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Cognitive Mechanisms Influencing Facial Emotion Processing in Psychopathy and Externalizing

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Psychopathy and externalizing are distinct forms of disinhibitory psychopathology whose destructive social behaviors are thought to be underpinned by different aberrations in social cognition. Facial emotion processing is a foundational component of social cognition, yet previous studies on facial emotion processing in psychopathy and externalizing have focused on traditional behavioral measures (e.g., response accuracy), which have limited reliability and precision. Diffusion modeling is a valuable tool for elucidating more reliable and precise sources of performance differences because it estimates parameters that reflect latent cognitive processes, including bias, drift rate (efficiency of evidence accumulation), threshold separation (extent of evidence accumulation), and nondecision time (time spent on non–decision-related processes such as stimulus encoding and motor response execution). In a sample of 92 incarcerated males, we applied diffusion modeling to an emotion identification task in which ambiguous blends of anger, happiness, and fear were identified while contextual threat (i.e., apparent movement of faces) was manipulated. Results indicated that psychopathy was associated with longer nondecision time (i.e., slower processing) across all the emotion blends in the task and particularly for mostly angry faces under greater ambiguity. In direct contrast, externalizing was associated with shorter nondecision time (i.e., faster processing) as well as greater threshold separation (i.e., more extensive evidence accumulation) for mostly angry faces under greater ambiguity, but this pattern of preferential processing of anger was only evident in the absence of contextual threat. These findings link psychopathy and externalizing to different profiles of cognitive processes influencing facial emotion processing.

Keywords: psychopathy, externalizing, facial emotion processing, diffusion modeling, social threat

Supplemental materials: https://doi.org/10.1037/per0000473.supp

Disinhibitory psychopathology refers to a class of syndromes characterized by poor impulse control, tendencies toward risk-taking, and antisocial behavior (Gorenstein & Newman, 1980). Two forms of disinhibitory psychopathology are psychopathy and externalizing. Psychopathy is typified by a combination of core personality traits such as manipulative interpersonal orientation and shallow affect (i.e., Factor 1), as well as impulsive behavior and a chronic antisocial lifestyle (i.e., Factor 2; Hare et al., 1990). Although externalizing overlaps with psychopathy's impulsive and antisocial features, externalizing is a latent construct that reflects the shared variance among externalizing disorders (e.g., substance use disorders) and traits (e.g., low constraint; Krueger et al., 2002). Psychopathy and externalizing are associated with elevated rates of aggressive behavior toward others (Garofalo et al., 2020; Venables & Patrick, 2012) and conflict in relationships (Mager et al., 2014). Though often phenotypically similar, these destructive social behaviors are thought to be underpinned by distinct sets of social–cognitive aberrations. For example, some researchers theorize that aggression in psychopathy is driven by reduced sensitivity to cues of distress in others (e.g., signs of fear and sadness; see Blair et al., 2014, for review). In contrast, aggression in externalizing is thought to be driven by increased sensitivity to cues of threat in others (e.g., signs of anger; Blair et al., 2014). To investigate social cognition in psychopathy and externalizing, a substantial body of research has focused on facial emotion processing.

Research on facial emotion processing in psychopathy has yielded mixed findings. Some studies identified specific impairments in the recognition of emotions signaling distress (i.e., sadness and fear; Blair et al., 2004; Fairchild et al., 2009). Other studies suggested that psychopathy is associated with global, not specific, impairments in facial emotion recognition (see Dawel et al., 2012). Finally, some studies reported no evidence of impairments (see Brook et al., 2013, for review; Glass & Newman, 2006). Thus, important questions remain regarding the precise nature of facial emotion processing aberrations in psychopathy.

Although no research has examined facial emotion processing as it relates to externalizing as a latent construct, findings from studies on specific externalizing disorders coalesce around a general pattern. Research suggests that various manifestations of externalizing are associated with an increased likelihood of identi-

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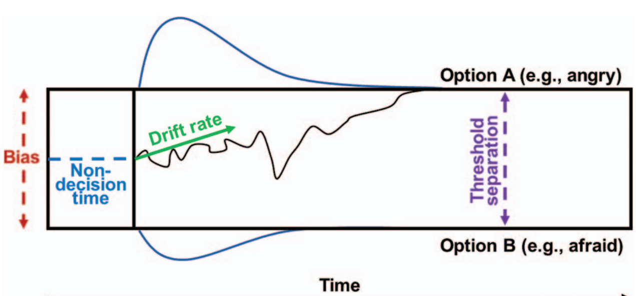
fying negative emotions in faces, particularly emotions signaling social threat (i.e., anger; Best et al., 2002; Dadds et al., 2006; Daros et al., 2014; Freeman et al., 2018; Leist & Dadds, 2009). Overall, externalizing appears to relate to hypervigilance for and hypersensitivity to social threat.

Many studies have examined facial emotion processing in psychopathy and externalizing. However, most use response accuracy, or the proportion of trials on which a participant "correctly" identifies the emotion displayed in a series of faces, and some use reaction times (RTs), or the average amount of time a participant takes to identify the emotion displayed in a series of faces, as the key outcomes. These traditional behavioral measures are increasingly recognized as having limited reliability and sensitivity to detect underlying sources of performance differences (Evans & Britton, 2018; White et al., 2010).

Computational approaches, such as diffusion modeling (DM; Voss et al., 2015), represent promising tools for elucidating more reliable sources of performance differences with regard to facial emotion processing (Brennan & Baskin-Sommers, 2020). DM, which is rooted in decision-making theory (Ratcliff, 1978), is based on the premise that decisions are made by accumulating evidence until one of two response thresholds is reached, at which point the corresponding response is made (see Figure 1; Ratcliff & McKoon, 2008). Within the diffusion model, several cognitive processes influence decision-making. First, bias refers to the starting point of the decision-making process; if the process begins closer to one response threshold versus the other, the decision-maker is said to be biased toward that response option. Second, drift rate refers to the rate at which evidence is accumulated; decision-makers with higher drift rate toward one response threshold are more efficient at accumulating evidence supporting that response option (i.e., quicker without a decrement in accuracy). Threshold separation refers to the amount of evidence accumulated for a decision. Decision-makers with lower threshold separation accumulate less evidence for a decision, resulting in faster responses and reduced accuracy. Finally, nondecision time refers to the amount of time spent on non–decision-related processes, namely, stimulus encoding and motor response execution. Identifying whether these cognitive processes contribute to facial emotion processing in psychopathy and externalizing could reveal novel mechanistic insights into social cognition in these forms of disinhibitory psychopathology, and help resolve ambiguities and inconsistencies, particularly in the psychopathy literature.

Figure 1

Schematic Representation of the Diffusion Model of Decision-Making



Note. The decision process begins at a starting point that may represent an a priori response bias toward either Option A or Option B (red). Evidence is accumulated for Option A or Option B, and drift rate represents the average rate of evidence accumulation (green). The amount of evidence accumulated for a decision is represented by threshold separation, the distance between the two thresholds (purple). Finally, the length of time taken for non–decision-related processes (e.g., encoding, motor execution) is represented by nondecision time (blue). The "noisy" black line represents the evidence accumulation process, whereas the dark blue curved lines above Option A and below Option B represent the RT distributions associated with each response. Parameter estimation is based on these RT distributions. See the online article for the color version of this figure.

