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The Role of Executive Function in Adolescent Adaptive Risk-Taking on the Balloon Analogue Risk Task

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Abstract

The present study examined the role of executive control functions (ECF) in adaptive risk-taking during adolescence. Healthy individuals aged 8–25 were administered ECF measures and the Balloon Analogue Risk Task (BART), a computerized measure of risk-taking propensity.

Findings demonstrated that adolescents who executed a more consistent response strategy evidenced better performance on the BART. Greater working memory (WM) predicted lower response variability and working memory capacity mediated the relationship between age and variability. Results suggest that intra-individual response variability may index adaptive risk-taking and that the development of ECF, specifically working memory, may play an integral role in adaptive decision making during adolescence and young adulthood.

Introduction

Adolescence is a critical period for development of brain networks that support decision making and is often marked by increased risk-taking as these neural systems mature. Traditional perspectives on risk-taking often emphasize its detrimental nature and significant research has examined the correlates and negative outcomes related to maladaptive risk behavior (e.g. use of alcohol and illicit substances) in adolescence (Humphreys, Lee, & Tottenham, 2013; Lavery, Siegel, Cousins, & Rubovits, 1993). However, risk-taking during this period can also be advantageous in facilitating the development of the skills necessary for becoming autonomous (Spear, 2000). For example, pursuit of age-appropriate opportunities for social, educational and professional development (e.g. going away to college) require some amount of risk. Previous research implicates the development of executive control functions (ECF), (e.g. working memory, processing speed, reasoning, and

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inhibitory control) as important cognitive components in the development of decision-making abilities. While deficits in ECF are repeatedly linked to maladaptive risk behaviors (Bechara & Martin, 2004; Brand et al., 2005; Romer, Betancourt, Giannetta, Brodsky, & Farah, 2010; Smith et al., 2014), the neuropsychological correlates of *adaptive* risk-taking during this life stage are not well understood. Thus, the present study aims to examine the role of ECF in adaptive risk-taking during adolescence.

Elevated risk-taking behavior during adolescence is often explained by a dual-systems theory, which proposes that the neural circuitry regulating reward-driven behavior develops earlier than the circuitry regulating executive control (Galvan et al., 2006; Steinberg, 2010). ECF, which are primarily driven by the executive control network, are used during risk-taking to evaluate and learn the outcomes of choices as positive or negative, and apply this information to consistently select consistently and execute future decisions (Pickering & Gray, 2001). For example, poor working memory, the ability to hold and manipulate information while executing a task or decision, increases the likelihood of choosing smaller, immediate rewards over larger but delayed rewards (Shamosh et al., 2008). Additionally, response variability during an inhibitory control task is related to statistical learning, the process of effectively evaluating patterns of data to make predictions, during adaptive risk-taking. This suggests that individuals use cognitive control to continuously monitor probabilistic outcomes and adjust behavior accordingly (Ma & Yu, 2015). Neuroimaging studies using functional magnetic resonance imaging (fMRI) have demonstrated that attenuated activity in regions of the brain responsible for ECF, such as the prefrontal cortex, are related to impairments in risky decision making in both adult and adolescent samples (Qi et al., 2015; Rao, Korczykowski, Pluta, Hoang, & Detre, 2008). As adolescence is a period of ongoing development of the ECF capacities implicated in risky decision making (Crone & Dahl, 2012; Luna, Marek, Larsen, Tervo-Clemmens, & Chahal, 2015), adolescents at different stages of ECF development are likely to execute risk-taking with varying levels of success.

In recent years, measures of intra-individual response variability have increasingly been used to index ECF. Specifically, behavioral and functional neuroimaging research suggests that lower variability indicates stronger inhibitory control and may support one's ability to execute advantageous decision making (Bellgrove, Hester, & Garavan, 2004; Wu et al., 2012). In contrast, extreme variability is associated with cognitive impairments, as evidenced by patients with damage to frontal control regions of the brain who show excessive variability in cognitive performance. Furthermore, increased variability in such patients has been related to greater error rates on behavioral tasks and accompanied by neurocognitive deficits in inhibitory control, attention and processing efficiency (Manly, Davison, Heutink, Galloway, & Robertson, 2000; Stuss, Murphy, Binns, & Alexander, 2003).

Because adolescents are characterized by a high degree of behavioral variability as neural systems mature, intra-individual response variability has been emphasized as an important component of, and relevant metric for evaluating, adolescent risk behavior (Goldenberg, Telzer, Lieberman, Fuligni, & Galvan, 2016; Van Duijvenvoorde et al., 2015). Goldenberg et al. (2016) suggested that variability during this period provides an adaptive flexibility that

allows adolescents to optimally navigate uncertainties of decision making during the transition to adulthood. Intra-individual variability of neuropsychological performance and behavioral response times is found to decrease through adolescence (Roalf et al., 2014; Williams, Hultsch, Strauss, Hunter, & Tannock, 2005) but, the relationship between age and variability in the context of risk-taking has not been examined during this life stage. Given that ECF improves over the course of adolescence, and ECF is related to decreasing response variability, research to examine the role of ECF in the relationship between age and response variability may help to elucidate underlying processes related to risk behavior.

