managers	Dwellers	Dysregulators
n	783	332	269	132	50
Sample (%)	100	42.4	34.4	16.9	6.4
Age					
Range	18-65	18-65	18-65	19-65	20-59
Mean *(SD)*	41.0 *(12.26)*	41.1 *(12.32)*	42.4 *(12.61)*	41.08 *(11.60)*	40.92 *(11.74)*
Gender (%)					
Women	93.0	94.0	90.0	94.7	98.0
Men	7.0	6.0	10.0	5.3	2.0
Race (%)					
Black	96.8	96.7	96.6	97.0	98.0
White	0.6	0.6	0.7	0.8	0.0
Other	2.5	2.7	2.7	2.2	2.0
Education (%)					
Less than 12th	18.3	14.2	20.4	22.7	22.0
High School Graduate	35.0	30.8	40.1	34.8	36.0
College, Technical Sc	46.7	55.0	39.4	42.4	42.0
Monthly Household Income (%)					
> $249	14.2	10.8	17.7	16.3	12.8
$250 - 499	7.1	6.5	8.3	4.7	10.6
$500 - 999	24.8	25.4	23.7	28.7	17.0
$1000 - 1999	30.7	31.6	29.3	28.7	38.3
< $2000	23.1	25.7	21.1	21.7	21.3
Overall Number of Traumas					
Range	0-17	0-14	0-15	0-17	1-16
Mean *(SD)*	5.36 (*3.44)*	4.32 *(3.20)*	5.61 *(3.14)*	6.56 *(3.51)*	7.76 *(3.86)*

Table 2

Summary of Correlations Between Emotion Dysregulation Subscales and Distal Outcomes

	Mean	Range	*SD*	Reliability	Anxiety Sensitivity (ASI)	Depression (BDI-II)	PTSD (PSS)	Food Addiction (YFAS)	Alcohol Abuse (AUDIT)	Drug Abuse (DAST)	Aggression (BQ-S)	CTQ Total	Sexual Abuse (CTQ)	Physical Abuse (CTQ)	Emotional Abuse (CTQ)	Emotional Neglect (CTQ)	Physcial Neglect (CTQ)
DERS Total	72.89	36-165	24.41	.94	.54*	.67*	.48*	.38*	.24*	.25*	.27*	.36*	.29*	.23*	.34*	.34*	.24*
Nonacceptance (DERS)	1.90	1-5	.92	.88	.47*	.55*	.41*	.31*	.19*	.21*	.16*	.31*	.29*	.19*	.30*	.25*	.20*
Goals (DERS)	2.37	1-5	.98	.83	.47*	.55*	.42*	.31*	.26*	.25*	.27*	.33*	.24*	.21*	.30*	.30*	.26*
Impusle (DERS)	1.88	1-5	.86	.85	.36*	.52*	.37*	.27*	.23*	.25*	.34*	.28*	.22*	.17*	.26*	.25*	.18*
Awareness (DERS)	2.23	1-5	.83	.73	.23*	.33*	.18*	.18*	.09*	.05	.09*	.16*	.10*	.11*	.15*	.18*	.10*
Strategies (DERS)	1.90	1-5	.82	.87	.50*	.63*	.46*	.33*	.18*	.22*	.23*	.34*	.28*	.20*	.32*	.31*	.21*
Clarity (DERS)	1.96	1-5	.82	.77	.44*	.55*	.37*	.36*	.18*	.18*	.17*	.27*	.20*	.18*	.25*	.28*	.16*

Note: *$p < .05$. DERS = Difficulties with Emotion Regulation, ASI = Anxiety Sensitivity Index, BDI-II = Beck Depression Inventory-II, PSS = Modified PTSD Scale, YFAS = Yale Food Addiction Scale, AUDIT = Alcohol Use Disorders Identification Test, DAST = Drug Abuse Screening Test, BQ-S = Behavior Questionnaire-Short

Table 3

LPA Fit Indices

k	LL	*npar*	AIC	BIC	CAIC	SABIC	SIC	AWE	VLMR-LRT	BLRT	cmP	Entropy
1	-6010.53	*12*	12045.053	12101.011	12129.01	12062.905	-6050.5055	12236.460	-	-		-
2	-5170.158	19	10378.316	10466.916	10510.66	10406.581	-5233.458	10680.50	<.01	<01	0	0.887
3	-4865.711	26	9783.422	9904.663	9964.15	9822.1	-4952.3315	10196.385	0.0165	<01	0.145846806	0.867
4	**-4760.082**	**33**	**9586.165**	**9740.048**	**9815.28**	**9635.256**	**-4870.024**	**10109.905**	**0.0457**	**<01**	**0.188547462**	**0.848**
5	-4701.292	40	9482.584	9669.11	9760.09	9542.09	-4834.555	10117.103	0.6063	<01	0.206948574	0.86
6	-4643.707	47	9381.414	9600.581	9707.31	9451.333	-4800.2905	10126.712	0.3799	<01	0.224724799	0.857
7	-4602.638	54	9313.276	9565.085	9687.56	9393.608	-4782.5425	10169.352	0.1693	<01	0.233932359	0.856

