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Efficient Vengeance: The role of processing fluency in making decisions about retaliation

Samuel J. West
Virginia Commonwealth University

EFFICIENT VENGEANCE: THE ROLE OF PROCESSING FLUENCY IN MAKING DECISIONS ABOUT RETALIATION

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By

Samuel J. West
M.A., University of North Carolina Wilmington, 2017
B.A., University of North Carolina Wilmington, 2014

Director: David S. Chester, Ph.D.
Assistant Professor
Department of Psychology

Virginia Commonwealth University
Richmond, Virginia
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Dedication

This project is dedicated to all of my friends and family who did not live long enough to see me get here: Doris H., Joyce W., Al W., Tom H., Austyn, Bailey, Mark, Robbie, Luke, Cliff, Scott, Sean, and Zach – I miss you all. Each of you contributed something meaningful to my life and I will never forget you.

I additionally dedicate this work to every working class person who dreams of something more. Let this document serve as proof positive that even the son of a construction worker, with enough grit, can reach the top of the ivory tower.

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Abstract

Aggressive behavior is a harmful and pervasive psychological and behavioral phenomenon. Inherent to every act of aggression are decisions regarding the modality, severity, and timing of such actions. Prevailing theories of aggression emphasize the role of cognitive processes in aggression, especially retaliatory aggression. Despite this emphasis, few cognitive processes have been examined for their possible involvement in making decisions about retaliatory aggression. Across two studies, I examined the role of *processing fluency* in making decisions about retaliation. I drew from contemporary models of aggression (e.g., the General Aggression Model) and processing fluency (e.g., the Multi-Source Account) to develop hypotheses in this novel extension of the aggression literature. Study 1 provided correlational evidence that processing fluency facilitates greater retaliation severity among vengeance-seekers and that such fluency linked with greater levels of antagonistic dispositions (i.e., Sadism). Study 2 extended these findings with a between-subjects experiment which provided evidence that induced angry rumination increased processing fluency for retaliation decisions, indirectly facilitating greater severity. Both studies also provided evidence that the Drift Diffusion Model can account for such decisions and that drift rate estimates are a valid measure of processing fluency. These findings hold major implications for contemporary theories of aggression and processing fluency, laboratory research, and clinical practice.

Keywords: retaliatory aggression, drift diffusion model, revenge, cognition, angry rumination, sadism

Introduction

Aggression is a costly and pervasive phenomenon that comes in many forms. Contemporary theories of aggression point to the involvement of cognitive processes in aggressive behavior (Bushman & Anderson, 2002; Finkel & Hall, 2018). Empirical work in this domain has largely focused on the cognitive accessibility and cognitive scripts for aggression, leaving the role of other processes unknown (e.g., Todorov & Bargh, 2002; Wilkowski & Robinson, 2010). Specifically, no known work has investigated the role of processing fluency during the decision-making process that inherently precedes aggressive acts. In what follows, I detail two studies that were conducted to test the role of processing fluency in making decisions about aggression, along with dispositions and emotional states that may be associated with such fluency.

Forms of Aggression

Theoretical models have generally coalesced around two overarching domains of aggression: reactive and proactive (Dodge & Coie, 1987; Steiner, Saxena, & Chang, 2003). Proactive aggression does not involve interpersonal provocation, tends to be less emotionally motivated, and is positively associated with conscientiousness (Koolen, Poorthuis, & van Aken, 2012; Raine et al., 2006). This form of unprovoked aggression is often instrumental such that it is used in service of other goals (Crick & Dodge, 1996; Sijtsema, Veenstra, Lindenberg, & Salmivalli, 2009). Conversely, reactive aggression involves some perceived interpersonal provocation and is associated with greater impulsivity, emotionality, and anger (Centifanti, Kimonis, Frick, & Aucoin, 2013; Koolen et al., 2012; Wilkowski & Robinson, 2010). Such retaliation is pursued in an attempt to repair the negative mood state caused by provocation (Bushman, 2002). Mounting evidence indicates retaliation does indeed function as mood-repair, as retaliatory aggression leads to greater neural activity in brain regions associated with rewarding experiences (e.g., Chester & DeWall, 2016). All forms of aggression however involve decision-making regarding the modality (e.g., physical, verbal, relational), severity, and time of action. The extent to which such decisions are explicitly reasoned may vary as a function of several factors.

Aggression and Decision Making

Aggression-related decisions are likely to involve elements of explicit and implicit decision-making depending on the type of aggression. Those more likely to engage in reactive aggression rely on implicit processes that lead to a greater likelihood of perceiving ambiguous interactions as intentionally provoking, a precursor for retaliatory aggression (Wilkowski & Robinson, 2010). According to the General Aggression Model (GAM), the initial appraisal of such ambiguous experiences occurs spontaneously and includes information regarding affective responses, goals, and intentions (Bushman & Anderson, 2002). The GAM predicts that explicit reappraisals will only occur if the individual considers the results of the initial appraisal unsatisfactory and has sufficient resources (e.g., time), whereas a failure to advance to reappraisal should result in a more immediate reaction (Bushman & Anderson, 2002). The GAM also predicts that failure at reappraisal may initiate a feedback loop that results in repeated failed attempts at reappraisal and rumination, which may foster a more controlled and planful form of retaliation (Bushman & Anderson, 2002; Denson, 2013).

The notion of planful retaliation is at odds with the conceptualization of reactive aggression as being necessarily impulsive. Recent research indicates that planful retaliation is explicitly reasoned, goal-oriented, and unemotional, whereas reactive retaliation is driven by anxiety and is impulsive (Book, Visser, Volk, Holden, & D’Agata, 2019). This dual pathway is unique to retaliatory aggression, as unprovoked or proactive aggression is necessarily associated with greater premeditation and positive affect prior to action (Hecht & Latzman, 2015). As such, planful retaliation involves explicit reasoning which in turn allows for the minimization of risks to the individual while maximizing the harm inflicted against their target. Various forms of aggression and associated decisions thus stem from different motives and are facilitated by different psychological processes.

Of particular interest to the current investigation are decisions regarding retaliatory aggression because such aggression is always motivated by perceived provocation and often holds the enactment of retaliation itself as a primary goal (Book et al., 2019). Conversely, proactive aggression is used as a tool to achieve personal goals, whereas such goals can vary widely across individuals (Crick & Dodge, 1996). Specifically, this work aims to examine the cognitive processes that underlie decisions about planful retaliatory aggression (i.e., severity of retaliation) due to the explicit nature and rationality of such decisions.

Cognition and Aggression

Many theories of aggression borrow heavily from the social and cognitive psychology literatures. Early theories of aggressive behavior relied on observational learning or imitation to explain aggression (e.g., Bandura, 1965). Contemporary theories of aggression such as the GAM have evolved beyond early theories, but still place an emphasis on learning and cognition as major factors behind aggression (Bushman & Anderson, 2002). Like with other types of knowledge, the GAM argues that cognitive scripts for aggression are generally built through indirectly observed and directly experienced acts of violence (Shiffrin & Schneider, 1977; Todorov & Bargh, 2002). The habitual activation of these scripts leads to a degree of automaticity in their influence on behaviors (e.g., Huesmann & Taylor, 2006; Schank, 1982).

Despite the emphasis on the involvement of cognition by prevailing theories of aggression, little work has examined other components of cognition and the role(s) they play in aggression. One cognitive process that is likely involved in aggression related decision-making is processing fluency.

Processing Fluency. Broadly defined as the cognitive effort an individual must exert in order to process information, processing fluency is enhanced by repeated exposure (Jacoby & Dallas, 1981). Various forms of processing fluency have been identified. *Perceptual fluency* relates to the ease of recognition of target stimuli on the basis of visual and other perceptual factors (e.g., image clarity; Whittlesea, Jacoby, & Girard, 1990). The focus of this investigation however is *conceptual processing fluency* (hereafter, 'processing fluency') which is defined as the relative ease of cognitive processing in relation to explicit, semantic information (e.g., choosing between two possible rewards; Lee & Labroo, 2004; Lanska, Olds, & Westerman, 2014). Theoretical accounts of processing fluency point to two possible sources. The *hedonic marker* account of processing fluency posits that fluently processed stimuli inherently evoke positive affect (Topolinski, Likowski, Weyers, & Strack, 2009; Winkielman, Schwarz, Fazendeiro, & Reber, 2003). A competing account, *fluency amplification*, posits that processing fluency increases the initial affective response evoked by a given stimuli, irrespective of valence (Albrecht & Carbon, 2014). Recent work provides evidence supporting of a synthesis of both accounts named the *Multi-Source Account* of processing fluency, wherein initial fluency produces an early preference (i.e., hedonic marking) which can then be strengthened through repeated exposure (i.e., fluency amplification; Gamblin, Banks, & Dean, 2020). In this view, processing fluency has a reciprocal relationship with preference, as individuals selectively expose themselves to stimuli that are initially appealing which leads to further exposure and thus greater processing fluency for related information (Constable, Bayliss, Tipper, & Kritikos, 2013). There are also other distinct cognitive processes that may improve processing fluency.

Processing Fluency and Other Cognitive Processes. Cognitive accessibility and spreading activation are two cognitive processes that facilitate processing fluency. The cognitive accessibility of information refers to how readily information can be retrieved in a given situation (Higgins, 1996). For example, the accessibility of angry emotions in dispositionally aggressive individuals leads to a greater likelihood of making hostile attributions to ambiguous behaviors, or the so-called 'hostile attribution bias,' (Dodge, 1980; Tiedens, 2001). Such accessibility likely increases the processing fluency for aggression-related concepts because accessibility acts as a source of information for guiding relevant behaviors (Jefferis & Fazio, 2008). Indeed, recent evidence indicates that aggressive individuals are more likely to perceive ambiguous facial expressions as angry due to an elevated efficiency in processing such information (Brennan & Baskin-Sommers, 2020). The availability heuristic is a mental shortcut defined as a reliance on the most cognitively accessible information for making various judgements which may also impact processing fluency (Tversky & Kahneman, 1973). However, a crucial distinction is that processing fluency in the context of value-based choice refers to the ease of processing all relevant information and the enactment of one's ultimate choice, whereas the availability heuristic refers to the weight placed on the most readily accessible memory in the decision making process (Jacoby & Dallas, 1981; MacLeod & Campbell, 1992). Thus, accessibility and the availability heuristic allow individuals to quickly retrieve relevant information and processing fluency allows individuals to synthesize retrieved information with novel information in service of making judgements. Another process that likely supports processing fluency is spreading activation.

Spreading activation refers to the way in which neural activity travels across interconnected knowledge structures and concepts in the brain. Specifically, the direct activation of one concept or ‘node’ is thought to activate other related nodes, such that the content of connected nodes is more readily accessible (Collins & Loftus, 1975). Spreading activation also occurs across emotional memory networks (Foster et al., 2017), whereas unpleasant moods facilitate further spreading activation to other unpleasant concepts (Mayer & Volnath, 1985). Therefore, the retrieval of a single angry memory should lead to the spreading activation of other angering memories, further improving processing fluency for related information (e.g., decisions about retaliation).

Processing Fluency and Decision-Making. Processing fluency extends to decision making in general, as judgements and decisions made more frequently are experienced more fluently (Alter & Oppenheimer, 2009). Aggressive individuals with a high degree of past exposure to aggression should thus demonstrate greater processing fluency for aggression-relevant decisions and a greater tendency to aggress themselves (Huesmann & Taylor, 2006; Wänke & Hansen, 2015). Indirect evidence for this expectation is demonstrated by a wide body of literature indicating that individuals who are routinely exposed to various forms of aggression are more likely than others to behave aggressively themselves (Huesmann, Moise-Titus, Podolski, & Eron, 2003; Miller, Grabell, Thomas, Bermann, & Graham-Bermann, 2012). Processing fluency may thus be one cognitive mechanism underlying dispositions that are typified by chronically accessible angry memories (i.e., trait angry rumination) and the hedonic enjoyment of harming others (i.e., Sadism).

Intersections of Cognition and Personality

The intersections of processing fluency and individual dispositions have yet to be examined in the context of aggression. One disposition of particular interest to the current investigation is that of trait angry rumination.

Angry Rumination and Cognition. Trait angry rumination refers to the extent to which one experiences intrusive memories of angering events and has been characterized as a 'chronic accessibility' of angering memories (Denson, Pedersen, Friese, Hahm, & Roberts, 2011; Rusting & Nolen-Hoeksema, 1998). It seems likely then that processing fluency and the associated processes of accessibility and spreading activation contribute to aggression resultant from angry rumination. Specifically, angry rumination about a single event may activate nodes of other angering memories, rendering angry feelings more readily accessible and thus elevated processing fluency for making decisions about aggression (Denson, 2013; Foster et al., 2017). This is reflected in the aggression literature, as angry rumination leads to greater instances of aggression against targets unrelated to the angry memory (Bushman, Bonacci, Pedersen, Vasquez, & Miller, 2005; Denson, Pedersen, & Miller, 2006). Further, rumination leads to faster spreading activation of related concepts (Foster, et al., 2011; Watkins & Teasdale, 2001), and maintains the accessibility of anger and thoughts of retaliation (Pedersen et al., 2011). Such increased accessibility should thus be accompanied by greater processing fluency, allowing angry ruminators to make decisions about retaliatory aggression with less cognitive effort.

Because angry ruminators often spend time planning and mentally practicing revenge scenarios, real-life decisions about retaliation should in turn require less cognitive effort (Denson, 2013). The literature supports this assertion, as self-referent information is processed with a higher degree of fluency than other types of information (Hessen-Kayfitz & Scoboria, 2012). Further, rumination about a provoking experience increases the likelihood of retaliation as a means of mood repair (Bushman, Baumeister, & Phillips, 2001; Chester & DeWall, 2016). In turn, the mood-repairing effects of revenge increase the likelihood of future retaliation, pointing to a feedback loop between angry rumination and aggression much like that proposed by the Multi-Source Account of processing fluency (Bushman, 2002; Gamblin et al., 2020). Due to trait angry rumination's links with distinct patterns of cognition and aggressive behavior it is an ideal candidate trait for examining how traits associated with aggression may be reflected by unique patterns of cognition. Another disposition that is likely relevant to such cognitive processes is that of Sadism.

Sadism and Cognition. Sadism refers to the tendency to derive hedonic pleasure from inflicting (or observing) harm on another person (Buckels & Paulhus, 2013). Sadistic individuals are more likely to engage in both provoked and unprovoked aggression than others due to this pleasure (Chester, DeWall, & Enjaian, 2019). Sadists are also generally more likely to commit violent crimes across various domains of offending (e.g., sexual assault; DeLisi et al., 2017). Sadistic aggression is accounted for by self-reports of Sadism even after controlling for trait aggressiveness, impulsivity, and other antagonistic traits (e.g., psychopathy; Chester et al., 2019). Similarly, Sadistic individuals are more likely to bide their time in service of inflicting more harm on a provocateur rather than seeking immediate vengeance (West, Lasko, Hall, & Chester, *under review*). Sadism is also associated with distinct patterns of cognition, as Sadistic individuals are quicker to classify violent images as being "happy" than others during laboratory tasks (Reidy, Zeichner, & Seibert, 2011).

Application of the Multi-Source Account of processing fluency to Sadism may lead to similar expectations as with trait angry rumination for different reasons. Because Sadistic individuals experience aggression as pleasurable (with or without provocation) it is likely that aggressive concepts are more connection-rich among Sadists because aggressive knowledge structures are linked to nodes for both positive and negative affective experiences. Indeed, although Sadists experience increased positive affect during aggressive acts, they experience increased negative affect afterwards (Chester et al., 2019). It could be then that a Sadistic individual's first decision to harm someone is fluently processed which leads to an initial increase in positive affect. The increase in negative affect that follows may then increase the likelihood they pursue such action again, initiating a feedback loop consistent with the Multi-Source Account of fluency (Chester et al., 2019; Gamblin et al., 2020).

A major distinction between trait angry rumination and Sadism is that Sadistic individuals need no angry memories to achieve the hypothesized processing fluency for aggression. Thus, it may not be that Sadists have a chronic accessibility of angry memories but instead have an addiction-like drive to pursue the 'high' they achieve from inflicting harm on others (Chester et al., 2019). In contrast, angry ruminators are better conceptualized as attempting to escape a cycle of self-reinforcing negative affect through the mental reliving of angering experiences (Bushman, 2002; Denson, 2013; Pedersen et al., 2011). In both cases, angry ruminators and Sadists should demonstrate greater processing fluency when making decisions about aggressive behavior. Testing such a premise however requires the estimation of specific cognitive processes at the individual level.