Efforts to study intra-individual response variability during risk-taking have used the Balloon Analogue Risk Task (BART), a computerized measure of risk-propensity. While the BART has traditionally used outcome variables that measure maladaptive risk-taking, research that instead examines intra-individual response variability during the task has demonstrated its potential as an index of adaptive risk-taking. Specifically, response variability on the BART was used in adult samples to distinguish between functional and dysfunctional impulsivity, constructs analogous to our interest in adaptive and maladaptive risk taking. While impulsivity and risk-taking are distinct constructs (Meda et al., 2009), impulsivity is a personality trait believed to strongly influence risky decision making (Lauriola, Panno, Levin, & Lejuez, 2014). “Functional impulsivity” is the tendency to act with relatively little forethought when such a strategy is advantageous (e.g. making split-second decisions to gain opportunities) while “dysfunctional impulsivity” conversely results in disadvantageous outcomes (e.g. buying thing one cannot afford). Those high in self-reported functional impulsivity evidenced lower response variability on the BART, which indicates that adaptive risk-taking may be characterized by a more consistent and controlled response strategy (Congdon et al., 2013). Since impulsivity influences risk behaviors, the relationship between response variability and an advantageous form of impulsivity suggests the potential for intra-individual response variability to measure adaptive risk-taking.

Given the role of ECF in the development of risk-taking processes, the present analysis aims to evaluate the extent to which ECF contributes to adaptive risk-taking in a sample of healthy adolescents and young adults, as measured by intra-individual response variability on the BART. Improved distinction between mechanisms of adaptive versus maladaptive risk-taking in adolescence will further elucidate the complexities of risky decision making during this sensitive developmental period. Understanding the role of neuropsychological abilities in optimal and non-optimal risk behavior could inform the development of interventions to enhance cognitive capacities in risk-vulnerable populations.

Methods

Participants.

A sample of 105 healthy individuals aged 8–25 (Mean = 17.91 +/− 3.63) were recruited as part of an ongoing longitudinal study via posted flyers, internet advertisements and referrals from previous study participants. Our sample was 56.73% female and 52.88% Caucasian, 21.15% African-American, 18.27% Asian, and 7.70% “Other”. Participants over age 18 provided written informed consent and minors provided written assent alongside parental written consent. The protocol was approved by the Northwell Institutional Review Board.

Participants were fluent English speakers with IQ above 70, estimated from combined scaled scores on the Wechsler Adult Intelligence Scale- Third Edition (Wechsler, 1999). Participants were excluded if they had a past or present Axis-I diagnosis, intellectual disability, head injury with loss of consciousness, medical illness with known cognitive effects, or were taking any medications intended to affect brain functioning.

Procedure.

Diagnostic interview.—Present and lifetime Axis-I disorders were ruled out by administration of the Structured Clinical Interview for the DSM-IV, Non-Patient Version (SCID-NP) (First, Spitzer, Gibbon, & Williams, 1997). Participants aged 8–15 were also administered supplemental sections of the Kiddie-Schedule for Affective Disorders and Schizophrenia- Present and Lifetime Version (K-SADS-PL) (Kaufman, Birmaher, Brent, & Rao, 1997) to rule out additional child-onset disorders. Interviews were conducted by trained graduate-level raters and supplemented by family informants whenever possible. Information from the interview was compiled into a case summary and presented to at least two faculty psychologists to confirm a consensus on the diagnosis.

Neuropsychological testing.—Subtests of the MATRICS Cognitive Consensus Battery (MCCB) (Kern et al., 2008) were administered to all participants. For the present analyses, we used participants' scores from the subtests that measure domains of ECF including: (1) Processing Speed, measured by the Brief Assessment of Cognition in Schizophrenia (BACS) Symbol Coding subtest (Keefe et al., 2004), the Trail Making Test: Part A (*Army Individual Test Battery*, 1944), and Category Fluency: Animal Naming (Spreen & Strauss, 1998), (2) Working Memory, measured by the spatial span subtest of the Wechsler Memory Scale, Third Edition (D. Wechsler, 1997) and Letter Number Span (Gold, Carpenter, Randolph, Goldberg, & Weinberger, 1997), and (3) Reasoning and Problem Solving, measured by the Neuropsychological Assessment Battery (NAB) Mazes subtest (Stern & White, 2003). The Stroop Interference Test was also administered to assess inhibitory control (Stroop, 1935). We also used scores from two non-ECF cognitive domains of the MCCB to distinguish the contributions of ECF from other cognitive functions: (1) Verbal Memory, measured by Hopkins Verbal Learning Test (HVLT) (Brandt, 1991) and (2) Visual Learning, measured by the Brief Visuospatial Memory Test-Revised (BVMT) (Benedict, Schretlen, Groninger, Dobraski, & Shpritz, 1996). All raw scores were standardized by age and sex into T-scores for each domain.