Furthermore, although evidence suggests that facial emotion processing is influenced by contextual factors (Aviezer et al., 2017), no research has investigated the impact of contextual threat, instated by manipulating the apparent movement of stimuli, on facial emotion processing in psychopathy and externalizing. For example, stimuli that appear to loom, or move closer, are perceived as more threatening and elicit more threat-related neural activity (Vieira et al., 2017), whereas stimuli that appear to recede, or move away, signal the absence of threat. There is preliminary evidence that psychopathic traits are associated with reduced neural responsiveness to looming stimuli (White et al., 2018), but no research has examined the impact of contextual threat on facial emotion processing in psychopathy. Similarly, no research has examined the impact of contextual threat on facial emotion processing in externalizing; however, previous research establishes that externalizing is associated with hyperreactivity in the context of threat (Baskin-Sommers et al., 2012), which leads to disruptions in cognitive processes (Baskin-Sommers & Newman, 2014). Thus, it is possible that contextual threat differentially impacts facial emotion processing in psychopathy versus externalizing.

The present study assessed the contributions of cognitive processes to facial emotion processing in psychopathy and externalizing using DM. The overarching goals of this approach were to advance the reliability of measures used to index facial emotion processing in psychopathy and externalizing and to derive profiles of cognitive processes influencing facial emotion processing in these forms of disinhibitory psychopathology. Additionally, we sought to characterize the impact of contextual threat on these cognitive processes. Following from evidence of intact facial emotion recognition accuracy but deficient processing of complex emotional information in psychopathy (Baskin-Sommers & Newman, 2014; Glass & Newman, 2006), we hypothesized that psychopathy would be associated with widespread disruptions to cognitive processes supporting facial emotion processing. Based on previous research (Leist & Dadds, 2009), we hypothesized that externalizing would be associated with heightened anger identification. Finally, based on evidence for hyperreactivity to threat in externalizing (Baskin-Sommers et al., 2012) and imperviousness to threat when it is not the primary focus of attention in psychopathy (Baskin-Sommers et al., 2011; White et al., 2018), we hypothesized that cognitive processes influencing facial emotion processing would be impacted by contextual threat in externalizing but not psychopathy.

Method

Participants

Participants were 98 men from a high-security correctional institution in Connecticut who ranged in age from 21 to 59 (M = 33.81, SD = 8.62). In terms of race, 60.2% of participants identified as Black, 36.7% identified as White, 1.0% identified as Asian, 1.0% identified as American Indian or Alaska Native, and 1.0% identified as multiracial. In terms of ethnicity, 19.4% of participants identified as Hispanic.

Before recruitment, study personnel received an institutional roster of inmates. Study personnel used this roster to review medical files and exclude individuals who had a history of psychosis or bipolar disorder, currently had mood or anxiety disorders, currently used psychotropic medication, had a family history of psychosis, had certain medical problems that could impede comprehension of or performance on the task (e.g., uncorrectable auditory or visual deficits, three or more serious head injuries), had an IQ below 70, or had a reading level below fourth grade. Then, individuals were selected randomly from the list of eligible inmates and invited to participate. Invited individuals were provided with information about study procedures and informed that any information collected during the study would remain confidential and would not affect their institutional or legal status in any way. They were informed that they could withdraw from the study at any time. All participants provided written informed consent. In keeping with Connecticut Department of Correction regulations, participants did not receive financial compensation.

After providing consent, participants completed an initial session that involved a series of clinical and neuropsychological assessments. Participants who did not meet eligibility thresholds (detailed earlier) on any of these assessments were excluded from further participation. After completing questionnaires assessing personality,[1] eligible participants returned for a second session in which they completed the experimental task (see Measures section in the following text). Both in-person sessions took place in a private testing space within the prison. The study protocol was approved by the Yale University Human Investigation Committee.

An a priori power analysis based on published studies on related topics (i.e., individual differences in facial emotion processing; Baskin-Sommers & Newman, 2014; Dawel et al., 2012) indicated that a sample size of approximately 90 participants would be sufficient to detect small- to medium-sized effects with 80% power. To ensure sufficient power to account for data loss due to invalid task performance, we collected data from 98 participants.

Measures

Psychopathy Checklist–Revised

The Psychopathy Checklist–Revised (PCL-R) is a measure of psychopathy that uses information gleaned from an interview and a review of institutional files to score individuals on 20 items (e.g., glibness/superficial charm, shallow affect, impulsivity, poor behavior controls; Hare, 2003). Interviewers score each item from 0 to 2, with 0 indicating that the item does not apply to the individual, 1 indicating that the item applies to a certain extent, and 2 indicating that the item applies to the individual. Scores can range from 0 to 40, with higher scores indicating higher resemblance to a prototypical psychopath. The reliability and validity of the PCL-R are well established (see Hare, 2003; Hare et al., 1990). In this study, reliability ratings were available for 14 randomly selected participants (interrater reliability = .99).

Multidimensional Personality Questionnaire–Brief Form

The Multidimensional Personality Questionnaire–Brief Form (MPQ-BF) is a 155-item self-report measure of personality that consists of 11 primary trait scales that converge into three higher order factors: Negative Emotionality (NEM), Positive Emotionality, and Constraint (CON; Patrick et al., 2002). The NEM factor is characterized by stress reactivity, aggression, and alienation. The CON factor is characterized by control, harm avoidance, and conformity to social norms. Both high NEM and low CON (i.e., impulsivity, low harm avoidance, and disinhibition) are related to externalizing tendencies (Eisenberg et al., 2000; Krueger et al., 2000; Miller et al., 2003). Following previous research (Baskin-Sommers et al., 2012), our measure of externalizing was calculated by subtracting CON from NEM (i.e., NEM−CON), such that higher scores represented higher NEM and lower CON, and thus higher levels of externalizing.

There are multiple approaches to measuring externalizing, and currently there is no consensus regarding a gold standard measure of externalizing. Despite the labeling of the MPQ-BF NEM factor (which measures aggression, alienation, and stress reactivity), it is worth noting that, according to other measures of personality, aggression falls under the domain of antagonism rather than negative emotionality or neuroticism; thus, the NEM factor is not a “pure” measure of negative emotionality and includes some elements of antagonism as well. Whereas antagonism is generally agreed to be a core element of externalizing, other measures of externalizing do not focus as heavily on the stress reactivity and alienation constructs that are included in the NEM factor. Given these differences across externalizing measures, we evaluated the extent to which our measure of externalizing (i.e., NEM−CON) aligned with a measure of externalizing that does not tap stress reactivity and alienation and conducted additional analyses to examine the validity of NEM−CON as a measure of externalizing. First, we calculated an alternative measure that is the average of the MPQ-BF scales of aggression, reverse-scored control (i.e., impulsivity), reverse-scored harm avoidance, and reverse-scored traditionalism (i.e., low social norm conformity). The correlation between NEM−CON and this alternative externalizing measure was very strong, $r(90)$ = .91. Second, we examined correlations between NEM−CON (as well as the alternative externalizing measure, for comparison) and external criterion variables and found that both NEM−CON and the alternative externalizing measure exhibited significant positive correlations with each external criterion variable. In most cases, however, NEM-CON appeared to exhibit stronger correlations than the alternative externalizing measure with external criterion variables (see Table 1). Finally, we conducted all of our main analyses using another established measure of externalizing, the Disinhibition scale of the MPQ-Tri (see Supplemental Results and Table S2 in the online

[1] Three participants did not complete the personality questionnaires and were thus excluded from analyses.

