An information processing / associative learning account of behavioral disinhibition in externalizing psychopathology

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Abstract

Externalizing psychopathology (EXT) is associated with low executive working memory (EWM) capacity and problems with inhibitory control and decision-making; however, the specific cognitive processes underlying these problems are not well known. This study used a linear ballistic accumulator computational model of go/no-go associative-incentive learning conducted with and without a working memory (WM) load to investigate these cognitive processes in 510 young adults varying in EXT (lifetime problems with substance use, conduct disorder, ADHD, adult antisocial behavior). High scores on an EXT factor were associated with low EWM capacity and higher scores on a latent variable reflecting the cognitive processes underlying disinhibited decision making (more false alarms, faster evidence accumulation rates for false alarms (*v*FA), and lower scores on a Response Precision Index (RPI) measure of information processing efficiency). The WM load increased disinhibited decision making, decisional uncertainty, and response caution for all subjects. Higher EWM capacity was associated with lower scores on the latent disinhibited decision making variable (lower false alarms, lower $v\mathrm{FA}_s$ and RPI scores) in both WM load conditions. EWM capacity partially mediated the association between EXT and disinhibited decision making under no-WM load, and completely mediated this association under WM load. The results underline the role that EWM has in associative – incentive go/no-go learning and indicate that common to numerous types of EXT are impairments in the cognitive processes associated with the evidence accumulation – evaluation – decision process.

Key Words: Externalizing psychopathology, working memory, decision-making, associative learning.

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Various types of externalizing psychopathology (EXT), such as conduct disorder, ADHD, antisocial personality, and substance use disorders, are associated with poor self-control, typically reflected in impulsive decision making and difficulties learning to avoid engaging in behaviors that are likely to result in negative consequences (Barkley, 2001; (Bobova, Finn, Rickert & Lucas, 2009; Finn, Mazas, Justus & Steinmetz, 2002). Recent research also indicates that EXT represents a spectrum of commonly occurring disorders or symptoms that share a common disinhibitory vulnerability (Bobova et al., 2009; Krueger et al., 2002). Evidence suggests that the psychological mechanisms thought to contribute to this disinhibitory vulnerability are not unique to any one EXT disorder, rather they are common to the shared covariance among different EXT disorders (Bogg and Finn, 2010). Dual process models of self-regulation posit that poor self-regulation is a result of an interaction between deficient cognitive control / reflective processes, such as reduced executive working memory (EWM) capacity, and strong impulsive processes, such as strong reward - approach processes and weak punishment – avoidance processes (Finn, 2002; Wiers, Ames, Hofmann, Krank & Stacey, 2010). The present study investigates the association between compromised EWM capacity, decision-making in an approach- avoidance associative learning context, and a dimensional characterization of EXT. We used a novel computational model, which characterizes the rate and efficiency of evidence accumulation in decision making, and a working memory load in order to elucidate the dynamic cognitive processes that may contribute to impaired self-regulation in EXT.

Executive Working Memory Capacity and Externalizing Psychopathology

Working memory has been described as a limited capacity information processing system comprised of interdependent component processes related to the executive control of attention (the central executive) and the active maintenance of short-term memory (Baddeley, 2000; Cowan et al., 2006; Engle, Tuholski, Laughlin & Conway, 1999; Miyake & Shah, 1999; Shipstead, Redick, Hicks & Engle, 2012). Although models differ in their emphasis on specific processes, all models acknowledge a role for attention, or attention control, in the working memory system. In fact, common to all models is a ‘central executive’ component (i.e., EWM) that directs the allocation of attention involved in shifting attention, resisting distraction, and encoding / retrieving information from long and short-term memory buffers while maintaining and updating working memory (Baddeley, 2000; Barrett, Tugade & Engle, 2004; Cowan et al., 2006; Miyake & Shah, 1999). Research suggests that the working memory system can be partitioned into separate capacities for the scope of attention (basic capacity, short-term memory) and the control of attention (e.g., Cowan et al., 2006; Engle et al., 1999; Shipstead et al., 2012). Research also suggests EMW capacity and short-term memory capacity are differentially associated with approach-avoidance learning and decision-making processes (Endres et al., 2011) and fluid intelligence (Engle et al., 1999). A number of studies indicate that EWM capacity primarily reflects the capacity to control attention, such as the capacity to retain goal-related information in primary memory while simultaneously retrieving information from long-term memory (Barrett et al, 2004; Shipstead et al. 2012). This process of attention control is inherent in the deliberation process involved in effective decision-making (Finn, 2002).

Increasing evidence suggests that reduced EWM capacity may be associated with the much broader phenotypic expression of the disinhibitory vulnerability that characterizes EXT psychopathology. Reduced EWM capacity has been associated with increased trait impulsivity (Gunn & Finn, 2013; Romer, Bentacourt, Gianetta, Brodsky & Farah, 2009) and a range of EXT, such as ADHD symptomatology (Barkeley, 1997; Barnett, Maruff & Vance, 2009 Martinussen, Hayden, Hogg-Johnson, & Tannock, 2005), childhood conduct problems (Barnett et al, 2009 Finn et al 2009), adult antisocial behavior (Finn et al., 2009), and substance use disorders (Finn et al., 2009; Bechara & Martin, 2004). In fact, studies by Finn and colleagues (Bogg & Finn, 2010;

Endres, Rickert, Bogg, Lucas & Finn 2011; Finn, Bobova, Finn, Rickert & Lucas, 2009) suggest that reduced EWM capacity is common to the covariance among a number of types of EXT and is not unique to any one specific disorder. EWM capacity is critical for the ongoing regulation of behavior (Barkley, 2001; Barrett et al., 2004, Finn, 2002). Although reduced EWM capacity has been consistently associated with both high levels of EXT and poor self-control / impaired decision making, the specific cognitive processes underlying this association have not been well studied.

Decision Making and Executive Working Memory Capacity

Research indicates that reduced EWM capacity is associated with poor decision-making on a variety of tasks, such as delay discounting (Bobova et al., 2009; Shamosh et al. 2008), Iowa gambling task (Bechara & Martin, 2004), and associative-learning go/nogo tasks with incentives (Endres et al., 2011). In addition, a WM load has been shown to impair decision-making on delay discounting tasks (Hinson, Jameson & Whitney, 2003) and the Iowa Gambling task (Hinson, Jameson & Whitney, 2002).

The current study employs a go/nogo, associative learning decision-making task to model the key self-control processes involved in learning in which contexts approach behavior is appropriate and in which contexts approach behavior leads to negative outcomes and behavior should be inhibited. The subject's task is use trial-and-error learning to discriminate numerical stimuli that reflect either approach/Go cues or avoidance/NoGo cues. Correct Go responses (hits) result in rewards (monetary gain) and incorrect Go responses result in negative consequences (monetary loss). These types of tasks have been useful in illustrating that those with EXT have relative difficulty learning to make decisions to inhibit behavior to avoid negative outcomes, as exemplified in their elevated false alarm rates (Endres et al, 2011; Finn et al., 2002; Newman & Kosson, 1986). While an insensitivity to punishment, or poor modulation of approach behavior, are motivational individual differences that might underlie impaired go/nogo decision making in EXT, the current study seeks to characterize the extent to which individual differences in aspects of the cognitive processes associated with EWM capacity are associated with impaired go/nogo decision making in EXT.

