Cognitive mechanisms underlying prosocial decision making in callous-unemotional traits

Drew E. Winters [a], Warren W. Pettine [b], Joseph T. Sakai [a]

[a] Department of Psychiatry, University of Colorado School of Medicine, Anschutz Medical Campus
[b] Yale School of Medicine, Department of Psychiatry

Corresponding author: Drew E. Winters
drew.winters@cuanschutz.edu

ORCID ID:
Drew E. Winters: 0000-0002-0701-9658
Joseph T. Sakai: 0000-0003-1600-6100

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Abstract

Callous-unemotional (CU) traits are characterized by a lack of prosocial emotions, which has been demonstrated with prosocial behavior paradigms. While shaping our understanding of prosocial behavior in youth with CU traits, most of this work relies on outcomes that don't reliably capture cognitive processes during prosocial behavior. Examining prosocial cognitive processes can cue researchers into cognitive mechanisms underlying core impairments of CU traits. Drift diffusion modeling is a valuable tool for elucidating more precise outcomes of latent cognitive processes during forced choice tasks such as drift rate (information accumulation toward a decision boundary) and threshold separation (amount of information considered) as well as metrics outside of the decision-making processing including bias (starting point in decision process) and non-decision time (cognitive processes outside of choice). In a sample of 87 adolescents (12-14, 49% female) we applied diffusion modeling to a prosocial behavior task in which participants either accepted or rejected trials where a real monetary value was given to them and taken away from a charity (self-serving trial) or money was given to a charity and taken from them (donation trial). Results revealed that CU traits associated with information accumulation toward accepting self-serving trials. Exploratory sex differences suggested males trended toward rejecting donation trials and females considered more information during self-serving trials. CU trait associations were independent of conduct problems. Results suggest a unique cognitive profile that are differentiated by sex at higher CU traits when making prosocial decisions involving knowledge accumulation toward self-serving decisions.

Keywords: drift diffusion modeling, callous-unemotional traits, prosocial, early adolescents

Prosocial behavior is a voluntary act that benefits another person such as helping, sharing, or communicating support (Eisenberg & Mussen, 1989). Prosocial emotions give rise to prosocial behavior (Decety et al., 2016; Krebs, 2015); and prosocial emotion impairments defines callous-unemotional (CU) traits, a youth antisocial phenotype related to affective impairments in psychopathy, involving profound impairments in remorse, guilt, and empathy (Frick & White, 2008). Accordingly, CU traits associate with antisocial behavior such as aggression, substance use, and arrests for serious crimes (Blair et al., 2014; Kahn et al., 2013; Winters et al., 2020). Although prosocial emotion decrements define CU traits, there is variability in prosocial behavior amongst these youth (e.g., Carlo et al., 2014), and engaging in prosocial behavior both reduces (Aitken et al., 2018; Andrade et al., 2014) and protects against antisocial behavior (Carlo et al., 2014; Sakai et al., 2016). Thus, understanding mechanisms underlying prosocial behavior amongst those with CU traits is a promising route to addressing antisocial outcomes. However, available treatments have limited efficacy, which establishes the need to identify mechanisms underlying core impairments, such as prosocial behavior, related to these traits (for review; White et al., 2022). Although substantial evidence exists for decrements in prosocial decision making (Sakai, Dalwani, Mikulich-Gilbertson, McWilliams, et al., 2017; Sakai et al., 2012; Sakai et al., 2016; Sakai et al., 2019), few studies have considered the latent cognitive processes involved in prosocial behavior in relation to CU traits. Such information can provide mechanistic insights into prosocial differences. Thus, the current study employs modeling techniques to capture cognitive processes during a prosocial behavior task as a function of CU traits.

Prosocial behavior is multifaceted and includes making charitable donations to others at the one’s own expense (e.g., donating to another reduces their reward; Moll et al., 2006). Costly prosocial decisions represent the prosocial act of helping another even though it comes at an expense to themselves. Costly prosocial decision paradigms, such as the altruistic antisocial (AlAn's) game, demonstrate that those with CU traits make less costly prosocial decisions, which can discriminate those with CU traits from controls (Sakai et al., 2012; Sakai et al., 2016; Sakai et al., 2019) as well as differences in brain activation (Sakai, Dalwani, Mikulich-Gilbertson, Raymond, et al., 2017). However, these studies focus on older adolescents and early adults. Early adolescence is a particularly important time period for prosocial development where brain activation is particularly pronounced and more adult like during costly prosocial decision paradigms (Do et al., 2019). This makes early adolescence an important time to examine differences in prosocial development – particularly in cognitive differences. Thus, it is plausible that differences observed in during prosocial decisions can be reflected in cognitive differences at higher CU traits.

While many studies have examined prosocial behavior in relation to CU traits, less is understood about the cognitive processes underlying differences in prosocial behavior. Studies in this area have primarily relied on a total of amount kept for themselves versus donating, accuracy, or reaction times as outcomes for prosocial tasks (Sakai et al., 2012; Sakai et al., 2016; Sakai et al., 2019). While important for understanding prosocial behavior, these metrics do not have the sensitivity to reliably detect underlying sources of differences (Evans & Britton, 2018; White et al., 2010). Drift diffusion modeling is a computational approach demonstrating promise for capturing latent cognitive processes during task performance (Voss et al., 2015). For example, prior work has demonstrated differences in facial processing amongst those with psychopathic traits (Brennan & Baskin-Sommers, 2020). Drift diffusion modeling is based on the idea that participants accumulate evidence until one of two response thresholds is reached and that decision is made (Figure 1; van den Bergh et al., 2020), which his consistent with decision-making theory (Ratcliff, 1978).