Measurement of Processing Fluency

Processing fluency has generally been operationalized as either measures of response speeds or self-reports of the degree of effort required to produce a given response. Various self-report measures have been developed over the years which ask participants to report on the ease of various judgements (e.g., Dragojevic & Giles, 2016), a general feeling of fluency (e.g., Forster, Leder, & Ansorge, 2016), or the complexity of a given task or series of decisions (e.g., Westerman, Klin, & Lanska, 2015). Processing fluency has also been measured as the amount of brain activation required to solve a given problem or to process novel information (Bohrn, Altmann, Lubrich, Menninghaus, & Jacobs, 2012). However, the most commonly implemented measure of processing fluency is response time (RT; e.g., Albrecht & Carbon, 2014). The use of RTs is the most common in this respect because they are an objective measure (unlike self-reports) and require very little resources to capture (unlike neuroimaging techniques). The reliance on RTs alone for the estimation of processing fluency also presents drawbacks. First, the use of RTs exclusively does not include information regarding the actual responses made by participants, making interpretations of such data more challenging in the context of value-based choice. Second, many studies of processing fluency rely on the mean RT values for each participant across a series of trials, artificially restricting the variance that exists among the observed data. Third, RTs present an inference problem as an outcome measure because they necessarily collapse the duration of all cognitive processes (e.g., stimulus processing, response caution, bias) into a single aggregated index (White, Servant, & Logan, 2018). However, advances in computational modeling allow for the estimation of individual cognitive processes (e.g., processing fluency) by incorporating all observed data in the estimation process.

Drift Diffusion Modeling

Drift Diffusion Modeling (DDM) is a computational modeling technique that allows for the estimation of specific cognitive elements of decision making (Ratcliff, 1978). Although DDM is most commonly applied to contexts where there is an objectively correct response, this analytic technique can be effectively applied to any dichotomous choice task (Ratcliff & McKoon, 2008). In DDM, trial-level participant responses and RTs are entered into the analysis which returns parameter estimates and model fit values for each participant. The full DDM allows for the estimation of nine parameters: four primary parameters, four inter-trial variability parameters linked to the four primary parameters, and a final response speed difference parameter. The latter set of parameters require clearly divergent decision-making trials (e.g., hard vs. easy), foundational work examining the ability of the basic DDM to explain decisions made during novel tasks, and substantially greater numbers of trials (Voss et al., 2013). However, recent work indicates that holding these secondary parameters constant in favor of a more parsimonious model yields greater accuracy (Lerche & Voss, 2016). Because the current investigation applied the DDM to a novel task I implemented the ‘basic’ DDM which estimates only the four primary parameters: drift rates, decision thresholds, relative starting points, and non-decision process duration.

Drift rates are defined as the rate at which information is accrued in favor of a given choice. In the context of decisions with a correct answer, drift rates represent the difficulty of determining the correct response such that lower drift rates reflect greater difficulty (Voss, Nagler, & Lerche, 2013). In the case of value-based choices (i.e., retaliation severity), drift rates represent the cognitive speed of information processing such that a higher drift rate implies greater cognitive efficiency for a given choice outcome (Schmiedek, Oberauer, Wilhelm, Süß, & Wittmann, 2007). In this context, drift rates still index the degree of difficulty involved in making decisions, but reflect the degree of difficulty in determining one’s preference rather than a correct response. Drift rate estimates also appear to reflect processing fluency, as both drift rates and processing fluency increase with repeated exposure (Alter & Oppenheimer, 2009; Ratcliff, Gomez, & McKoon, 2004).

Decision thresholds are defined as the amount of information required to make a given decision. High thresholds are typically interpreted as a more conservative or cautious decision-making style (Voss et al., 2013). Like drift rates, the application of decision thresholds to value-based decision-making alters interpretations, such that smaller threshold values reflect *stronger preferences* rather than a lack of consideration for the alternative option. Research comparing the knowledge structures of connoisseurs against more casual consumers supports this contextual account, as connoisseurs are more confident in their knowledge and ability to make distinctions and decisions about their reward of choice (e.g., wine; Langlois, Dacremont, Peyron, Valentin, & Dubois, 2011). Further, RTs are inversely correlated with choice certainty in decision-making tasks for correct and incorrect choices (Kiani, Corthell, & Shadlen, 2014) and shorter RTs are indicative of preference strength in tasks that do not impose a correct-incorrect dichotomy (Konovalo & Krajbich, 2019). Such a relationship is mirrored by the DDM as decision thresholds and drift rates are typically negatively associated (Ratcliff & McKoon, 2008).

Non-decisional processing provides an estimate of the duration of all non-decisional processes such as information encoding. The non-decision parameter effectively indexes how long it takes for the information accumulation process to begin. This parameter is often used to model changes centered around switching from task-to-task in terms of reconfiguration of the working memory for the new task and encoding differences across age groups (Rattcliff, Spielder, & McKoon, 2000; Schmitz & Voss, 2012). The relative starting bias parameter estimates a priori biases for a given choice. This parameter quantifies the bias in favor of a given option prior to the information accumulation process (Voss et al., 2013). Each of these four parameters are often used as predictors or outcomes in traditional inferential statistical models.

The Present Research

No known research has provided a direct test of the role that processing fluency may play in facilitating decisions about retaliation. Application of the Multi-Source Account of processing fluency yields an expectation that individuals preferring greater retaliation should have greater processing fluency for such decisions because they make them more frequently (Chester & Lasko, 2019; Gamblin et al., 2020). If processing fluency can account for decision-making regarding the retaliation severity, then the frequency of high-severity decisions should be positively associated with processing fluency (i.e., drift rates) and negatively associated with decision thresholds. Likewise, processing fluency should account for more variance in decisions regarding retaliation severity than the amount of information needed to choose (decision thresholds), relative biases, and non-decision processes.

The Multi-Source Account of processing fluency also yields specific hypotheses in respect to trait angry rumination and Sadism. Angry ruminators repeatedly relive provoking experiences and mentally practice revenge scenarios, which should improve the processing fluency for related decisions (e.g., retaliation severity). If the fluency amplification component of the Multi-Source Account is correct, then trait angry rumination should be positively associated with processing fluency for, and negatively associated with the amount of information required to make, decisions about retaliation severity. Conversely, Sadistic individuals find aggression intrinsically rewarding and need no prior provocation to plan and enact aggressive acts, though Sadism still demonstrates a positive association with retaliatory aggression (Chester et al., 2019). If the hedonic marker component of the Multi-Source Account is correct, then Sadism should be positively associated with processing fluency for retaliation decisions but not with decision thresholds, as the mental rehearsal typical of angry rumination is not a feature of Sadism.

Study 1 provided an initial test of a processing fluency account of aggressive decision-making and antagonistic traits (i.e., trait angry rumination and Sadism) through application of the DDM. Study 2 provided an experimental test of the ability of emotional experiences (i.e., anger) to increase processing fluency for retaliation, indirectly fostering greater retaliation severity. The methods, hypotheses, and analysis plan for Study 1 and 2 were both preregistered and are publicly available (Study:1 https://osf.io/4hbkr, Study 2: https://osf.io/ypxzd).

Study 1

Aim 1.1: The primary aim of Study 1 was to provide an initial test of a processing fluency account of retaliatory aggression.

Hypothesis 1.1a: The DDM will demonstrate a substantial fit to the retaliation decision data, such that less than 10% of participants will exhibit unacceptable fit values.

Hypothesis 1.1b: Retaliation severity will be positively associated with processing fluency (drift rates).

Hypothesis 1.1c: Retaliation severity will be negatively associated with the amount of information needed to make such decisions (decision thresholds).

Hypothesis 1.1d: Processing fluency (drift rates) for decisions about retaliation severity will account for more variance in retaliation severity than the amount of information needed to choose (decision threshold) and encoding duration (non-decision processes).

Aim 1.2: The secondary aim of Study 1 was to test the associations between processing fluency of aggression (drift rates) and antagonistic dispositions.

Hypothesis 1.2a: Trait angry rumination will demonstrate a positive association with processing fluency (drift rates) for retaliation decisions.

Hypothesis 1.2b: Sadism will demonstrate a positive association with processing fluency (drift rates) for retaliation decisions.

Hypothesis 1.2c: Trait angry rumination will demonstrate a negative association with the amount of information required (decision thresholds) to make retaliation decisions.

Hypothesis 1.2d: Sadism will not be associated with the amount of information required (decision thresholds) to make retaliation decisions.

Methods

Participants

Participants were 212 undergraduates enrolled in an introductory psychology course. Of this original sample, 14 participants failed an attention check during the primary outcome measure used in Study 1 and were thus excluded from all analyses. The final sample contained 198 participants: 145 females, 41 males, 1 non-binary, and 11 missing gender data; age: M = 19.23, SD = 3.70, range = 18-54; race: 2 Arab, 41 Asian, 42 Black, 11 Latino, 1 Pacific Islander, 72 White, 18 mixed-race, and 11 missing race data. Participants received credit towards their class research requirement for participation.

An *a priori* power analysis was not used to determine the appropriate sample size as no estimates of the hypothesized effect existed in the literature at the outset of the present research. Studies of aggression typically capture small-to-medium main effects, r = .24 (Richard, Bond, & Stokes-Zoota, 2003). Thus, a minimum threshold of 130 participants provided at least 80% power to detect main effects of this magnitude or larger. As such, the sample used in Study 1 surpassed this threshold for 80% statistical power.

Measures

Aggression Choice Questionnaire Modified. Retaliation severity was measured using a modified version of the Aggression Choice Questionnaire (ACQ). The original ACQ was developed for measuring the delay discounting of retaliatory aggression (West et al., *under review*). I modified this measure to exclude the intertemporal choice component in order to obtain an explicit assessment of participant decisions about retaliation severity (Appendix A). The instructions of the ACQM were presented on an initial introductory screen which asked participants to "…take a moment and think about a person who has really hurt you." Participants were then asked to complete a series of dichotomous choices between smaller (coded as 0) and greater (coded as 1) levels of revenge severity (e.g., "Would you rather inflict pain level 4 or pain level 8?") against their selected target. They completed three practice trials to ensure they understood how the task worked before completing the full 50-trial ACQM. Retaliation severity was computed as the number of greater severity decisions made. Because the DDM is commonly applied to lexical decision tasks, the ACQM was constructed to be similar in form. Specifically, response options were displayed horizontally in the middle of the screen and participants responded using their keyboard by pressing the "E" key to select the option displayed on the left and the "I" key to choose the option on the right. The location of response options was randomized such that in half of the trials the lesser option was on the left, but was on the right in the remaining trials (Figure 1). The trials of the ACQM were also presented randomly within participants. Two follow-up questions were administered after the ACQM which asked participants to indicate the nature of their relationship (i.e., complete stranger, acquaintance, friend, close friend, family member, romantic partner, or other) and the degree of closeness they perceived (i.e., "Please indicate how close you are with this person"), on a scale of 1 (not close at all) to 5 (very close), with their target.

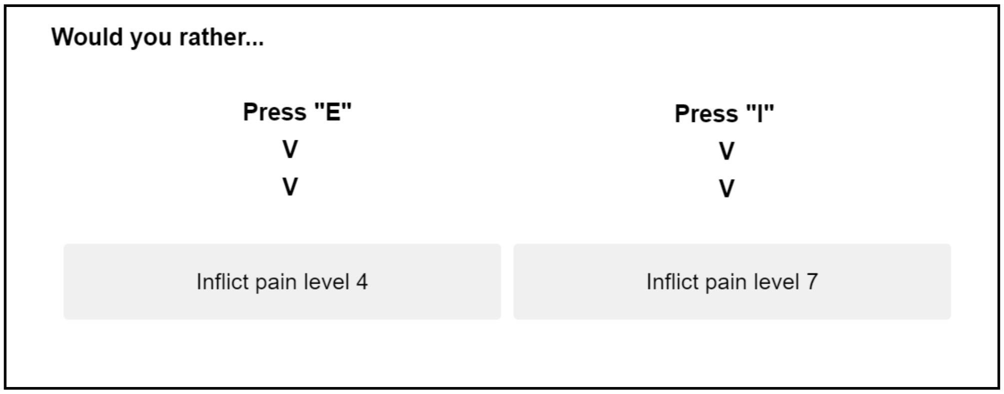

Figure 1. Example of a typical ACQM trial.

Angry Rumination Scale. Dispositions toward angry rumination were measured using the Angry Rumination Scale (ARS; Sukhodolsky, Golub, & Cromwell, 2001; Appendix B). The ARS asked participants how frequently they experienced each of 19 examples of rumination (e.g., “I have long-living fantasies of revenge after a conflict is over,”) on a scale of 1 (almost never) to 4 (almost always). Trait angry rumination scores were computed as the mean of all 19 responses for each participant.

Processing Fluency Scale. Subjective feelings of processing fluency during the ACQM were measured using the five item Processing Fluency Scale (PFS; Graf, Mayer, & Landwehr, 2018; Appendix C). Participants were asked to report the extent to which they experienced processing fluency (“Think back to when you evaluated and ultimately decided on the decisions you made on the task you just completed. The process of making these choices was…”) regarding the decisions made during the ACQM. Five bi-polar response scales were then used to respond to this same statement on a scale of 1 (e.g., “effortful”) to 5 (e.g., “effortless”). Self-reported processing fluency scores were computed as the average value of these five responses for each participant.

Short Sadistic Impulses Scale. The Short Sadistic Impulses Scale was used to measure the extent to which participants derive hedonic pleasure from hurting others (SISS; O'Meara et al., 2011; Appendix D). Participants were asked to rate 10 items (e.g., "I have fantasies which involve hurting people") on a scale of 1 (strongly disagree) to 5 (strongly agree). Sadism scores were then computed as the mean of the 10 responses for each participant.

Procedure

Participants signed up for an online study ostensibly interested in examining the impact of personality traits on memory and decision-making. Online study sessions lasted no longer than one hour and were conducted using the Qualtrics internet survey platform. After providing informed consent, participants completed the ACMQ and PFS. Participants then completed a questionnaire battery including a demographics questionnaire (Appendix E) the ARS, and SSIS. Because Study 1 was completed online in an environment of the participants' choosing, I included two attention check items that instructed participants to select a specific number from an array. One of these items was presented during the ACQM to ensure attentiveness during this measure because it was the primary outcome of interest, the second was placed in the questionnaire battery. Participants were then debriefed and granted credit towards their class research requirement for participation.

Data Preparation

All data preparation and subsequent analyses were conducted in SPSS version 27 unless otherwise noted. The fast-dm software suite was used to apply the DDM to participant data from the ACQM (Voss & Voss, 2007).

Drift Diffusion Model Analytic Approach

Pre-processing. Prior to the application of the DDM I subjected trial-level response data from the ACQM to a screening for RT outliers as the DDM is particularly sensitive to extreme RT values (Voss, Voss, & Lerche, 2015). However, the DDM considers each participant's set of RTs as a distinct distribution. This necessitates a within-participant RT screening rather than screening the entire sample at once. As such, I split participant responses and RTs from the ACQM into individual data files, applied a base-10 log transformation to each set of participant RTs, and then standardized the transformed RTs. Trials with standardized RTs beyond +/- 3SD from the participant's mean were excluded from the DDM analyses. This procedure necessitated a second screening for participants who had less than 40 total trials of data following the outlier screening as the DDM requires a minimum of 40 trials to properly estimate the desired parameters (Voss et al., 2013). Four participants from Study 1 were excluded from the DDM analyses for this reason. As a result, the DDM was applied to 194 individual ACQM datasets.

Assessment of Model Fit. For each participant I estimated relative starting bias, decision thresholds, drift rates, and non-decision processes. Following this initial estimation, I conducted a Monte Carlo data simulation to generate 1,000 individual datasets with 50 trials worth of data each. The responses and RTs in these simulated datasets were based off of the mean DDM parameters derived from the empirical data using the *construct-samples* function from fast-dm as is necessary for the assessment of DDM model fit (Voss & Voss, 2007). I then applied the same DDM estimation routine to the simulated data to find the 5% quintile of the fit index distribution which served as the cutoff for acceptable model fit for the observed parameter estimates (Voss et al., 2013). Application of the model fit cutoff differed on the basis of the estimator used. Specifically, DDM applications using the Kolmogorov-Smirnov (KS) method returned *p*-values such that higher values reflected a better fit because a significant KS statistic indicates poor model fit. Conversely, the Maximum-Likelihood (ML) estimator relied on -LL values for assessing model fit such that lower values reflected a better fit (Voss & Voss, 2007).

Results and Discussion

Descriptives. In addition to the 14 participants that failed the attention check question during the ACQM, four failed the second attention check during the questionnaire battery and thus their data was only excluded from analyses involving the questionnaire (i.e., PFS, ARS, and SSIS) data. Missingness across all variables in Study 1 was 7.58%. A Little's Missing Completely at Random (MCAR) analysis indicated that missingness was not systematic, $\chi^2(17) = 12.47$, $p = .771$. However, given the low level of missingness I did not impute missing values per my preregistered analysis plan. All descriptive and internal reliability statistics from Study 1 are presented in Table 1. No variables from Study 1 demonstrated significant skew and kurtosis (i.e., absolute values beyond 2) excepting the mean RT variable from the ACQM which was severely skewed and kurtotic but was not transformed at the sample-level (see the "Pre-processing" section above for more details).