Table 1
Zero-Order Correlations Between Two Measures of Externalizing (NEM−CON and an Alternative Measure of Externalizing) and External Criterion Variables

External criterion variable	Correlations with each externalizing measure	
	NEM−CON	Alternative EXT measure
PCL-R Psychopathy Factor 2	.428*	.407*
MPQ-Tri Disinhibition	.843*	.689*
CD symptoms	.304*	.281*
APD symptoms	.324*	.392*
RISQ lifetime drug misuse	.308*	.371*
RISQ lifetime alcohol misuse	.236*	.245*
AQ anger	.492*	.432*
RPQ reactive aggression	.478*	.454*

Note. NEM−CON = Multidimensional Personality Questionnaire–Brief Negative Emotionality minus Constraint (i.e., the externalizing measure used in the present study); Alternative EXT measure = a score consisting of the average of the Multidimensional Personality Questionnaire–Brief scales of Aggression, reverse-scored Control (i.e., Impulsivity), reverse-scored Harm Avoidance, and reverse-scored Traditionalism (i.e., Disinhibition); PCL-R = Psychopathy Checklist–Revised; MPQ-Tri = Triarchic Psychopathy scales derived from the Multidimensional Personality Questionnaire–Brief Form (Brislin et al., 2015); CD = conduct disorder; APD = antisocial personality disorder; RISQ = Risky, Impulsive, and Self-Destructive Behavior Questionnaire (Sadeh & Baskin-Sommers, 2017); AQ = Buss-Perry Aggression Questionnaire (Buss & Perry, 1992); RPQ = Reactive Proactive Questionnaire (Raine et al., 2006).
* $p < .05$.

supplemental materials; Brislin et al., 2015). Together, these analyses showed that NEM−CON demonstrated strong evidence of convergent validity, and all but one effect of NEM−CON was replicated using the Disinhibition scale of the MPQ-Tri.

Ambiguous Emotion Identification Task

Participants completed a two-alternative forced-choice task in which they identified the emotion displayed in a series of ambiguous emotional faces. The task is a valid measure of emotion identification ability (see Brennan & Baskin-Sommers, 2020).

Stimuli. Stimuli consisted of emotional face images from the Racially Diverse Affective Expression (RADIATE) face stimulus set (publicly available at http://fablab.yale.edu/page/assays-tools; Conley et al., 2018; Tottenham et al., 2009). Images of 39 different men of three racial/ethnic backgrounds (Black, White, and Hispanic) displaying anger, fear, and happiness were selected from the RADIATE set. The racial/ethnic composition of the face stimuli (i.e., 38.46% Black, 33.33% White, 28.21% Hispanic) roughly mirrored that found in our sample. Stimuli were generated by blending two images (each conveying a different emotion) of the same face using face morphing software (Abrosoft, 2018, Fantamorph Deluxe for Mac, Version 5.5.0) to create 70%–30% blends. The 70%–30% level of blending was chosen to achieve a moderate level of ambiguity (Schönenberg & Jusyte, 2014) and elicit variable but sufficiently high accuracy levels to provide data suitable for DM (Ratcliff & McKoon, 2008). Moderately ambiguous blends also helped prevent ceiling effects for accuracy levels, which have been implicated in previous studies' failure to detect effects of psychopathy on facial emotion identification (Dawel et al., 2012). Three types of emotion blends were created: anger–fear, anger–happiness, and fear–happiness. Anger, fear, and happiness are among the most commonly used emotional expressions in previous studies on emotion processing in disinhibitory psychopathology (Baskin-Sommers & Newman, 2014; Blair et al., 2004; Dawel et al., 2012). Within each blend, one of the two emotions served as the dominant (i.e., 70%) emotion, and the other emotion served as the nondominant (i.e., 30%) emotion, creating two levels of the dominant emotion condition within each blend type (e.g., within the anger–fear blends, half of the faces displayed anger as the dominant emotion, and half of the faces displayed fear as the dominant emotion). In total, six blends per face were created (3 emotion blend types × 2 dominant emotion types; see Figure 2A). The process of generating six different image types for each of the 39 faces resulted in 234 unique images.

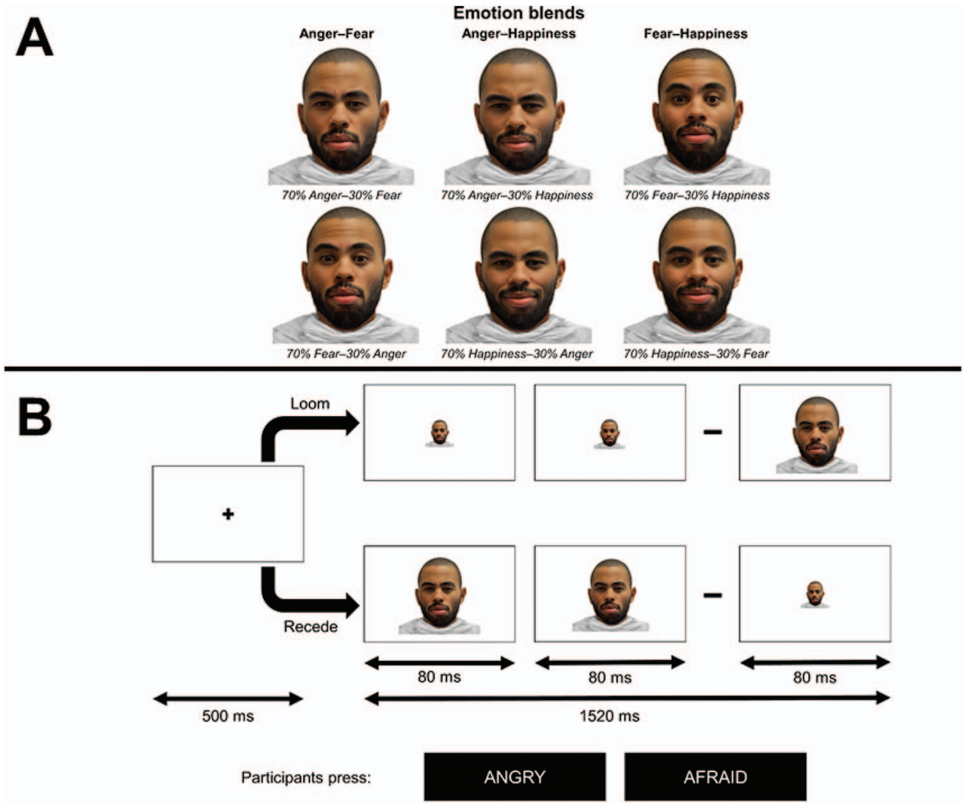
The task consisted of three separate blocks that corresponded to the three emotion blends: anger–fear, anger–happiness, and fear–happiness (e.g., the anger–fear block consisted of anger–fear blended faces only). Ordering of blocks was counterbalanced. Furthermore, within each block, half of the faces appeared to loom (i.e., move toward the participant), and half of the faces appeared to recede (i.e., move away from the participant). Each block consisted of 156 trials (39 faces × 2 dominant emotion types × 2 movement types) for a total of 468 trials in the task.

Task Procedure. Participants were seated approximately 60 cm away from a 27-in. BenQ high-performance LED gaming monitor (Model XL2720Z; BenQ, Taipei, Taiwan). Participants were instructed to identify the emotion expressed in each face as quickly and accurately as possible using the two shift keys on the keyboard. At the beginning of each block, each shift key was assigned to one of the two emotions represented in the faces. Keyboard covers with corresponding labels were placed over the keyboard in each block to aid the participant in key–response mappings. Key–response mappings were counterbalanced across participants to counteract any effects of assigning a particular response option to either the dominant or nondominant hand. Before each block began, participants completed 10 practice trials in which they pressed the corresponding key for the emotion word (e.g., "angry" or "afraid" before the anger–fear block) that appeared on the screen. To proceed to the next practice trial (and ultimately to the main task), participants were required to press the correct key on each practice trial (and were given multiple chances if needed).