Note. Loglikelihood (LL), Number of free parameters (*npar*), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Consistent Akaike Information Criterion (CAIC), Sample-Size Adjusted Bayesian Information (SABIC), Approximate Weight of Evidence Criterion (AWE), the Vuong-Lo-Mendell-Rubin Likelihood Ratio Test p-value (VLMR-LRT), the BLRT p-value (bootstrapped LRT), and entropy (Asparouhov & Muthén, 2008, 2012; Nylund et al., 2007, Maysn, 2013), Schwarz Information Criterion (SIC), correct model probability (cmP). Smaller approximate fit indices, including the AIC, CAIC, BIC, SABIC, and AWE indicate superior model fit (D'Unger, Land, McCall, & Nagin, 1998; Nylund-Gibson & Choi, 2018).

Table 4

Predictor and distal outcome means and standard deviations

		Total Sample	Regulators	Managers	Dwellers	Dysregulators
	CTQ Total	43.77 *(19.32)*	36.57 *(16.45)*	46.08 *(17.59)*	52.23 *(20.79)*	56.62 *(23.20)*
	Sexual Abuse	9.15 *(5.96)*	7.51 *(4.67)*	9.34 *(6.03)*	11.50 *(6.65)*	12.88 *(7.52)*
Predictors	Physical Abuse	8.33 *(4.19)*	7.27 *(3.85)*	8.86 *(4.08)*	9.44 *(4.28)*	9.59 *(5.04)*
Means *(SD)*	Emotional Abuse	9.63 *(5.20)*	7.75 *(4.34)*	10.29 *(4.81)*	11.84 *(5.86)*	12.71 *(6.09)*
	Physical Neglect	9.91 *(5.29)*	6.12 *(2.66)*	7.04 *(3.09)*	7.52 *(3.13)*	8.34 *(4.40)*
	Emotional Neglect	6.81 *(3.10)*	8.06 *(4.60)*	10.57 *(5.03)*	11.96 *(5.56)*	13.13 *(5.92)*
	Anxiety Sensitivity (ASI)	28.56 *(15.74)*	19.85 *(12.49)*	33.53 *(14.73)*	39.27 *(13.77)*	49.23 *(15.07)*
	Depression (BDI-II)	17.17 *(12.26)*	8.94 *(7.58)*	19.68 *(10.28)*	27.84 *(11.47)*	35.55 *(11.20)*
Distal Outcome	PTSD (PSS)	15.49 *(12.54)*	9.53 *(10.34)*	17.887*(11.75)*	22.07 *(12.15)*	32.29 *(11.04)*
Means *(SD)*	Food Addiction (YFAS)	2.54 *(1.74)*	1.77 *(1.26)*	2.84 *(1.71)*	2.98 *(1.93)*	4.14 *(2.12)*
	Alcohol Abuse (AUDIT)	7.14 *(8.29)*	4.66 *(6.15)*	8.65 *(9.05)*	9.68 *(9.46)*	9.55 *(9.66)*
	Drug Abuse (DAST)	1.83 *(2.47)*	1.06 *(1.73)*	2.24 *(2.72)*	2.60 *(2.98)*	2.93 *(2.63)*
	Aggression (BQ-S)	4.54 *(3.56)*	3.39 *(3.08)*	5.086 *(3.61)*	5.81 *(3.70)*	6.33 *(3.78)*

Note: CTQ = Childhood Trauma Questionnaire, BDI-II = Beck Depression Inventory-II, PSS = Modified PTSD Scale, YFAS = Yale Food Addiction Scale, AUDIT = Alcohol Use Disorders Identification Test, DAST = Drug Abuse Screening Test, BQ-S = Behavior Questionnaire-Short