Table 1

Descriptive and Internal Reliability Statistics from Study 1

	N	*M*	*SD*	Skew	Kurtosis	Outliers	*ω*
Angry rumination	193	2.19	0.56	0.54	0.06	1	0.92
Decision thresholds	194	3.26	2.01	1.61	1.94	4	-
Drift rates	194	-0.63	1.43	-0.17	0.94	1	-
Non-decision	194	0.21	0.17	1.72	6.05	2	-
Processing fluency (SR)	193	3.85	0.79	-0.38	-0.53	0	0.77
Relative bias	194	0.44	0.18	-0.04	-0.37	0	-
Response time	198	1.32	1.19	4.01	21.60	-	0.90
Retaliation severity	198	15.56	17.30	0.85	-0.73	0	0.99
Sadism	183	1.54	0.51	1.09	0.68	2	0.79

Note. Response time = untransformed mean reaction time across all ACQM trials in seconds. SR = Self-report. Sample-level RT outliers not reported here as the DDM requires RT outliers to be screened within-participants.

Retaliation Targets. The follow-up questions from the ACQM provided some insight into who participants thought of as their target during the ACQM. The single most common category was family member (24.70%), followed by acquaintances (15.20%), romantic partners (14.60%), friends (12.60%), close friends (9.10%), and complete strangers (8.10%). The remaining 15.70% of participants chose “other” for this question. Of these responses the single most common (67.47%) was one of the above categories with some indication of “former” appended to it (e.g., “ex-romantic partner”, “former close friend”). I also asked participants to indicate how close they were with their chosen target. The most common response in Study 1 was the lowest degree of closeness (i.e., “not close at all”) accounting for 42.00% of all responses. The remaining responses were comprised of 17.60% at the second degree of closeness, 11.90% at the third, 11.40% at the fourth, and 17.10% at the highest degree of closeness (i.e., “very close”). On average participants rated their degree of closeness with their ACQM target at 2.46, *SD* = 1.53. As such, it appears that participants largely selected retaliation targets they did not consider to be close with personally.

Drift Diffusion Modeling. Per my pre-registered analysis plan I initially applied the DDM using the Kolmogorov-Smirnov (KS) estimator and level 5 precision. The model fit assessment procedure indicated that participants with fit values under the critical cut off, *p(KS)* = 0.92, demonstrated a poor model fit. Examination of the empirical fit values indicated that 27 participants (13.71% of the sample) had poor model fit. This high proportion of poor fit values suggested that the DDM approach used resulted in an unacceptable fit to the data. As such, I re-estimated the DDM using the Maximum-Likelihood (ML) estimator per my preregistered analysis plan because it is more appropriate for tasks with less than 100 trials (Voss et al., 2013). I then conducted the same simulation procedure for assessing model fit and fit the DDM to the simulated data. Examination of the fit values indicated that participants with a fit index above the cutoff, *-LL* = 148.00, were of poor model fit. Review of participant fit estimates revealed that two participants (1.03% of the sample) exhibited poor fit, thus providing support for *Hypothesis 1.1a*. As such this application of the DDM and the resultant parameter estimates were retained. This outcome provides initial evidence that the DDM can indeed account for decisions made about retaliation severity in dichotomous choice tasks. However, the failure of the KS estimator to fit the data appropriately indicate that more trials in future studies may allow for the use of more robust estimators such as the KS.

Accuracy of Web Data Collection. The collection of RT data over the internet can be problematic due to the use of many different device and software arrangements used by participants as such variations can introduce measurement error. As such, several diagnostic analysis steps were necessary to ensure that systematic variance in the DDM parameters were not due to artifacts rising from differences across devices (i.e., browser versions and operating systems). Participants completed Study 1 primarily using the Google Chrome browser (67.20%), followed by the Safari browser (26.80%), the remaining 6.10% of participants used Microsoft Edge or Mozilla Firefox. An exploratory one-way ANOVA indicated no significant differences across the groups for mean RTs during the ACQM, $F(2, 195) = 1.21$, $p = .300$, drift rates, $F(2, 191) = 0.38$, $p = .687$, decision thresholds, $F(2, 191) = 0.59$, $p = .555$, relative bias, $F(2, 191) = 0.28$, $p = .755$, or non-decision processes, $F(2, 191) = 1.73$, $p = .180$. Regarding operating systems, 58.30% of participants completed Study 1 on a computer with MacOS, 38.20% used Windows, and 3.00% used a device with the ChromeOS. As with various internet browsers, an exploratory one-way ANOVA revealed no differences across operating systems in respect to mean RTs during the ACQM, $F(2, 195) = 0.48$, $p = .618$, drift rates, $F(2, 191) = 1.14$, $p = .323$, decision thresholds, $F(2, 191) = 0.07$, $p = .933$, relative bias, $F(2, 191) = 1.55$, $p = .215$, or non-decision processes, $F(2, 191) = 0.31$, $p = .736$. As such, it appears that the collection of RTs online and the resulting DDM parameter estimates were not significantly impacted due to participant's use of various devices and software.

Validation of Drift Rates as a Measure of Processing Fluency. Although there are parallels in the literature between processing fluency and drift rates, drift rates have yet to be established as a valid tool for measuring processing fluency. As such, I computed an exploratory bivariate correlation between drift rates and self-reported processing fluency which revealed no significant association between the two, $r(192) = .02$, $p = .787$. This lack of association appeared to be due to a subset of participants that selected the less-severe options on most of the ACQM trials. These participants thus reported the processing fluency for repeatedly choosing this option rather than the few instances where they did choose greater retaliation severity because the wording of the PFS failed to specify that I was interested in their fluency for greater-severity decisions.

Identifying such participants required the use of a *k*-means cluster analysis. *k*-means cluster analysis is an algorithm-based, data-driven technique that assigns participants to independent groups (clusters) based on how similar they across a set of selected variables (Hartigan & Wong, 1979). This analysis allows researchers to identify subsets of participant by using empirical means rather than arbitrary approaches (i.e., median splits). Participants exhibiting the above characteristics should exhibit low drift rates yet high self-reported processing fluency. In order to identify this possible subset of participants, I thus conducted a *k*-means cluster analysis containing the standardized drift rate and PFS variables for two, three, and four cluster solutions. A three-cluster solution (Table 2) fit the data best as all other tested solutions yielded less proportionate cluster memberships, whereas a more proportionate allocation of participants to clusters reflects a better fit to the data (Gupta, Datta, & Das, 2018).

Table 2

Distribution of Participants Across Clusters and ANOVA Results

	Two	Three	Four
Cluster 1	85	53	47
Cluster 2	106	74	69
Cluster 3	-	64	29
Cluster 4	-	-	46
Cluster 5	-	-	-
Drift Rates	$F(1, 189) = 44.40$	$F(2, 188) = 130.14$	$F(3, 187) = 123.27$
PFS	$F(1, 189) = 165.89$	$F(2, 188) = 188.10$	$F(3, 187) = 173.02$

Note. All ANOVA results are significant at the $p < .001$ level.

The three-cluster solution (Figure 2) revealed two clusters whose PFS and drift rates aligned with one another, Cluster 1 had PFS values and drift rates that were above the sample mean ($n = 53$) Cluster 2 had PFS value and drift rates that were below the sample mean ($n = 74$). A third cluster emerged whose PFS and drift rate values were inconsistent ($n = 64$), such that average PFS values were above the sample mean but average drift rates were below the sample mean. Exploratory independent-samples *t*-tests also revealed that Cluster 3 exhibited the lowest average retaliation severity of these clusters (Table 3). This finding suggests that those in Cluster 3 were not as motivated to seek vengeance against their target and thus reported on the relative ease with which they made less-severe decisions.

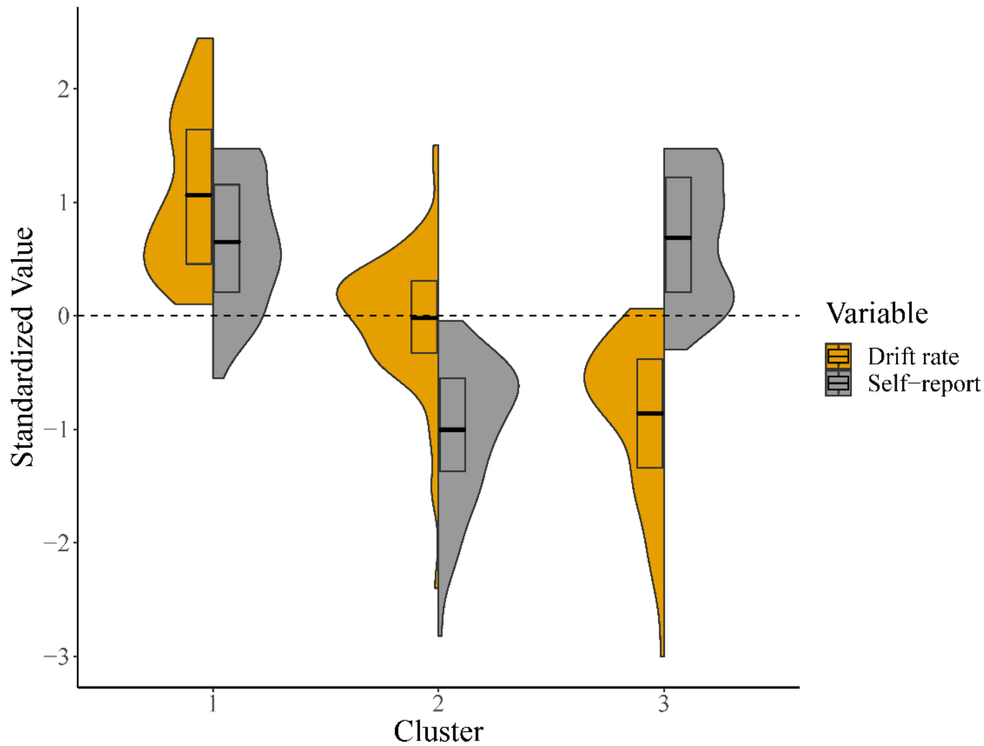

Figure 2. Grouped violin and boxplots depicting the standardized values of the self-report PFS variable and drift rates across the three clusters found in Study 1. Bars in the boxplots represent cluster means rather than medians. The dashed horizontal line represents the sample mean.

Table 3

Results of Exploratory t-tests Comparing Retaliation Severity Across Clusters

	M(*SD*)	Cluster 2	Cluster 3
Cluster 1	36.65 (13.56)	$t(125) = 10.87$; $d = 1.96$	$t(54.08) = 18.78$; $d = 3.82$
Cluster 2	12.03 (11.99)	-	$t(78.22) = 7.50$; $d = 1.20$
Cluster 3	1.39 (2.11)	-	-

Note. All tests significant at the $p < .001$ level.

I thus reverse-coded the PFS items for participants in Cluster 3 so their answers would reflect the degree of fluency they felt when they *did* make more severe choices and then re-computed the PFS scores. The recoded PFS variable demonstrated marginally improved internal consistency, ω = 0.88. A bivariate correlation between the recoded PFS variable and participant drift rates revealed strong convergence between them, $r(189) = .72$, $p < .001$. I also examined this association without the Cluster 3 participants (and thus without the recoded PFS values) and found similar results, $r(125) = .57$, $p < .001$. These findings suggest that drift rates do reflect processing fluency in value-based choice tasks, but that a subset of participants in Study 1 were either unmotivated to retaliate against their target or were unable to accurately self-report their feelings of fluency. The recoded PFS variable was used for all subsequent analyses involving self-reports of processing fluency.

Processing Fluency and Retaliation Severity. A bivariate correlation analysis supported *Hypothesis 1.1b*, as drift rates showed a strong positive association (Figure 3) with retaliation severity, $r(192) = .85$, $p < .001$. I reconducted this analysis using the recoded self-report of processing fluency and found comparable results, $r(193) = .71$, $p < .001$. The results of a bivariate correlation analysis revealed a significant negative association between decision thresholds and retaliation severity, $r(192) = -.23$, $p = .001$, providing support for *Hypothesis 1.1c*. These findings taken jointly support a processing fluency account of retaliatory aggression consistent with the Multi-Source Account of processing fluency (Gamblin et al., 2020). These findings further indicate that aggressive individuals process retaliation-related decisions more efficiently and require less information to decide how much harm to inflict. These findings are also consistent with work indicating that dispositionally aggressive individuals are more efficient at processing aggression-related information (Brennan & Baskin-Sommers, 2020).

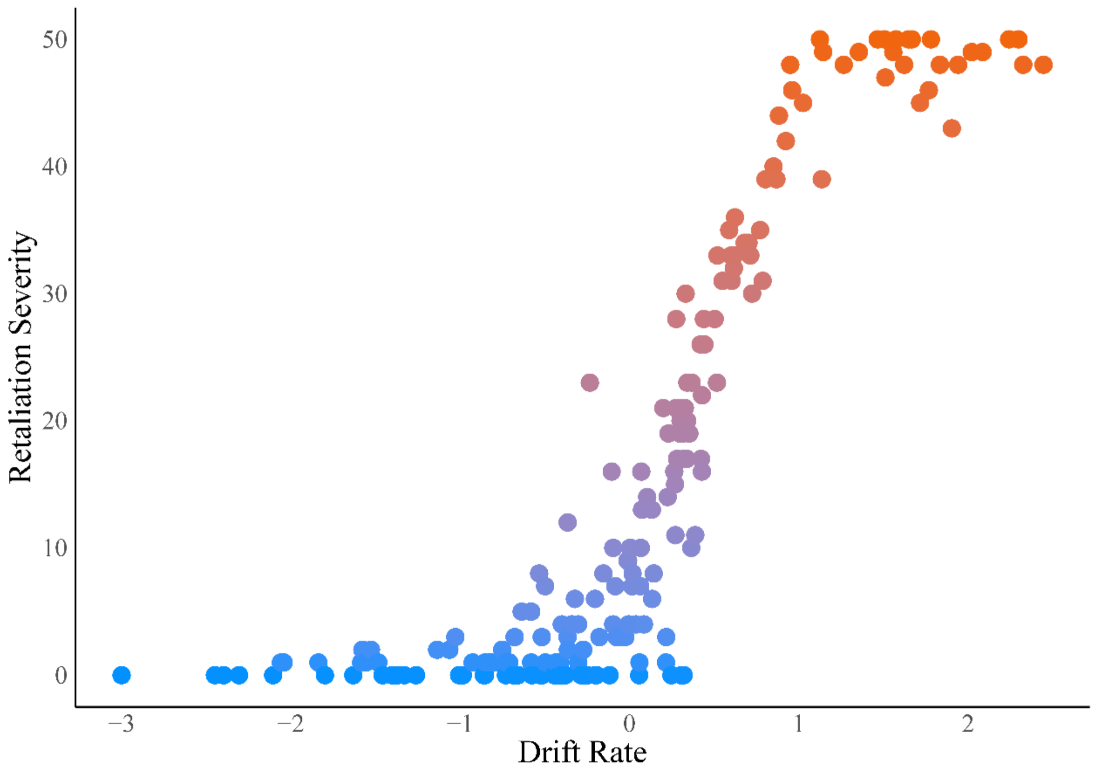

Figure 3. Scatterplot depicting the association between retaliation severity and standardized drift rates.

Processing Fluency and Trait Correlates. See Figure 4 for all zero-order correlations. In support of *Hypothesis 1.2a,* a bivariate correlation revealed a small-to-moderate positive association among trait angry rumination and drift rates from the ACQM. A similar association was found between trait angry rumination and the recoded self-report of processing fluency. *Hypothesis 1.2b* was supported by a bivariate correlation indicating there was a small-to-moderate positive relationship between Sadism and drift rates. Again, there was a similar association found between Sadism and the recoded self-report variable. These findings provide preliminary evidence that antagonistic dispositions are linked with aggressive behaviors in part due to a distinct cognitive profile that may underlie higher levels of such traits. This interpretation is consistent with the GAM and data indicating that individuals with personality disorders typified by extreme violence (e.g., Antisocial Personality Disorder) possess distinct cognitive styles which facilitate the decision making inherent to such behaviors (Bushman & Anderson, 2002; Gilbert & Daffern, 2011).