Balloon analogue risk task (BART).—The Balloon Analogue Risk Task is a well-validated computerized measure of risk-taking propensity and has been correlated to real-life risk behavior in a variety of populations (Lejuez et al., 2002; Poldrack et al., 2016). We used a two-balloon version developed by the Consortium for Neuropsychiatric Phenomics (CNP) (Poldrack et al., 2016) and programmed in E-Prime 1.0. Participants inflate a series of balloons in two different colors that, unknown to them, denote either a high (balloons with a probability of explosion ranging from 1 to 32 inflations) or low likelihood (balloons with a probability of explosion ranging from 1 to 128 inflations) of exploding. Points are earned for every inflation and participants are informed that the goal is to earn as many points as possible over the course of the task. They are instructed they must decide when during each

trial to “cash out” to collect their points and that if the balloon explodes before they “cash-out”, the points for that trial are lost. Participants are not informed that each color indicates different probabilities of exploding (Lejuez, 2002; Poldrack, 2016). All participants are administered 40 trials and receive an equal number (20 each) of high-risk and low-risk balloons randomized across the task. The first presented balloon is 152 × 152 pixels in size and increases 2×2 pixels in height and width after each successive pump to appear as if it is being inflated. This continues until the participant cashes out or the balloon explodes, after which the participant is shown the next balloon. Accumulated points are shown after the end of each trial and the grand total is presented at the end. The BART has most often been used to study risk-propensity by examining Mean Adjusted Inflations (MAI), the average number of inflations on balloons that did not explode as an outcome variable; higher values indicate greater risk-propensity. The total amount of points a player earns over the course of the task can also be used, where higher values signify more successful performance (Koscielniak, Rydzewska, & Sedek, 2016; McCormick & Telzer, 2017).

More recently, investigations of the BART have incorporated a measure of intra-individual variability using the Coefficient of Variation of adjusted inflations (COV), calculated as the standard deviation of adjusted inflations divided by the mean of adjusted inflations (Congdon et al., 2013; Demartini et al., 2014; Jentsch, Woods, Groman, & Seu, 2010). COV is computed in this way to ensure that mean level of adjusted pumps does not confound the examination of variability. The COV can be used to index control; it infers how well participants learn which balloons are more likely to pop and how consistently they apply that knowledge over the course of the task. A higher value of COV indicates higher variability and suggests less inhibitory control. In this version of the task, COV can be calculated for high-risk and low-risk balloons separately. In addition, having two balloons allowed us to calculate a measure of learning across the task; we calculated a “low risk pump ratio” as the number of inflations of low risk balloons on the second half of the task divided by number of low-risk inflations on the first half, as well as a “high risk pump ratio” defined as the number of inflations on high risk balloons on the second half of the task divided by the amount of high risk inflations on the first half.

A lower number, closer to 0, indicates decreasing inflations of that type of balloon across the task. For the low risk balloons, a higher number indicates learning to maximize the opportunity to earn points across the task whereas a number closer to 1 (where the inflations do not differ much) indicates less ability to learn adaptively. For the high risk balloons, a higher number would indicate increasing inflations of the high risk balloons across the task, suggesting less adaptive risk-taking with greater risk of explosion.

The BART offers a unique opportunity to measure both advantageous and disadvantageous risk-taking because in order to optimize performance, the player must engage in some amount of risk while at the same time exerting inhibitory control (Humphreys et al., 2013). Furthermore, our use of a two-balloons version allows for a more nuanced evaluation of how participants learn about outcome probabilities and how they consistently apply that information throughout the task.

Analyses.—Linear regressions were performed to examine the relationship between ECF capacities and response variability during BART performance, as measured by COV. All regressions included age and sex as covariates, given the significant cognitive changes that occur with age during adolescence, and previously established gender differences during risk-taking (Cazzell, Li, Lin, Patel, & Liu, 2012). Regression analyses were bootstrapped due to the tendency for variables in a neuropsychological battery to be highly correlated. Bootstrapping is a resampling procedure that involves repeatedly sampling cases from the dataset and approximating the effect in each resampled dataset in order to obtain an empirical estimation of the overall effect. Several authors suggest that bootstrapping works to mitigate the effect of multicollinearity and reduce Type I errors when making multiple comparisons, especially when examining neurocognitive data and conducting mediation analyses (Blakesley et al., 2009; Preacher & Hayes, 2008; Schutte, Axelrod, & Montoya, 2015; Tierney, Yao, Kiss, & McDowell, 2005). SPSS Software (version 24) was used to conduct all statistical analyses.

We first computed a global measure of ECF for each subject by averaging the T-scores from the MCCB's four ECF domains: Working Memory, Processing Speed, Reasoning and Problem-Solving and Inhibitory Control. We ran a linear regression in which global ECF was entered as a predictor variable and COV was entered as the outcome variable. We then ran a stepwise multiple regression with the four ECF domains as well as the two non-ECF domains (i.e. Verbal Memory and Visual Learning) entered as predictors in order to elucidate the specific neurocognitive processes that predicted COV. The non-ECF domains were included to distinguish the contributions of ECF from other cognitive capacities.