Table 5

Childhood Maltreatment as Predictors of Class Membership

	Estimate	SE	*p* Value	OR
Total Abuse/Neglect				
Regulators vs. Managers	.05	.01	.00	1.05
Regulators vs. Dwellers	.06	.01	.00	1.06
Regulators vs. Dysregulators	.07	.01	.00	1.07
Managers vs. Dwellers	.01	.01	.06	1.01
Managers vs. Dyregulators	.02	.01	.01	1.02
Dwellers vs. Dysregulators	.01	.01	.26	1.01
Sexual Abuse				
Regulators vs. Managers	.08	.02	.00	1.08
Regulators vs. Dwellers	.13	.02	.00	1.14
Regulators vs. Dysregulators	.15	.03	.00	1.17
Managers vs. Dwellers	.05	.02	.01	1.05
Managers vs. Dyregulators	.08	.02	.00	1.08
Dwellers vs. Dysregulators	.03	.03	.33	1.03
Emotional Abuse				
Regulators vs. Managers	.16	.04	.00	1.17
Regulators vs. Dwellers	.20	.03	.00	1.22
Regulators vs. Dysregulators	.23	.04	.00	1.25
Managers vs. Dwellers	.04	.02	.05	1.04
Managers vs. Dyregulators	.07	.03	.02	1.07
Dwellers vs. Dysregulators	.02	.03	.44	1.02
Physical Abuse				
Regulators vs. Managers	.18	.08	.03	1.20
Regulators vs. Dwellers	.19	.07	.01	1.21
Regulators vs. Dysregulators	.20	.07	.01	1.22
Managers vs. Dwellers	.01	.03	.79	1.01
Managers vs. Dyregulators	.02	.04	.68	1.02
Dwellers vs. Dysregulators	.01	.04	.83	1.01
Emotional Neglect				
Regulators vs. Managers	.14	.03	.00	1.15
Regulators vs. Dwellers	.18	.03	.00	1.19
Regulators vs. Dysregulators	.21	.04	.00	1.23
Managers vs. Dwellers	.04	.02	.09	1.04
Managers vs. Dyregulators	.07	.03	.01	1.07
Dwellers vs. Dysregulators	.03	.03	.26	1.03
Physical Neglect				
Regulators vs. Managers	.18	.07	.01	1.20
Regulators vs. Dwellers	.21	.06	.00	1.23
Regulators vs. Dysregulators	.26	.07	.00	1.30
Managers vs. Dwellers	.02	.03	.49	1.02
Managers vs. Dyregulators	.08	.04	.06	1.08
Dwellers vs. Dysregulators	.06	.04	.19	1.06

Note.These values were calculated using the 3-step approach recommended by Asparouhov and Muthén (2014). Regression coefficients (estimates) were converted into odds ratios to determine the likelihood that a person with a particular characteristic wouldbe classified in to a particular profile.

Table 6

Chi-Square Estimates for Equality Tests of Means Across Classes

	Anxiety Sensitivity (ASI)	Depression (BDI-II)	PTSD (PSS)	Food Addiction (YFAS)	Alcohol Abuse (AUDIT)	Drug Abuse (DAST)	Aggression (BQ-S)
n	658	765	694	471	724	721	715
Overall Test	346.87*	631.87*	248.49*	93.33*	60.50*	66.83*	71.15*
Regulators vs. Managers	138.07*	222.43*	79.64*	46.10*	36.31*	36.18*	35.66*
Regulators vs. Dwellers	159.23*	312.29*	91.46*	26.67*	27.68*	28.92*	38.24*
Regulators vs. Dysregulators	188.78*	274.60*	153.02*	46.70*	11.16*	15.85*	22.38*
Managers vs. Dwellers	12.07*	49.57*	8.62*	0.30	0.95	1.32	2.92
Managers vs. Dysregulators	49.98*	90.64*	56.10*	13.04*	0.34	2.01	3.75
Dwellers vs. Dysregulators	16.71*	17.46*	23.00*	8.48*	0.01	0.37	0.56

Note. *$p < .05$. ASI = Anxiety Sensitivity Index, BDI-II = Beck Depression Inventory-II, PSS = Modified PTSD Scale, YFAS = Yale Food Addiction Scale, AUDIT = Alcohol Use Disorders Identification Test, DAST = Drug Abuse Screening Test, BQ-S = Behavior Questionnaire-Short