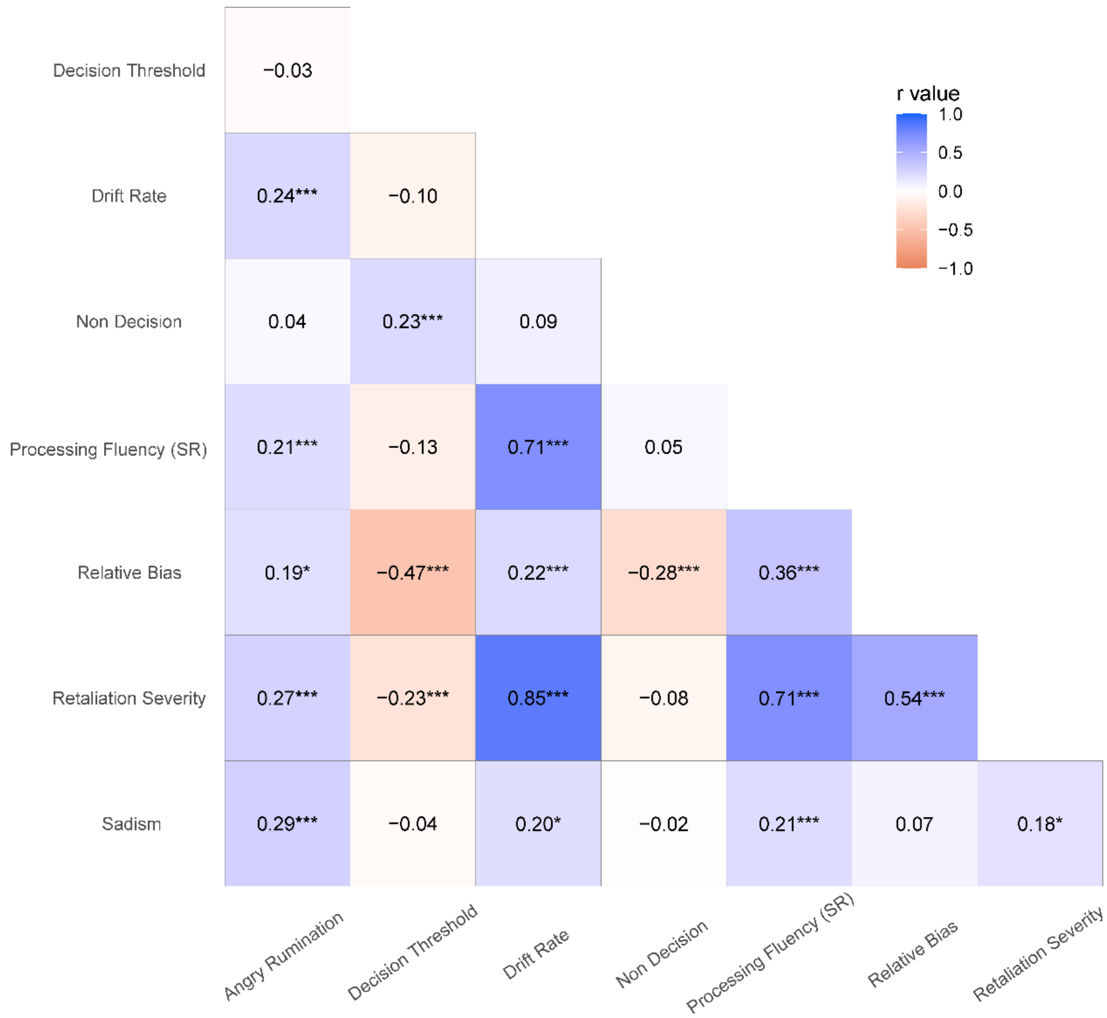

Figure 4. All zero-order correlations from Study 1. SR = self-report. *p < .05, **p < .01, ***p < .001.

Decision Thresholds and Trait Correlates. A bivariate correlation analysis failed to provide support for *Hypothesis 1.2c*, as was no significant association between trait angry rumination and decision thresholds emerged. However, a significant positive association did emerge between trait angry rumination and relative bias, indicating that angry ruminators evinced a greater bias toward greater retaliation severity prior to presentation of the options during the ACQM. An initial bivariate correlation analysis supported *Hypothesis 1.2d,* as no significant association emerged between Sadism and decision thresholds. However, non-significant *p*-values only provide evidence against rejecting null hypotheses, not evidence directly supporting the null hypothesis.

Equivalency Testing. Equivalency tests are a type of analysis that allows researchers to test for the equivalency of an effect size to a selected value (i.e., 0). The two one-sided tests (TOST) approach to equivalency testing allows researchers to directly test null hypotheses. This analytic approach tests for the statistical equivalence of a given effect size (i.e., the association between Sadism and decision thresholds) to zero while ruling out the presence of the smallest effect size of interest (SESOI) though a standard null hypothesis test. As such, I conducted an equivalence test by applying the two one-sided tests (TOST) approach via the *TOSTr* function from the TOSTER package for R version 4.0.3 (Lakens, Scheel, & Isager, 2018). Because no known estimates of the effects being examined in the current study could be found, I relied on the number of participants to determine the SESOI for this analysis. Specifically, I conducted a specificity power analysis using G*power 3.1.9 for a bivariate correlation with 80% power (Faul, Erdfelder, Buchner, & Lang, 2009). This analysis indicated that my sample allowed me to reliably detect small associations ($r = .20$). As such, the SESOI bounds of the equivalence test were set as -.20 and .20. This analysis revealed a significant TOST result (indicated by a 90% CI that *includes* zero), 90% CI: -0.17, 0.08, $p = .018$, and a non-significant null hypothesis test (indicated by a 95% CI that includes zero), 95% CI: -0.19, 0.10, $p = .539$, supporting *Hypothesis 1.2d*.

Hierarchical Linear Regression. To test *Hypothesis 1.1d* all four DDM parameters were entered into a hierarchical regression model predicting retaliation severity. The results (Table 4) of this analysis indicated that drift rates remained a significant predictor at every step of the analysis and appeared to have the strongest partial correlation with retaliation severity at the last step.

Table 4

Hierarchical Linear Regression Results Predicting Retaliation Severity

Step	Predictors	*t*	*β*	*p*	Partial	VIF
1	Drift Rate	22.44	.85	<.001	.85	1.00
2	Drift Rate	22.86	.84	<.001	.86	1.01
	Decision Threshold	-4.08	-.15	<.001	-.29	1.01
3	Drift Rate	27.73	.77	<.001	.90	1.05
	Decision Threshold	0.78	.02	.439	.06	1.28
	Relative Bias	12.33	.39	<.001	.67	1.33
4	Drift Rate	28.03	.78	<.001	.90	1.08
	Decision Threshold	1.06	.03	.291	.08	1.30
	Relative Bias	11.66	.37	<.001	.65	1.40
	Non-decision	-2.28	-.07	.024	-.17	1.13

Note. VIF = variance inflation factor.

The assumption of multicollinearity was met by the model (i.e., all variance inflation estimates < 1.40). Visual inspection of the normal Q-Q plot indicated that the assumption of normality was satisfied. However, visual inspection of a scatter plot of the standardized regression residuals and the fitted values suggested that the assumption of homoscedasticity was violated (Figure 5).

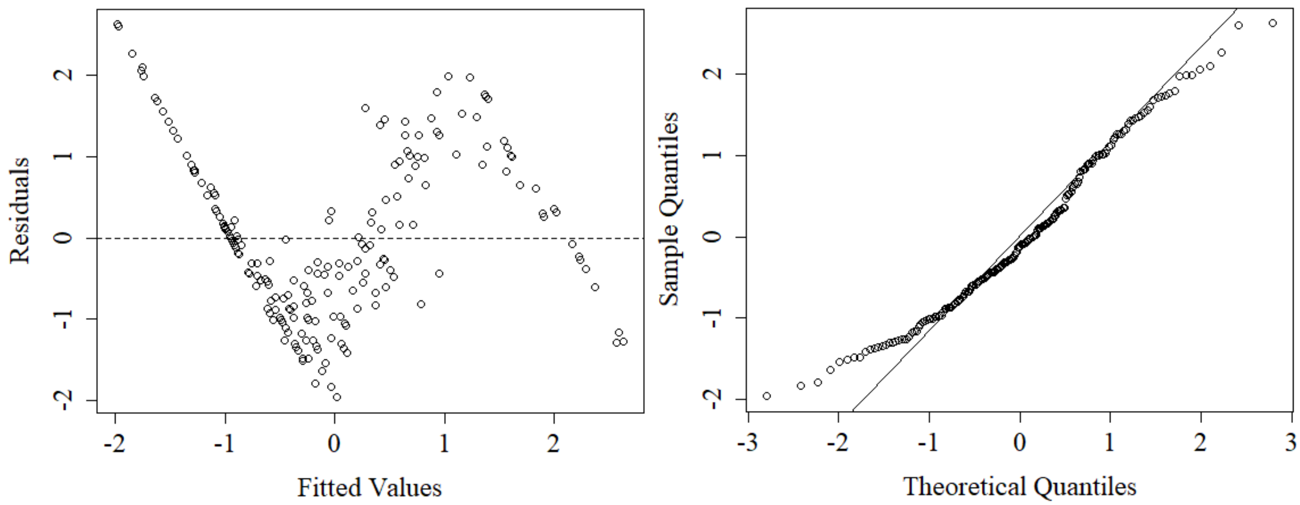

Figure 5. Scatterplot of residual and fitted values (left) and normal Q-Q plot (right) from the hierarchical linear regression model from Study 1.

Closer inspection of the dependent variable revealed that retaliation severity was overdispersed such that the standard deviation was greater than the sample mean and 21.70% of participants chose the lesser option exclusively, reflecting the Pareto distribution (Figure 6). As such, the retaliation severity data were not normally distributed. The negative binomial distribution accounts for such overdispersion and is particularly well-suited to handle overdispersed count data such as the retaliation severity variable (Lloyd-Smith, 2007). Thus, to ensure that my linear regression findings were not an artifact of this violated assumption I reconducted the final step of the analysis using a negative binomial regression via the *glm.nb* function from the MASS package in R (Venables & Ripley, 2013). This analysis revealed similar results (Table 5) excepting that decision threshold remained a significant predictor in the model. However, drift rates again emerged as the strongest predictor such that each raw unit increase in drift rates led to the selection of approximately 3.71 high severity options during the ACQM.

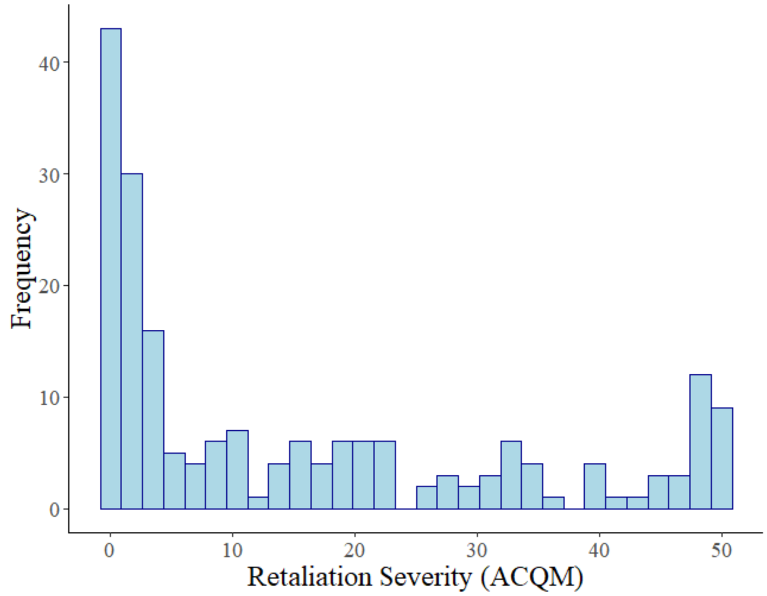

Figure 6. Distribution of the retaliation severity variable from Study 1.

Table 5

Negative Binomial Regression Results Predicting Retaliation Severity

Predictor	*Z*	*Exp(B)*	*p*
Decision Threshold	-10.68	0.48	<.001
Drift Rates	25.89	3.71	<.001
Non-decision	3.45	1.19	<.001
Relative Bias	11.45	1.92	<.001

I also replicated this analysis using the recoded self-report of processing fluency and found similar results. Specifically, self-reported processing fluency also appeared to be the strongest predictor in the model (Table 6). As such, I proceeded with my planned dominance analyses to confirm these observed differences in predictor strength.

Table 6

Negative Binomial Regression Results Predicting Retaliation Severity Using Self-Reports of Processing Fluency

Predictor	*Z*	*Exp(B)*	*p*
Decision Threshold	-7.93	0.45	<.001
Processing Fluency (SR)	11.42	2.46	<.001

Non-decision	1.34	1.19	<.001
Relative Bias	7.69	1.12	.180

Note. SR = self-report.

Dominance Analysis. In order to confirm that processing fluency was indeed the strongest predictor of retaliation severity I conducted a planned dominance analysis. Dominance analysis provides a superior test of the importance of a given predictor than does hierarchical linear regression, as dominance analysis considers the relative strength of predictors within every possible subset of predictors rather than in a linear stepwise fashion (Azen & Budescu, 2003). However, there is currently no clear means by which to apply the negative binomial distribution to dominance analyses. Given the similarity of results between the linear and negative binomial regression models, I used the linear regression model for the dominance analysis. The dominance analysis was conducted using the ‘dominanceanalysis’ package for R version 4.0.3 (Bustos-Navarrete & Coutinho-Soares, 2020). I entered all four of the DDM parameters into a dominance analysis as predictors of retaliation severity. In order to lend greater stability to the analysis I used a 5,000 bootstrap procedure. This analysis indicated (Table 7) that drift rates exhibited complete dominance over the other three DDM parameters in 100% of the 5,000 bootstrap samples, thus lending support to *Hypothesis 1.2d.*

Table 7

Bootstrapped Dominance Analysis Results Predicting Retaliation Severity

a	*b*	*Dab*	*mDab*	*SE*	*Prop*
Decision Threshold	Drift Rates	0.00	0.00	0.00	1.00
Decision Threshold	Non-decision	0.50	0.51	0.08	0.97
Drift Rates	Non-decision	1.00	1.00	0.00	1.00
Relative Bias	Decision Threshold	1.00	1.00	0.01	1.00
Relative Bias	Drift Rates	0.00	0.00	0.00	1.00
Relative Bias	Non-decision	1.00	1.00	0.00	1.00

Note. a = predictor 1, b = predictor 2, Dab = degree of dominance of a over b, 1.00 indicates complete dominance of a over b, 0.00 indicates complete dominance of b over a, values between 0 and 1 indicate incomplete dominance. mDab = the mean dominance values from the 5,000 sample bootstraps, Prop = proportion of the 5,000 bootstraps that replicated the original dominance analysis result (Dab), SE = the standard error of the mean dominance weights.

I re-conducted this analysis replacing drift rates with self-reports of processing fluency and found similar results – self-reported processing fluency exhibited complete dominance in predicting retaliation severity over the DDM parameters (Table 8). These findings along with the results of the hierarchical regression are consistent with research demonstrating that decisions that are made more frequently are processed more fluently and further bolster claims of processing fluency as a cognitive component of retaliatory decision-making (Alter & Oppenheimer, 2009).

Table 8

Bootstrapped Dominance Analysis Results Predicting Retaliation Severity Using Self-reports of Processing Fluency

a	*b*	*Dab*	*mDab*	*SE*	*Prop*
Decision Threshold	Processing Fluency (SR)	0.00	0.00	0.00	1.00
Decision Threshold	Non-decision	0.50	0.53	0.13	0.92
Processing Fluency (SR)	Non-decision	1.00	1.00	0.00	1.00
Relative Bias	Decision Threshold	1.00	1.00	0.04	1.00
Relative Bias	Processing Fluency (SR)	0.00	0.00	0.00	1.00
Relative Bias	Non-decision	1.00	1.00	0.00	1.00

Note. a = predictor 1, b = predictor 2, Dab = degree of dominance of a over b, 1.00 indicates complete dominance of a over b, 0.00 indicates complete dominance of b over a, values between 0 and 1 indicate incomplete dominance. mDab = the mean dominance values from the 5,000 sample bootstraps, Prop = proportion of the 5,000 bootstraps that replicated the original dominance analysis result (Dab), SE = the standard error of the mean dominance weights, SR = self-report.

Study 1 provided initial evidence of processing fluency's role in making decisions about retaliation and that Sadism and trait angry rumination are associated with such fluency. However, Study 1 was correlational in nature and did not allow me to examine factors that may cause changes in processing fluency. For example, it could have been the case that the observed associations among trait angry rumination, Sadism, and processing fluency in Study 1 were due to extraneous variables. Similarly, the internal validity of Study 1 was relatively low as in all correlational studies due to a lack of experimental controls. It could be that there is some feature of rumination in general that facilitates processing fluency rather than angry rumination specifically. Likewise, it could have been general negative affect rather than anger specifically that facilitated the observed fluency in Study 1. Beyond these design-based limitations, application of the DDM to novel tasks requires that manipulations only alter one of the model parameters (Ratcliff & Childers, 2015). To address these limitations in Study 2 I employed a between-subjects experimental manipulation aimed at altering drift rates but not the other DDM parameters that allowed me to examine the specific effects of angry rumination on processing fluency.

Study 2

Study 2 implemented an experimental manipulation of angry rumination to test how angered states as a causal factor for increased processing fluency for decisions about retaliation severity. According to the existing evidence, self-referent information (e.g., angry memories) is processed more fluently than information about others (Hessen-Kayfitz & Scoboria, 2012). Induced angry rumination should thus lead to the activation of related memories and emotional experiences, which should in turn increase processing fluency for related decisions such as retaliation severity (Foster et al., 2017; Sweklej, Balas, Pochwatko, & Godlewska, 2014).

To this end, I used a boredom rumination induction as a comparison condition to the angry rumination condition. Boredom, like anger, is a negatively valanced affective state that is accompanied by sensation-seeking tendencies and rumination (Bench & Lench, 2019; Denson, 2013; Sousa & Neves, 2020; van Tilburg & Igou, 2017). Further, experiences of boredom and anger last approximately the same amount of time (e.g., two hours; Verduyn & Lavrijsen, 2015).

Unlike anger however, boredom is a low arousal experience that is not typified by the mental planning and rehearsal of retaliation scenarios involved in angry rumination (van Tilburg & Igou, 2017). Thus, the use of a boredom rumination induction was an appropriate comparison to the angry rumination condition as it allowed me to control for sensation-seeking, negative affect, and simple rumination as reasons for observed differences in processing fluency.