Although prior research clearly demonstrates that different forms of EXT are associated with more false alarms on incentivized go/no-go associative learning tasks, studies have not characterized the cognitive processes underlying these faulty choices. We theorize that EWM capacity plays a central role in the decision-making processes in go/no-go associative learning tasks. First, good performance rests on the capacity to store in, and retrieve from, long-term (secondary memory) information about which numbers are Go and which are NoGo. On each trial, the individual compares the current number (in primary memory) with information stored in long-term memory about its association with response outcomes (win or lose). Thus, response accuracy depends upon the capacity to shift attention between primary and secondary memory, which is essentially the attention control mechanism of EWM described by Engle and colleagues (Barrett et al, 2004; Shipstead et al. 2012). Second, to learn whether any numerical cue is a Go or NoGo cue, one must respond to either cue, encode the associated response outcome (win or lose), and then store these cue-contingency associations in long-term memory. In theory, this involves the shifting of attention from a ‘cue – respond’ mode on Go trials to a ‘cue – inhibit’ mode on NoGo trials. Shifting attention to cue-inhibit mode is needed to avoid a false alarm, and is hypothesized to reflect the attention control mechanism associated with EWM capacity (Barrett et al, 2004; Finn, 2002).

During this dynamic deliberative process, the approach-avoidance conflict resolves as the attention-switching process accumulates evidence (drifts) towards an internal criterion for sufficient evidence (threshold) in favor of either the Go response or NoGo non-response. In theory, this process of scanning secondary memory traces and then shifting attention back to primary memory requires that attention control be efficient so that learned associations will be based on accurate information. Efficient attention control is characterized by good discrimination between Go and NoGo cues, fast evidence accumulation for correct Go responses (hits), and slow evidence accumulation for incorrect Go responses (false alarms). Consistent with this notion, Endres et al (2011) reported that greater EWM capacity was associated with better discrimination (higher d-prime) between Go and NoGo stimuli and lower false alarm rates, and EWM capacity completely mediated the effect of greater EXT on poor Go/NoGo discriminability and high false alarm rates . Although Endres et al (2011) suggested that the poor discrimination between Go and NoGo stimuli associated with EXT reflected a relative insensitivity to punishment, their Signal Detection model of Go/NoGo task performance did not tap the dynamic trial-level deliberative processes noted above. For those with low EWM capacity, the deliberation process would be less accurate or efficient in terms of having more false alarms and less resolution of the conflict between 'Go-approach' and 'NoGo-avoid' processes. Here, the central hypothesis proposed is that EXT and reduced EWM capacity are responsible for less efficient evidence accumulation process while deliberating over Go-approach and NoGo-avoid decisions. On NoGo trials, the rate of evidence accumulation for incorrect (false alarm) responses is too high relative to that for correct inhibitions, which leads to higher false alarm rates (see Figure 1, Panel D) and reflects a tendency to jump to the conclusion that a given stimulus is a Go cue when in fact it is a NoGo cue.

A Computational Model Approach to Studying EWM in Go/No-Go Learning

The current study uses a linear ballistic accumulator (LBA) computational model (Brown & Heathcote, 2008) to estimate the rates of evidence accumulation for Go and No Go cues as well as other decision parameters, such as response threshold. Previous studies have utilized other computational models, such has the Expectancy Valence model (Busemeyer & Stout, 2002; Yechiam et al., 2006) or the Signal Detection model (Endres et al., 2011), to investigate different biases in choice behaviors. However, these models are not suited to investigate the dynamic processes associated with EWM capacity during the deliberative decision-making process because they do not account for reaction time (RT) performance, which is invaluable to estimate evidence accumulation rates in the deliberative process. The LBA model uses full RT distributions for correct and incorrect responses and choice accuracy to estimate the rate (v) at which evidence is accumulated for both correct Go responses (v for hits or v_{HT}) and incorrect Go responses (v for false alarms or v_{FA}), as well for correct and incorrect non-responses (v_{NoGo} in Figure 1). Whichever accumulation process crosses an internal decision threshold (b) first, governs the decision. Figure 1 depicts high and low efficiency evidence accumulation processes and their parameter values (top and bottom rows, respectively) for Go and NoGo trials (left and right columns, respectively). Figure 1 Panels A and B illustrate clear separation (good discrimination) between Go and NoGo responses that characterize high efficiency processes, while Panels C and D illustrate greater conflict (poor discrimination) in evidence accumulation that characterize low efficiency processes. Note, high efficiency and accuracy is characterized by greater differences between the overall rate of evidence accumulation for correct (vHT) versus incorrect (vFA) Go responses, such that vHT is far greater than vFA (compare Panel A with B). This difference is quantified by the model-derived Response Precision Index (RPI).

The current study tests the hypotheses that (i) high scores on an EXT latent factor will be associated with low EMW capacity, and that both will be associated with a composite measure of disinhibitory decision making indicated by poor response inhibition (high false alarms), lower accuracy and efficiency of the evidence accumulation process (low RPI values), and a faster evidence accumulation process for incorrect responses (higher v_{FA} values), (ii) that a WM load will increase disinhibited decision making (increases in false alarms and v_{FA} values and decreases in RPI values), and (iii) that EMW capacity will mediate the association between EXT and the composite measure of disinhibited decision making.

Method

Participants

Sample Characteristics. The sample consisted of 510 young adults (271 men, 239 women; mean age = 21.2 SD = 2.4) with a range of lifetime EXT diagnoses and problems (conduct disorder, ADHD, adult antisocial behavior, alcohol, and other drug problems). EXT Diagnoses and problems were ascertained with the Semi-Structured Assessment for the Genetics of Alcoholism (SSAGA-II; Bucholz et al., 1994) using DSM-IV diagnostic criteria (*Diagnostic and Statistical Manual of Mental Disorders, 4th ed. DSM-IV,* American Psychiatric Association, 1994).The sample was 77% White, 8% African American, 6% Asian, Indian, or Middle Eastern, 6% Hispanic or Latino, and 3% multiple ethnicities. Thirty-four percent (n= 173) had a lifetime DSM-IV diagnosis of alcohol dependence, 27% (n=138) had lifetime alcohol abuse, 28% (n=145) had lifetime other drug dependence, 18% (n=94) had lifetime other drug abuse, 11% (n=56) had a lifetime ADHD diagnosis, 19% (n=99) had lifetime conduct disorder, and 12% (n=63) had lifetime antisocial personality disorder. Thirty one percent (n=160) had no lifetime EXT diagnoses, 22.5% (n=115) had one lifetime diagnosis, 25% (n=129) had two, 9% (n=48) had three, 8% (n=40) had four, 3% (n=17) had five, and one participant had six lifetime EXT diagnoses. For the analyses, EXT was measured as a latent variable representing the covariance among lifetime problems of ADHD, conduct disorder, adult antisocial behavior, alcohol, and other drugs.

Recruitment. Participants were recruited using advertisements placed in local and student newspapers and around the community. This approach has been effective in attracting responses from individuals who vary in EXT problems and disorders (c.f., Endres et al., 2011; Finn et al., 2002; 2009). Advertisement respondents were telephone screened for inclusion criteria of being between 18 and 30 years of age, read/speak English, at least 6th grade education, no history of psychosis or head trauma. If they met these criteria, they were interviewed about current and lifetime alcohol, drug, ADHD, childhood conduct, and adult antisocial problems. Subjects were invited to participate in the study if they fell within the range of these EXT problems that were targeted for the sample composition (25% / 50% / 25% with low, moderate, and high EXT problems) based on the distributions observed our earlier studies that employed a dimensional model of EXT (e.g., Endres et al., 2011; Finn et al., 2009). On the day of testing subjects were further screened to ensure no alcohol or drugs use in the past 12 hours, a breath alcohol level of 0.0%, no current withdrawal symptoms or fatigue. None of the subjects failed this screening.