Stimulus presentation and response collection were controlled using the Psychophysics Toolbox extension (Version 3; Brainard, 1997; Kleiner et al., 2007; Pelli, 1997) as implemented in MATLAB (2017; MathWorks, Natick, Massachusetts). Stimuli were presented in random order for each participant. Each trial began with a fixation cross (500 ms), after which a face was displayed on the screen for a total of 1,520 ms. Following previous research (Vieira et al., 2017), we created movement effects by rapidly changing the visual angle of stimuli. Faces increased (on looming trials) or decreased (on receding trials) in size by a factor of 1.05, resulting in 19 frames (each lasting 80 ms) per trial (see Figure 2B). The intertrial interval varied randomly between 1,000 and 2,000 ms (average 1,500 ms).

Task Behavioral Variables. At the simple behavioral level, the dependent variable derived from this task was response frequency, which provided a measure of emotion identification. In the anger–fear and anger–happiness blocks, the response frequency variable was anger identification (i.e., the proportion of trials on

Figure 2
Schematic Representation of Ambiguous Emotion Identification Task Trials



Note. Sample task stimuli (A). Stimuli displayed blends of anger–fear (left column), anger–happiness (middle column), and fear–happiness (right column). Within each blend type, one of the two emotions was the dominant (i.e., 70%) emotion. Schematic representation of trial layout and timing (B). On each trial, participants viewed a serial presentation of images that either increased in visual angle (i.e., a looming trial, depicted it the upper row of images) or decreased in visual angle (i.e., a receding trial, depicted in the lower row of images). Shown here are the first frame, second frame, and last frame (of 19 total frames on each trial) for each trial type. Participants pressed one of two keys to identify the emotion displayed in the face. See the online article for the color version of this figure.

which participants identified faces as angry). In the fear–happiness block, the response frequency variable was fear identification (i.e., the proportion of trials on which participants identified faces as afraid). Although RT was measured in the task, it was used solely for the purpose of estimating the DM parameters (and not as a dependent variable in its own right; however, see Supplemental Results in the online supplemental materials for analyses examining basic task effects on RT and response accuracy, and see Supplemental Method and Results in the online supplemental materials for a description of a control task used to rule out generally low response accuracy in facial emotion identification associated with psychopathy or externalizing).

Data Processing and Analysis

Data Quality Control

Participants were excluded from analyses if their task data were invalid based on the following criteria: (a) no response given (or response given in $<$300 ms) on more than 20% of trials, or (b) accuracy at or below chance (i.e., $\leq$50%). Three participants were excluded from analyses on the basis of these criteria, and the final sample consisted of 92 participants. Excluded participants did not differ from included participants in terms of psychopathy (95% confidence interval [CI] for the mean difference [$-$6.79, 3.84], p = .584) or externalizing (95% CI for the mean difference [$-$0.89, 2.72], p = .317).

Diffusion Modeling

Following established guidelines (Voss et al., 2015), we removed trials with no response (i.e., omissions) and trials with RTs less than 300 ms (i.e., premature responses) from individual participants' data before subjecting them to DM. Rates of omissions and premature responses were low (i.e., 2.59% and 0.24%, respectively, of trials per participant on average in the final sample). We used *fast-dm-30* software (Voss & Voss, 2007; Voss et al., 2015) to estimate parameters on the basis of response and RT data from the task. The diffusion model uses RT distributions for the two response options to estimate bias, threshold separation, drift rate, and nondecision time (see Supplemental Method in the online supplemental materials for further details regarding DM parameter estimation). The Kolmogorov–Smirnov estimation procedure was used because it accounts for exact RT distributions (as opposed to binning RT data) and is robust to contaminants.

Because response options varied by block, we performed DM on each block separately. We did not allow the bias parameter to vary by any stimulus characteristics (i.e., dominant emotion or movement) because relative starting point is not impacted by stimulus features. However, we allowed threshold separation, drift rate, and nondecision time to vary by dominant emotion and movement. For the anger–fear and anger–happiness blocks, "angry" responses were set as Response Option A, whereas non-"angry" responses were set as Response Option B (see Figure 1). Thus, positive starting point values for these two blocks indicate a bias toward anger, and positive drift-rate values indicate a drift rate toward anger (and conversely, negative values indicate a bias toward the nonanger emotion—i.e., happiness or fear, depending on the block—and drift rate toward the nonanger emotion, respectively). For the fear–happiness block, "afraid" responses were set as Response Option A, and "happy" responses were set as Response Option B. Thus, positive starting point values for this block indicate a bias toward fear, and positive drift-rate values indicate a drift rate toward fear. To maximize parsimony and accuracy of the model, we opted for a four-parameter model, in which the four main parameters were allowed to vary whereas the remaining parameters were fixed at 0 (Lerche & Voss, 2016).

Following parameter estimation, model fit was assessed using Kolmogorov–Smirnov test statistics (values $>.05$ generally indicate acceptable fit), along with visual inspection of quantile-quantile (Q-Q) plots (which indicate acceptable fit if all data points lie near the main diagonal). These indices revealed that the model fitted the data well.

Results

Emotion Identification

We conducted a series of repeated measures general linear models (GLMs) to examine emotion identification as a function of task conditions as well as psychopathy and externalizing. Emotion identification within each block was analyzed using separate models, resulting in three separate 2 (dominant emotion [anger–fear block]: mostly angry, mostly afraid; dominant emotion [anger–happiness block]: mostly angry, mostly happy; or dominant emotion [fear–happiness block]: mostly afraid, mostly happy) × 2 (movement: looming, receding) repeated measures GLMs with psychopathy and externalizing entered simultaneously as continuous between-subjects independent variables (see Table 2 for zero-order correlations between psychopathy, externalizing, and a subset of task dependent variables; see Table S1 in the online supplemental materials for an expanded set of zero-order correlations). As noted earlier, anger identification served as the dependent variable for the anger–fear block and anger–happiness block, and fear identification served as the dependent variable for the fear–happiness block. The analysis revealed both task effects and externalizing effects, but no psychopathy effects.

Within each of the three blocks, we detected main effects of dominant emotion on emotion identification: anger–fear: $F(1, 89) = 457.85$, $p < .001$, $\eta_p^2 = .84$, 90% CI [.79, .87]; anger–happiness: $F(1, 89) = 3388.26$, $p < .001$, $\eta_p^2 = .97$, 90% CI [.97, .98]; fear–happiness: $F(1, 89) = 2276.18$, $p < .001$, $\eta_p^2 = .96$, 90% CI [.95, .97]. In both the anger–fear and anger–happiness blocks, mostly angry faces were more likely to be identified as angry (anger–fear: $M = 67.4\%$, 95% CI [64.5%, 70.3%]; anger–happiness: $M = 79.2\%$, 95% CI [77.4%, 81.0%]) compared with mostly afraid faces ($M = 28.5\%$, 95% CI [26.1%, 30.8%]) and mostly happy faces ($M = 15.6\%$, 95% CI [13.8%, 17.5%]). In the fear–happiness block, mostly afraid faces were more likely to be identified as afraid ($M = 82.9\%$, 95% CI [81.2%, 84.6%]) compared with mostly happy faces ($M = 19.6\%$, 95% CI [17.3%, 21.8%]). These main effects provide a key demonstration of task validity by indicating that participants were able to discriminate between the two types of emotion blends within each block and identify the dominant emotion.