There are many cognitive metrics within the diffusion model that influence decision making. Characteristics of the information accumulation process involve threshold separation and drift rate. *Threshold separation* refers to the amount of information that is considered before reaching the decision threshold and *drift rate* represents the information accumulation processes until the decision point is reached – with positive drift representing the upper decision point and negative drift representing the lower decision point. There are also metrics prior to the decision-making process, which includes starting point, or *bias*, and non-decision time. The *bias* represents the starting point between the two decision points a participant begins; and the *non-decision time* represents the time participants spend on processes other than deciding such as encoding and motor response. Importantly, recent advances to these models have reduced the introduction of bias into the model by not imposing assumptions of normally distributed non-decision time (van den Bergh et al., 2020). Identifying if, and which, cognitive processes contribute to prosocial behavior in youth with CU traits can reveal important mechanisms into socio-affective impairments underlying CU traits.

Thus, the present study assesses cognitive contributions to prosocial behavior as a function of CU traits. CU traits are personality dimension defined by impairments in prosocial emotions, which is not analogous prosocial behavior. It is important to study the personality dimension of CU traits with observable prosocial behavior to understand how it can influence prosocial behavior – such as we do in the present study. Here we use drift diffusion modeling on a prosocial behavior paradigm to better understand the cognitive processes underlying prosocial behavior amongst youth with CU traits. We hypothesize that CU traits will associate with differences in the information accumulation processes. Specifically, that they will consider less information during self-serving decisions and will have steeper drift rates toward accepting self-serving trials. We also hypothesize that CU traits will associate with greater bias toward accepting self-serving trials and there will be more non-decision time during donation trials. Finally, given substantial sex differences in relation to CU traits (Raschle et al., 2018), we will conduct exploratory analyses on sex as a moderator. We hypothesize that sex will moderate all the above hypothesized associations. Such information is promising for better understanding the cognitive processes underlying prosocial behavior in these youth and identifying mechanisms underlying core impairments in CU traits.

Methods

Analysis Preregistration

The study objectives, hypotheses, a prior power analysis, methods, and statistical plan were preregistered on the Open Science Framework (https://osf.io/29r8y). We have no substantive deviations from this preregistration to report. The code used for analysis can be found in GitHub (https://github.com/drewwint/pub_prosocial_DDM).

Power Analysis

Using G*Power (Faul et al., 2009), we conducted an a prior power analysis for associations between two continuous variables. We first consulted a prior investigation using drift diffusion modeling with psychopathy (Brennan & Baskin-Sommers, 2020), which produced high f values for calculating power (e.g., threshold separation f= 5.04; drift f = 347.67; non-decision f= 12.81). Thus, we decided to assume a moderate f^2 value (0.15) to ensure an adequate sample. Using a two-tailed f test for associations between CU traits and drift-diffusion outcomes with 4 covariates suggested a sample of 73 participants was required for 80% power.

Recruitment

The Colorado Multiple Institutional Review Board approved the protocol and recruitment strategies as well as both parental and child consent and assent procedures. Recruitment consisted of community participants via online adds and study tasks were completed online via testable (see citation for more info on testable: Rezlescu et al., 2020). Participants were recruited using online adds, where the study was described as: “The study is designed to test responses to a game. During this game you will be asked to make several decisions that involve donating or keeping money”. Because recruitment and study completion occurred completely online, acceptance into the study required the responsible adult who was consenting to upload a government issued identification to verify a responsible adult was knowledgeable and consented to the child participating. This was an intentional safeguard to ensure quality of the data. Participants were selected based on recruitment goals for the study for age (12-14 years) and matched on both sex and high to normative CU traits. Participant meeting the low prosocial emotion specifier criteria were considered high whereas those not meeting it were considered normative (see Measures under Callous-Unemotional Traits for specifics on how the low prosocial emotion specifier was derived). Reimbursement for time spent on the task included $15 for completion with the chance to earn up to an additional $9.80 depending on how they performed during the task. Participants were excluded if 1) they did not complete assent/consent processes and 2) study was not completed within one month after being accepted. Recruitment goal was for a total of 100 participants (to account for some needing to be removed), but resources ended at 87. This recruitment goal involved a preset number of cells participants needed to fit involving equal numbers of males to females and those high and normative in CU traits. Thus, our final sample numbers need to be considered in context that we intentionally sampled so that we had equal numbers in the categories of sex and CU traits.

Participants

The recruited sample consisted of 87 male and female adolescents (ages 12-14 12.86±0.75, males = 44, females = 43) that were predominantly White (White = 69%, Black = 10%, Pacific Islander = 10%, American Indian = 3%, Asian = 2%, Other = 6%). There were slightly more participants qualifying for the LPE specifier versus normative CU traits (LPE = 50, normative = 37), but we intentionally selected participants to match on this specifier – so this is expected (see Recruitment section). A total of six participants met cut-off scores for conduct problems and all three were also qualified for the LPE specifier.

Measures

Callous-Unemotional Traits. CU traits was assessed using the 24-item self-report measure Inventory of Callous-Unemotional Traits (ICU; Frick, 2004). Two items are commonly removed because they demonstrate poor psychometric properties (Kimonis et al., 2015) and removing these items still had adequate reliability in our current sample ($\alpha = 0.78$). Participants rate items on a four-point. Likert scale from 0 (“not true at all”) to 3 (“definitely true”). Higher scores indicate higher CU traits.

The low prosocial emotions specifier was derived from the ICU using the 9-item split coding method outlined by Kimonis et al. (2015). This specifier was used for the purpose of matching on, and recruiting for, severity. This method of calculation required we used nine items from this measure to indicate those that qualified for the low prosocial emotion specifier and those that did not. This low prosocial emotion specifier calculation approach has been used by multiple studies (e.g., Kimonis et al., 2015; Sakai et al., 2016; Winters & Sakai, 2021; Winters &

Sakai, 2022). If participants qualified, we used this as an indicator they are high in CU traits and those they did not qualify were considered normative.