The implementation of the rumination manipulation also allowed me to further examine the ability of the DDM to accurately account for decisions about retaliation severity. When the DDM is applied to novel tasks such as in the current work analytic steps are needed to validate that a given experimental manipulation actually affects the parameter of interest in the model (Ratcliff & Childers 2015). The manipulation used in Study 2 should thus only impact the drift rates estimated by the DDM and none of the other parameters (i.e., decision thresholds, relative bias, and non-decision processes).

Aim 2.1: The primary aim of Study 2 was to test the ability of induced angry rumination to increase processing fluency for decisions about retaliatory aggression, thereby increasing retaliation severity.

Hypothesis 2.1a: Those exposed to an angry rumination induction will exhibit greater processing fluency (drift rates) for decisions about the severity of retaliation against a provocateur than those in the boredom rumination condition.

Hypothesis 2.1b: Those exposed to an angry rumination induction will make more severe retaliation decisions than those in the boredom rumination condition.

Hypothesis 2.1c: Processing fluency (drift rates) will exhibit an indirect effect on the link between condition and retaliation severity. Specifically, those assigned to the angry rumination condition will exhibit significantly greater drift rates for retaliation decisions which will in turn predict greater retaliation severity.

Given the associations found among trait angry rumination, retaliation severity, and processing fluency in Study 1, it is likely that this disposition will also play a role in the expected indirect effect in Study 2. Specifically, it seems that dispositional angry ruminators will be more impacted by the manipulation because angry ruminators spend more time reliving angering experiences and practicing revenge scenarios (Denson, 2013). Reliving of such events should relate to greater feelings of anger following the manipulation whereas mental rehearsal of revenge should facilitate greater processing fluency and thus retaliation severity. Thus, as an exploratory aim in Study 2 I examined the ability of trait angry rumination to moderate the expected indirect effect at each path in the model described for *Hypothesis 2.1c*.

Methods

Participants

Participants in Study 2 were 250 undergraduates enrolled in an introductory psychology course. Of these participants, 35 failed the attention check during the ACQM, and were thus excluded from all analyses. The final sample consisted of 215 undergraduates: 161 females, 37 males, and 1 non-binary, 16 missing gender data; age: $M = 18.59$, $SD = 1.10$, range = 18-24; race: 2 Arab, 33 Asian, 37 Black, 23 Latinx, 76 White, 27 mixed-race, 17 missing race data. Participants received credit towards their class research requirement.

As in Study 1, no estimates of the hypothesized effects existed in the literature that could be used for a traditional *a priori* power analysis. A Monte Carlo *a priori* power analysis was computed for a simple indirect effect using the MCPowerMed web application (Schoemann, Boulton, & Short, 2017). This application allows for the estimation of needed sample sizes based on correlation coefficients. I used a small-to-moderate (*r* = .20) effect size between rumination condition and processing fluency as prior work demonstrates similarly sized effects of experimental manipulations of affective states on drift rates (e.g., Tipples, 2015). I used a large effect size (*r* = .50) for the association between processing fluency and the frequency of severe retaliation decisions, as drift rates often show large associations with the choices made during the task from which drift rates were estimated (e.g., Ratcliff et al., 2004). Finally, I used a moderate-to-large effect size (*r* = .40) between rumination condition and retaliation severity as is demonstrated in prior research manipulating rumination (e.g., Denson et al., 2011). I computed a 5000-sample Monte Carlo simulation based on the above parameters which indicated that I would need at least 185 participants to achieve 80% power for the planned indirect effect analysis, 95% CI = 78%, 81%. Thus, my sample of 215 participants provides an adequate level of power for this analysis. All participants were recruited from the VCU SONA participant pool to complete a one-hour study session for which they were compensated 1 research credit. Thus, all participants were at least 18 years of age and enrolled in an introductory psychology course at VCU.

Measures

Discrete Emotions Questionnaire. The state anger scale from the DEQ served as a manipulation check for the angry rumination induction (Harmon-Jones, Bastian, & Harmon-Jones, 2016; Appendix F). This measure asked participants to report the extent to which they experienced a given emotion (e.g., “Angry”) during a specific experience (e.g., writing an essay) on a scale of 1 (not at all) to 7 (an extreme amount). The original DEQ contains 32 items which span the emotions of anger, disgust, fear, anxiety, sadness, desire, relaxation, and happiness. I implemented items from the anger, fear, sadness, relaxation, and happiness sub-scales, reducing the measure to 20 items total. State anger scores were computed as the mean of the four items comprising this subscale.

Procedure

As in Study 1, participants signed up for an online study ostensibly examining the impact of personality traits on memory and decision-making. Online study sessions lasted no longer than one hour. After providing informed consent participants were randomly assigned to either the angry rumination or boredom rumination condition. Those assigned to the angry rumination condition were asked to “Take a moment and think of someone who has really hurt or angered you in the past. Once you have found such a person please write a detailed summary of what you remember about this event…” (Appendix G). Those in the boredom rumination condition were given identical instructions except they were asked to write about a person who bored them in the past. Participants were asked to write about their recalled memory for 10 minutes. Following the writing task, participants completed the DEQ as a manipulation check, the ACQM, and PFS. Participants were instructed to use the person they wrote about during the essay writing task as the target for their retaliation choices. After completing the ACQM participants then completed a questionnaire battery including a demographics questionnaire, ARS, and SSIS. Two attention check items were also included in Study 2 as detailed in Study 1.

Data Preparation

All data preparation and analyses were conducted in SPSS version 27 unless otherwise noted. Data preparation in Study 2 followed the same protocol as detailed in Study 1. Experimental condition was coded such that 0 = boredom rumination condition and 1 = angry rumination condition.

Drift Diffusion Model Analytic Approach

Pre-processing. Prior to the application of the DDM I subjected trial-level response data from the ACQM to a screening for RT outliers as described in Study 1. No participants were found to have less than 40 trials after removing all RT outliers.

Assessment of Model Fit. All model specification and fit assessment procedures for the DDM estimates in Study 2 were identical to the those detailed in Study 1. I conducted the same 1000-sample Monte Carlo simulation and model fitting procedure as detailed in Study 1 using the mean observed parameter values obtained from the DDM to obtain the cutoff value for acceptable model fit.

Results and Discussion

Descriptives. In addition to the participants who failed the attention check during the ACQM, five participants failed the attention check embedded in the questionnaire battery and thus were excluded from analyses using the questionnaire data (i.e., PFS, ARS, and SSIS). As in Study 1, missingness was minimal such that the combined missingness for Study 2 was 7.44%. A Little's MCAR analysis indicated that missingness was not systematic, $\chi^2(7) = 7.90$, $p = .341$. However, given the low level of missingness I did not impute missing values per my preregistered analysis plan. All descriptive and internal reliability statistics from Study 2 are presented in Table 9. The retaliation severity variable exhibited significant skew and kurtosis (i.e., +/- 2). Given that the retaliation severity variable was a count variable containing zeros, the base-10 log transformation was not appropriate for addressing this skew. As such, the retaliation severity variable was not transformed. The mean RT variable from the ACQM was also severely skewed and kurtotic but was not transformed (see the *Pre-processing* section of Study 1 for more details).

Table 9

Descriptive and Internal Reliability Statistics from Study 2

Variable	*N*	*M*	*SD*	Skew	Kurtosis	ω	Outliers
Anger	215	2.94	1.92	0.64	-0.93	0.95	0
Angry rumination	210	1.99	0.52	0.80	0.47	0.91	2
Decision threshold	215	3.54	2.08	1.05	0.36	-	4
Drift rates	215	-1.31	1.32	0.80	1.83	-	4
Non-decision	215	0.17	0.14	1.17	2.33	-	3
Processing fluency (SR)	210	3.81	0.90	-0.56	-0.29	0.83	1
Relative bias	215	0.40	0.18	-0.01	-0.84	-	0
Response time	215	0.99	0.81	6.23	50.40	0.90	-
Retaliation severity	215	7.34	13.40	2.13	3.43	0.99	10
Sadism	195	1.51	0.56	1.51	1.92	0.85	5

Note. Response time = untransformed mean reaction time across all ACQM trials in seconds. SR = Self-report. RT outliers not reported here as the DDM requires RT outliers to be screened within-participants.

Retaliation Targets. The follow-up questions from the ACQM provided insight into who participants thought of as the subject of their essay and target for the ACQM. The single most common category was family member (20.90%), followed by acquaintances (17.20%), friends (14.00%), close friends (13.00%), complete strangers (7.40%), and romantic partners (6.50%). The remaining 20.90% of participant chose “other” for this question. Of these responses the single most common target was some form of educator (50.98%). We also asked participants to indicate how close they were with their chosen target. The most common response in Study 2 was the lowest degree of closeness (i.e., “not close at all”) accounting for 43.70% of all responses. The remaining responses were comprised of 13.00% at the second degree of closeness, 14.00% at the third, 11.20% at the fourth, and 18.10% at the highest degree of closeness (i.e., “very close”). On average participants rated their degree of closeness with their ACQM target at 2.47, *SD* = 1.56. Thus, participants largely selected retaliation targets they did not consider to be close with personally as was observed in Study 1.

Drift Diffusion Modeling. Per my pre-registered analysis plan I first applied the DDM to the ACQM data using the KS estimator with level 5 precision. The fit index cutoff value obtained from the model fit procedure was $p(KS) = .93$, whereas participants with a fit index below this threshold were considered to be of poor fit. As in Study 1, the KS estimator did not fit the data well, as 33 participants (15.35% of the sample) were identified as being of poor fit. As such, I re-applied the DDM using the ML estimator and conducted another Monte Carlo simulation before fitting the DDM to the simulated data. The resultant fit index cutoff was $-LL = 143.71$, whereas participants with fit values greater than this threshold were considered to be of poor fit. No participants were found to have poor fit using the ML estimator and thus the recovered parameters were retained for the remaining analyses.

Accuracy of Web Data Collection. Several diagnostic analysis steps were necessary to ensure that any systematic variance in the DDM parameters were not due to artifacts rising from differences across devices (i.e., browser versions and operating systems). Participants completed Study 2 primarily using the Google Chrome browser (63.70%), followed by the Safari browser (30.7%), the remaining 5.6% of participants used various different browsers (i.e., Microsoft Edge, Mozilla Firefox, and Opera). An exploratory one-way ANOVA indicated no significant differences across the groups for mean RTs during the ACQM, $F(2, 212) = 0.03$, $p = .975$, drift rates, $F(2, 212) = 0.79$, $p = .454$, decision thresholds, $F(2, 212) = 0.11$, $p = .896$, relative bias, $F(2, 212) = 0.51$, $p = .602$, or non-decision processes, $F(2, 212) = 0.07$, $p = .933$. Regarding operating systems, 61.40% of participants completed Study 2 on a computer with MacOS, 36.70% used Windows, and 1.90% used a device with the ChromeOS. As with various internet browsers, an exploratory one-way ANOVA revealed no significant differences across operating systems in respect to mean RTs during the ACQM, $F(2, 212) = 0.16$, $p = .855$, drift rates, $F(2,$

212) = 1.40, p = .249, decision thresholds, $F(2, 212) = 0.05$, p = .949, relative bias, $F(2, 212)$ = 0.67, p = .515, or non-decision processes, $F(2, 212) = 0.49$, p = .612. As such, it appears that the collection of RTs online and the resulting DDM parameter estimates were not significantly impacted due to participant's use of various devices and software.

Validation of Drift Rates as a Measure of Processing Fluency. As in Study 1, I examined the association between drift rates from the ACQM and self-reported processing fluency for the same decisions. Similar to Study 1, there was no significant association between them, $r(213) = -.10$, p = .154. I thus conducted the same *k*-means cluster analysis detailed in Study 1 to determine if this was due to a subset of participants primarily choosing the less-severe option (and thus reporting on fluency for the lesser option, rather than the greater option). As in Study 1 a three-cluster solution appeared to fit the data best (Table 10).

Table 10

Distribution of Participants Across Clusters and ANOVA Results

Cluster Number	Two	Three	Four
Cluster 1	79	44	57
Cluster 2	131	68	18
Cluster 3	-	98	48
Cluster 4	-	-	87
Cluster 5	-	-	-
Drift Rates	$F(1, 208) = 128.35$	$F(2, 207) = 124.50$	$F(3, 206) = 175.21$
PFS	$F(1, 208) = 119.50$	$F(2, 207) = 184.60$	$F(3, 206) = 128.81$

Note. All ANOVA results are significant at the $p < .001$ level.

Inspection of the three clusters (Figure 7) revealed a similar pattern as observed in Study 1. Cluster 1 (n = 44) had drift rates above the sample mean and self-reports just below the sample mean. Cluster 2 (n = 68) had drift rates and self-reports of fluency below the sample mean. Finally, Cluster 3 (n = 98) exhibited the same inverse pattern as in Study 1, such that self-reports were above the sample mean but drift rates were below the sample mean. As in Study 1, those in

Cluster 3 had the lowest degree of retaliation severity in relation to the other clusters (Table 11), indicating again that this group of participants were either not motivated to retaliate against their target or were unable to accurately self-report on their experienced degree of fluency.

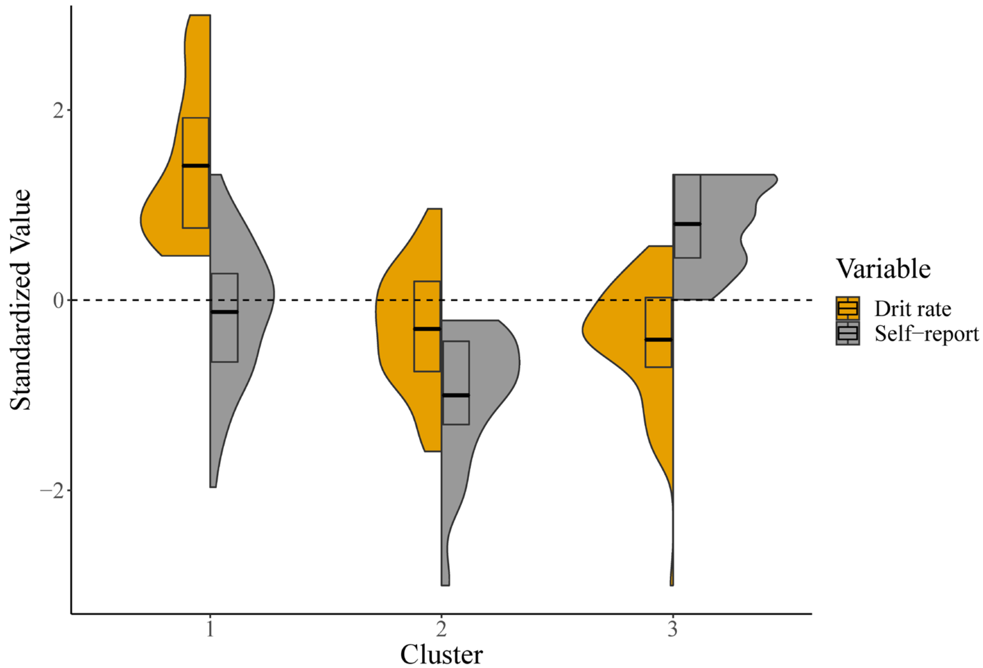

Figure 7. Grouped violin and boxplots depicting the standardized values of the self-report PFS variable and drift rates across the three clusters found in Study 2. Bars in the boxplots represent cluster means rather than medians. The dashed horizontal line represents the sample mean.

Table 11

Results of Exploratory t-tests Comparing Retaliation Severity Across Clusters

	M(*SD*)	Cluster 2	Cluster 3
Cluster 1	28.42 (16.63)	*t*(47.55) 10.00, *d* = 2.33	*t*(43.42) = 10.90; *d* = 2.94
Cluster 2	2.97 (5.10)	-	*t*(79.59) = 2.75; *d* = 0.50
Cluster 3	1.08 (1.72)	-	-

Note. All tests significant at the $p < .001$ level excepting the comparison between Clusters 2 and 3 ($p = .007$).

I thus reverse-coded the PFS items for participants in Cluster 3 so that their responses indicated the fluency of making stronger retaliation decisions. The recoded PFS variable yielded marginally improved internal consistency, ω = 0.87, and demonstrated a moderate-to-strong positive association with drift rates during the ACQM, $r(208) = .45$, $p < .001$. A similar association was found without these participants, $r(110) = .36$, $p < .001$. The recoded PFS variable was used for all subsequent analyses involving self-reports of processing fluency.

Replication of Study 1 Analyses

Correlational Analyses. All zero-order correlations from Study 2 are presented in Figure 8. Replicating my findings from Study 1, drift rates demonstrated a strong, positive association with retaliation severity and decision thresholds yielded a moderate, negative association with retaliation severity. Contrary to Study 1, trait angry rumination was not significantly associated with drift rates or decision thresholds. However, state anger stemming from the rumination manipulation was positively associated with drift rates during the ACQ but not decision thresholds. As in Study 1, Sadism was positively associated with drift rates and self-reported processing fluency.