Furthermore, we detected a main effect of movement on anger identification in the anger–fear block, $F(1, 89) = 13.13$, $p < .001$, $\eta_p^2 = .13$, 90% CI [.04, .24]. Examination of the means indicated

Table 2

Zero-Order Correlations Between Independent Variables and Key Task Dependent Variables

Measure	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1) MPQ-BF NEM	—													
2) MPQ-BF CON	−.16	—												
3) EXT	.76*	−.76*	—											
4) PCL-R Total	.29*	−.23*	.34*	—										
5) PCL-R Factor 1	.06	−.07	.08	.78*	—									
6) PCL-R Factor 2	.37*	−.29*	.43*	.83*	.36*	—								
7) AF anger identification	.17	−.09	.17	−.09	−.11	−.05	—							
8) TS: Mostly angry looming faces AF	−.15	−.08	−.05	−.14	−.19	−.09	.05	—						
9) TS: Mostly angry receding faces AF	.13	−.17	.20	.02	−.11	.08	.27*	.42*	—					
10) TS: Mostly afraid looming faces AF	−.11	−.06	−.03	−.12	−.21*	.00	−.10	.45*	.28*	—				
11) TS: Mostly afraid receding faces AF	−.21*	−.12	−.06	.01	−.08	.05	−.12	.34*	.41*	.50*	—			
12) NT: AF	.21*	.14	.04	.28*	.22*	.21	−.01	−.21*	.00	−.29*	−.16	—		
13) NT: AH	.14	.15	.00	.30*	.27*	.21	−.02	−.18	−.05	−.18	−.12	.69*	—	
14) NT: FH	.17	.17	−.01	.34*	.26*	.28*	−.11	−.09	−.04	−.10	−.07	.65*	.82*	—

Note. MPQ-BF = Multidimensional Personality Questionnaire–Brief Form; NEM = Negative Emotionality; CON = Constraint; EXT = Externalizing (NEM−CON); PCL-R = Psychopathy Checklist–Revised; AF = anger–fear block; TS = threshold separation; NT = nondecision time; AH = anger–happiness block; FH = fear–happiness block.
* $p < .05$.

that looming faces were more likely to be identified as angry (M = 49.3%, 95% CI [47.3%, 51.3%]) compared with receding faces (M = 46.6%, 95% CI [44.4%, 48.7%]).

Finally, in terms of externalizing effects, we detected a main effect of externalizing on anger identification in the anger–fear block, $F(1, 89) = 4.31$, $p = .041$, $\eta_p^2 = .05$, 90% CI [.001, .13]. Regression analysis indicated that externalizing was positively associated with anger identification, $B = 0.01$, $SE = 0.01$.[2]

DM Parameters

Next we examined DM parameters as a function of task conditions as well as psychopathy and externalizing. DM parameters were examined separately within each block using a series of 2 (dominant emotion [anger—fear block]: mostly angry, mostly afraid; dominant emotion [anger–happiness block]: mostly angry, mostly happy; or dominant emotion [fear–happiness block]: mostly afraid, mostly happy) × 2 (movement: looming, receding) repeated measures GLMs with psychopathy and externalizing entered simultaneously as continuous between-subjects independent variables. Regression analyses were used to examine associations with bias because bias was not permitted to vary by conditions within each block.

Bias

We failed to detect significant associations between bias and psychopathy (all ps ≥ .518). We also failed to detect significant associations between bias and externalizing (all ps ≥ .140).

Drift Rate

Examination of drift rate as a dependent variable revealed task effects but no psychopathy or externalizing effects. Within each of the three blocks, we detected main effects of dominant emotion on drift rate: anger–fear: $F(1, 89) = 347.67$, $p < .001$, $\eta_p^2 = .80$, 90% CI [.73, .83]; anger–happiness: $F(1, 89) = 1303.93$, $p < .001$, $\eta_p^2 = .94$, 90% CI [.92, .95]; fear–happiness: $F(1, 89) = 1333.47$, $p < .001$, $\eta_p^2 = .94$, 90% CI [.92, .95]. In both the anger–fear and anger–happiness blocks, drift rate toward anger was higher for mostly angry faces (anger–fear: $M = 0.66$, 95% CI [0.53, 0.78]; anger–happiness: $M = 1.18$, 95% CI [1.09, 1.26]) compared with mostly afraid faces ($M = -0.64$, 95% CI [−0.74, −0.53]) and mostly happy faces ($M = -1.18$, 95% CI [−1.29, −1.07]). In the fear–happiness block, drift rate toward fear was higher for mostly afraid faces ($M = 1.41$, 95% CI [1.33, 1.50]) compared with mostly happy faces ($M = -1.00$, 95% CI [−1.11, −0.89]). These main effects support the validity of the drift rate parameter estimates by indicating that participants were better able to accumulate evidence for the dominant emotion displayed in the faces across all three blocks.

Furthermore, we detected a main effect of movement on drift rate toward anger in the anger–fear block, $F(1, 89) = 7.80$, $p = .006$, $\eta_p^2 = .08$, 90% CI [.01, .18]. Examination of the means indicated that drift rate toward anger was stronger for looming faces ($M = 0.06$, 95% CI [−0.04, −0.15]) compared with receding faces ($M = -0.04$, 95% CI [−0.14, 0.06]).

Finally, we detected a Dominant Emotion × Movement interaction for drift rate toward anger in the anger–happiness block, $F(1, 89) = 6.26$, $p = .014$, $\eta_p^2 = .07$, 90% CI [.01, .16]. This interaction indicated that the difference in drift rate for mostly angry versus mostly happy faces was greater for receding faces (mostly angry: $M = 1.44$, 95% CI [1.33, 1.55]; mostly happy: $M = -1.05$, 95% CI [−1.05, 0.66]) compared with looming faces (mostly angry: $M = 1.39$, 95% CI [1.29, 1.49]; mostly happy: $M = -0.95$, 95% CI [−1.07, −0.84]). This interaction suggested that participants engaged in more efficient evidence accumulation in the context of receding faces.

Threshold Separation

Examination of threshold separation as a dependent variable revealed both task effects and externalizing effects, but no psychopathy effects. Within the anger–fear block, we detected a main effect of dominant emotion on threshold separation, $F(1, 89) = 5.07$, $p = .027$, $\eta_p^2 = .05$, 90% CI [.003, .14]. Examination of the means indicated that threshold separation was lower for mostly afraid faces ($M = 1.19$, 95% CI [1.17, 1.22]) compared with mostly angry faces ($M = 1.22$, 95% CI [1.20, 1.25]).