Assessment Procedures and Materials

Executive Working Memory Capacity was assessed using two different complex-span tests, the Operation-Word Span test (Conway & Engle, 1994) and a modified version of the Auditory Consonant Trigram test (Brown, 1958), that we refer to as the Auditory Consonant test (Endres et al., 2011; Finn et al., 2009). These tasks operationalize EWM capacity as the total number of memory items that can be correctly recalled after performing a second unrelated cognitive task. For example, recalling word or letter strings of various sizes in their correct order of presentation after solving a mathematical operation or counting backwards by threes for a predetermined length of time. Studies indicate that these types of tests are valid measures of executive WM capacity (Endres et al., 2011; Engle, Tuholski, Laughlin & Conway, 1999). EWM capacity was measured as a latent factor of the covariance among the total number of items correctly recalled on the operation word span and Auditory Consonant tasks (Endres et al., 2011; Engle et al., 1999; Finn et al., 2009).

The Go/No-Go Associative Learning Task

The go/no-go associative learning task was similar to that used by our research group in the past (Endres et al., 2011, Finn et al., 2002). The task involved the serial presentation on a computer screen for 750 msec of ten different 2-digit numbers (five “go” and five “no-go” cues) pseudo randomly presented within 9 blocks of 10 trials. The two-digit stimuli were counterbalanced for odd and even values both above and below 50. Responses made after a go cue within the 750 msec presentation (i.e. a hit) resulted in winning $0.25 (WIN $0.25 on green background presented for 1000 msec). Responses after the no-go cue (i.e., a false alarm) resulted in losing $0.25 (LOSE $0.25 on red background presented for 1000 msec). Subjects were informed that they had a limited amount of time to respond and that they could only win or lose money if they correctly or incorrectly pressed the spacebar. Subjects also were instructed that, “in order to maximize wins and minimize losses,” they should “attempt respond as quickly and as accurate as possible.”

Working Memory (WM) Load Manipulation. Subjects were randomly assigned to a WM load or no-WM load condition. The WM load involved performing a secondary task after the conclusion of each trial. The secondary task involved presentation of a 3-digit number (1000 ms), counting backwards by 3s for 8 sec, and then recalling the 3-digit number. We assume that the WM load depletes EWM capacity by requiring the constant shifting from the primary go/nogo task to the secondard WM load task throughout the task. The WM load also interferes with any memory rehearsal between go/nogo trials. The no-WM load condition involved waiting for 10 sec after each trial.

Dependent measures of Associative - Go/NoGo Learning

Dependent measures of go/no-go learning were the standard measures of false alarm rates and hit rates and the parameter estimates derived using the Linear Ballistic Accumulator (LBA) model (Brown & Heathcote, 2008). The LBA model was used rather than a full Diffusion model (Ratcliff, Spieler & McKoon, 2000), because the LBA model is computationally and parametrically simpler, and both models yield the same conclusions (Donkin, Brown, Heathcote & Wagenmakers, 2011).

The LBA model assumes that over the course of the task participants learn which are the Go or NoGo cues by collecting or accumulating evidence for when to respond (Go) and when to avoid a response (NoGo). The model also assumes that trial-level decisions are driven by the competition between two separate 'evidence accumulators,' one for Go and one for NoGo choices. These accumulators begin each trial with a random starting level of activation, and evidence rises towards a decision threshold. Once the evidence in a particular accumulator reaches the threshold, the person makes the associated response (or withholds their response). If the Go-approach accumulator is first to reach threshold, a Go response is made, but if the NoGo-avoid accumulator is first then no response is made (Brown & Heathcote, 2008).

The LBA model had 6 free parameters (A, b, v_{HT}, v_{FA}, s and t_0). The t_0 parameter reflects the time taken for non-decision processes, such as stimulus encoding time. The A parameter represents the maximum amount of initial evidence in favor of a Go or NoGo decision with which each accumulator could begin a trial. The b parameter represents the threshold for sufficient evidence for a response. The v parameters reflect the average rate of evidence accumulation for a given response or nonresponse. The s parameter represents decision uncertainty, or randomness in decision making, and is the standard deviation of the evidence accumulation rate across trials. We estimated v for approach responses only, letting accumulation rate for avoid responses be 1-v. For Go trials we estimated accumulation rate for correct responses (vHT) and incorrect 'avoid' responses were 1-vHT. For No-Go trials we estimated accumulation rate for incorrect responses (vFA) and correct 'avoid' responses were 1-vFA. The vHT parameter is estimated using hit rates and reaction times for hits. Likewise, the vFA parameter is estimated using observed values of false alarm rates and reaction times for false alarms. Thus, vHT is partly a function of hit rates and vFA is partly a function of false alarm rates. High values of v reflect faster accumulation of evidence for a response. The rate at which evidence accumulates is assumed to vary between trials, according to a normal distribution with mean v and standard deviation s.

The LBA model was fit to each individual's data using the quantile maximum product estimation methods outlined in Heathcote, Brown & Cousineau (2004; for a similar approach see

Farrell, Ludwig, Ellis & Gilchrist, 2010)[1]. Best-fitting parameters were found using SIMPLEX in the R statistical package (The R Foundation for Statistical Computing, 2012). Figure 1 illustrates the evidence accumulation process for Go responses and NoGo avoidance nonresponses and illustrates their association with hits, correct inhibitions, and false alarms.

Finally, we also derived two global decision-making process indexes that characterize response precision (RPI) and response caution. RPI reflects the overall accuracy and efficiency of the evidence accumulation process (and is similar to d-prime in signal detection theory). While d-prime is a function of both hit rates and false alarm rates, and reflects the discriminability of the signal (targets – Go cues) in the presence of noise (non-targets or NoGo cues), RPI is a function of the evidence accumulation processes for both correct responses (*v*HT) and incorrect responses (*v*FA). High RPI values (illustrated in the top panels of Figure 1) reflect a larger difference (separation) in the accumulation rates (illustrated as vectors) for correct (*v*HT in Panel A) and incorrect responses (*v*FA in Panel B). Whereas, lower RPI values reflect smaller differences in these two factors (Panels C and D). Thus, the RPI is considered as measure of the strength of evidence accumulation processes for instances when an approach response is made. We compute RPI as follows:

$$\mathrm{RPI} = \frac{v_{\mathrm{HT}} - v_{\mathrm{FA}}}{s}$$

Since *v* takes into account both RT and accuracy, our RPI measure is a more sensitive measure of performance than d-prime, as it takes into account the relative speed of hit and false alarm responses. The inclusion of *s* into RPI acts to normalize the difference between hit and false alarm rates based on overall variability in processing (i.e., it transforms accumulation rate parameters into an ‘effect size’). In a manner similar to d-prime, increases in *v*FA will result in decreases in RPI, if *v*HT and *s* remain about the same, or if *v*HT decreases and/or *s* increases. In fact, when increases in

[1] Because ‘avoid’ responses yield no response times, the model was fit to choice probability and response time distribution for approach responses, and to the overall probability that avoid responses were made.