Figure 1

Plot of estimated means of emotion dysregulation subscales by class

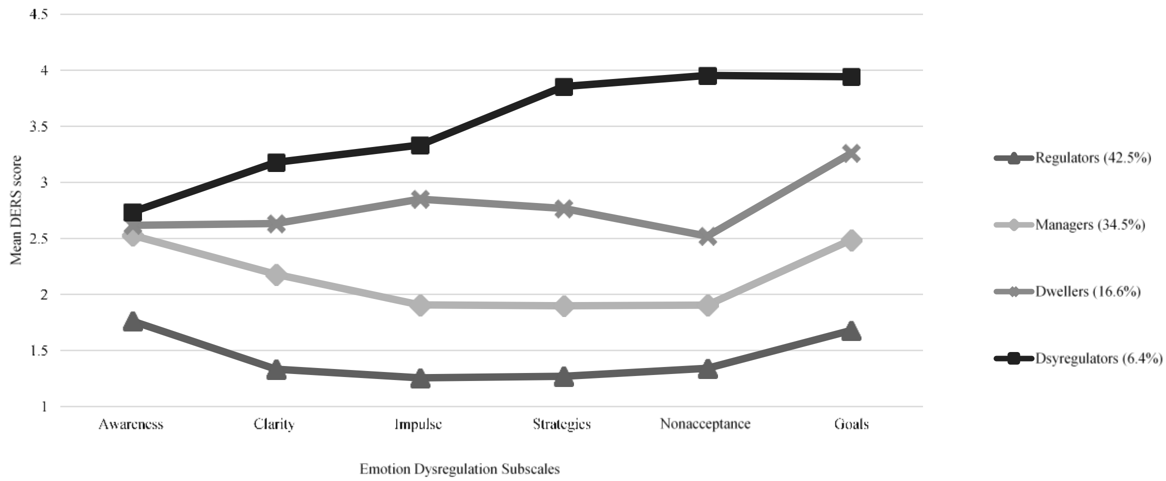
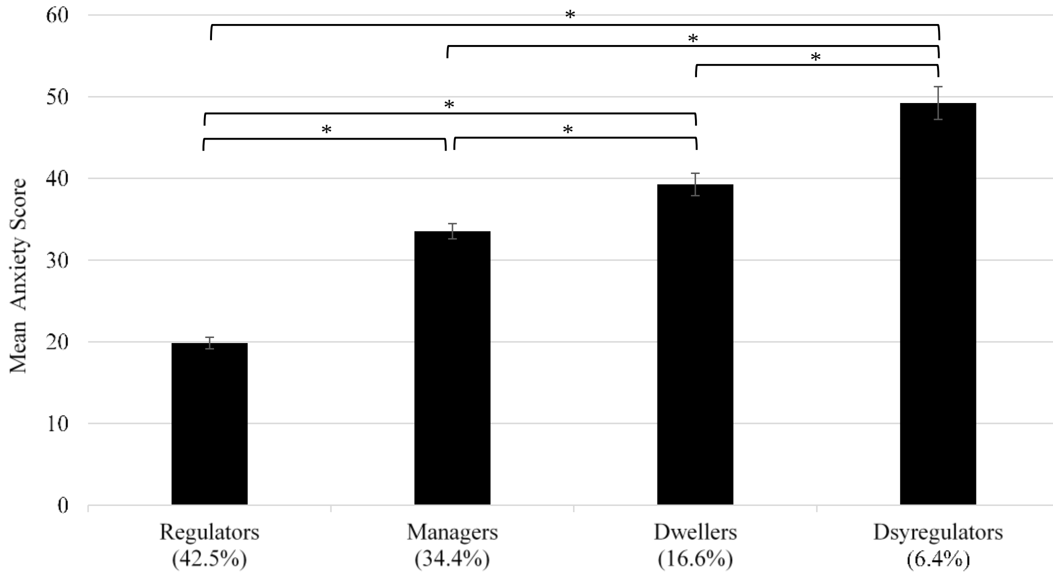