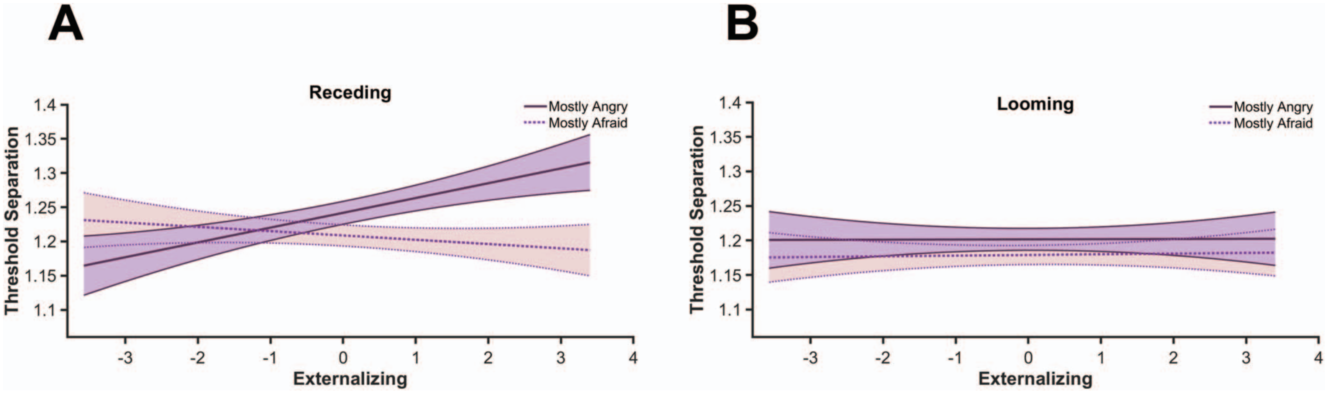
Furthermore, within the anger–fear and anger–happiness blocks, we detected main effects of movement on threshold separation: anger–fear: $F(1, 89) = 8.69$, $p = .004$, $\eta_p^2 = .09$, 90% CI [.02, .19]; anger–happiness: $F(1, 89) = 14.44$, $p < .001$, $\eta_p^2 = .14$, 90% CI [.05, .25]. In both blocks, threshold separation was lower for looming faces (anger–fear: $M = 1.19$, 95% CI [1.17, 1.21]; anger–happiness: $M = 1.23$, 95% CI [1.20, 1.25]) compared with receding faces (anger–fear: 1.23, 95% CI [1.20, 1.25]; anger–happiness: $M = 1.27$, 95% CI [1.25, 1.30]). Thus, participants accumulated less evidence and demonstrated greater impulsivity in the context of looming faces.

Finally, in terms of externalizing effects, we detected a Dominant Emotion × Movement × Externalizing interaction in the anger–fear block, $F(1, 89) = 4.74$, $p = .032$, $\eta_p^2 = .05$, 90% CI [.002, .14]. To represent and interpret this interaction, two difference scores were calculated by subtracting threshold separation for mostly afraid faces from threshold separation for mostly angry faces, for both looming and receding faces. Higher scores represent a larger difference in the amount of evidence accumulated for mostly angry faces versus mostly afraid faces. We detected a significant effect of externalizing on the difference score for receding faces, $B = 0.03$, 95% CI [0.01, 0.05], $SE = 0.01$, $p = .028$, $\eta_p^2 = .06$, but not for looming faces, $B = -0.001$, 95% CI [−0.02, 0.02], $SE = 0.01$, $p = .942$, $\eta_p^2 = .00$ (see Figure 3). Thus, higher levels of externalizing were associated with a larger difference in threshold separation for mostly angry faces compared with mostly afraid faces, but only in the context of receding faces. More specifically, whereas higher levels of externalizing were not associated with differences in the amount of evidence accumulated for mostly afraid versus mostly angry looming faces, higher levels of externalizing were associated with more evidence accumulation for mostly angry relative to mostly afraid receding faces.

[2] We ran all analyses with the addition of age and IQ as covariates, as both were related to task dependent variables and recent evidence suggests that IQ accounts for emotion processing deficits in psychopathy (Olderbak et al., 2018). All results reported in the manuscript remained unchanged after adjusting for age and IQ, except for the main effect of externalizing on anger identification in the anger–fear block, which was no longer significant, $F(1, 89) = 1.40$, $p = .241$, $\eta_p^2 = .02$, 90% CI [.00, .08].

Figure 3

Relationship Between Externalizing and Threshold Separation as a Function of Dominant Emotion for Receding Faces (A) and Looming Faces (B) in the Anger–Fear Block



Note. Error bands represent 1 *SE*. See the online article for the color version of this figure.

Nondecision Time

Examination of nondecision time as a dependent variable revealed task effects, as well as psychopathy and externalizing effects. Within the anger–fear block, we detected a main effect of dominant emotion on nondecision time, $F(1, 89) = 12.81$, $p = .001$, $\eta_p^2 = .13$, 90% CI [.04, .23]. Examination of the means indicated that nondecision time was shorter for mostly angry faces ($M = .68$, 95% CI [.65, .70]) compared with mostly afraid faces ($M = .70$, 95% CI [.68, .73]).

Within each of the three blocks, we detected main effects of movement on nondecision time: anger–fear: $F(1, 89) = 139.06$, $p < .001$, $\eta_p^2 = .61$, 90% CI [.50, .68]; anger–happiness: $F(1, 89) = 212.68$, $p < .001$, $\eta_p^2 = .71$, 90% CI [.62, .76]; fear–happiness: $F(1, 89) = 134.12$, $p < .001$, $\eta_p^2 = .60$, 90% CI [.49, .67]. Across all three blocks, nondecision time was longer for looming faces (anger–fear: $M = .73$, 95% CI [0.70, 0.75]; anger–happiness: $M = .67$, 95% CI [.65, .69]; fear–happiness: $M = .67$, 95% CI [.65, .69]) compared with receding faces (anger–fear: $M = .65$, 95% CI [.63, .67]; anger–happiness: $M = .58$, 95% CI [.57, .60]; fear–happiness: $M = .60$, 95% CI [.58, 0.62]). These main effects suggest that participants took longer to encode and execute motor responses on trials involving looming faces.

Turning to the psychopathy effects, we detected main effects of psychopathy on nondecision time within each of the three blocks: anger–fear: $F(1, 89) = 7.81$, $p = .006$, $\eta_p^2 = .08$, 90% CI [.01, .18]; anger–happiness: $F(1, 89) = 10.46$, $p = .002$, $\eta_p^2 = .11$, 90% CI [.03, .21]; fear–happiness: $F(1, 89) = 13.06$, $p < .001$, $\eta_p^2 = .13$, 90% CI [.04, .24]. Regression analyses indicated that psychopathy was positively associated with nondecision time in all three blocks (anger–fear: $B = 0.03$, $SE = 0.01$; anger–happiness: $B = 0.03$, $SE = 0.01$; fear–happiness: $B = 0.04$, $SE = 0.01$). Furthermore, within the anger–fear block, we detected a Dominant Emotion × Psychopathy interaction, $F(1, 89) = 6.43$, $p = .013$, $\eta_p^2 = .07$, 90% CI [.01, .16]; psychopathy was positively associated with nondecision time for mostly angry faces, $B = 0.04$, 95% CI [0.02, 0.07], $SE = 0.01$, $p < .001$, $\eta_p^2 = .13$, but no association was detected for mostly afraid faces, $B = 0.02$, 95% CI [−0.003, 0.05], $SE = 0.01$, $p = .082$, $\eta_p^2 = .03$ (see Figure 4).[3]