*v*FA are accompanied by decreases in *v*HT and/or increase in *s*, the RPI measure decreases dramatically and reflects decreased efficiency in the evidence accumulation processes. Thus, the RPI measure provides more overall information about the decision process that cannot be obtained simply by examining *v*FA and *v*HT. Information about all three parameters allows for interpretation of changes in RPI.

In contrast, the response caution index is a measure of the distance traveled by the evidence accumulation process. It is given by

$$\text{Response Caution Index} = b - A$$

The response caution index is a function of both the b parameter (amount of information required to make a response) and the *A* parameter (the amount of initial information in favor of a Go or No Go decision). The Response Caution Index reflects the subject's preference for accuracy over speed, such that high values reflect a tendency for slower, more cautious deliberation over decisions. Often when people are more cautious in their decisions, they require more information before making a decision (i.e., the *b* parameter increases). If increases in *b* are accompanied by no change in the *A* parameter, or decreases in *A*, then the response caution index will increase. Likewise, when people are more cautious in their decisions, they may start each decision process afresh without initially favoring a particular choice. This would reflect a lower the *A* parameter value. Thus, reductions in the *A* parameter value in the presence of the same or increasing values in the *b* parameter would be reflected in high Response Caution Index values as well. In this way, the Response Caution Index provides an overall measure of the degree of caution in a decision and information about b and A parameter values allows for the interpretation about what is driving the changes in response caution.

Data Analyses

First, multiple regression with SPSS version 20.0 (IBM SPSS, 2011) was used to test the primary hypotheses regarding the effect of the WM load manipulation on the primary dependent measures, false alarm rate, log(v_{FA}), and RPI. Models assessed the main effects of load, the EXT latent factor and sex, and all interactions. The respective weights of each indicator variable are depicted in SEM in figure 5. The significance tests for the primary dependent measures were corrected using the Bonferroni method. We used the natural log transformation ($\log_e$) to ensure that the distribution of *v* parameters across participants was normal. These models also were run for the each additional LBA parameter and index with Bonferroni corrections. Measures were log transformed as necessary. For these regressions the EXT factor score was computed using maximum likelihood factor analysis of the lifetime problem counts (alcohol, other drug, ADHD, childhood conduct, and adult antisocial behavior problem counts). The respective weights of each indicator variable are depicted in SEM in figure 4. The maximum likelihood factor analysis yielded one factor (eigen value = 3.372) accounting for 67.45% of the variance in the problem counts.

SEM with AMOS 18.0 (Arbuckle, 2009) was used to assess the hypotheses regarding EWM capacity mediating the association between an EXT factor and latent factor reflecting the cognitive processes underlying disinhibited decision making (false alarm rates, log(v_{FA}), and RPI). Higher values on this latent disinhibited decision making variable reflects higher false alarm rates, higher evidence accumulation rates for false alarms (log(v_{FA})), and lower RPI scores. Mediation was assessed using the bootstrapped (k = 20,000) and bias-corrected 95% confidence intervals (CIs) around the indirect and direct effects (Preacher, Rucker, & Hayes, 2007). Sex was not included in this model because it was not associated with the EWM capacity latent variable, or either of its indicators, ts(508) = -.2 – 1.06, ps = .3 - .8).

Results

LBA Model Results

The fit of the LBA model is examined by assessing whether the model can predict subjects' accuracy and response time data. As can be seen in Figure 2, the LBA model's predicted values for reaction times (RTs) closely match the actual values (data) indicating an excellent fit to the data. Sample data and LBA model predictions were comparable in terms of (a) cumulative probability of RT quantiles for Hits and RT quantiles for false alarms, and (b) the specific effect of WM load on RT quantiles for false alarms. Similar to the effects present in the sample data, the LBA model predicted an increase false alarm rates in the WM load condition.

Externalizing Psychopathology and WM Load

Regression analyses of the primary dependent measures revealed significant main effects of EXT and WM Load on false alarm rates, ts(502) = 2.8 & 14.3, ps < .01, log(v_{FA}), ts(502) = 2.9 & 11.7, ps < .01, and RPI, ts(502) = -2.8 & -10.6, ps < .01. The close mirroring of effects on false alarm rates, log(v_{FA}), and RPI in part reflects the fact that these variables are partly a function of each other. EXT was associated with higher false alarm rates, higher log(v_{FA}) values, and lower RPI values. The WM load significantly increased false alarm rates, and log(v_{FA}), and lowered RPI values. There were significant EXT by Load by Sex interactions on false alarm rates and log(v_{FA}) ts(502) = -2.4 & -2.7, ps < .05. These interactions revealed that EXT was significantly associated with higher false alarm rates for men in both load and no-load conditions (ps < .005), but for women, only in the no WM Load (p < .01) and not the WM Load condition (r= -.15, p = .11). On the log(v_{FA}) measure, EXT was associated with faster log(v_{FA}) values in men in both no-load and load conditions, ßs = .24 & .20, ps < .01 & .05, while for women EXT was associated with faster log(v_{FA}) values in the no-load, ß = .30, p < .005, but slower v_{FA} values in the load condition, , ß = -.19, p < .05. Figure 3 displays these results

The additional regressions revealed that WM Load increased *s* values (p < .005) (No-Load: M=.20, SD=.14 / Load: M=.27, SD=.18), Response Caution Index scores, p < .005, (M=.092, SD=.10 vs M=.145, SD=.10 and *b* values, p < .001 (M=.30, SD=.09 vs M=.34, SD=.13), and decreased hit rates, p < .001 (M=.87, SD=.09 vs M=.84, SD=.11) and) and log(t_0) values, p < .001

(M= -.81, SD=.64 vs M= -1.27, SD=.90). The WM did not affect the *A* or log(v_{HT}) parameters, ps = >.0.9. Changes in the *b* and/or the *A* parameters can be associated with changes in the Response Caution Index. The pattern of results observed here indicates that the increase in response caution after the WM load is due to the increase in the *b* parameter, since the *A* parameter was unchanged by the load.

Externalizing Psychopathology, EWM Capacity, WM-Load and LBA Decision Parameters.

Tests of mediation by EWM capacity were conducted for the full sample and within the WM load and no load conditions. Mediation effects were examined via significance tests of the indirect effects of EXT (via EWM capacity) on disinhibited decision making. The EXT factor accounted for 67.4% among the indicators, the disinhibited decision making factor accounted for 85.5% of the variance among indicators, and the EWM capacity factor accounted for 75.3 % of the variance among its indicator variables, justifying the use of each factor in the SEM model.

The SEM with the full sample fit the data adequately, $\chi2$ (31) = 56.3, p = .004; NFI= .98; RMSEA= .04. In the full sample model the effect of EXT on disinhibited decision making was completely mediated by EWM capacity. The indirect effect of EXT on disinhibited decision making was significant, ß = .065, p = .015, 95% CI [.032, .102], but the direct effect was not significant, ß = .039, p = .42, 95% CI [-.039, .110]. EXT was significantly associated with EWM capacity, ß = -.270, p < .001, 95% CI [-.35, -.18]. EWM capacity was significantly associated with disinhibited decision making, ß = -.241, p < .001, 95% CI [-.33, -.14].