The continuous total score of the ICU was used for analysis because continuous analyses retain more information and have greater power (Bitzer et al., 2014) as well as univariate investigation of CU traits revealed a normal distribution. However, for recruitment matching on high and normative CU traits, we identified those higher or normative on CU traits using the low prosocial emotion specifier coding method. This approach of recruiting for severity indicator using the low prosocial emotion specifier and analyzing on the continuous measure has been used in prior work (e.g., Winters & Sakai, 2021; Winters & Sakai, 2022).

Conduct Problems. The Strengths and Difficulties Questionnaire (SDQ) was used to assess conduct problems (Goodman, 1997; Goodman et al., 2003). The SDQ is a brief behavioral screening demonstrating test-retest reliability, internal consistency, and cross-informant correlation. We used the five-item conduct problem subscale, which demonstrated adequate reliability in our current sample ($\alpha = 0.86$). Participants rate items such as "I take things that are not mine from home, school or elsewhere" on a scale of 0 ("not True") to 2 ("Certainly True"). Higher scores indicate more conduct problems.

Parent report of age and sex. Participant age and sex assigned at birth was reported by parents during initial screening. These were used as potential confounders in our model and sex was tested as a potential moderator.

Prosocial behavior. A costly helping behavioral paradigm called the altruistic/antisocial or AlAn's game (Sakai et al., 2019) was used to assess prosocial behavior. The AlAn's has been used to understand prosocial decisions amongst adolescents in both clinical and typically developing populations (Sakai et al., 2012; Sakai et al., 2016) including in the fMRI (Sakai, Dalwani, Mikulich-Gilbertson, Raymond, et al., 2017). Studies using the AlAn's reveal that youth with higher CU traits are more likely to engage in more self-serving and less prosocial behavior in comparison to those that are typically developing. The AlAn's V.2 was used in the current study because it is shorter (~20 minutes) and easily deployed in formats outside the lab. During the task, subjects are asked to accept or reject real monetary offers where they will either gain or lose money and a charity (Red Cross) will lose or gain money (respectively). Both subjects and the Red Cross begin with $2.50 that can either increase or decrease between 2-32 cents throughout the game depending on what trials the participants accept or reject (see supplemental material for diagram and further explanation of the task). There are 36 trials consisting of active, calculation and attention control trials. Active trials involve either an increase or decrease in their money amount and a decrease or increase (respectively) in donation amount. Calculation trials are intended to ensure participants understand values used in the game where two values for self and Red Cross are presented and participants are asked which value is bigger. Attention control trials are for ensuring participants are paying attention that involve both the participant and Red Cross receiving money, thus; they should logically accept. The attention and calculation trials are to ensure participants understand and engage with the game, which were used to identify participants to exclude (see analysis identifying careless responses).

Analysis

Identifying Careless Responses. We identified participants that were careless in their responses (i.e., those that did not participate) by identifying highly patterned responses to self-report measures and those that did not adequately respond to calculation and attention trials during the AlAn's game. For highly patterned responses we took a three-pronged approach to identify participants using the 'careless' package in r (Yentes & Wilhelm, 2018) to derive long string, item-variability, and even-odd metrics of patterned responses. Participants that were outside the median and 3 * the median absolute deviation were identified as participants with highly patterned responses. Similarly, we identified participants that were below the median and 3 * the median absolute deviation on accuracy for attention and calculation trials to identify those that did not adequately pay attention to the AlAn's game. This resulted in a total of 15 participants needing to be removed resulting in 72 participants for the formal analysis. We further assessed if removing these participants biased the sample demographics or outcomes variables using t-tests, which did not reveal any significant difference in sex, age, race, CU traits, conduct problems, or outcomes of the drift diffusion model.

Drift diffusion modeling. Drift diffusion model metrics were derived on the individual-level using the 'DstarM' r package (van den Bergh et al., 2020). This approach obtains Drift diffusion model distributions using the numerical procedure (Voss & Voss, 2008) but reduces bias by not imposing assumptions that non-decision time is uniformly distributed (van den Bergh et al., 2020). The participants reaction times, task condition, and responses were fed into the Drift diffusion model for estimation. Conditions were set for self-serving trials, donation trials, calculation, and attention trials. A follow-up step was performed for estimating non-decision time for each trial type separately. The Drift diffusion uses reaction time distributions for the response options for each trial to estimate bias, threshold separation, drift rate and non-decision time (see: van den Bergh et al., 2020). The assumption of the drift diffusion model is that for each unit of time (represented by reaction time) the brain extracts a constant piece of evidence from the stimulus (drift) that is disturbed by noise (diffusion) that accumulates over time that stops once enough evidence is reached to decide (Bitzer et al., 2014). In this model the use of reaction time characterizes the common metrics such as decision arrived over trials to infer cognitive processes occurring during the decision-making process. We coded responses such that the upper response meant accepting that trial and lower response meant reject trial. This is important for interpreting results from different trials (e.g., accepting self-serving trials indicated more money for themselves than donating and vice versa for donation trials). Similarly, initial starting point that is positive indicates a prior bias for accepting a certain trial whereas a lower bias indicates bias for rejecting a trial type.