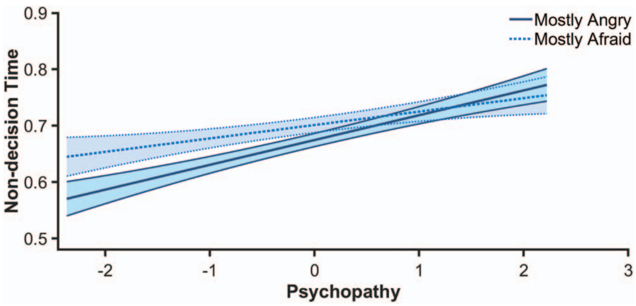
Finally, turning to the externalizing effects, within the anger–fear block, we detected a Dominant Emotion × Externalizing interaction, $F(1, 89) = 4.85$, $p = .030$, $\eta_p^2 = .05$, 90% CI [.003, .14], such that as externalizing increased, the difference in nondecision time for mostly angry faces compared with mostly afraid faces increased. More specifically, higher levels of externalizing were associated with shorter nondecision times for mostly angry faces compared with mostly afraid faces. This interaction was qualified by a Dominant Emotion × Movement × Externalizing interaction, $F(1, 89) = 4.98$, $p = .028$, $\eta_p^2 = .05$, 90% CI [.003, .14]. To represent and interpret this interaction, two difference scores were calculated by subtracting nondecision time for mostly angry faces from nondecision time for mostly afraid faces, for both looming and receding faces. Thus, higher scores represent a larger difference in the amount of time taken to encode and/or execute responses to mostly angry faces versus mostly afraid faces. We detected a significant effect of externalizing on the difference score for receding faces, $B = 0.02$, 95% CI [0.01, 0.03], $SE = 0.01$, $p = .001$, $\eta_p^2 = .11$, but not for looming faces, $B = 0.003$, 95% CI [−0.01, 0.02], $SE = 0.01$, $p = .707$, $\eta_p^2 = .002$ (see Figure 5). Thus, higher levels of externalizing were associated with shorter nondecision times for mostly angry versus mostly afraid faces, particularly in the context of receding faces.

Follow-Up Serial Mediation Model

As a follow-up to the externalizing effects we observed, to determine whether differences in threshold separation and nondecision time helped to account for the association between externalizing and heightened anger identification, we ran a serial me-

[3] We ran all GLM analyses using psychopathy Factor 1 (i.e., Interpersonal–Affective Traits) and Factor 2 (i.e., Impulsive–Antisocial Traits) as simultaneously entered independent variables and observed that the psychopathy-related effects reported here appeared to be driven primarily by the overlap between Factor 1 and Factor 2 (rather than the unique variance associated with either factor). Additional analyses indicated that the effects of externalizing reported here were accounted for by its overlap with PCL-R Factor 2 (see Supplemental Results in the online supplemental materials for further details).

Figure 4
Relationship Between Psychopathy and Nondecision Time as a Function of Dominant Emotion in the Anger–Fear Block



Note. Psychopathy scores are *z* scored. Error bands represent 1 *SE*. See the online article for the color version of this figure.

diation model using the PROCESS macro for SPSS (Hayes, 2018), Model 6. Externalizing was the independent variable, nondecision time difference score (i.e., mostly afraid minus mostly angry receding anger–fear faces) was the first mediator, threshold separation difference score (i.e., mostly angry minus mostly afraid receding anger–fear faces) was the second mediator, anger identification for anger–fear faces was the dependent variable, and psychopathy was included as a covariate. We used a nonparametric resampling procedure (bootstrapping) with 1,000 samples to estimate the indirect effect through both mediators in serial.

The path from externalizing to nondecision time difference score was significant, $B = 0.02$, $SE = 0.01$, $p = .001$, 95% CI [0.01, 0.03]. The path from nondecision time difference score to threshold separation difference score also was significant, $B = 1.03$, $SE = 0.16$, $p < .001$, 95% CI [0.71, 1.35]. Additionally, the path from threshold separation difference score to anger identification was significant, $B = 0.16$, $SE = 0.07$, $p = .035$, 95% CI [0.01, 0.31]. Consistent with results reported earlier, the association between externalizing and anger identification (i.e., the total effect) was significant, $B = 0.01$, $SE = 0.01$, $p = .041$, 95% CI [0.001, 0.03]. Furthermore, after controlling for the mediators, the association between externalizing and anger identification (i.e., the direct effect) was no longer significant, $B = 0.01$, $SE = 0.01$, $p = .295$, 95% CI [−0.01, 0.02]. Finally, the analysis indicated a significant indirect effect of externalizing on anger identification through both mediators, $B = 0.003$, $SE = 0.002$, 95% CI [0.001, 0.01][4]. Thus, a serial cascade of cognitive processes appeared to link externalizing to heightened anger identification.

Discussion

Both psychopathy and externalizing are associated with aberrations in social cognition that are thought to underlie the destructive social behaviors that characterize both forms of disinhibitory psychopathology. The present study used a computational approach to examine the contributions of underlying cognitive processes to a foundational component of social cognition, facial emotion processing. We found that psychopathy and externalizing are associated with different profiles of cognitive processing for facial emotions.

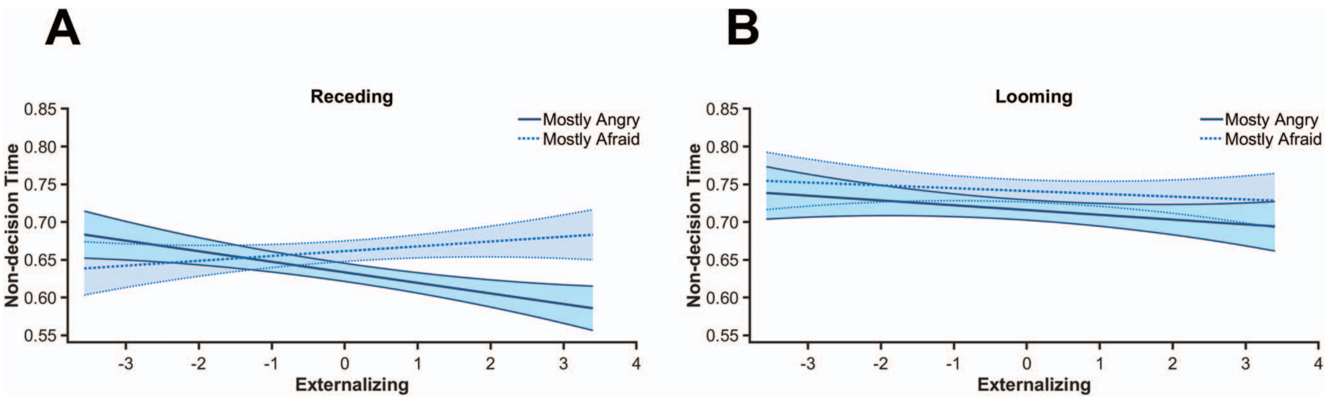
Consistent with hypotheses, psychopathy was associated with pervasive slowing of processing time that was evident across all three types of emotion blends, but it was not associated with differences in emotion identification according to a traditional behavioral measure. Longer nondecision time for the entire range of emotional stimuli is consistent with previous research linking psychopathic traits with slower recognition of (Hartmann & Schwenck, 2020) and diminished reactivity to facial emotion in general (Decety et al., 2014; Gillespie et al., 2019). These results extend previous work by suggesting that slowed facial emotion processing does not stem from cognitive processes involved in decision-making (e.g., lower drift rate or greater threshold separation), but instead from processes outside of the domain of decision-making (e.g., visual encoding and attention). These results also complement previous research linking psychopathy to slower, more serial processing of complex, multidimensional emotional information (Baskin-Sommers et al., 2013; Sadeh & Verona, 2012; Tillem et al., 2016).