The model in the no WM Load condition fit the data well, $\chi2$ (31) = 40.3, p = .122; NFI= .97; RMSEA= .035. This model revealed that the effects of EXT on disinhibited decision making was partially mediated by EWM capacity. There was significant indirect effect of EXT on disinhibited decision making, ß = .071, p < .01, 95% CI [.02, .138], and a significant direct effect was well, ß = .172, p < .01, 95% CI [.068, .272]. The model in the WM Load condition fit the data adequately, $\chi 2$ (31) = 73.9, $p < .001$; NFI= .95; RMSEA= .073. This model revealed that the effects of EXT on disinhibited decision making was completely mediated by EWM capacity The indirect effect of EXT on disinhibited decision making was significant, ß = .069, $p < .01$, 95% CI [.024, .116], but the direct effect was not significant, ß = -.020, $p = .81$, 95% CI [-.14, .105]. There was significant indirect effect of EXT on disinhibited decision making, ß = .071, $p = .01$, 95% CI [.02, .138], and a significant direct effect was well, ß = .172, $p < .01$, 95% CI [.068, .272]. Figure 4 presents the models for the no load and load conditions. Finally, none of the indicators of the EXT latent variable were uniquely associated with the decision-making variable over and above their covariance with other EXT indicators. This was assessed via modification indices and model respecification analyses.

Discussion

This study used a linear ballistic accumulator (LBA) computational model of go/no-go associative-incentive learning conducted with and without a working memory (WM) load to investigate the dynamic cognitive processes associated with impaired inhibitory, no-go, decisions in those with EXT. The primary results of the study were that (i) high scores on an latent EXT factor were associated with low EWM capacity and higher scores on a disinhibited decision-making latent variable indicated by the three interrelated measures of false alarm rates, evidence accumulation rates for false alarms, and response precision (RPI), (ii) low EWM capacity was associated with more disinhibited decision making regardless of the WM load and partially mediated the association between EXT and disinhibited decision making, (iii) the WM load increased disinhibited decision making for all subjects, and (iv) EXT was associated with disinhibited decision making for men, regardless of WM load; however, EXT was associated with disinhibited decision making for women only in the no-WM load condition

The secondary analyses suggested additional ways that the WM load interfered with information processing that were unrelated to either EXT or EWM capacity. The WM load increased general uncertainty in decision-making (*s* parameter) and response caution. As noted below, the WM-load related increases in the uncertainty (*s*) parameter along with the increase in logvFA (evidence accumulation rate) resulted in the decrease in the RPI (efficiency in evidence accumulation) measure after WM load. In addition, because WM load did not affect the *A* parameter, the WM load related increase in the response caution index was solely due to increases in the thresholds (*b* parameter) for the amount of information necessary for a decision. The higher decision thresholds under WM load suggests that the WM load resulted in more cautious decisions due to subjects needing to collect more evidence before making a decision. Finally, the WM load also decreased the nondecision t_0 parameter values, suggesting that subjects spent less time encoding the stimulus under WM load.

Consistent with studies of different types of EXT (e.g., Endres et al., 2011, Finn et al, 2002; Newman & Kosson, 1986), the EXT latent variable was significantly associated with poor passive avoidance learning (high false alarms), but not with hit rates. However, our results extend this research by including measures of the rate of evidence accumulation for hits (*v*HT) and false alarms (*v*FA) and our response precision index (RPI) measure of the overall efficiency of the evidence accumulation process. Both the EXT and the EWM capacity latent variables were associated with lower scores on the RPI measure of efficiency in the evidence accumulation process. Examination of the data indicate that these associations were due to the association between EXT (and EWM capacity) and lower evidence accumulation rates for false alarms (*v*FA values), because neither EXT or EWM capacity were associated with differences in the evidence accumulation process for hits (*v*HT) or the measure of decision uncertainty (the *s* parameter), which, together with *v*FA, are the basis of RPI scores. Thus, our results suggest that the lower RPI efficiency scores associated with EXT and low EWM capacity reflects a tendency to decide too quickly that a NoGo cue is in fact a Go cue (higher *v*FA values and false alarm rates). In other words, the less efficient evidence accumulation process observed in those with high EXT and/or low EWM capacity is mostly due faulty evidence accumulation process on NoGo trials reflecting a pattern of not deliberating long enough in contexts when one really should be inhibiting a response. This may be partly due to difficulty switching from a Go mode to a NoGo mode, an insensitivity to punishment, or both.

The finding that lower scores on our measures of EWM capacity were associated with disinhibited decision making regardless of the WM load condition suggests a role for attention control processes in learning to adaptively avoid engaging in behaviors that lead to negative outcomes. The analyses also show that EWM capacity partially mediated the association between EXT and the disinhibitory decision-making, suggesting low EWM capacity plays an important role in the inhibitory control difficulties that are known to characterize those with high EXT.

The WM load disrupted the passive-avoidance learning process, resulting in dramatic increases in disinhibited decision-making for all subjects. The load was associated with significant increases in false alarms, evidence accumulation rates for false alarms (*v*FA values), and decision uncertainty (*s* parameter), all of which are reflected in a significant reduction in RPI. The reduced efficiency of the evidence accumulation process (i.e., reduced RPI scores) under WM load was due to the substantial increases in *v*FA values and the decision uncertainty *s* parameter. In a kind of paradoxical manner, the WM load also increased the decision threshold value (*b*) meaning that subjects required more information before making a decision. As noted above, the increase in *b* was responsible for the observed increase in response caution, because the A parameter was unaffected by the load. The WM load did not affect the evidence accumulation rate for hits (*v*HT), suggesting that the load was specifically affecting those cognitive processes associated response inhibition. The pattern of sex differences in the association between EXT and disinhibited decision making in the

WM load condition was unexpected and difficult to explain. In the WM load condition, EXT was associated with more disinhibited decision making in men, but somewhat less disinhibited decision making in the women. The WM load resulted in greater increases in disinhibited decision making in the low EXT women on measures of false alarms and evidence accumulation rates for false alarms. Our data do not provide any basis for the interpretation of this unexpected sex difference.

Limitations & Conclusion

This study was not without limitations. First, we assumed that our WM load specifically depleted EWM capacity. However, the WM load effects may not have been specific just to the WM system and may have depleted executive functions more broadly in a manner similar to that conceptualized in studies of the effects of different self-regulatory depletion (i.e., ego depletion) manipulations shown to disrupt executive functions (Baumeister. Bratslavsky, Muraven & Tice, 1998). Thus, we cannot be sure if the effects of the effects of the WM load on decision-making parameters were specifically due to compromised WM capacity rather than some broader depletion of executive function capacity beyond EWM capacity. Second, our sample is comprised mostly of young white adult college students and biased towards those interested in participating in research studies. Participants were not randomly selected and thus may not be representative of the distribution and severity of EXT psychopathology in the general population. Third, our data is cross-sectional by design and the regression paths in the SEMs cannot be interpreted as causal pathways. The models are structured as complex regression in order to test predictions about mediation of associations.

Aside from these limitations, this study makes three important contributions to the literature on the association between EXT, EWM capacity, and disinhibited decision-making in incentive approach – avoidance learning contexts. First, the poor passive avoidance associative learning (high false alarms) of those high in EXT was associated with measures of inefficient and faulty evidence accumulation processes in the presence of cues that behavior should be inhibited. The high evidence accumulation processes and high false alarm rates of those with EXT suggest that they lack proper attention control during the deliberation process on NoGo trials. Second, this pattern of disinhibited decision making was significantly associated with low EWM capacity, consistent with the important role that executive attention control plays in learning to inhibit approach behavior. Low EWM capacity partially mediated the association between EXT and disinhibited decision making. Third, a WM load dramatically increased disinhibited decision making in all subjects further highlighting the central role that WM processes play in this type of associative incentive go/no-go learning task.