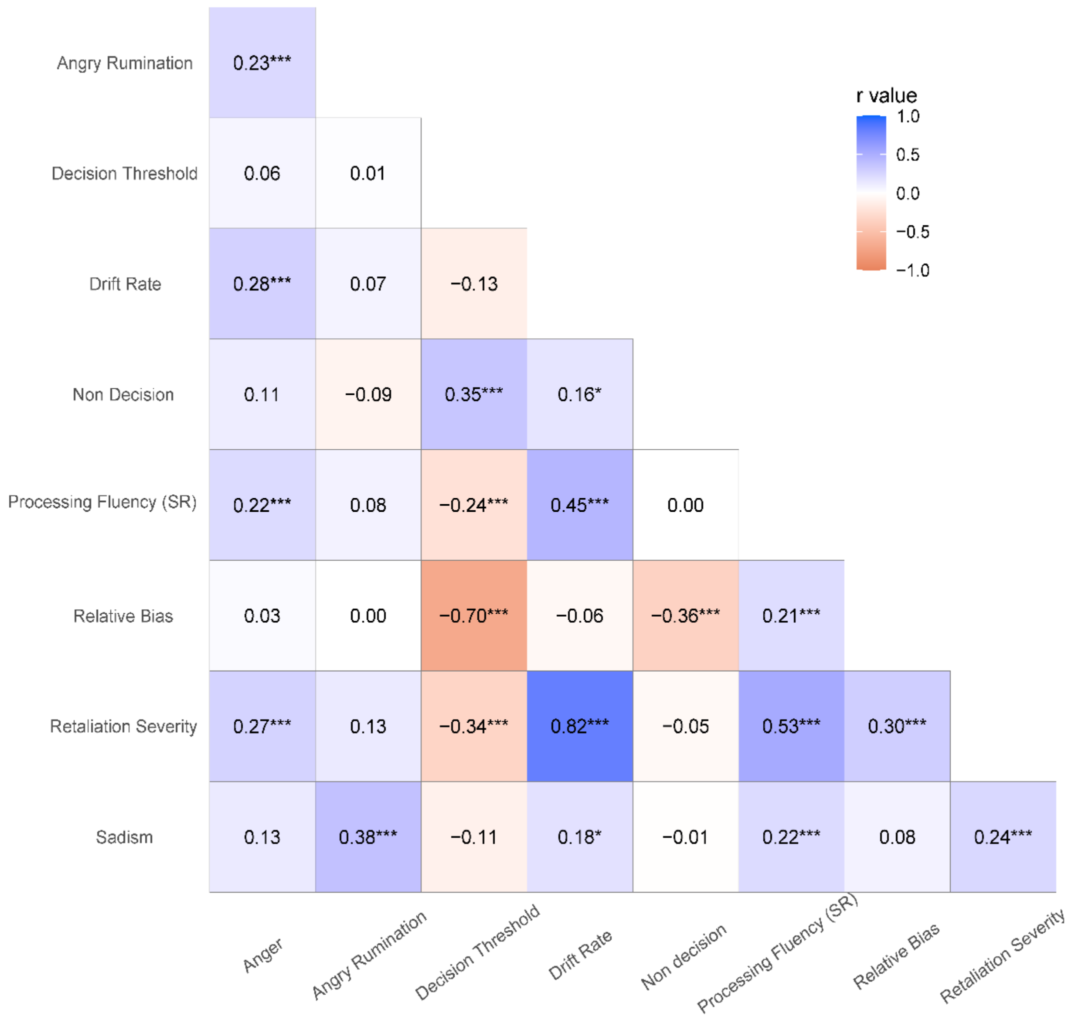

Figure 8. All zero-order correlations from Study 2. SR = self-report **p* < .05, ***p* < .01, ****p* < .001.

Hierarchical Linear Regression. I also replicated the hierarchical linear regression analysis from Study 1 which produced similar results (Table 12). As in Study 1, the assumptions of the linear regression were met excepting the assumption of homoscedasticity (Figure 9).

Table 12

Hierarchical Linear Regression Predicting Retaliation Severity

Step	Predictor	t	β	p	Partial	VIF
1	Drift Rates	21.13	.82	<.001	.82	1.00

2	Drift Rates	22.05	.79	<.001	.83	1.02
	Decision Threshold	-6.57	-.24	<.001	-.41	1.02
3	Drift Rates	26.47	.85	<.001	.88	1.07
	Decision Threshold	0.68	.03	.498	.05	2.10
	Relative Bias	8.24	.37	<.001	.49	2.07
4	Drift Rates	26.62	.86	<.001	.88	1.11
	Decision Threshold	1.07	.05	.285	.07	2.18
	Relative Bias	7.96	.36	<.001	.48	2.11
	Non-decision	-2.13	-.07	.034	-.15	1.22

Note. VIF = variance inflation factor.

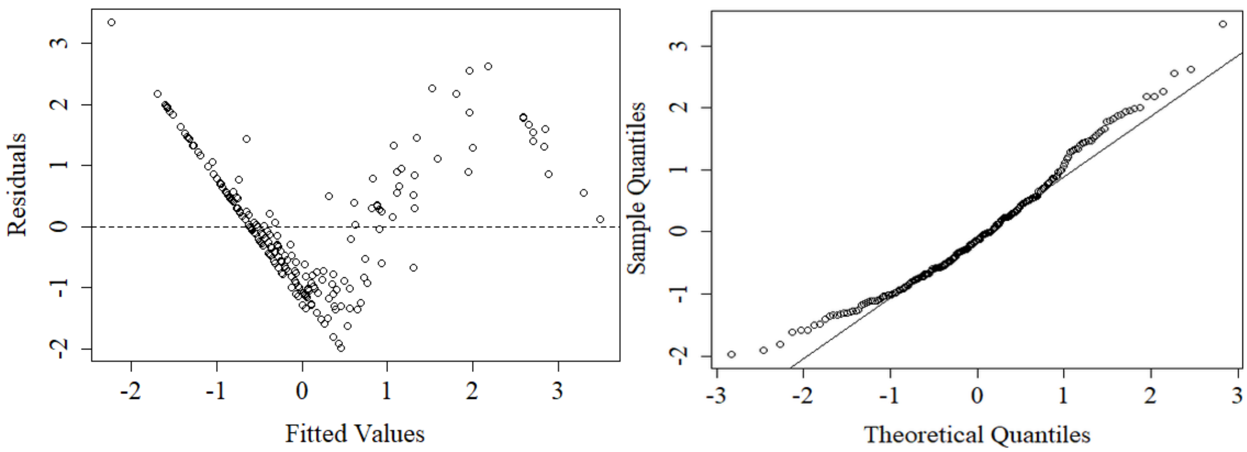

Figure 9. Scatter plot of residual and fitted values (left) and normal Q-Q plot (right) from the hierarchical linear regression model from Study 2.

Negative Binomial Regression. Inspection of the retaliation severity variable again revealed an overdispersed distribution. Indeed, 35.30% of participants in Study 2 selected the lesser option exclusively during the ACQM (Figure 10). As such, I recreated the final step of the hierarchical model using a negative binomial regression. Both drift rates (Table 13) and self-reports of processing fluency (Table 14) emerged as the strongest predictors in their respective models. This analysis revealed that a single raw unit increase in drift rates was associated with the selection of approximately 3.82 more greater-severity options during the ACQM.

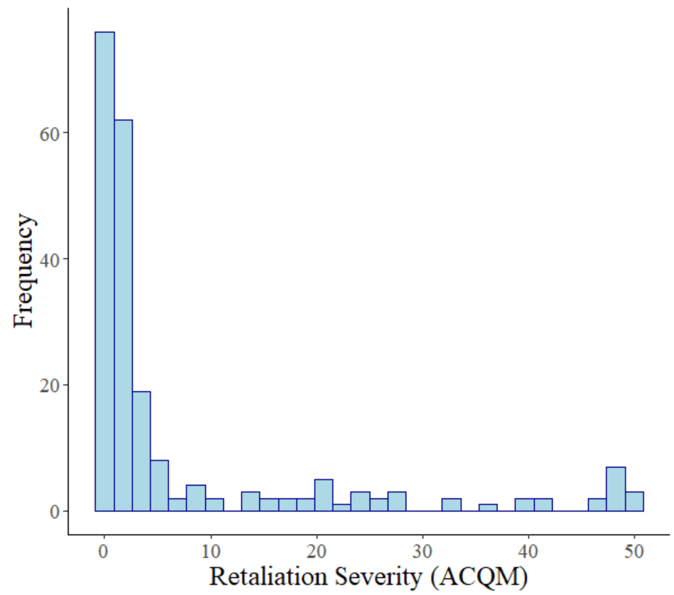

Figure 10. Distribution of the retaliation severity variable from Study 2.

Table 13

Negative Binomial Regression Results from Study 2 Predicting Retaliation Severity.

Predictor	*Z*	*Exp(B)*	*p*
Decision Threshold	-8.14	0.45	<.001
Drift Rate	27.05	3.82	<.001
Non-decision	1.57	1.09	.117
Relative Bias	10.33	2.10	<.001

Table 14

Negative Binomial Regression Results Predicting Retaliation Severity Using Self-Reports of Processing Fluency

Predictor	*Z*	*Exp(B)*	*p*
Decision Threshold	-12.89	0.55	<.001
Processing Fluency (SR)	30.02	2.41	<.001
Non-decision	1.96	1.05	.050
Relative Bias	10.62	1.34	<.001

Note. SR = Self-report.

Dominance Analysis. Finally, I replicated the dominance analysis as conducted in Study 1, which also revealed largely identical results such that drift rates exhibited complete dominance over the other DDM parameters as a predictor of retaliation severity (Table 15).

Table 15

Bootstrapped Dominance Analysis Results Predicting Retaliation Severity

a	*b*	*Dab*	*mDab*	*SE*	*Prop*
Relative Bias	Decision Threshold	0.50	0.65	0.23	0.69
Relative Bias	Drift Rate	0.00	0.00	0.00	1.00
Relative Bias	Non-decision	1.00	0.82	0.24	0.63
Decision Threshold	Drift Rate	0.00	0.00	0.00	1.00
Decision Threshold	Non-decision	0.50	0.55	0.15	0.90
Drift Rate	Non-decision	1.00	1.00	0.00	1.00

Note. a = predictor variable 1, b = predictor variable 2, Dab = degree of dominance of a over b, 1.00 indicates complete dominance of a over b, 0.00 indicates complete dominance of b over a, mDab = the mean dominance values from the 5,000 sample bootstraps, Prop = proportion of the 5,000 bootstraps that replicated the original dominance analysis result (Dab), SE = the standard error of the mean dominance weights.

Re-conducting this analysis using the self-reported processing fluency variable again revealed similar results to the drift rate model and the models from Study 1 (Table 16). As such, processing fluency again exhibited complete dominance over all other DDM parameters whether measured by drift rates or self-reports of processing fluency.

Table 16

Bootstrapped Dominance Analysis Results Predicting Retaliation Severity Using Self-Reports of Processing Fluency

a	*b*	*Dab*	*mDab*	*SE*	*Prop*
Decision Threshold	Processing Fluency (SR)	0.00	0.00	0.00	1.00
Decision Threshold	Non-decision	0.50	0.53	0.13	0.92
Processing Fluency (SR)	Non-decision	1.00	1.00	0.00	1.00
Relative Bias	Decision Threshold	1.00	1.00	0.04	1.00
Relative Bias	Processing Fluency (SR)	0.00	0.00	0.00	1.00
Relative Bias	Non-decision	1.00	1.00	0.00	1.00

Note. a = predictor variable 1, b = predictor variable 2, Dab = degree of dominance of a over b, 1.00 indicates complete dominance of a over b, 0.00 indicates complete dominance of b over a, values between 0 and 1 indicate incomplete dominance. mDab = the mean dominance values from the 5,000 sample bootstraps, Prop = proportion of the 5,000 bootstraps that replicated the original dominance analysis result (Dab), SE = the standard error of the mean dominance weights, SR = self-report.

Study 2 Hypothesis Tests

Manipulation Check. In order to ensure the success of the rumination manipulation I compared the reported degree of state anger between the anger and boredom conditions. This analysis revealed that those in the angry rumination condition reported significantly greater feelings of anger following the essay writing task than those in the boredom condition, $t(192.45) = 9.54$, $p < .001$, $d = 1.29$, 95% CI = 1.00, 1.58. This finding suggests that the rumination manipulation worked as intended.

Processing Fluency. As predicted in *Hypothesis 2.1a,* an independent samples *t*-test revealed that participants in the angry rumination condition demonstrated significantly greater drift rates for aggression decisions than those in the boredom condition, $t(198.52) = 4.81$, $p < .001$, $d = 0.65$, 95% CI = 0.38, 0.93. In order to ensure that this finding was not simply an artifact of the DDM, I re-tested this hypothesis using the self-reports of processing fluency. This analysis yielded a similar result, such that those in the anger rumination condition reported greater fluency for retaliation choices, $t(208) = 3.46$, $p < .001$, $d = 0.48$, 95% CI = 0.20, 0.75.

Retaliation Severity. The results of an independent samples *t*-test supported *Hypothesis 2.1b*, as those in the anger condition exhibited a preference for significantly greater retaliation severity, $t(171.12) = 4.15$, $p < .001$, $d = 0.56$, 95% CI = 0.29, 0.83, than those in the boredom condition.

Validating the Impact of Anger on Drift Rates. I performed three exploratory equivalency tests comparing the decision threshold, relative bias, and non-decision parameters across conditions to ensure the anger rumination manipulation only impacted drift rates. I used the same strategy as in Study 1 to determine the equivalency bounds for these analyses. Specifically, a sensitivity analysis in G*Power revealed that the sample collected for Study 2 could reliably detect between-subjects effect sizes of $d = 0.38$ and above at 80% power (Faul et al., 2009). Thus, the equivalency bounds were set to -0.38, 0.38 for these analyses. Results indicated that any differences between the conditions in relative bias, decision thresholds, and non-decision processes were statistically equivalent to zero (Table 17). These findings taken with the large difference found in drift rates indicate that the rumination manipulation only had a significant impact on drift rates.

Table 17

Equivalency Testing Results Comparing DDM Parameters Across Conditions

	90% CI (TOST)	p_{TOST}	95% CI (NHST)	p_{NHST}
Decision Threshold	-0.39, 0.55	.006	-0.48, 0.64	.779
Relative Bias	-0.04, 0.04	.003	-0.05. 0.05	1.00
Non-decision	-0.04, 0.02	.012	-0.05, 0.03	.601

Note. NHST = null hypothesis statistical testing, TOST = two one-sided tests.

Indirect Effect Analysis. In order to test *Hypothesis 2.1c*, I conducted an indirect effect analysis using model 4 from the PROCESS macro for SPSS with a 5,000 sample bootstrap procedure (Hayes, 2016). Specifically, I modeled rumination condition as the independent variable, processing fluency (i.e., drift rates) as the mediator, and retaliation severity as the dependent variable. This analysis revealed a significant model (Figure 11; Table 18), $R^2 = .68$, $F(2, 212) = 222.48$, $p < .001$ and a significant indirect effect of drift rates on retaliation severity, $\beta = 0.51$, 95% BCACI = 0.31, 0.69.

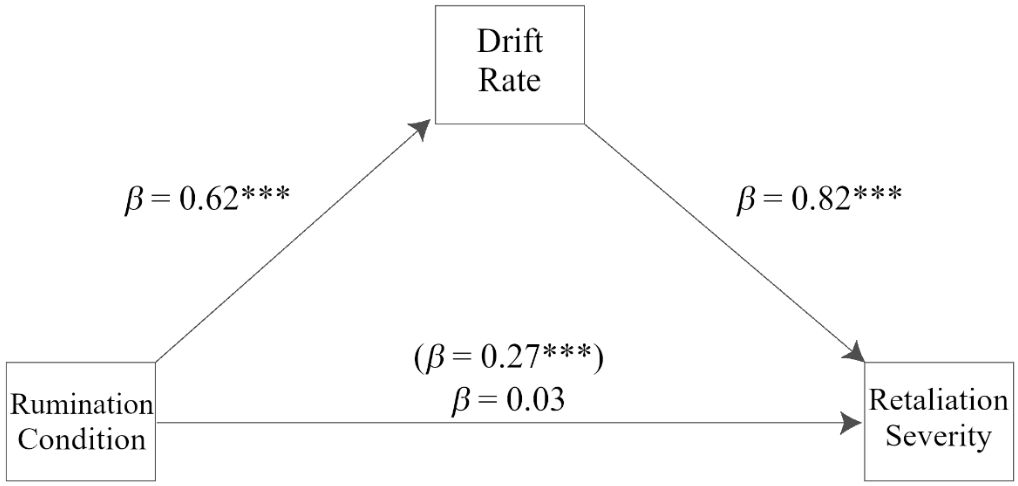

Figure 11. Indirect effect model from Study 2 displaying standardized regression coefficients. Values inside parentheses represent the C-prime path. *** $p < .001$.