Figure 2a

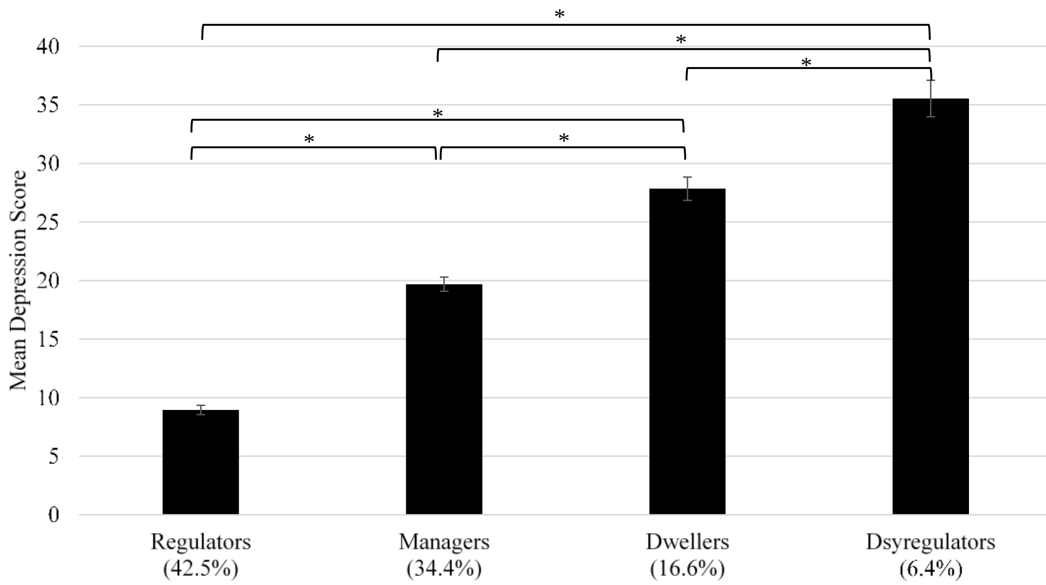
Anxiety sensitivity scores based on latent profile membership (% of sample)



Note. *p < .05

Figure 2b

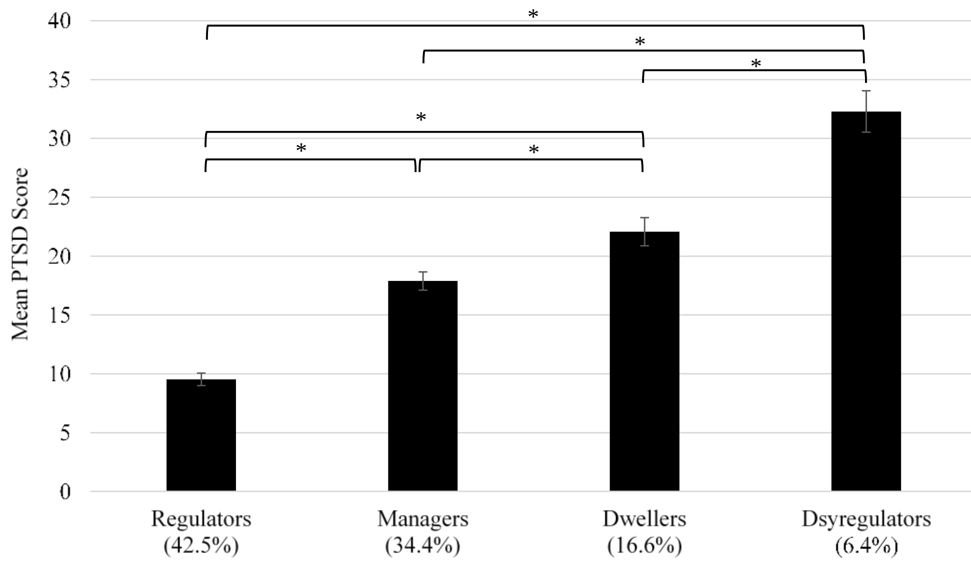
Depressive symptom scores based on latent profile membership (% of sample)



Note. $*p < .05$

Figure 2c

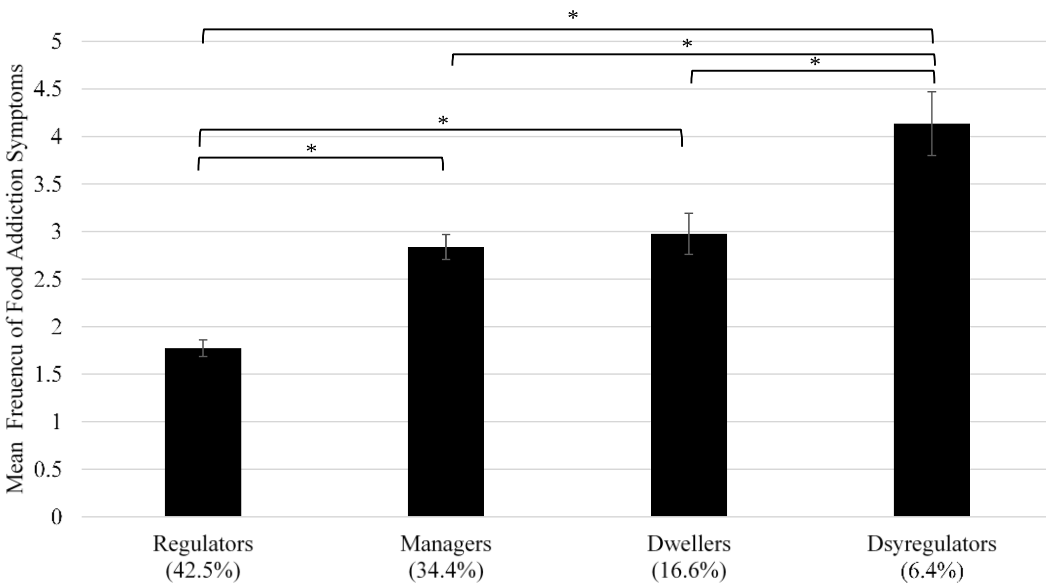
PTSD symptom scores based on latent profile membership (% of sample)