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Figure Legends

Figure 1. Hypothetical Liner Ballistic Accumulator (LBA) units illustrating the accumulation of evidence that leads to 4 possible Go/NoGo stimulus-response-outcome scenarios. Decisions are governed by LBA unit parameters: non-decision time (t0), starting position (A), threshold (b), and mean rate of evidence accumulation (v). After initial non-decision time (t0) related sensory processing, evidence accumulations rates (vector arrows) for the Go responses and NoGo nonresponses (i.e., inhibition) begin at the same starting position (A), and then race over time (decision time) towards the decision threshold (b). V_{NoGo} is the evidence accumulation rate for an inhibition. There are two types of evidence accumulation rates for Go responses, a Hit ($V_{HT(Go)}$) and a False Alarm ($V_{FA(Go)}$). The dotted vertical line depicts the reaction time for all Go responses. Whichever accumulator crosses b first governs the response or inhibition on a given trial. Top Panels depict high efficiency evidence accumulation processes characterized by a large separation between evidence accumulation rates for Go (left) and NoGo (right) trials. Bottom panels depict low efficiency evidence accumulation processes and small separation between evidence accumulation rates for Go and NoGo trials. In <u>top left</u> panel, $V_{HT(Go)}$ rates (value of .85) accumulate faster than V_{NoGo} rates (.15) (a response wins over an inhibition), which correctly leads to a "hit" on a Go trial. In <u>top right</u> panel, $V_{FA(Go)}$ rates (.3) accumulate slower than V_{NoGo} rates (.7), which leads to a "correct rejection" (inhibition) on a NoGo trial. The $V_{FA(Go)}$ rate of .3 reflects what is observed in the no Load condition. * In <u>bottom left</u> panel, $V_{HT(Go)}$ rates (.55) accumulate faster than V_{NoGo} rates (.45), leading to a "hit" on a Go trial, but the close proximity of the vectors illustrates the greater competition between Go responses and NoGo inhibitions (approach – avoidance conflict), which leads to a slower reaction time. In <u>bottom right</u> panel, $V_{FA(Go)}$ rates (illustrated as a rate of 0.7) accumulate faster than V_{NoGo} rates (.3), which leads to a "false alarm" on a NoGo trial. The $V_{FA(Go)}$ rate of .7 reflects what is observed in the WM Load condition.

Figure 2. Reaction time (RT) distribution quantiles for the LBA model predictions (hashed lines) plotted against participants actual RT data (solid lines) for Hits (HT) and False Alarms (FA) by working memory (WM) Load. Panel A depicts the distribution for the No WM Load condition. Panel B depicts the distribution for the WM Load condition. RT quantiles reflect the cumulative probability of observing HT or FA responses on or before six different decision-time intervals. Panel A and Panel B illustrate that LBA model predicted HT ("X") and FA ("X") were a close fit to the actual HT (open square) and FA (filled square) data. Comparisons suggests the LBA model is sensitive to the experimental effects of cognitive load, as indicated by a significant increase in actual and predicted FA under the load condition relative to the no-load condition.

RTqsHT (Data) = reaction time quantiles for Hits – observed data.

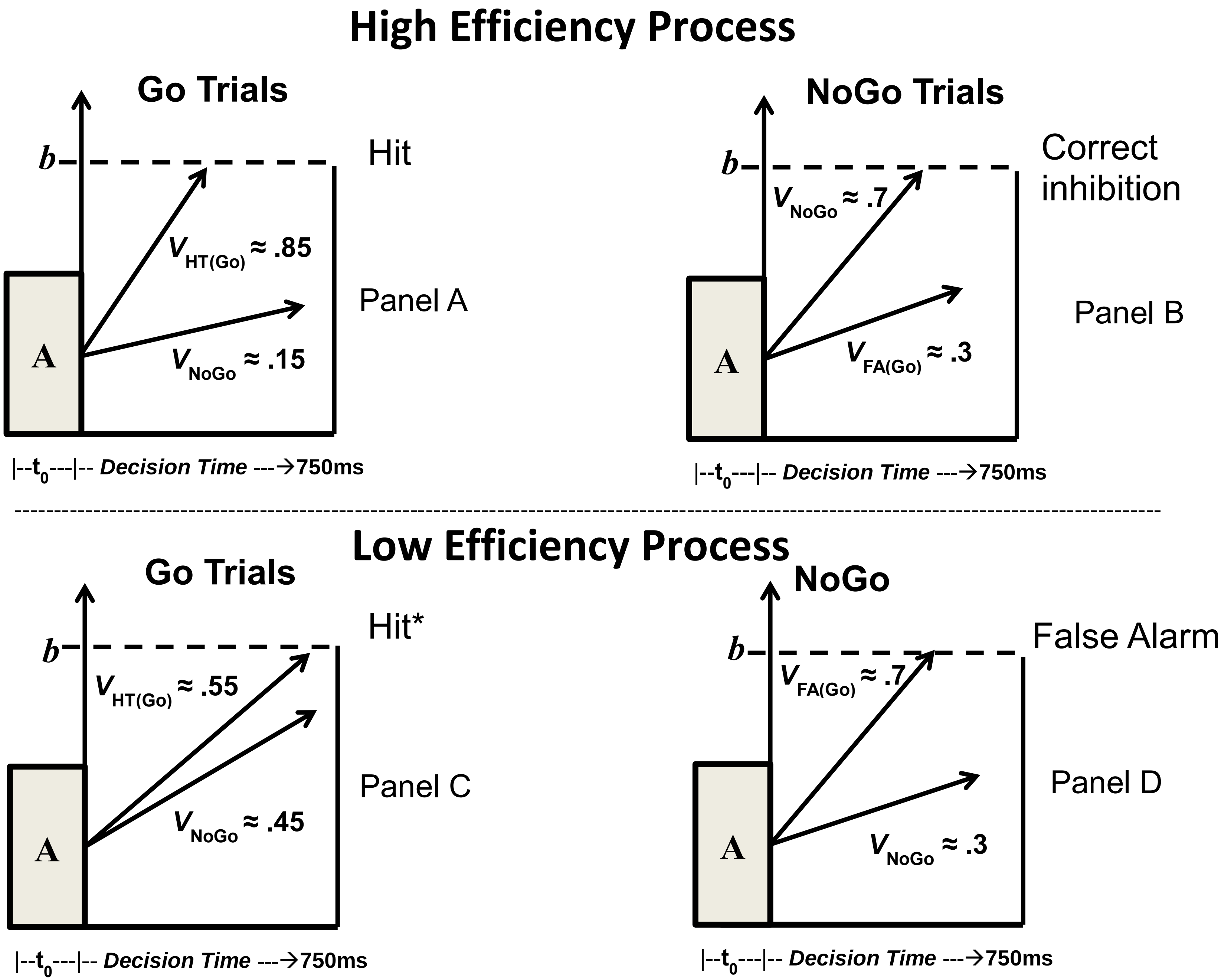
RTqsHT (LBA) = reaction time quantiles for Hits – LBA model predicted values.