Table 18

Indirect Effect Analysis Results

Outcome	Predictor	t	β	p	95% CI
Drift Rates	Condition	4.77	0.62	<.001	0.36, 0.86
Retaliation Severity	Condition	4.11	0.27	<.001	0.14, 0.39
Retaliation Severity	Drift Rates	19.92	0.82	<.001	0.74, 0.90
	Condition	0.41	0.03	.682	-0.13, 0.19

I again re-tested this hypothesis using the recoded self-report of processing fluency. This analysis produced similar results (Table 19) such that the model was significant, $R^2 = .31$, $F(2, 207) = 46.12$, $p < .001$, as was the indirect effect of self-reported processing fluency, $\beta = 0.23$, 95% BCACI = 0.10, 0.37. As such, *Hypothesis 2.1c* was supported using both drift rates and self-reported processing fluency values.

Table 19

Indirect Effect Analysis Results Using Self-Reports of Fluency as the Mediator

Outcome	Predictor	t	β	p	95% CI
Processing Fluency (SR)	Condition	3.46	0.47	<.001	0.20, 0.73
Retaliation Severity	Condition	4.33	0.29	<.001	0.16, 0.41
Retaliation Severity	Processing Fluency (SR)	8.22	0.49	<.001	0.37, 0.60

	Condition	2.92	0.34	.004	0.11, 0.57

Note. SR = Self-report.

Exploratory Moderation Analysis. In order to explore the possibility of trait angry rumination to moderate this indirect effect I conducted a moderated-mediation analysis using model 59 from the PROCESS macro and a 5,000-sample bootstrap procedure (Hayes, 2016). Condition was modeled as the independent variable, processing fluency (drift rate) was modeled as the mediator, retaliation severity was modeled as the dependent variable, and trait angry rumination was modeled as a moderating factor for all three paths of the indirect effect model. This analysis revealed a significant model, $R^2 = .69$, $F(5, 204) = 88.85$, $p < .001$. A significant conditional effect of trait angry rumination on the indirect effect of processing fluency (drift rates) was found at every level of the moderator (Table 20). I then inspected the interaction terms at each step of the analysis in order to understand which of these was driving the moderation effect. However, all three interaction terms were insignificant (Figure 12). As such, it appears that trait angry rumination may indeed moderate the indirect effect of drift rates on aggression, but the current sample is likely underpowered to provide stable estimates of these interaction terms.

Table 20

Conditional Indirect Effects from the Exploratory Moderated Mediation Analysis

Level of Moderator	β	*SE*	95% CI
-1 SD	0.40	0.15	0.16, 0.73
0 SD	0.51	0.12	0.29, 0.76
+1 SD	0.63	0.19	0.28, 1.02

Note. SE = standard error of the bootstrapped estimate.

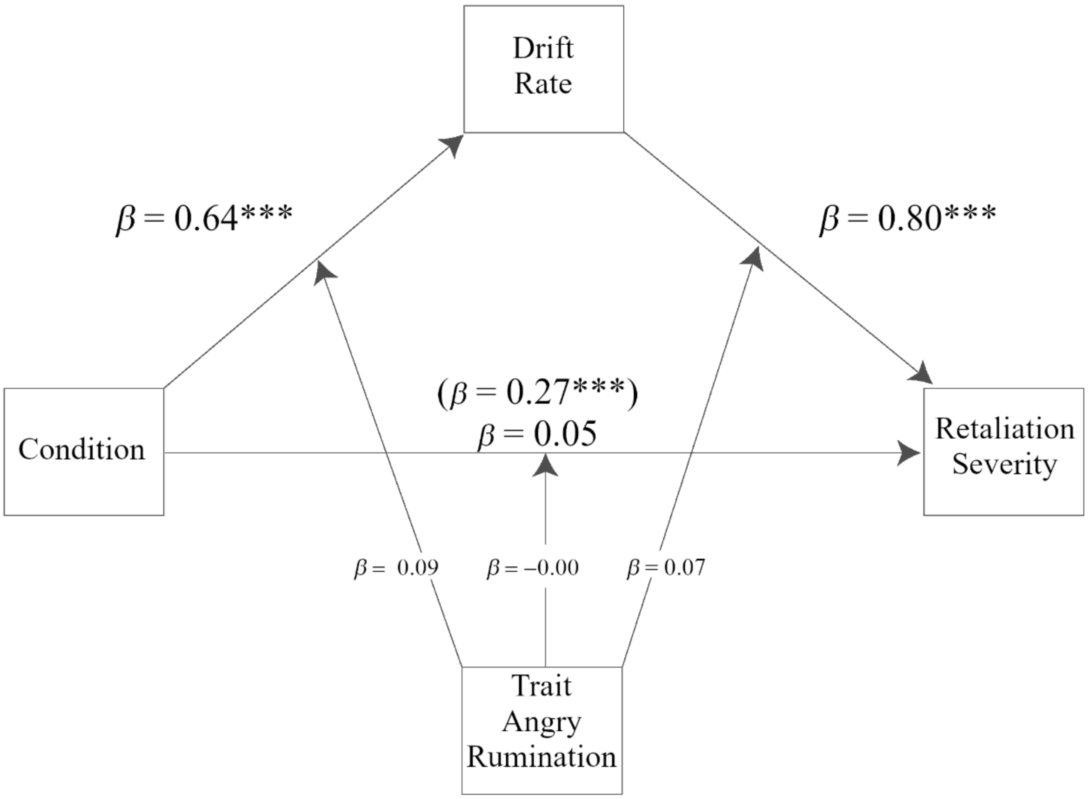

Figure 12. Exploratory moderated mediation results from Study 2 displaying standardized path coefficients. Values inside parentheses represent the C-prime path. ***$p < .001$.

General Discussion

Much is known about the various processes that facilitate and inhibit aggressive behaviors. Despite this ever-growing body of literature, no known work has sought to examine the role of processing fluency in making decisions about aggression. I conducted two studies that applied the Multi-Source Account of processing fluency in the first known attempt to estimate the involvement of processing fluency in decisions regarding the severity of retaliation against a provocateur and how such fluency may be reflected by antagonistic traits. Further, these studies mark the first time that drift diffusion modeling has been applied to aggression data and provide an initial validation of drift rates as a measure of processing fluency in value-based tasks. Across both studies I found evidence that processing fluency indeed facilitates the selection of more severe forms of retaliation and that such fluency is impacted by emotional states (i.e., anger) and is linked with antagonistic traits.

Application of the Drift Diffusion Model to Aggression

Validating the DDM for use with the ACQM. Studies 1 & 2 provided evidence that decisions about retaliation severity were indeed accounted for by the DDM. However, the model I initially planned to apply to these data using the KS estimator did not fit the data well. Prior research indicates this was likely due to the number of trials included in the ACQM, as the KS estimator performs better with at least 100 trials of data per participant (Voss et al., 2013). As a result, the ML estimator was applied to the data which found near-perfect fits in both studies. A crucial step in validating applications of the DDM to novel research contexts is to target a single parameter with a manipulation (Ratcliff & Childers, 2015). As such, I attempted to manipulate a single parameter of the DDM, drift rates, in Study 2 by using an angry rumination manipulation. The results provided clear evidence that indeed, induced angry rumination led to significantly greater drift rates, but did not impact any of the other DDM parameters. This finding is consistent with other work indicating that emotions related to the responses of a given DDM task increase drift rates (Tipples, 2015). Thus, these studies provide substantial evidence that the DDM can indeed be used to measure specific cognitive processes underlying decisions about retaliatory aggression.

Drift Rates as Processing Fluency. In both studies I found evidence that drift rates serve as a valid assessment of processing fluency. Specifically, self-reports of processing fluency evinced moderate-to-strong positive associations with drift rate estimates. However, these associations were marred by a subset of participants in both studies that almost exclusively chose the less-severe option during the ACQM. It seems likely that these participants were not motivated to retaliate against their chosen target, which suggests that the degree to which retaliation is rewarding is itself an individual difference. This was especially clear in Study 2 which saw far more participants placed in Cluster 3, presumably due to the boredom condition. As such, their responses to the PFS items indexed how fluent selections of the lesser options were. Reverse-coding the responses for these participants and excluding them outright both revealed positive associations between drift rates and self-reports of processing fluency in both studies.

In Studies 1 & 2 I also replicated every focal hypothesis test involving processing fluency by replacing participant drift rates with self-reports of processing fluency. Each one of these analyses produced significant results in the same direction as those using drift rates. However, the effect sizes of these follow-up analyses were often smaller in magnitude in contrast those using the drift rate estimates. These findings are consistent with work indicating that drift rates are a 'process-pure' measure in contrast to self-reports and basic RT values as measures of processing fluency (Schubert, Frischkorn, Hagemann, & Voss, 2016). Researchers seeking to use drift rates in this manner should plan to collect similar self-report data and should consider what such self-reports of fluency mean in the context of their primary measure of interest (i.e., value-based tasks vs. accuracy tasks).

Impact of Processing Fluency on Retaliation Severity

Across both studies processing fluency demonstrated a significant, positive association with the degree of retaliation severity. These findings provide initial support for the role of processing fluency in retaliatory aggression and are consistent with other research indicating that more aggressive individuals possess greater cognitive efficiency for the processing of related information (Brennan & Baskin-Sommers, 2020). Study 2 replicated these findings and provided evidence that evoked anger leads to a greater desire for severe retaliation indirectly through elevated processing fluency. However, both studies also contained a subset of participants who were not aggressive and effectively exhibited greater fluency when making less-severe retaliation decisions. These findings make good sense as non-aggressive individuals should have increased processing fluency for making non-aggressive decisions. This subset of participants was larger in Study 2 due presumably to the control condition. These findings together indicate that processing fluency's role in facilitating decisions about aggression is linked with affective states.

One component that likely plays a role in retaliation severity that was not examined in the current work is the temporal distance that lies between initial provocation and retaliatory decision-making. Indeed, it seems likely that provoking events that happened years prior to the decision-making event (e.g., the ACQM) may impact both fluency and retaliation severity. Likewise, a longer period between provocation and retaliation inherently includes a greater likelihood of erroneous memories. The opposite is also possible given that individuals high in trait angry rumination repeatedly relive angering experiences, it could be that such individuals have high fluency for these decisions (Denson, 2013). Given the positive association found in Study 1 between trait angry rumination and relative bias during the ACQM, it could be that angry rumination exerts influence on retaliation severity via response biases rather than processing fluency.

Effects of State Anger on Processing Fluency. Study 2 demonstrated that participants induced to ruminate over an angering incident pursued greater retaliation severity and demonstrated greater processing fluency than those induced to ruminate over a boring incident. These findings are consistent with the revenge-as-reward literature (e.g., Chester, 2017) as participants who felt angrier also pursued greater retaliation severity. According to the hedonic marking component of the Multi-Source Account of processing fluency, stimuli that are fluently processed evoke positive affect (Gamblin et al., 2020). As such, the degree of fluency experienced during retaliatory aggression may be a cognitive mechanism underlying the tendency to use retaliation as a means of mood repair (e.g., Bushman, 2002). The current work also provided evidence that elevated processing fluency for decisions about retaliation is a cognitive manifestation of antagonistic traits.

Trait Correlates of Processing Fluency for Retaliation

Sadism. In Studies 1 & 2 Sadism was positively associated with retaliation severity. These findings are consistent with evidence indicating that individuals higher in Sadism are more aggressive (Buckels et al., 2013; Chester et al., 2019; DeLisi et al., 2017; Reidy et al., 2011). Sadism was also positively associated with processing fluency in both Studies 1 & 2. These findings are consistent with the hedonic marking component of the Multi-Source Account of processing fluency, which posits that Sadistic individuals who process decisions about retaliation more fluently should derive greater pleasure during the decision-making process (Chester et al., 2019; Gamblin et al., 2020). Further, Sadism was unrelated to decision thresholds in Studies 1 & 2, indicating the specificity of Sadism’s links to distinct patterns of cognition regarding aggression. These findings taken together may point to processing fluency as a central mechanism in the development of Sadism, as Sadists may derive such pleasure in part from the experience of fluency itself which is then misattributed to the aggressive act. Such an interpretation is consistent with the perceptual fluency/attribution model, which posits that fluency is increased by repeated exposure to some stimulus, said fluency is accompanied by an increase in positive affect, and said affect is then attributed to the stimulus rather than fluency

(Bornstein & D'Agostino, 1994). This interpretation is also consistent with evidence that Sadists experience increases in positive affect during aggression (i.e., when choosing the degree of severity), but greater negative affect following the act itself (Chester et al., 2019).

Trait Angry Rumination. In Studies 1 & 2 trait angry rumination was positively associated with retaliation severity. These findings are consistent with evidence indicating that trait angry rumination is positively linked with the retaliatory aggression and a lower likelihood of forgiving others (Barber, Maltby, & Macaskill, 2005; García-Sancho, Salguero, & Fernández-Berrocal, 2016). In Study 1 trait angry rumination was positively associated with processing fluency for making such decisions. Conversely, my prediction that trait angry rumination would be negatively associated with decision thresholds was not supported. However, the zero-order correlations from Study 1 revealed that trait angry rumination was positively associated with the relative starting bias parameter. This suggests that my general expectation was correct – that angry ruminators need to accrue less information to make retaliation decisions – but that my hypothesis focused on the wrong parameter from the DDM. These findings taken together provide some support for the fluency amplification component of the Multi-Source Account of processing fluency, as angry ruminators repeatedly relive provoking events and mentally rehearse revenge scenarios (Gamblin et al., 2020). In contrast, Study 2 failed to replicate these associations with trait angry rumination. However, there was a significant moderation effect of trait angry rumination on the indirect effect of condition on retaliation severity through processing fluency. Despite this significant effect, none of the interaction terms emerged as significant. As such, it remains unclear if trait angry rumination is truly linked with greater processing fluency for making decisions about retaliation severity.

Practical and Theoretical Implications

Aggression. Contemporary theories of aggression often emphasize the involvement of cognitive factors in aggressive behavior. One such model is the GAM, which places an emphasis on the formation of cognitive scripts for aggression (Bushman & Anderson, 2002). The GAM points to two specific cognitive processes underlying such cognitive scripts: spreading activation and cognitive accessibility (Anderson & Bushman, 2018). In both Studies 1 and 2 processing fluency emerged as the strongest predictor of retaliation severity. As such, it could be the case that processing fluency for decisions about retaliation severity may more accurately describe the cognitive script portion of GAM. In this instance, it would not be the knowledge structures developed over the life course that facilitate retaliatory aggression at the cognitive level, but the relative efficiency with which such information is processed and synthesized with new information (i.e., opportunities for revenge). Conversely, it could also be that processing fluency for aggression is couched within aggressive scripts, acting as a facilitator rather than a primary mechanism.

My findings also hold implications for another contemporary meta-theory of aggression – I-cubed (Finkel & Hall, 2018). This framework posits that aggressive acts are often an interaction of three factors: Instigating events (e.g., provocation), Impellors (traits or states that facilitate aggressive responses), and Inhibitors (traits or states that inhibit aggressive responses). Despite the broad approach of I-cubed meta-theory, few specific cognitive factors have been identified as impellors or inhibitors. Given that processing fluency evinced strong positive associations with retaliation severity in both Studies 1 & 2, it seems that processing fluency for retaliation may fit well within I-cubed as an impelling factor. Similarly, Studies 1 & 2 both provided evidence that decision thresholds are negatively associated with processing fluency and retaliation severity, suggesting that decision thresholds may fit within I-cubed as an inhibiting factor. My findings also hold implications for psychological theories beyond the realms of aggression and processing fluency.

The findings in this work also hold implications for research on intergroup conflict. Broadly construed, people are likely to be more aggressive against outgroup members than ingroup members with or without provocation (Tajfel, Turner, & Austin, 1979). Some work suggests that this is due in part to a process of dehumanization, such that when groups are engaged in competition members see competing group members as being less than human (Leidner, Castano, Zaiser, & Giner-Sorolla, 2010; Loughnan, Haslam, Sutton, & Spencer, 2014). It could be then that these observed effects of intergroup aggression are altering processing fluency for doing harm against outgroup members by reclassifying them at the cognitive level so that such decision-making can go unabated by the considerations typically reserved for humans. This notion makes good sense given that intergroup aggression is strongly tied to evolutionary goals of survival. These considerations likely extend to digital environments such as social media platforms where individual group memberships are plainly displayed on personal profiles. The recently documented rise in extremism on social media platforms (e.g., Bright, 2018) may thus involve processing fluency, such that digital conflicts between members of opposing groups are likely processed with high fluency. Conversely, conflicts between individuals who do not display such group identifiers are likely more ambiguous and thus require more cognitive effort. Future work should examine these possibilities experimentally by manipulating target group membership to examine how group membership may impact processing fluency for retaliation decisions.

Other Psychological Theories. One theoretical model that has gained much attention in recent years is the Identity-Value Model (IVM) of self-regulation. This theory posits that one's identity is at the core of self-regulation and that the extent to which a certain behavior is relevant to one's identity determines the subjective valuation of that behavior (Berkman, Livington, & Kahn, 2017). The researchers who developed this model have argued that cognitive factors likely influence the valuation processes involved in IVM, but these factors remain unknown (Berkman, Hutcherson, Livingston, Kahn, & Inzlicht, 2017). My findings point toward processing fluency as one such factor, as the scale used to measure Sadism in both studies effectively indexed the extent to which participants identified with value-based statements (e.g., "I enjoy seeing people hurt,") about aggression. Given that Sadism was positively associated with fluency (drift rates and self-reports) in both studies it may be that processing fluency is linked with one's identity. In this view identity-consistent behaviors are processed more fluently, and identity-inconsistent behaviors are subjected to greater decision thresholds and thus more cautious responding.