Note. **p* < .05

Figure 2d

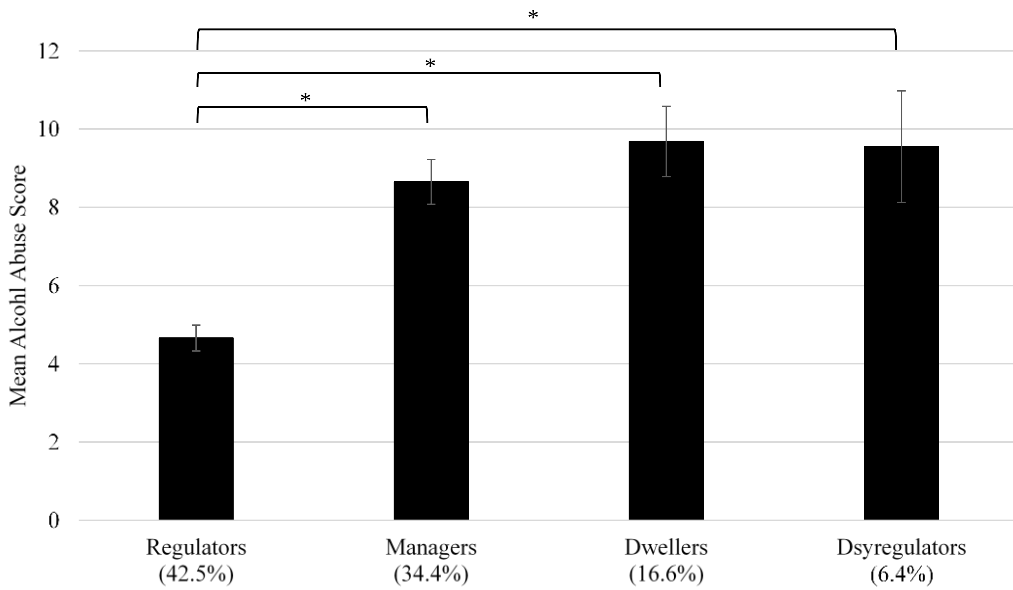
Food addiction symptom scores based on latent profile membership (% of sample)



Note. *p < .05

Figure 2e

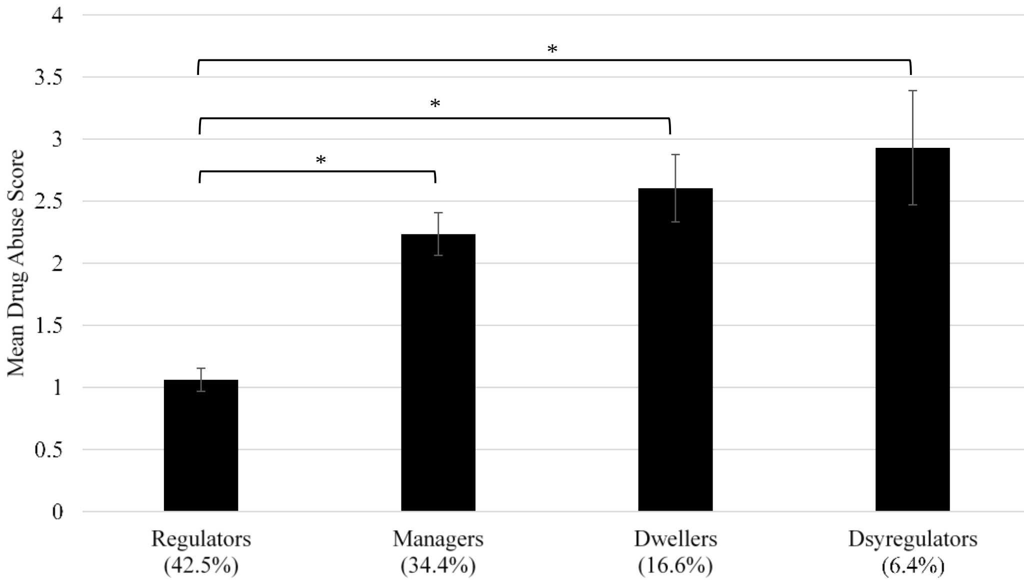
Alcohol abuse symptom scores based on latent profile membership (% of sample)