Analytic approach. Hypotheses were tested with path analysis in the r package 'lavaan' (Rosseel, 2012). This improves estimation by allowing the estimation of multiple dependent variables in one model while also accounting for expected correlation between them. In this vein, the present analysis modeled metrics involving information accumulation – drift rate and threshold separation – in one model and metrics involving pre-decision metrics – non-decision time and starting point – in a separate model. Preliminary investigation indicated no violations to normality; thus, all models were estimated using maximum likelihood. No values were missing so there was no need to account for missingness. For all models we tested for suppression effects of conduct problems by examining models with and without conduct problems as a control (e.g., Hyde et al., 2016; Lozier et al., 2014). No suppression effects were detected so all models reported control for conduct problems. We then derived multigroup modes separated by sex, constrained parameters by sex, and compared model differences using likelihood ratio tests to test sex as a moderator.

Results

Distribution of CU traits and conduct problems

Present sample distributions of CU trait scores (30.23±6.68) correspond to other community samples (Byrd et al., 2013; Essau et al., 2006) and SDQ conduct scores (1.51±1.71) are commensurate with population norms (https://sdqinfo.org/norms/USNorm1.pdf).

Knowledge accumulation different at higher CU traits and moderated by sex

For threshold separation, higher CU traits associates with higher knowledge accumulation during self-serving trials across all participants (std.β= 0.273, p= 0.013, R^2= 0.133; Table 1); however, this was primarily driven by females as females had a significant increase, but males did not (Males: std.β= -0.235, p= 0.079; Females: std.β= 0.452, p= 0.003; Table3, Figure 1). Sex, age or conduct problems did not statistically explain variation in threshold separation.

For drift rate, higher CU traits associates with a greater tendency for accepting self-serving trials (std.β= 0.305, p= 0.022; R^2= 0.112; Table 1), which stayed consistent across sex (ΔX^2= 0.1, p = 0.76); however, males at higher CU traits had a drift rate toward rejecting donation trials whereas females did not (Males: std.β= -0.419, p= 0.022; Females: std.β= 0.131, p= 0.474; Table3, Figure 2). Sex, age, or conduct problems did not statistically explain variation in drift rate for males but females higher in age demonstrated a negative association with donation trials (std.β= 0.393, p= 0.012; Table3).

Bias is different by sex at higher CU traits

For stating point bias, higher CU traits across sex did not associate (Table2) but, when accounting for sex as a moderator, females significantly started lower on self-serving trials as a function of CU traits (Females: std.β= 0.473, p= 0.012; Table4, Figure 3). Sex, age or conduct problems did not statistically explain variation in bias.

No differences in non-decision time as a function of CU traits

Non-decision time did not significantly associate with CU traits even when accounting for sex as a moderator (Table 2, Table4).

Discussion

CU traits uniquely associated with differences in cognitive processes during prosocial decision making that are core impairments thought to drive persistent antisocial behavior. Using a computational approach, the present study examined contributions of underlying cognitive processes related to prosocial behavior in early adolescents. This analysis revealed that CU traits, independently of conduct problems, associated with an information accumulation process leaning toward self-serving decisions. Additionally, analyses revealed a profile of cognitive processes that are distinct for males and females.

Higher CU traits associate with self-serving decisions with males less likely to donate

Consistent with our hypotheses, CU traits associated with a drift rate that tended to accept trials where they benefited (gained more money) at the expense of the Red Cross. This is consistent with the broader literature examining outcomes or end total amounts of money at the end of the game (Sakai, Dalwani, Mikulich-Gilbertson, McWilliams, et al., 2017; Sakai et al., 2012; Sakai et al., 2016; Sakai et al., 2019), which held across sexes. However, it was not until we tested sex as a moderator that it was revealed that males higher in CU traits tended to drift toward rejecting donation trials. This indicates a cognitive process of accumulating information in support of self-serving decisions at higher CU traits, which has not previously been shown. Accumulating evidence toward self-serving decisions may be a viable mechanism for leveraging alternative information to aid accumulation in support of less self-serving decisions. Moreover, this novel finding indicates differences between males and females in the information accumulation process when making decisions that not only include self-serving decisions but also less tendency to donate – suggesting different needs by sex to promote prosocial behavior amongst those higher in CU traits.

The amount of knowledge accumulation indicated females were more likely to accumulate more information during self-serving trials. Higher levels of knowledge accumulation suggest more conservative decision processes (Voss et al., 2004) because it indicates females are less likely to reach the limit rejecting these trials, which means they opt for decisions with the greatest payoff to themselves. Thus, the present evidence suggests that females, relative to males, are more conservative when considering self-serving trials. This does not suggest that males are not conservative but relatively females, in the present results, appear to have greater conservative behavior when considering their own gain over another's.

Sex differences in bias

Bias during self-serving trials is lower for females relative to males

Contrary to hypothesized, CU traits did not associate with an initial bias toward accepting self-serving trials; however, when considering sex as a moderator females had a slightly lower bias than males. Interestingly, females did not significantly differ from males on drift rate toward accepting self-serving trials. This would suggest that while the starting place for making self-serving decisions was lower for females, there was still a tendency during the information accumulation process toward accepting these trials. In other words, females may still end up accepting more self-serving trials despite an initial bias that is lower than males.

No association between CU traits and non-decision time

Contrary to hypothesized, CU traits did not associate with non-decision time for either self-serving or donation trials. This held when considering sex as a moderator. This suggest there was no significantly different non-decision processes during these trials at higher CU traits.

Conduct problems did not explain differences in knowledge accumulation

Importantly, conduct problems did not significantly associate drift rate whereas CU traits did. What differentiates youth with CU traits form those with conduct disorder are profound socio-affective impairments involving a lack of prosocial emotions and these youth higher in CU traits display a higher level of antisocial behavior (Colins et al., 2020). Thus, it is plausible, as the result of this analysis suggests, that the symptoms of conduct disorder may have less influence on prosocial decisions on the presence of CU traits.