To evaluate the influence of ECF on learning over the course of the task, we also ran two stepwise multiple regressions to examine the contributions of ECF to the low-risk pump ratio and high-risk pump ratio. In each model, the four ECF domains and two non-ECF domains were entered as predictors. One model entered low-risk pump ratio as the outcome variable and the other entered high-risk pump ratio as the outcome variable.

To evaluate the role of ECF in the relationship between age and reduced intra-individual response variability, we conducted a formal mediation model to evaluate if global ECF mediated the relationship between age and COV. We also planned to conduct a formal mediation analysis for any ECF domain that was found to be a significant predictor of COV. Using an approach by Baron and Kenny (Baron & Kenny, 1986), a series of regression models were conducted to examine: 1) whether age is associated with COV, 2) whether age is associated with ECF, 3) whether the ECF domain is associated with COV, and 4) whether age remains significantly associated with COV after controlling for the ECF domain. In order to increase confidence in the direction of the mediation relationship, we also conducted mediation analyses to test if the opposite relationship was significant (i.e. age as mediator between ECF and COV).

To establish if response variability predicted advantageous risk-taking (the ability to maximize points), the COV across all balloons, and the COVs across high-risk and low-risk balloons were each entered as predictor variables into three simple linear regressions with the total number of points earned during the BART entered as an outcome variable. To

investigate if COV measured a construct distinct from the traditional BART variables that measure maladaptive risk-propensity, the same stepwise multiple regression that was conducted to examine contributions to COV was conducted to examine the impact of the four ECF domains and two non-ECF domains on the most traditionally used BART variable to measure maladaptive risk-propensity, mean adjusted inflations. Additionally, equivalent simple regressions were conducted to examine if COV predicted mean adjusted inflations.

Results

The distributions of BART variables were heavily skewed and thus were square-root transformed to correct for non-normality and reduce the extremeness of outliers (Field, 2013). Mean and standard deviation for age, IQ, executive control function standardized scores and raw BART performance variables were computed for the complete sample (Table 1). Descriptive statistics were also calculated separately for subgroups of age (8–12, 13–16, 17–21, 22–25) and compared to a publicly available dataset of adults in order to display developmental patterns (Supplementary Table 1) (Poldrack et al., 2016). Cognitive domains were correlated as is typical in a neurocognitive battery performance; relationships are displayed in a correlation matrix (Table 2) but VIFs and Tolerance statistics were within normal limits for all stepwise regressions (Tables 3–5). According to statistical guidelines, tolerance values below 0.2 indicates a potential problem and tolerance below 0.1 indicates a serious problem (Menard, 1995); cut-off values for Variance Inflation Factor (VIF) values are debated but common standards are that they should be below 4 −10 (O'Brien Robert M, 2007).

Regression Analyses.

Global ECF significantly explained 20.7% of the variance of COV ($F(3,104) = 8.77$, $p < .001$. Stronger global ECF predicted lower variability ($B = -.45$, $t = -4.15$ $p < .001$), an indication of stronger cognitive control. Next, the stepwise multiple regression to examine the specific cognitive domains contributing to response variability indicated that working memory contributed most significantly to COV and explained 7.2% of its variance ($F(1, 92) = 7.05$, $p = .009$, (Table 3). Results indicate that increased working memory capacity significantly predicted lower variability ($B = -.27$ $t = -2.66$, $p = .009$), above and beyond the other ECFs and cognitive functions (Figure 1).

Regressions also demonstrated that Reasoning and Problem-Solving capacity was most predictive of the Low-Risk Pump Ratio and explained 6.7% of its variance ($F(1, 91) = 6.45$, $p = .013$) (Table 4). The negative relationship ($b = -.26$, $p = .013$) indicates that increased pumps on low-risk balloons over the course of the task (indicating the participant learned to optimize their pumping strategy), was related to greater Reasoning and Problem-Solving capacity. No variables contributed to High-Risk Pump Ratio.

The regression to examine the impact of cognitive domains on mean adjusted inflations demonstrated that different cognitive domains contributed to mean adjusted inflations compared to the ECFs that predicted COV (Table 5). Two predictors, Visual Learning ($p = .002$, $b = .31$) and gender ($p = .02$, $b = .27$), significantly predicted Mean Adjusted

Inflations (F(2, 92) = 7.42, p= .001). This suggests that different cognitive and demographic functions contribute to adaptive and maladaptive forms of risk-taking.

Simple linear regressions revealed that lower COV across all balloons significantly predicted higher total points (F(3,104)= 2.79,p = .04, b = −.15) and that lower COV across low-risk balloons also predicted adaptive risk-taking, as measured by higher total points earned (F(3,104)= 3.09, p = .02, b = −.17). Results were not significant for COV across high-risk balloons. These results demonstrate that greater consistency across balloons, specifically across low-risk balloons, was related to stronger performance on the BART, as measured by a greater number of points earned. Simple linear regressions also revealed that COV across balloons, as well as across low and high risk balloons individually, did not predict maladaptive risk-propensity, as measured by MAI. All results are displayed in Table 6.

Mediation Analyses.