Note. *p < .05

Figure 2f

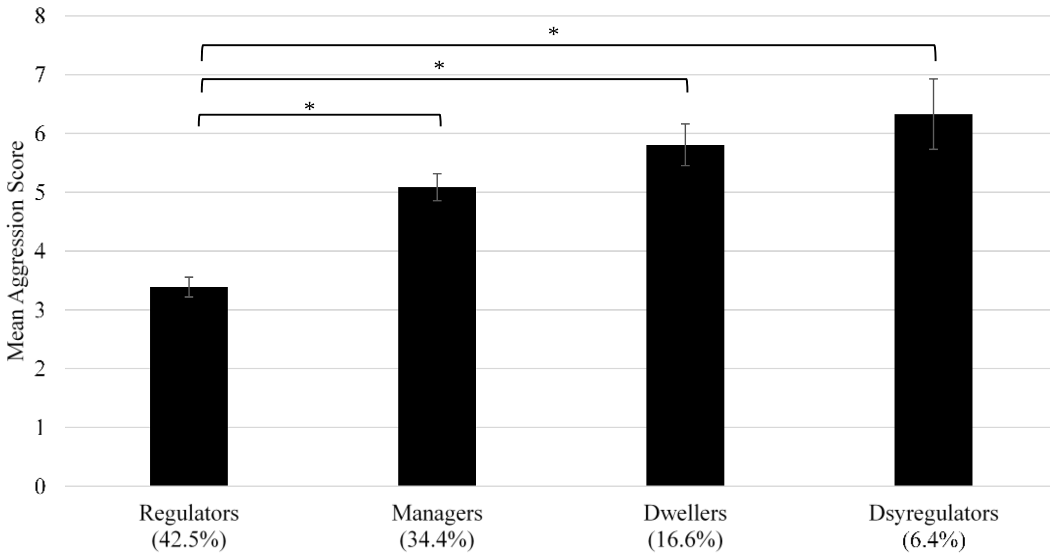
Drug abuse symptom scores based on latent profile membership (% of sample)



Note. *p < .05

Figure 2g

Aggressive behavior scores based on latent profile membership (% of sample)



Note. *p < .05

Supplementary Table 1

Summary of findings of latent class solutions of emotion dysregulation and related symptoms