This indicates a distinct set of cognitive processes underlying CU traits from cognitive processes underlying conduct problems related to prosocial decisions, which is consistent with theoretical accounts of CU traits involving a lack of prosocial emotions above and beyond conduct problems (Frick & White, 2008). However, the current finding extends this theoretical concept by evidencing distinct cognitive processes underlying the information accumulation process during prosocial decisions that differentiates CU traits from conduct problems. Specifically, there is a tendency to accumulate knowledge in support of self-serving decisions; therefore, beyond behavioral proclivity, higher in CU traits associate with greater cognitive support of self-serving decisions above and beyond symptoms of conduct problems.

Conduct problems did, however, positively associate with non-decision time during self-serving trials. This suggests conduct problems are involved with a delay in cognitive processes such as encoding and motor response prior to decisions. However, CU traits did not associate with non-decision time – thus, further evidencing distinct cognitive processes between conduct problems and CU traits. This finding is opposite from prior investigations in adults with psychopathy during a facial processing task (Brennan & Baskin-Sommers, 2020), which may reflect differences between different tasks targeting different processes. However, it is also possible that conduct problems in youth play a more significant role in non-decision cognitive processes than CU traits during prosocial decisions.

Limitations

These results must be interpreted under the following limitations. First the current sample size is modest and drawn from the community, which may not generalize to forensic populations. However, community samples demonstrate the same neurocognitive impairments as forensic samples (Viding & McCrory, 2012) and provide a greater advantage for parsing commonly comorbid conditions, such as conduct problems, from outcome associations (e.g., Umbach & Tottenham, 2021; Winters et al., 2021). Moreover, our sample over recruited for those higher in CU traits indicating a higher level of severity observed in community samples. Second, we did not account for ADHD symptoms, which are commonly comorbid with externalizing symptoms and account for cognitive differences. Future work should include ADHD symptoms as a covariate. Third, future studies could benefit from more trials for both self-serving and donation trials to capture a more nuanced information accumulation process. Fourth, cognitive processes related to non-decision time is not specific and future work could include psychological measures to help parse motor component other cognitive processes (e.g., encoding). Fifth, because participants completed the task online, each participant completed the study in different conditions. Future work could benefit from having participants complete the task in the same condition (e.g., a lab computer). Sixth, the Inventory of Callous-Unemotional Traits has seen some issues during confirmatory factor analysis such as a lack of consensus between studies and high number of correlated residuals that likely represent characteristics of the sample (Morales-Vives et al., 2019). We mention this because it is important to note the potential limitations of the measure; however, when the Inventory of Callous-Unemotional Traits was compared to other measures of callousness and psychopathy in youth, it demonstrated the strongest prediction of aggression, conduct disorder, crime seriousness, and age of crime onset (Ray et al., 2016). This may suggest the Inventory of Callous-Unemotional Traits is best suited for the current study. Future work could build on these results by using alternative and multidimensional measures of callousness. In this same vein, it is hard to know if we would reach the same conclusions using different measures of conduct and CU traits and future studies could build on these results by testing different measures to see if the same conclusions are reached. Finally, the present sample, after removing for poor data, was one participant away from the sample size necessary for 80% power. While this may have had little to no impact, it is worth noting the possibility that some effects may have been missed. In this same vein, results on sex differences are considered preliminary given the study was not powered for testing sex interactions. These results should be replicated in larger samples, including a portion of the forensic population, that include additional controls for ADHD symptoms.

Conclusions

In conclusion, the present results demonstrate differences in cognitive processes amongst community adolescents with CU traits that are distinct from conduct problems and moderated by sex. As the first study applying drift diffusion modeling to prosocial decision making as a function of CU traits, these results provide novel evidence of distinct cognitive processes relevant for understanding prosocial behavior in youth with CU traits, as well as differences in these cognitive processes by sex. CU traits related to an information accumulation process toward accepting self-serving trials with males having a unique knowledge accumulation process toward rejecting donation trials and females demonstrating a more conservative decision style during self-serving trials. These associations were independent of conduct problems, which extends theoretical knowledge of differences between CU traits and conduct problems by evidencing distinct cognitive processes related to CU traits. Additionally, these results demonstrate differences between males and females with CU traits. These cognitive differences plausibly underly differences in behavioral profiles of CU traits from conduct problems as well as differences between males and females with these traits. Given prosocial decision making is a core component of CU traits, future studies should continue to examine latent cognitive processes related to CU traits during prosocial behavior to better understand cognitive mechanisms underlying prosocial decisions in these youth.

Figure 1. Graphical representation of a diffusion model. The decision starting point can represent a prior response bias toward one option over the other (purple). The length of time for non-decision related processes (e.g., encoding, motor response) is captured by non-decision time (red). The level of information accumulates until it reaches either the upper or lower decision boundary which can accumulate toward the upper option (orange) or lower option (blue). The amount of evidence accumulated for a decision is called threshold separation which is the distance between the two thresholds (green). The upper option, in this experiment, indicates accepting the trial whereas the lower option indicates rejecting the trial. For a color version of the article please see the online version.

Figure 2. Drift rate for self-serving trials increases as a function of CU traits regardless of sex but males, relative to females, drift rate for donation trials decreases significantly at higher CU traits.

Figure 3. Threshold separation for self-serving trials increases at higher CU traits but is primarily driven by females.

Figure 4. Starting point bias is not a function of CU traits unless accounting for sex as a moderator.