Results indicated that our sample mirrored previous findings of increased age being related to lower response variability, as measured by COV (p = .03, b = −.24). This allowed us to continue examining whether the other three criteria required for mediation were significant for the ECF that predicted COV, Working Memory (Baron & Kenny, 1986). All criteria for a significant mediation model were met for Working Memory. Results demonstrated that as age increased, intra-individual response variability decreased, and greater Working Memory capacity (Figure 2) was found to significantly mediate this relationship. Global ECF did not mediate the relationship between age and COV.

Our analysis testing whether the opposite direction of mediation was true (i.e. age as mediator between Working Memory and COV) was not significant, which increases our confidence that age-related changes in Working Memory underlie the relationship between age-related changes in intra-individual variability (Supplemental Material Table 2).

Discussion

This study evaluated the extent to which ECF contributes to adaptive risk taking in adolescence and young adulthood, as measured by performance during a computerized risk-propensity task. Results demonstrate first, that lower response variability is associated with earning more total points during the BART, indicating that greater behavioral consistency contributed to adaptive risk taking. Second, findings demonstrate that this lower intra-individual response variability is predicted by more developed ECF, specifically Working Memory capacity. Our finding that non-ECF domains (i.e. Visual Learning and Verbal Memory) did not contribute to response variability supports the idea that the strength of ECFs specifically, rather than any cognitive domain, contribute to risky decision making performance. Our finding that a specific ECF domain, working memory, but not global ECF, mediated the relationship between age and response variability indicates that global cognitive functioning is not specific enough to explain the relationship between age and response variability during risk-taking.

Taken together, this suggests that working memory is a critical cognitive process that impacts behavior during risk-taking. Specifically, greater working memory appears to allow

for more consistent control over one's responses in the context of risk-taking, leading to advantageous outcomes. Our findings align with previous neuroimaging findings that intra-individual variability during adolescence is related to greater maturation of white matter integrity in frontal brain regions associated with working memory (Tamnes, Fjell, Westlye, Østby, & Walhovd, 2012), and that damage to these areas is linked with impairments in working memory (Levy & Goldman-Rakic, 2000). Furthermore, lower response variability across all balloons, and across low-risk balloons alone, was related to better overall BART performance, as measured by the total number of points earned during the task. Taken together, it appears that adolescents who executed a more consistent response strategy, specifically one that favored low-risk balloons, were able to earn a greater number of points. This provides support for the potential of intra-individual response variability to be used as an index of adaptive risk-taking capacity.

Mediation analyses demonstrated that the observed relationship between age and increasing response consistency was mediated by stronger working memory. This is consistent with previous research that demonstrates reductions in intra-individual response variability from childhood into young adulthood, as individuals gain increasing cognitive control (Roalf et al., 2014; Williams et al., 2005). More developed working memory may have allowed individuals to better remember the differences in probability of whether each balloon type would explode and apply this information throughout the task to optimize performance. In a real-life context, greater working memory may allow adolescents and young adults to more effectively process information to navigate uncertain options during risk-taking that ultimately leads to advantageous outcomes.

This study uniquely demonstrates the neuropsychological correlates of intra-individual response variability during risk-taking in a healthy sample of adolescents and young adults, and emphasizes the importance of working memory during adaptive decision making processes. Our results provide further support that intra-individual response variability can be used to index ECF capacity and that the BART can be used to measure adaptive risk-taking. ECFs were not related to Mean Adjusted Inflations, the traditional metric for risk-propensity that has been linked to maladaptive behaviors such as excessive alcohol and illicit substance use. This lack of relationship suggests that when COV is used as an outcome variable during the BART, it is indexing a facet of risk-propensity that is distinct from what is traditionally measured by MAI. Our findings align with previous research demonstrating COV's utility as a unique metric of risk-taking behavior (Demartini et al., 2014). COV appears to probe the ability to evaluate and recognize probabilities of risk/reward outcomes and consistently apply that information during decision making. In contrast, MAI better indexes the continued seeking of rewards despite the potential for negative consequences. Distinguishing the nature of these variables will provide a useful foundation for further exploration of the unique processes related to adaptive versus maladaptive risk-taking. Furthermore, individuals who scored higher on an index of reasoning and problem-solving ability also showed increased inflations for low-risk balloons over the course of task which suggests a greater capacity for learning optimal responses that lead to favorable outcomes. This may indicate that while COV is broadly associated with global executive function, the capacity to continue to learn the rules across the task is more specifically associated with problem solving ability.

A critical direction of future research will be to further explore age-related trends in the relationship between ECF and risk-taking. Our Supplementary Material displays the descriptive statistics of BART performance and ECF capacity when our sample is divided into smaller age quartiles (i.e. 8–12, 13–16, 17–21, 22–25) in order to illustrate mean behavior during different stages of adolescent and young adulthood. This grouped data indicates that there may be a benefit to future dense sampling of the transition from late childhood to early adolescence as it may be a period of particular change in amount of variability (i.e. higher COV) coupled with degree to which pumping behavior is risk-averse (i.e. lower MAI). However, our sample is limited by an uneven number of participants at the tail ends of our age brackets, which hindered our ability to meaningfully examine age-related differences between our younger and older participants. Future studies should attempt to explore changes in risk behavior as related to executive functioning in a sample that is more equally distributed across age in this important developmental period.