Because we did not detect any aberrations associated with the processing of fear specifically, our results are inconsistent with theoretical accounts that psychopathy relates to specific deficits in processing distress cues in others. However, we did find that higher levels of psychopathy were associated with longer nondecision time for anger–fear blended faces that were mostly angry. Close examination of this finding reveals that individuals with *lower* levels of psychopathy showed differentiation in terms of nondecision time between mostly angry and mostly afraid faces, such that they processed mostly angry faces more quickly than mostly afraid faces. By contrast, in individuals with *higher* levels of psychopathy, nondecision time became undifferentiated, and mostly angry faces were processed no more quickly than mostly afraid faces. This result suggests a lack of modulation of processing time by social threat (i.e., level of anger displayed in the face). The pattern of slower processing of social threat in individuals with higher compared with lower levels of psychopathy aligns with previous findings that psychopathy is related to blunted amygdala reactivity to angry faces (Hyde et al., 2014), perhaps reflecting reduced attentional orienting to social threat. Moreover, slowed processing of social threat may even contribute to previously identified deficits in the automatic avoidance of social threat in psychopathy (von Borries et al., 2012), potentially helping to explain why individuals with psychopathy often appear fearless and unperturbed in the face of social threat.

Additionally, consistent with hypotheses, we found no evidence of contextual influences on facial emotion processing in psychopathy. It is possible that, for individuals with higher levels of psychopathy, slower encoding made contextual information less accessible, thereby preventing this information from influencing facial emotion processing. This interpretation is consistent with the perspective that apparent emotion deficits in psychopathy can be explained by an attention bottleneck that, once established, im-

[4] We also tested an alternative model in which the order of the mediators was flipped (i.e., threshold separation served as the first mediator; nondecision time served as the second mediator). The indirect effect for this alternative serial mediation model was not significant, suggesting that nondecision time impacts threshold separation in the cascade of processes underlying heightened anger identification in externalizing, rather than vice versa.

Figure 5
Relationship Between Externalizing and Nondecision Time as a Function of Dominant Emotion for Receding Faces (A) and Looming Faces (B) in the Anger–Fear Block



Note. Error bands represent 1 *SE*. See the online article for the color version of this figure.

pedes the processing of contextual information (Baskin-Sommers et al., 2013).

In contrast to the psychopathy effects and consistent with hypotheses about externalizing, facial emotion processing in externalizing *was* influenced by contextual information, such that higher externalizing was associated with quicker processing and more extensive evidence accumulation for mostly angry faces, but only in the absence of contextual threat (i.e., receding faces). The mediation model suggested a cascade of processes starting with shorter nondecision time for mostly angry (vs. mostly afraid) receding faces, leading to greater threshold separation for mostly angry (vs. mostly afraid) receding faces, finally manifesting in the pattern evident using a traditional behavioral measure, heightened anger identification. The association between externalizing and heightened anger identification is consistent with hypotheses as well as previous findings linking heightened anger identification to a range of behaviors (e.g., aggression; Wilkowski & Robinson, 2012) and disorders (e.g., alcohol use disorder; Freeman et al., 2018) associated with latent externalizing. The mediation model, though, demonstrates the role of underlying cognitive processes in this association. Moreover, the specific sequencing of variables in the indirect path (i.e., nondecision time followed by threshold separation) suggests that the nondecision time parameter may better represent processing that occurs before the evidence accumulation process (i.e., encoding of stimuli), rather than after (i.e., motor response execution), ultimately leading to heightened anger identification among individuals with higher levels of externalizing.

Taking less time to encode mostly angry faces appears to be an exaggeration of the general tendency among participants to process mostly angry faces more quickly under heightened ambiguity. Notably, this effect was directly opposite to the pattern observed for psychopathy. Accelerated processing of anger might reflect a phenomenon whereby angry faces are detected more efficiently than other types of emotional faces (Fox et al., 2000), which confers adaptive value by allowing individuals to quickly and automatically detect and orient to social threat in the environment. The fact that this adaptive tendency appeared to be exaggerated among individuals with higher levels of externalizing is consistent with research linking externalizing to preferential processing of threat-related information (Smith & Waterman, 2004). Quicker encoding of mostly angry faces, in turn, appeared to have a direct impact on threshold separation, or the extent of evidence accumulation, for these faces. That is, quicker encoding of the faces may have allowed for more time to accumulate evidence about them. Yet these tendencies toward quicker encoding and more extensive evidence accumulation for mostly angry faces emerged only in the absence of contextual threat. The contextual specificity of these effects suggests that individuals with higher levels of externalizing are able to process anger more adeptly, but the presence of contextual threat disrupts this ability, perhaps by inducing emotion dysregulation. Thus, when not faced with immediate threat, individuals with higher levels of externalizing displayed faster encoding of mostly angry faces, potentially buying them more time to accumulate more evidence and be less impulsive in identifying mostly angry faces, ultimately increasing their likelihood of accurately identifying these faces as angry.

The fact that all of the externalizing effects were limited to the anger–fear blended faces is worth further comment. As noted earlier, these faces represented highly ambiguous blends that were the most difficult for participants to distinguish (see Supplemental Results in the online supplemental materials). The emergence of heightened anger identification and quicker processing of anger only under greater ambiguity in externalizing is consistent with previous research linking externalizing behaviors and disorders to amplified threat perception particularly at higher levels of ambiguity (Brennan & Baskin-Sommers, 2020; Lynch et al., 2006; Schönenberg & Jusyte, 2014). Moreover, the emergence of contextual influences on cognitive processes only under greater ambiguity in externalizing may reflect greater sensitivity of cognitive processing to salient contextual information (Baskin-Sommers & Newman, 2014). Taken together, it appears that individuals with higher levels of externalizing are only more likely to perceive faces as threatening and to be more heavily influenced by contextual information (i.e., the presence vs. absence of contextual threat) under conditions of greater ambiguity.

Several limitations of the present study are worth noting. First, our task included only three emotions. Our choice of emotions was theoretically motivated and guided by previous research; however, future research should include a wider range of emotions (e.g., sadness, disgust), particularly to probe the extent to which the pervasive slowing of processing time in psychopathy extends to other emotions. Second, the nondecision time parameter estimated by DM is relatively nonspecific, in that differences in nondecision time cannot be pinpointed to one cognitive process in particular (e.g., encoding vs. motor response execution). Our mediation model provided some support for the interpretation that shorter nondecision times in externalizing better reflected encoding than motor response execution. Moreover, theoretical perspectives and a wealth of empirical evidence support the interpretation that longer nondecision times in psychopathy reflect deficits in encoding of complex visual information. However, combining DM with other techniques (e.g., electroencephalography; Nunez et al., 2017) can help parse encoding and motor components and could provide more fine-grained information about the precise source(s) of differences in nondecision time. Finally, because our sample was limited to male offenders, it is unclear whether the results would generalize to other populations. Future research should seek to replicate findings in female and/or nonincarcerated (e.g., community) samples.

In conclusion, this study is the first to apply DM to facial emotion processing in psychopathy or externalizing. By directly comparing psychopathy and externalizing, the present study provides novel evidence of different profiles of cognitive processes influencing facial emotion processing in these forms of disinhibitory psychopathology. Psychopathy was related to slowed processing of emotional faces in general, and in particular of faces conveying a higher degree of social threat (i.e., mostly angry faces) under heightened ambiguity. Externalizing was associated with more rapid processing of and more extensive evidence accumulation for mostly angry faces in the absence of contextual threat and under greater ambiguity, and these differences in cognitive processes helped to account for the behavioral pattern of heightened anger identification in externalizing. These findings add to a continually growing body of research that differentiates the cognitive-affective mechanisms associated with psychopathy and externalizing. Future research that looks beyond traditional behavioral measures and applies computational modeling to experimental paradigms can yield more reliable and mechanistically informative insights into the influences of cognitive processes on crucial psychological functions.

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