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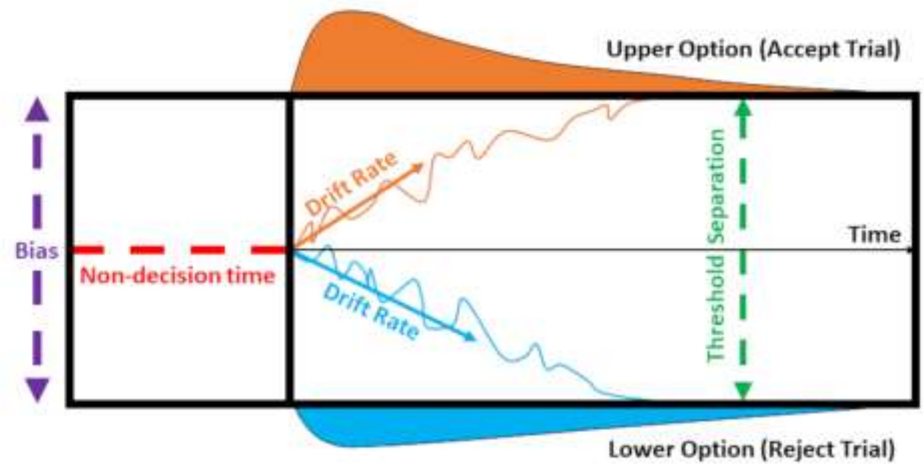

Figure 2. Graphical representation of a diffusion model. The decision starting point can represent a prior response bias toward one option over the other (purple). The length of time for non-decision related processes (e.g., encoding, motor response) is captured by non-decision time (red). The level of information accumulates until it reaches either the upper or lower decision boundary which can accumulate toward the upper option (orange) or lower option (blue). The amount of evidence accumulated for a decision is called threshold separation which is the distance between the two thresholds (green). The upper option, in this experiment, indicates accepting the trial whereas the lower option indicates rejecting the trial. For a color version of the article please see the online version.

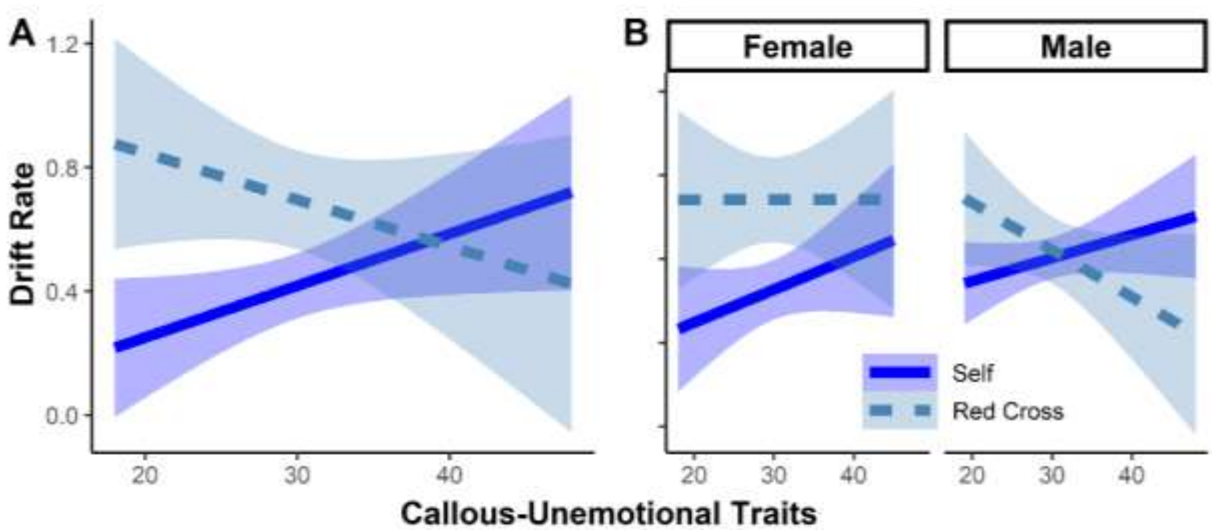

Figure 2. Drift rate for self-serving trials increases as a function of CU traits regardless of sex but males, relative to females, drift rate for donation trials decreases significantly at higher CU traits.

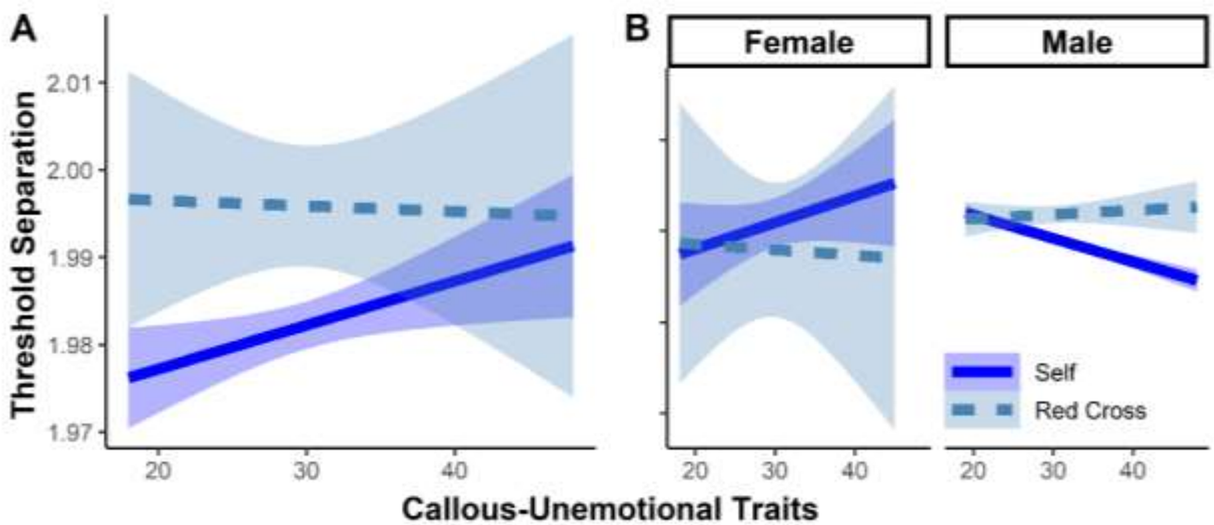

Figure 3. Threshold separation for self-serving trials increases at higher CU traits but is primarily driven by females.