Study	Sample	Emotion regulation as LPA/LCA indicators		Mental health outcomes measured			
Sample size and characteristics		Number of indicators	Indicators	Number of outcomes	Distal outcomes	Class solution	Nature of classes
Brewer et al., 2016	1568 College students 72.1% white, 68.8% female	2	2 emotion regulation strategies: cognitive reappraisal and affective supression (ERQ; Gross & John, 2003)	6	Psychosocial wellbeing, psychological distress, cognitive strength and wellbeing, social wellbeing	4	Well-adjusted (31.1%, high levels of all positive outcomes and low levels of all negative outcomes) Average (41.6%, near-average levels of all psychosocial adjustment outcome) Coping with Distress (15.0%, high in active-emotional coping and avoidant coping) Maladjusted (12.2%, low levels of all positive outcomes and high levels of all negative outcomes)
Chesney et al., 2019	176 College students 80.1% white, 83% female	6	6 emotion regulation subscales: acceptance (DERS; Gratz & Roemer, 2004), cognitive reappraisal, expressive suppression (ERQ; Gross & John, 2003), problem solving, avoidance, (CRI; Moos, 1993), rumination (CERQ; Garnefski & Kraaij, 2006a)	2	Depression, anxiety	4	Adaptive (46.0%, high levels of positive emorion regulation strategies and low negative emotion regulation strategies) Accepting with Suppression (40.3%, regulated via acceptance and expressive suppression) Non-accepting (10.2%, low acceptance with moderately high use of avoidance and rumination) Maladaptive (3.41%, high on avoidance, expressive suppression, and rumination, and low acceptance, cognitive reappraisal, and problem solving)
Dixon-Gordon et al., 2015	531 College students 69.1% white, 73.6% female	6	6 emotion regulation stretegies: acceptance, cognitive reappraisal, problem solving, experiencial avoidance, expressive suppression, self-criticsm, worry/rumination (internally derived measure)	5	Anhedonic depression, anxious arousal, fear of negative evaluation, borderline personality symptoms, disordered eating	5	Low Regulators (31.6%, low use of all strategies) Worriers/Ruminators (18.1%, excessive use of worrying and rumination) Avoiders (5.27%, excessive use of expressive suppression and experiential avoidance) Adaptive Regulators (18.6%, relatively higher use of adaptive strategies) High Regulators (26.4%, high use of all strategies)
Grommisch et al., 2019	179 Community sample 65% women	9	9 momentary emption regulation strategies: situation selection, situation modification, distraction, rumination, reappraisal, acceptance, suppression, social sharing, ignoring (internally derived measure)	6	Life satisfaction, depression, anxiety, stress, pleasant affect, unpleasant affect	5	C1: "diversity of profiles (suppression focus)" (29.1%) C2: "diversity of profiles (active regulation focus)" (25.1%) C3: "predominantly multi-ER (moderate level) profile" (24.5%) C4: "predominantly no ER profile" (12.9%) C5: "predominantly multi-ER (high level) profile" (8.4%)
Lougheed & Hollenstein, 2012	177 Adolecents 75% white, 52% female	5	5 emotion regulation strategies: reappraisal, suppression, concealing, emotional engagement, adjusting (ERQ; Gross & John, 2003), (ASQ; Hofmann & Kashdan, 2010), (DERS; Gratz & Roemer, 2004)	3	Depression, anxiety, social anxiety	6	Average Strategy Use (31.6%, scores on all indicators within 1 SD of the sample means) Adjustment Propensity (31.1%, high on adjusting) Suppression Propensity (19.2%, high on suppression) Concealing/Suppression (2.8%, high on both suppression and concealing) Emotionally Disengaged (10.7%, low on emotional engagement No Strategies (4.5%, low on all five indicators)
Suh et al., 2020	194 College students 64.4% women	11	6 emotion regulation subscales: clarity, awareness, strategies, impulsive, non-acceptance, goal-directed (DERS; Gratz & Roemer, 2004) 5 mindfulness subscales: observing, describing, acting with awareness, nonjudging of inner experience, and non-reactivity to inner experience (FFMQ; Baer et al12)	1	Work–family–school conflict	3	Healthy (57.5%, high scores in all facets of mindfulness and low scores on all facets of difficulties in emotion regulation) Observant yet Judgemental (33.3%, high in observing and low on nonjudging of inner experience) Unhealthy without Strategies (9.2%, greatest emotion dysregulation and overall low mindfulness)
van Eck et al., 2017	627 College students 47% white, 60% female	10	6 emotion regulation subscales: clarity, awareness, strategies, impulsive, non-acceptance, goal-directed (DERS; Gratz & Roemer, 2004) 4 distress tolerance subscles: tolerance, appraisal, absorption, regulation (DTS; Simons and Gaher 2005)	7	Depressive symptoms, anxiety symptoms, suicidal ideation, ADHD symptoms, hostility, conduct problems, substance use	3	Functional (44%, least problems with emotion regulation and distress tolerance) At Risk (41%, moderate levels of deficits among emotion regulation and distress tolerance subscales) Challenges (15%, highest level of deficit severity)
Wong et al., 2013	560 Young adults at high risk for il	7	2 emotion regulation strategies: cognitive reappraisal and affective supression (ERQ; Gross & John, 2003) 7 coping strategies (Brief COPE; Carver, 1997)	2	Illicit drug use (age of first use, most recent use)	4	Suppressors (15%, overall highest endorsement of suppression) Others-reliant copers (27% of sample, emotional and instrumental support seeking) Self-reliant copers (27%, low endorsement of emotional and instrumental support seeking, and moderate to high endorsement of other coping and ER strategies) Active copers (30% highest on reappraisal, high on all of the coping dimensions, including active coping, emotional and instrumental support seeking, positive reframing, and planning)

Supplemental Table 2

Summary of Correlations Emotion Dysregulation Subscales

		1	2	3	4	5	6
1	DERS Total	-					
2	Nonacceptance	.78*	-				
3	Goals	.78*	.54*	-			
4	Impusle	.83*	.55*	.66*	-		
5	Awareness	.57*	.24*	.26*	.33*	-	
6	Strategies	.90*	.69*	.69*	.74*	.37*	-
7	Clarity	.80*	.55*	.51*	.56*	.56*	.63*

Note: **p* < .05. DERS = Difficulties with Emotion Regulation