An additional limitation is that due to the longitudinal design of our study, we were unable to do a true manipulation check of whether participants explicitly learned the difference in risk probability between the two different colored balloons. While our behavioral analyses revealed differences in the relationship between ECF and Low-Risk Pump Ratio relative to the High-Risk Pump Ratio, because we were unable to confirm whether participants understood the difference between the risk level of each balloon, we should be cautious in our interpretation of these results. Future research with the BART may benefit from including a manipulation check afterwards in order to understand whether behavior during high-risk and low-risk conditions reflects conscious learning of the differences in risk probability.

Our study is also limited by the lack of a measure of real-life advantageous risk behavior, which hinders our ability to validate COV as a potential measure of adaptive risk taking. Additionally, we are limited by a small sample and the use of multiple comparisons. Despite our sample size, a study of 105 healthy individuals being administered the two-balloon version of the BART has not previously been conducted and thus, this is also a unique strength of the present study. Future research should attempt to expand our sample size by pooling results of adolescents administered the CNP version of the BART. Additionally, future studies should examine BART performance in relation to real-life behaviors that reflect both adaptive and maladaptive risk-taking in order to further explicate these distinct dimensions of risk-taking.

In summary, our results demonstrate that strong ECF, specifically working memory, plays an integral role in adaptive decision making during adolescence and young adulthood. These findings contribute to a more nuanced understanding of the multifaceted complexities of decision making during an important developmental period. Furthermore, strengthening ECF may be helpful in developing effective interventions for risk-vulnerable populations, in order to help adolescents improve their ability to apply cognitive control during decision making.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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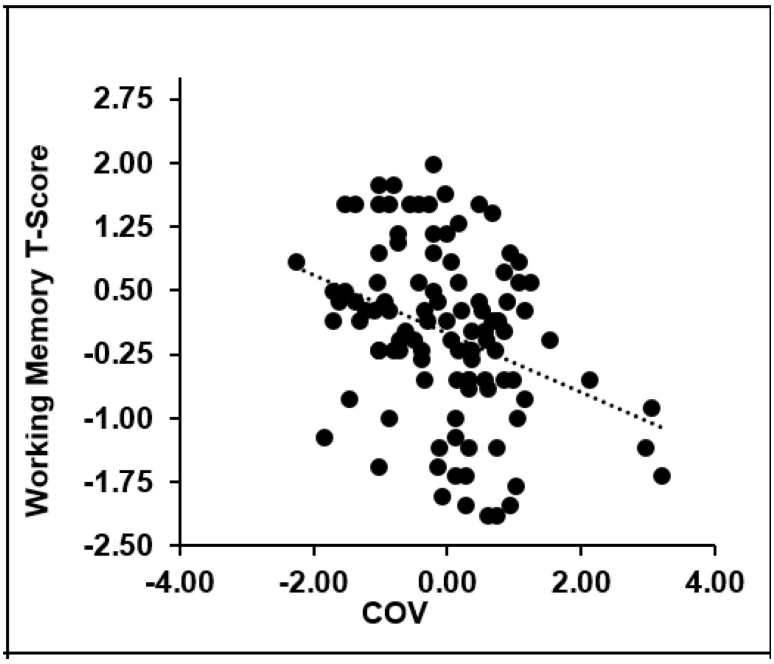
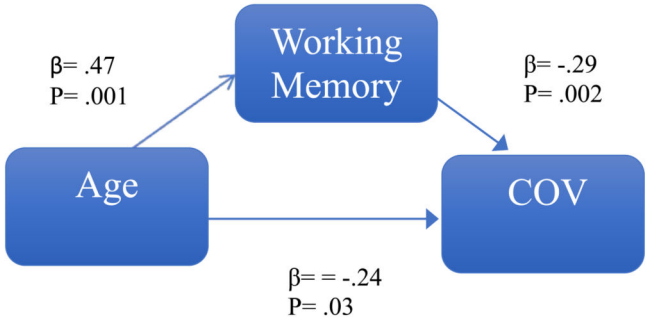


Figure 1.

The negative relationship between Coefficient of Variation (COV) and Working Memory demonstrate that stronger Working Memory capacity predicted lower variability during the Balloon Analogue Risk Task, an indication of stronger cognitive control under risky conditions. Graph reflects z-scores of each variable.