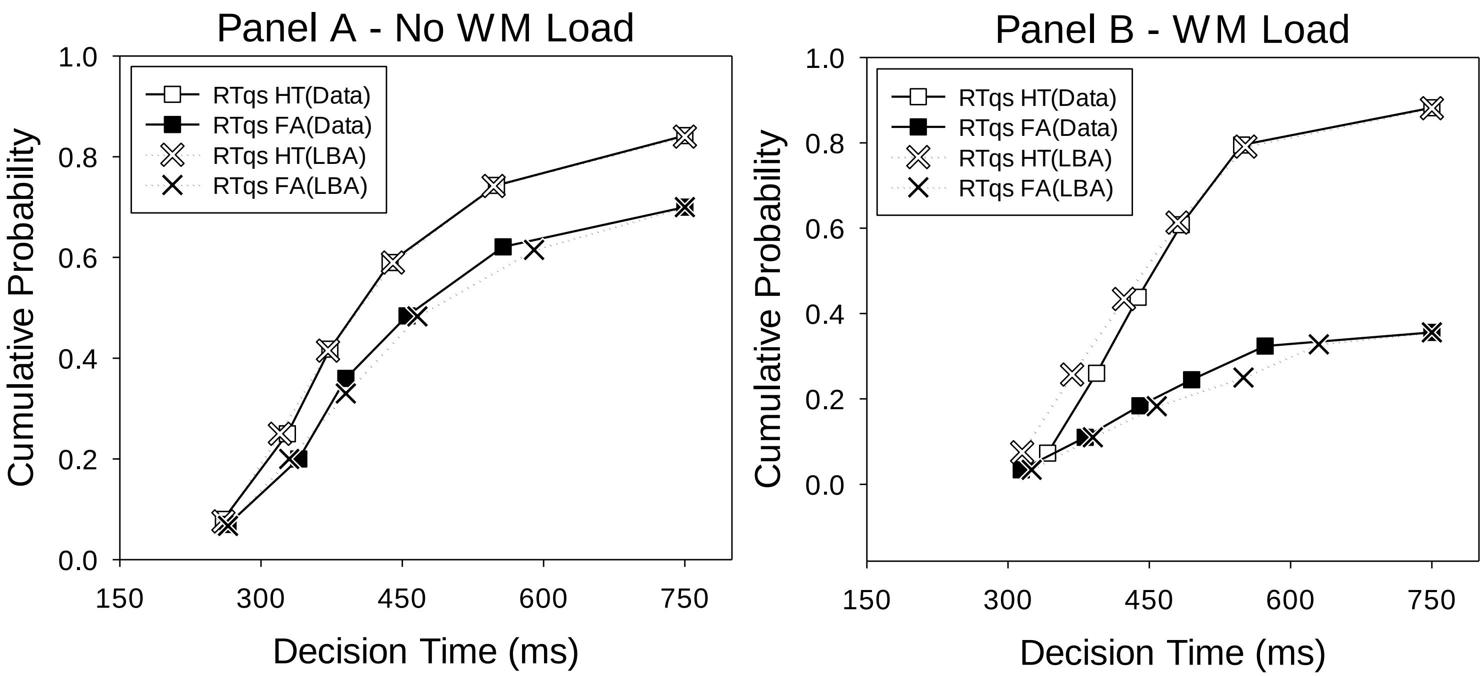
RTqsFA (Data) = reaction time quantiles for False Alarms – observed data.

RTqsFA (LBA) = reaction time quantiles for False Alarms – LBA model predicted values

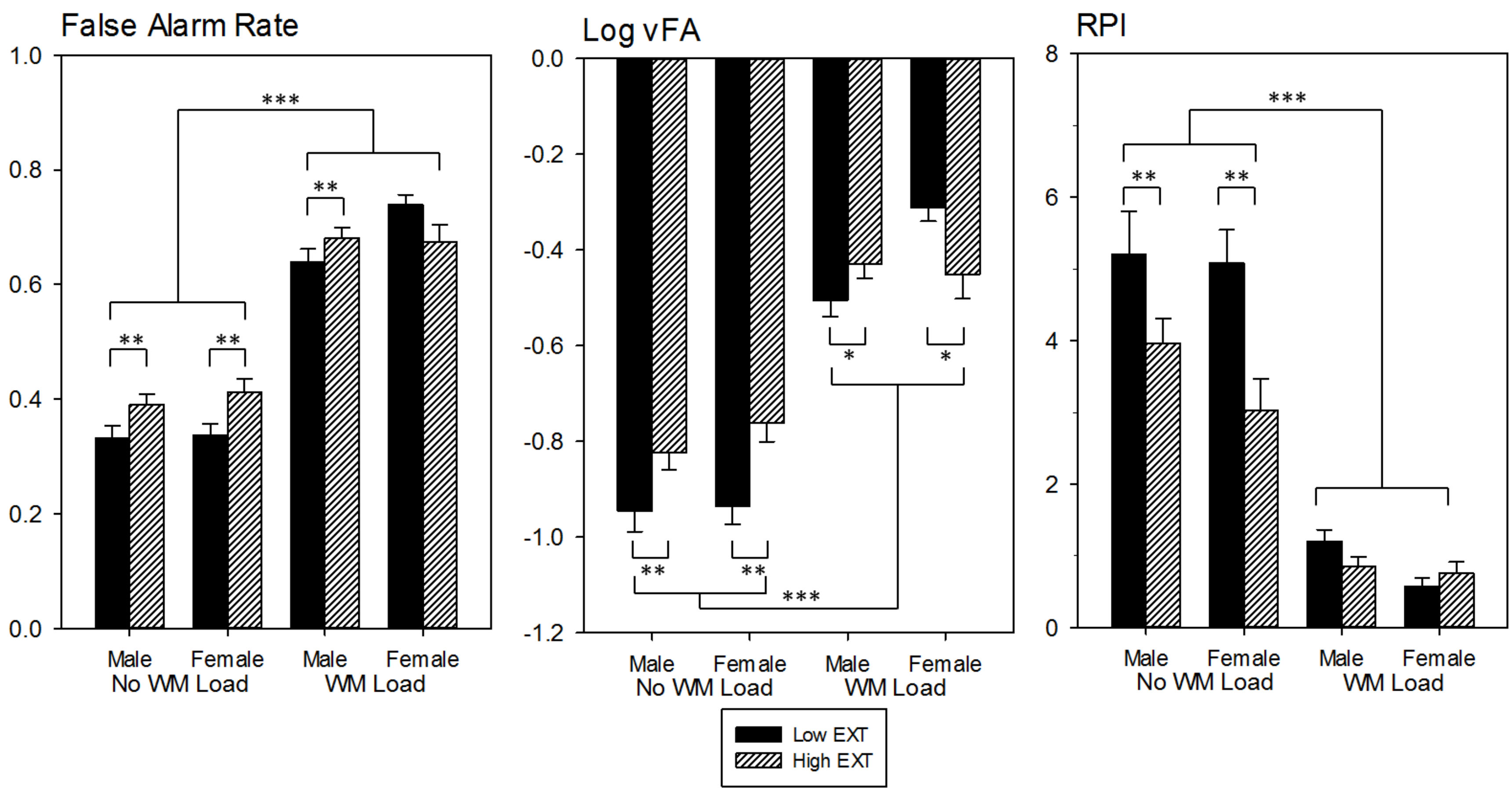
Figure 3. Bar graphs for measures of disinhibited decision making on the go/ no go incentive learning task with and without working memory (WM) load. The left panel depicts mean false alarms rates. The middle panel depicts mean Log(v_{FA}) parameter (log transformed evidence accumulation rate for false alarms). The right panel depicts the mean RPI parameter (response precision index). The mean values (with standard errors) are presented for the sample divided into low and high externalizing (EXT) psychopathology (median split), Sex and WM load condition (load/no WM load). Significant differences are illustrated using brackets and asterisks. Note: the values and effects for each measure closely mirror each other, because, as explained in the text, each is, in part, a function of the other. * = $p < .05$; ** = $p < .01$; *** = $p < .001$