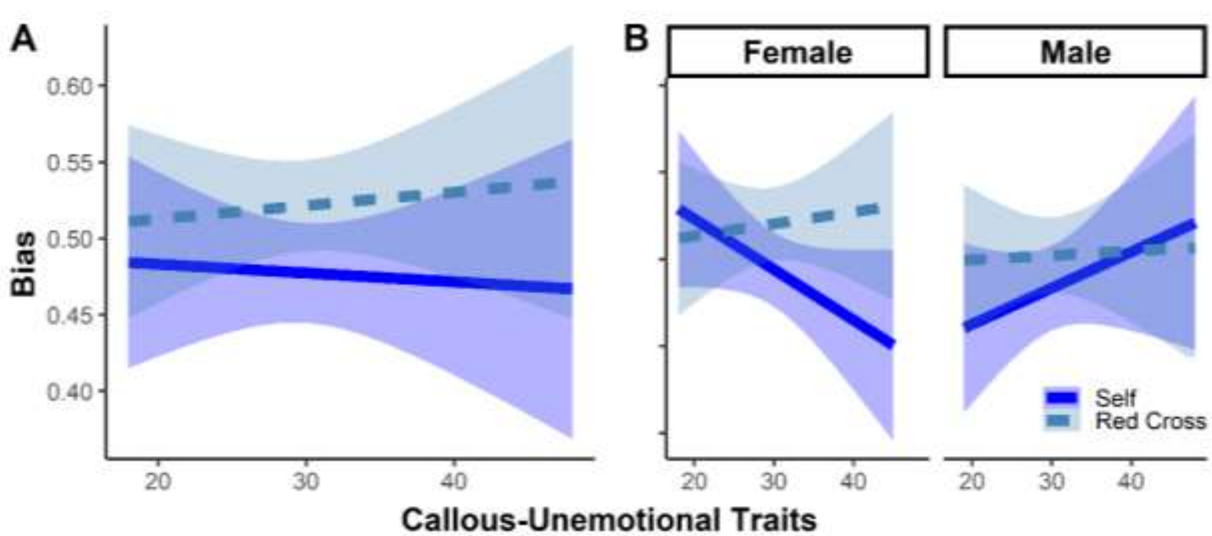

Figure 4. Starting point bias is not a function of CU traits unless accounting for sex as a moderator.

Table1. Descriptive information for dependent and independent variables

		Descriptives	Correlations											
		mean±SD or n(%)	2	3 [1]	4 [1]	5	6	7	8	9	10	11	12	13
1	CU traits	29.92±6.44	0	0.01	0.03	0.56*	0.27*	0.24*	-0.03	-0.01	-0.14	0.04	-0.02	-0.22
2	Age	12.88±0.77		0.03	-0.05	-0.04	-0.17	0.05	0.02	-0.17	-0.26*	-0.11	-0.07	-0.03
3	Male [1]	38(53%)			0.06	0.11	0.03	0.13	-0.15	0.03	-0.23	-0.18	-0.06	0.05
	Female	34(47%)												
4	White [1]	55(76%)				0.09	-0.01	-0.01	0.19	0.27	0.12	-0.03	0.02	-0.08
	Non-White	17(23%)												
5	CP	1.33±1.48					0.24*	0.08	0.12	0.03	-0.06	-0.06	0.2	-0.18
6	A-self	1.98±0.01						0.09	0.11	0.01	0.26	-0.15	0.11	0.02
7	V-self	0.42±0.46							-0.11	0.18	-0.41*	0.24*	0.14	-0.08
8	Z-self	0.48±0.14								0.02	-0.07	0	0.04	0.02
9	A-donate	2±0.03									-0.12	-0.13	0.14	-0.21
10	V-donate	0.7±0.68										0.17	-0.03	0.07
11	Z-donate	0.52±0.13											0.08	-0.08
12	ND-self	0.61±0.14												-0.06
13	ND-donate	0.6±0.14												

Note:
CU = callous-unemotional, CP = conduct problems, A = threshold separation, V= drift rate, Z= starting point (bias), ND = non-decision time
[1] = spearman correlations

Table 2. Results of information accumulation cognitive processes across whole sample

						95% CI	
	β	std. β	se	z	p	lower	upper
Threshold separation: **Self trials**							
R2 = 0.133							
CU traits	0.001*	0.273	0.0002	2.489	0.013	0.0001	0.001
Male	-0.003	-0.143	0.003	-1.298	0.194	-0.009	0.002
Age	-0.002	-0.152	0.002	-1.378	0.168	-0.006	0.001
CD	0.0001	0.099	0.0001	0.947	0.343	-0.0001	0.000
Threshold separation: **Red Cross trials**							
R2 = 0.048							
CU traits	-0.0001	-0.016	0.001	-0.142	0.887	-0.001	0.001
Male	0.008	0.133	0.007	1.153	0.249	-0.005	0.021
Age	-0.007	-0.177	0.004	-1.523	0.128	-0.015	0.002
CD	0.00002	0.011	0.0003	0.096	0.924	-0.0005	0.001
Drift Rate: **Self trials**							
R^2= 0.112							
CU traits	0.022*	0.305	0.010	2.289	0.022	0.003	0.040
Male	0.204*	0.224	0.103	1.988	0.047	0.003	0.406
Age	0.022	0.036	0.067	0.328	0.743	-0.109	0.152
CD	-0.041	-0.131	0.041	-0.991	0.322	-0.121	0.040
Drift Rate: **Red Cross trials**							
R^2= 0.135							
CU traits	-0.016	-0.154	0.014	-1.185	0.236	-0.044	0.011
Male	-0.293	-0.215	0.151	-1.940	0.052	-0.589	0.003
Age	-0.229	-0.256	0.098	-2.336	0.019	-0.420	-0.037
CD	0.013	0.027	0.059	0.213	0.831	-0.103	0.128