A. *Mediation analysis results demonstrate Working Memory mediates the relationship between age and Coefficient of Variation. All four criteria for a mediation analysis were met: 1) Age related to COV (p=.03, beta=-.24, 2) Age related to Working Memory (p=.001, beta= .47) 3) Working memory related to COV (p=.002, -.29, and 4) The relationship between Age and COV disappearing once Working Memory was added to the model (p=.38, beta= -.10).*

Model 1: Working Memory T-Score			
Predictor Variable	Outcome Variable	P-Value	Beta
Age	COV	.03	-.24
Age	Working Memory	.001	.47
Working Memory	COV	.002	-.29
Age + Working Memory*	COV	.38	-.10
Model 2: Global ECF			
Predictor Variable	Outcome Variable	P-Value	Beta
Age	COV	.03	-.24
Age	Global ECF	.00	.57
Global ECF	COV	.00	-.46
Age + Global ECF	COV	.002	-.43



B. *Mediation analysis results demonstrate Global ECF does not mediate the relationship between age and Coefficient of Variation. All four criteria for a mediation analysis were not met because Age and COV are still related when Global ECF is added into the model (p=.00, beta= -.45).*

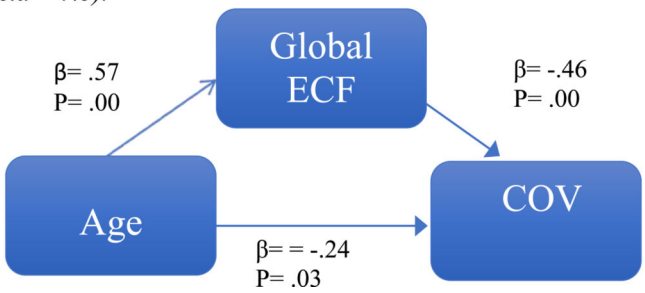


Figure 2.

*Mediation analyses results to examine the role of executive control functions in the relationship between age and Coefficient of Variation of adjusted inflations (COV) during the BA*RT

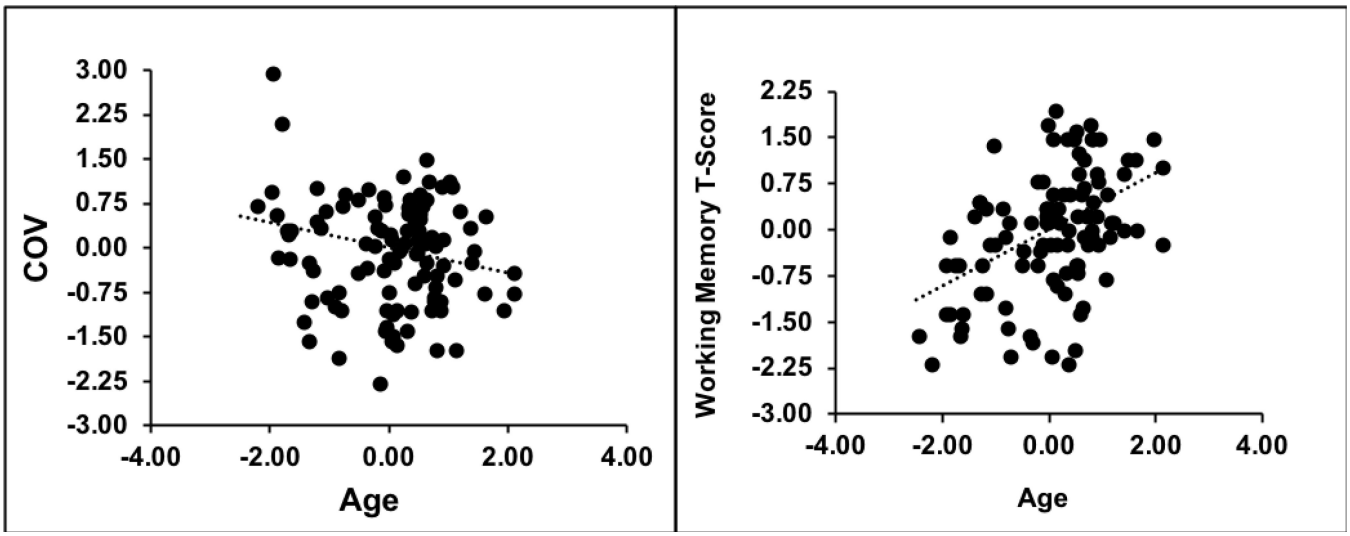


Figure 3.

Relationships supporting the results that executive control functions mediated the relationship between increasing age and decreasing intra-individual variability, which reflects greater cognitive control: Working memory increases with age (right); Coefficient of variation (COV) decreases with age (left). All graphs reflect z-scores of respective variables.

Table 1

Descriptive Statistics

	Mean (Standard Deviation)
Age	17.91 (3.63)
IQ	104.27 (11.13)
Executive Control Functions	
Processing Speed	44.30 (10.93)
Working Memory	44.75 (8.78)
Verbal Learning	41.48 (8.24)
Visual Learning	40.04 (8.53)
Reasoning and Problem Solving	43.10 (9.33)
Inhibitory Control (Stroop Interference)	54.22 (9.29)
Global Executive Control Function	46.21 (7.36)
BART Performance	
Mean Adjusted Pumps	13.65 (7.46)
Total Points Earned	2041.25 (1135.5)
Coefficient of Variation (COV) – All balloons	0.45 (.20)
COV- Low Risk Balloons	0.45 (.29)
COV- High Risk Balloons	0.46 (.21)
Total Explosions	9.36 (4.61)
Low-Risk Balloon Pump Ratio	1.13 (.62)
High-Risk Balloon Pump Ratio	1.17 (.66)

Note. BART = Balloon Analogue Risk Task; COV = Coefficient of Variation of adjusted inflations during the BART

Table 2.