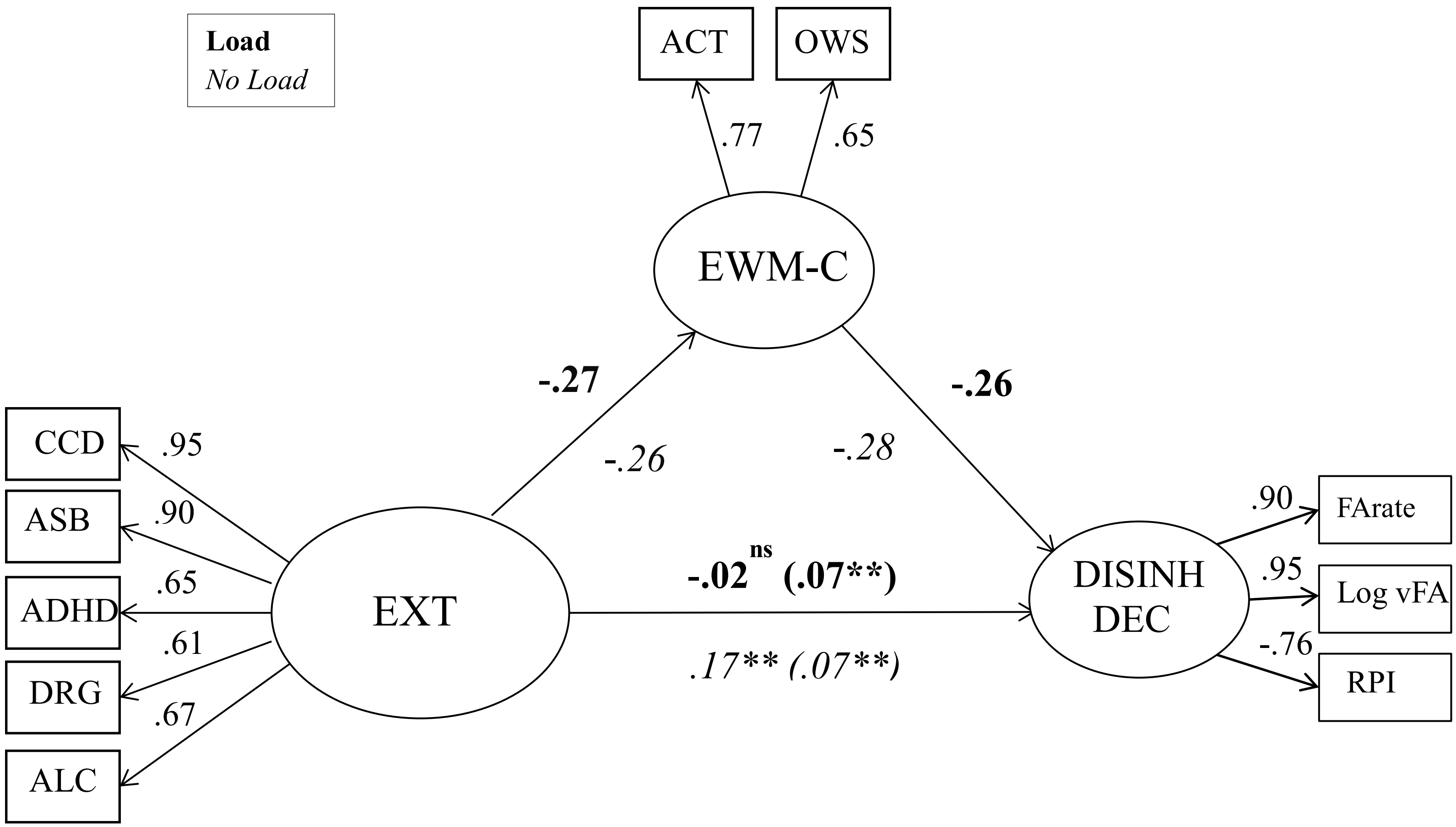
Figure 4. Structural equation model of the association between latent Externalizing Psychopathology (EXT) factor, a latent Executive Working Memory Capacity (EWM capacity) factor, and a latent Disinhibited Decision Making (DISINH DEC) factor. Regression Path weights in the WM load condition are depicted in **bold**, the no Load is depicted in *italics*. Path weights inside parentheses indicate the indirect effects of EXT on DISINH DEC. CCD = lifetime childhood conduct problems; ASB = lifetime adult antisocial behavior problems; ADHD lifetime attention deficit disorder problems; DRG = lifetime problems with drugs; ALC = lifetime alcohol problems; ACT = Auditory Consonant Trigram performance; OWS = Operation Word Span performance. FA rate = false alarm rate; Log vFA = log transformed evidence accumulation rate for false alarms; RPI = response precision index. ns = nonsignificant; ** $p < .01$; All path weights are significant at $p < .001$.


High Efficiency Process
Go Trials
Hit
b
A
V_HT(Go) ≈ .85
V_NoGo ≈ .15
Panel A
|--t0---|-- Decision Time ---→750ms
NoGo Trials
Correct inhibition
b
A
V_NoGo ≈ .7
V_FA(Go) ≈ .3
Panel B
|--t0---|-- Decision Time ---→750ms
Low Efficiency Process
Go Trials
Hit*
b
A
V_HT(Go) ≈ .55
V_NoGo ≈ .45
Panel C
|--t0---|-- Decision Time ---→750ms
NoGo
False Alarm
b
A
V_FA(Go) ≈ .7
V_NoGo ≈ .3
Panel D
|--t0---|-- Decision Time ---→750ms



Panel A - No WM Load
RTqs HT(Data)
RTqs FA(Data)
RTqs HT(LBA)
RTqs FA(LBA)
Cumulative Probability
0.0
0.2
0.4
0.6
0.8
1.0
150
300
450
600
750
Decision Time (ms)
Panel B - WM Load
RTqs HT(Data)
RTqs FA(Data)
RTqs HT(LBA)
RTqs FA(LBA)
Cumulative Probability
0.0
0.2
0.4
0.6
0.8
1.0
150
300
450
600
750
Decision Time (ms)


False Alarm Rate
1.0
0.8
0.6
0.4
0.2
0.0
***
**
**
**
Male
Female
Male
Female
No WM Load
WM Load
Log vFA
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
-1.2
*
*
**
**
***
Low EXT
High EXT
RPI
8
6
4
2
0
***
**
**



Load
No Load
ACT
OWS
.77
.65
EWM-C
-.27
-.26
-.26
-.28
CCD
ASB
ADHD
DRG
ALC
.95
.90
.65
.61
.67
EXT
-.02ns (.07)**
*.17** (.07**)*
DISINH
DEC
.90
.95
-.76
FArate
Log vFA
RPI