Table 3. Results of pre-trial cognitive processes across whole sample

	β	std. β	se	z	p	95% CI lower	95% CI upper
Non-decision: **Self trials**							
R^2= 0.69							
CU traits	-0.004	-0.191	0.003	-1.393	0.164	-0.010	0.002
Male	-0.015	-0.055	0.031	-0.481	0.631	-0.076	0.046
Age	-0.010	-0.055	0.020	-0.487	0.626	-0.049	0.030
CD	0.028*	0.310	0.013	2.235	0.025	0.004	0.053
Non-decision: **Red Cross trials**							
R^2= 0.059							
CU traits	-0.004	-0.167	0.003	-1.214	0.225	-0.009	0.002
Male	0.014	0.053	0.031	0.460	0.646	-0.047	0.076
Age	-0.006	-0.035	0.020	-0.308	0.758	-0.046	0.034
CD	-0.009	-0.100	0.013	-0.717	0.473	-0.034	0.016
Bias: **Self trials**							
R^2= 0.037							
CU traits	-0.003	-0.142	0.003	-1.016	0.310	-0.009	0.003
Male	-0.030	-0.109	0.032	-0.929	0.353	-0.093	0.033
Age	0.005	0.030	0.021	0.255	0.799	-0.036	0.046
CD	0.020	0.210	0.013	1.489	0.136	-0.006	0.045
Bias: **Red Cross trials**							
R^2= 0.041							
CU traits	0.002	0.101	0.003	0.728	0.467	-0.003	0.007
Male	-0.032	-0.128	0.029	-1.093	0.275	-0.090	0.026
Age	-0.019	-0.112	0.019	-0.972	0.331	-0.056	0.019
CD	-0.008	-0.099	0.012	-0.707	0.480	-0.032	0.015

Table 4. Testing moderation for information accumulation cognitive processes by sex

	Male			Female			Likelihood Ratio Test				
	β	std.β	p	β	std. β	p	Model	Df	X^2	ΔX^2	p
Threshold separation: **Self trials**											
CU traits	<-0.001	-0.235	0.079	0.001*	0.452	0.003	Free	8	16.2		
							Constrained	9	23.6	7.43	0.001
Age	<-0.001	-0.041	0.755	-0.01	-0.247	0.094					
CD	<0.001*	0.488	<0.001	0.000	0.218	0.114					
Threshold separation: **Red Cross trials**											
CU traits	<0.001	0.204	0.204	<-0.001	-0.006	0.972	Free	8	16.21		
							Constrained	9	16.22	0.01	0.95
Age	0.0001	0.049	0.759	-0.02	-0.282	0.085					
CD	<-0.001	-0.148	0.354	<0.001	0.087	0.592					
Drift Rate: **Self trials**											
CU traits	0.025*	0.418	0.022	0.019	0.236	0.214	Free	8	16.2		
							Constrained	9	16.3	0.1	0.76
Age	-0.074	-0.160	0.285	0.178	0.241	0.137					
CD	-0.073*	-0.320	0.076	0.009	0.021	0.910					
Drift Rate: **Red Cross trials**											
CU traits	-0.041*	-0.419	0.022	0.015	0.131	0.474	Free	8	16.2		
							Constrained	9	20.2	3.9	0.047
Age	-0.125	-0.165	0.271	-0.41*	-0.393	0.012					
CD	0.084	0.226	0.213	-0.15	-0.240	0.167					

Table 5. Testing moderation for pre-decision cognitive processes by sex

	Male			Female			Likelihood Ratio Test				
	β	std.β	p	β	std. β	p	Model	Df	X^2	ΔX^2	p
Non-decision: **Self trials**											
CU traits	-0.003	-0.153	0.337	0.002	0.12	0.489	Free	8	8.9		
							Constrained	9	10.2	1.4	0.24
Age	-0.035	-0.202	0.204	0.019	0.103	0.538					
CD	-0.001	-0.061	0.703	-0.002	-0.143	0.405					
Non-decision: **Red Cross trials**											
CU traits	-0.005	-0.203	0.206	-0.004	-0.177	0.266	Free	8	8.85		
							Constrained	9	8.90	0.04	0.83
Age	-0.014	-0.079	0.622	0.018	0.098	0.523					
CD	0.001	0.127	0.436	0.004	0.37	0.019					
Bias: **Self trials**											
CU traits	0.003	0.138	0.476	-0.009*	-0.473	0.012	Free	8	8.9		
							Constrained	9	13.1	4.3	0.038
Age	0.013	0.073	0.644	-0.006	-0.035	0.825					
CD	0.007	0.074	0.705	0.032	0.31	0.095					
Bias: **Red Cross trials**											
CU traits	0.002	0.092	0.622	0.002	0.119	0.552	Free	8	8.85		
							Constrained	9	8.86	0.003	0.95
Age	-0.052	-0.327	0.032	0.034	0.202	0.228					
CD	-0.009	-0.116	0.53	-0.008	-0.078	0.695					