Practical Implications for Research. In Studies 1 & 2 the DDM was able to account for decisions about retaliation severity with only two participants out of a combined total of 408 evincing poor model fits. As such, DDM could possibly be used to address some outstanding controversies in the aggression literature. One such controversy is that of the relationship between playing violent video games and aggressive behavior. Myriad research indicates that there is a positive association between playing violent games and aggression, with some evincing a causal link (e.g., Anderson & Bushman, 2001; Anderson et al., 2010; Anderson & Dill, 2000). However, this body of literature has been scrutinized by other researchers, with some arguing that the observed effects are due to methodological artifacts or publication bias (Ferguson, 2007; Ferguson & Kilburn, 2010; Elson & Ferguson, 2014). Research examining the effects of violent video games on perceptual judgements indicates that playing aggressive games increases the processing fluency for general perceptual judgement tasks across various stimuli (Green, Pouget,

& Bavelier, 2010). Interestingly, one of the publications critical of the violent video game literature also provides evidence that playing violent video games improves visuospatial cognition (Ferguson, 2007). It could be the case then that violent video game play improves the processing fluency for decisions relating to aggression rather than directly causing aggressive behaviors. Application of the DDM to this empirical question could provide some much-needed clarity on a contentious area of aggression research.

Implications for Clinical Practice. Clinical practice also stands to benefit from these findings, as drift rates for a given decision could be targeted by potential interventions as evinced by the manipulation in Study 2 and previous research (e.g., Starns, Ratcliff, & White, 2012). For example, a recent study found that drift rates during a perceptual decision-making task were lowered when the task outcome affected a family member rather than the participant themselves (Bottemanne & Dreher, 2019). Similarly, decision thresholds can also be altered through intervention, as several studies have indicated that time pressure tends to reduce the amount of information needed to make a choice (Milosavljevic, Malmaud, Huth, Koch, & Rangel, 2010; Ratcliff & Rouder, 1998). As such, mental health practitioners could use these findings to develop new approaches for addressing aggressive behavior by emphasizing that the impact of decisions about aggression extend well beyond the individual and that the urgency they may feel is not rational.

Limitations and Future Directions

The studies presented here provide substantial evidence that processing fluency plays a role in making decisions about retaliation. However, this evidence must be interpreted in the context of several limitations. First, the exclusive reliance on internet-based data collection may have impacted the resultant data. Participants completed both studies in an environment of their choosing and some environments (e.g., at a busy coffee shop) could have introduced contaminants to the estimation of the DDM parameters. However, the analysis routine implemented by the fast-dm software is more robust against contaminants than other applications of the DDM (Ratcliff & Childers, 2015). Further, the model fit of the DDM to the participant data suggests that such contamination should be a minimal issue, but the nature of the current studies do not allow for this to be directly estimated. Future work should be conducted in a tightly controlled laboratory environment to rule out this possibility.

Second, the evidence validating drift rates as a measure of fluency required an unplanned transformation of the self-report fluency data. This limitation is an intrinsic aspect of the way that drift rates are estimated by the DDM. Specifically, participants with a negative drift rate estimate made a majority of low-severity choices. Some of these participants however reported these decisions as being highly fluent, thus resulting in self-reported fluency scores reflecting the ease of choosing the lesser option repeatedly. This is also a limitation of applying the DDM to value-based decision making, as tasks with an objectively correct response typically yield positive drift rate estimates. Future work should examine novel applications of the DDM to value-based decision making in order to better understand the implications of the DDM parameters across various contexts. Further, the use of more specific language in self-reports of processing fluency such as the PFS would aid in resolving ambiguities regarding what such measures are asking of respondents.

Third, Study 2 utilized an active control (i.e., the boredom condition) instead of a true neutral control. It could be then that anger did not increase drift rates but rather boredom decreased them. This limitation stems from the nature of the primary outcome measure used in both studies. Indeed, the ACQM requires that participants have a target in mind prior to beginning the task which effectively makes the use of a truly neutral control condition impossible. However, given that the self-reported state anger experienced from the essay writing task in Study 2 was positively associated with drift rates it does appear that the anger manipulation increased drift rates.

Fourth, there was a clear subset of participants in both studies that were not motivated to retaliate against their targets. This limitation appears to be due to a combination of factors. First, it was not explicitly stated that participants should think of a person who had harmed them that they had not yet forgiven. As such, it may be that some participants thought of a person who they had previously forgiven or made amends with. Second, in Study 2 participants in the boredom condition never thought of a person that they were angry with which led to a greater degree of zero-inflation than did Study 1. Complicating this issue further, participants thought of a diverse array of individuals as their targets (e.g., family members, complete strangers). Future research should address this concern by using provocation manipulations in the laboratory so that the provoking event is the same distance in time from the decision making process and the target and form of provocation is held constant across participants. Similarly, the role of forgiveness in retaliatory aggression remains understudied. Future work should also attempt to incorporate options to forgive targets of aggression in such tasks. This approach would allow researchers to confirm if low drift rates are truly indicative of low processing fluency or were observed in the current work because the option some participants wanted to pick (i.e., do zero harm) was not available.

Finally, the current investigation used a hypothetical measure of retaliation severity. It could be that participants would not have actually sought the level of retaliation severity indicated during the ACQM if it were linked to real-world consequences for their target.

However, research comparing decision-making tasks using real and hypothetical rewards (i.e., monetary sums) indicates that results do not differ across these measures (Johnson & Bickel, 2002; Madden, Begotka, Raiff, & Kastern, 2003). Further, recent work indicates that retaliatory aggression is subjected to delay discounting as with other rewards and thus such hypothetical decisions should approximate the cognitive processes that are active during real aggressive decision-making (West et al., *under review*). This is reflected by the number of participants who chose the less-severe option almost exclusively. Indeed, despite the ACQM being completely hypothetical participants who did not wish to retaliate made very few severe retaliation decisions. Future research in this area should attempt to apply the DDM to laboratory paradigms of aggressive behavior to confirm these assumptions.

Conclusions

Retaliatory aggression is a rewarding experience that functions as a form of mood repair (Bushman, 2002; Chester, 2017). Despite contemporary models of aggression placing an emphasis on the cognitive processes that facilitate retaliation, little research has attempted to directly estimate the involvement of specific cognitive mechanisms in making decisions about retaliation. Across two studies I found that processing fluency as estimated by the DDM or self-reports played an important role in facilitating decisions about retaliation severity. These studies mark the first attempt at examining the role of processing fluency in aggressive decision making by applying the Multi-Source Account of processing fluency and DDM to decisions about retaliation severity. I also provided evidence that angry rumination increases processing fluency for retaliation decisions and that such fluency indirectly facilitates a preference for greater retaliation severity. These findings hold far reaching implications for psychological theories, the conduct of aggression research, and clinical approaches to aggressive behavior. Indeed, this work provides support to a view of vengeful individuals as possessing greater cognitive efficiency for retaliatory decision-making rather than necessarily impulsive hot-heads. These findings stand to broaden our understanding of the intersections of personality, cognition, and aggression, ultimately furthering to the search for a more peaceful world.

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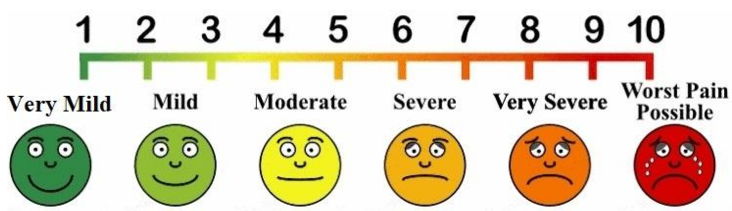
Appendix A

Aggression Choice Questionnaire Modified (ACQM)

Please take a moment and think about a person who has really hurt you and you feel a great amount of anger towards. If you cannot think of a specific person, imagine a fake person who has really hurt you and you feel a great amount of anger towards.

Once you have done this, please indicate how much pain and suffering that you would like to inflict on this person in each of the following questions, using the scale below as a reference. Keep in mind that 'pain' is multifaceted and can involve physical, verbal, societal, or social aspects.



Would you like to...

1. Inflict pain level 7 inflict pain level 9?
2. Inflict pain level 3 or inflict pain level 8?
3. Inflict pain level 1 or inflict pain level 3?
4. Inflict pain level 3 or inflict pain level 9?
5. Inflict pain level 6 or inflict pain level 10?
6. Inflict pain level 2 or inflict pain level 9?
7. Inflict pain level 8 or inflict pain level 10?
8. Inflict pain level 2 or inflict pain level 7?
9. Inflict pain level 4 or inflict pain level 8?
10. Inflict pain level 2 or inflict pain level 5?
11. Inflict pain level 4 or inflict pain level 5?
12. Inflict pain level 3 or inflict pain level 6?
13. Inflict pain level 9 or inflict pain level 10?
14. Inflict pain level 7 or inflict pain level 8?
15. Inflict pain level 3 or inflict pain level 5?

16. Inflict pain level 1 or inflict pain level 4?
17. Inflict pain level 1 or inflict pain level 10?
18. Inflict pain level 5 or inflict pain level 8?
19. Inflict pain level 5 or inflict pain level 10?
20. Inflict pain level 7 or inflict pain level 10?
21. Inflict pain level 3 or inflict pain level 7?
22. Inflict pain level 3 or inflict pain level 4?
23. Inflict pain level 4 or inflict pain level 10?
24. Inflict pain level 6 or inflict pain level 8?
25. Inflict pain level 4 or inflict pain level 6?
26. Inflict pain level 4 or inflict pain level 7?
27. Inflict pain level 5 or inflict pain level 6?
28. Inflict pain level 8 or inflict pain level 9?
29. Inflict pain level 1 or inflict pain level 8?
30. Inflict pain level 2 or pain level 3?
31. Inflict pain level 1 or inflict pain level 5?
32. Inflict pain level 5 or inflict pain level 7?
33. Inflict pain level 2 or inflict pain level 6?
34. Inflict pain level 3 or inflict pain level 10?
35. Inflict pain level 4 or inflict pain level 9?
36. Inflict pain level 5 or inflict pain level 9?
37. Inflict pain level 6 or inflict pain level 7?
38. Inflict pain level 2 or inflict pain level 4?
39. Inflict pain level 6 or inflict pain level 9?
40. Inflict pain level 10 or inflict pain level 5?
41. Inflict pain level 7 or inflict pain level 3?
42. Inflict pain level 5 or inflict pain level 3?
43. Inflict pain level 10 or inflict pain level 1?
44. Inflict pain level 9 or inflict pain level 5?
45. Inflict pain level 5 or inflict pain level 2?
46. Inflict pain level 6 or inflict pain level 1?

47. Inflict pain level 4 or inflict pain level 1?
48. Inflict pain level 9 or inflict pain level 2?
49. Inflict pain level 7 or inflict pain level 5?
50. Inflict pain level 8 or inflict pain level 3?

ACQM Follow-up 1: Please indicate the type of relationship you have with the individual you thought of while completing this task:

- Complete Stranger
- Acquaintance
- Friend
- Close friend
- Family Member
- Romantic Partner
- Other (please specify)

ACQM Follow-up 2: Please indicate how close you are with this person on a scale of 1 (not close at all) to 5 (very close).

1 (not close at all) 2 (somewhat close) 3 (moderately close) 4 (close) 5 (very close)

Appendix B

Angry Rumination Scale

Everyone gets angry and frustrated occasionally, but people differ in the ways that they think about their episodes of anger. Statements below describe ways that people may recall or think about their anger experiences. Please read each statement. Using the scale provided, write the number in each blank that shows how typical each statement is of you. There are no right or wrong answers. Please respond honestly to all items.

1	**2**	**3**	**4**
almost never	**sometimes**	**often**	**almost always**

_____1. I ruminate about my past anger experiences.

_____2. I ponder about the injustices that have been done to me.

_____3. I keep thinking about events that angered me for a long time.

_____4. I have long-living fantasies of revenge after a conflict is over.

_____5. I think about certain events from a long time ago and they still make me angry.

_____6. I have difficulty forgiving people who have hurt me.

_____7. After an argument is over I keep fighting with this person in my imagination.

_____8. Memories of being aggravated pop up into my mind before I fall asleep.

_____9. Whenever I experience anger, I keep thinking about it for a while.

_____10. I have had times when I could not stop being preoccupied with a particular conflict.

_____11. I analyze events that make me angry.

_____12. I think about the reasons people treat me badly.

_____13. I have daydreams and fantasies of a violent nature.

_____14. I feel angry about certain things in my life.

_____15. When someone makes me angry I can't stop thinking about how to get back at this person.

_____16. When someone provokes me, I keep wondering why this should have happened to me.

_____17. Memories of even minor annoyances bother me for a while.

_____18. When something makes me angry, I turn this matter over and over again in my mind.

_____19. I re-enact the anger episode in my mind after it has happened.

Appendix C

Processing Fluency Scale

"Think back to when you evaluated and ultimately decided on the decisions you made on the task you just completed. The process of making these choices was…"

Item 1: 1 = *difficult*; 5 = *easy*

Item 2: 1 = *disfluent*; 5 = *fluent*

Item 3: 1 = *effortful;* 5 = *effortless*

Item 4: 1 = *incomprehensible*; 5 = *comprehensible*

Item 5: 1 = *unclear;* 5 = *clear*

Appendix D

Short Sadistic Impulses Scale

Please use the following response options to indicate the extent to which you agree with each statement below.

1 (strongly disagree)

2 (disagree somewhat)

3 (neither agree nor disagree)

4 (agree somewhat)

5 (strongly agree)

1. I enjoy seeing people hurt.
2. I would enjoy hurting someone physically, sexually, or emotionally.
3. Hurting people would be exciting.
4. I have hurt people for my own enjoyment.
5. People would enjoy hurting others if they gave it a go.
6. I have fantasies which involve hurting people.
7. I have hurt people because I could.
8. I wouldn't intentionally hurt anyone.
9. I have humiliated others to keep them in line.
10. Sometimes I get so angry I want to hurt people.

Appendix E

Demographic Information

1. How old are you? (in years) ___________

2. What biological sex were you assigned to at birth?
    a. Male
    b. Female

3. What gender do you identify with?
    a. Male
    b. Female
    c. Additional Gender Category/Other, please specify:____________

4. Which of these categories best describes you? (you can choose more than one)
    a) Native Hawaiian / Pacific Islander
    b) American Indian / Alaskan Native
    c) Asian or Asian American
    d) African American or Black
    e) Hispanic / Latino
    f) White
    g) Other, Specify:_______________________

5. How many years of education have you completed? ______________

6. Please select the range that your parent's combined income falls under:

A) $0 – $19,050

B) $19,050 – $77,400

C) $77,400 – $165,000

D) $165,000 – $315,000

E) $315,000 – $400,000

F) $400,00 – $600,000 or above

Appendix F

The Discrete Emotions Questionnaire

Please indicate your response using the scale provided.

To what extent did you experience these emotions while you were writing your essay?

1	2	3	4	5	6	7
Not at all	Slightly	Somewhat	Moderately	Quite a bit	Very much	An extreme amount

Anger (Ag)
Sad (S)
Easygoing (R)
Happy (H)
Terror (F)
Rage (Ag)
Grief (S)
Chilled out (R)
Lonely (S)
Pissed off (Ag)
Liking (H)
Scared (F)
Mad (Ag)
Satisfaction (H)
Empty (S)
Panic (F)
Calm (R)
Fear (F)
Relaxation (R)
Enjoyment (H)

Ag = Anger items, F = Fear items, Ax = Anxiety items, S = Sadness items, R = Relaxation items, H = Happiness items.

Appendix G

Essay Writing Instructions

Angry Rumination Induction

"Take a moment and think of a time someone really hurt or angered you in the past. Once you have found such a person please write a detailed summary of what you remember about this experience in the box on the next page. Please focus on the elements of the experience that were especially provoking or upsetting to you in your response. Do not include any personally identifying information about the person you are writing about other than your general relationship with them (e.g., cousin, brother, friend, stranger). We would like for you to write for 10 minutes. If you finish writing your summary before the time is up, simply re-write the summary from memory – please do not copy and paste. It is okay if you do not completely finish either – just write as much as you can with as many details as you can recall."

Boredom Rumination Induction

"Take a moment and think of someone who has really bored you or made you disinterested in the past. Once you have found such a person please write a detailed summary of what you remember about this experience in the box on the next page. Please focus on the elements of the experience that were especially boring or uninteresting to you in your response. Do not include any personally identifying information about the person you are writing about other than your general relationship with them (e.g., cousin, brother, friend, stranger). We would like for you to write for 10 minutes. If you finish writing your summary before the time is up, simply re-write the summary from memory – please do not copy and paste. It is okay if you do not completely finish either – just write as much as you can with as many details as you can recall."