Correlation matrix between cognitive domains and IQ

		IQ	Processing Speed	Working Memory	Verbal Learning	Visual Learning	Reasoning and Problem Solving	Inhibitory Control
IQ	Pearson Correlation	1	.346**	.423**	.368**	.249*	.052	.324**
	Sig.		.000	.000	.000	.010	.599	.002
Processing Speed	Pearson Correlation	.346**	1	.659**	.296**	.333**	.474**	.361**
	Sig.	.000		.000	.002	.001	.000	.000
Working Memory	Pearson Correlation	.423**	.659**	1	.300**	.487**	.404**	.299**
	Sig.	.000	.000		.002	.000	.000	.004
Verbal Learning	Pearson Correlation	.368**	.296**	.300**	1	.305**	.022	.356**
	Sig.	.000	.002	.002		.002	.826	.000
Visual Learning	Pearson Correlation	.249*	.333**	.487**	.305**	1	.436**	.108
	Sig.	.010	.001	.000	.002		.000	.304
Reasoning and Problem Solving	Pearson Correlation	.052	.474**	.404**	.022	.436**	1	.047
	Sig.	.599	.000	.000	.826	.000		.654
Inhibitory Control	Pearson Correlation	.324**	.361**	.299**	.356**	.108	.047	1
	Sig.	.002	.000	.004	.000	.304	.654	

Table 3.

Stepwise Regression: Examining Cognitive Functions that Predict Intra-Individual Response Variability: Results indicate that Working Memory most significantly contributes to COV. The variables excluded from the model are included below to display multicollinearity statistics among variables.

Model		Beta	Std. Error	Sig.	R	R Square	Adjusted R Square
1	(Constant)		.09	.53			
	Working Memory	−.27	.09	.009	.27	.07	.06

Excluded Variables		Sig.	Tolerance	VIF
1	Sex	.910	1.000	1.000
	Age	.265	.797	1.254
	Processing Speed	.270	.580	1.726
	Verbal Learning	.473	.850	1.176
	Visual Learning	.213	.723	1.383
	Reasoning and Problem Solving	.184	.834	1.198
	Inhibitory Control	.169	.911	1.098

DV: COV

Table 4.

Stepwise Regression: Examining Cognitive Functions that Predict Low-Risk Pump Ratio: Results indicate that Reasoning and Problem Solving most significantly contributes to Low-Risk Pump Ratio. The variables excluded from the model are included below to display multicollinearity statistics among variables.

Model		Beta	Std. Error	Sig.	R	R Square	Adjusted R Square
1	(Constant)		.093	.663			
	Reasoning and Problem Solving	−.26	.09	.013	.26	.067	.057

Excluded Variables		Sig.	Tolerance	VIF
1	Sex	.485	1.000	1.000
	Age	.851	.937	1.068
	Processing Speed	.898	.786	1.272
	Verbal Learning	.980	.832	1.202
	Visual Learning	.079	.984	1.016
	Working Memory	.578	.827	1.209
	Inhibitory Control	.877	.998	1.002

Dependent Variable: Low-Risk Pump Ratio

Table 5.

Stepwise Regression: Examining Cognitive Functions that Predict Mean Adjusted Inflations: Results indicate that Visual Learning and Gender most significantly contribute to Mean Adjusted Inflations. The variables excluded from the model are included below to display multicollinearity statistics for all included variables.

Model		R	R Square	Adjusted R Square	Beta	Std. Error	t	Sig.	Collinearity Statistics	
									Tolerance	VIF
1	Visual Learning	.300	.090	.080	.30	.10	3.00	.003	1.00	1.00
2	Visual Learning	.376	.142	.122	.31	.10	3.13	.002	.999	1.001
	Sex				.23	.10	2.32	.02	.999	1.001

Excluded Variables		Sig.	Tolerance	VIF
1	Sex	.027	1.000	1.000
	Age at Clinical	.589	.963	1.039
	Processing Speed	.830	.855	1.170
	Working Memory	.511	.722	1.385
	Verbal Learning	.190	.899	1.113
	Reasoning and Problem Solving	.583	.832	1.202
	Inhibitory Control	.299	.987	1.013
2	Age at Clinical	.987	.900	1.111
	Processing Speed	.798	.817	1.224
	Working Memory	.470	.722	1.386
	Verbal Learning	.536	.797	1.254
	Reasoning and Problem Solving	.585	.832	1.202
	Inhibitory Control	.353	.984	1.016

Dependent Variable: Mean Adjusted Inflations

Table 6

Results from simple linear regressions that distinguish contributions to COV, MAI and Total Points Earned. Results demonstrate 1) Global ECF predicts COV but is not predictive of MAI, 2) COV and Low-Risk COV predict Total Points Earned but are not related to Mean adjusted Inflations, and 3) the lack of relationship between COV and Mean Adjusted Inflations.

Predictor Variable	Outcome Variable	R	R^2	F	P-value	Beta
*COV Across All Balloons	Total Points Earned	.277	.077	2.79	.04	−.15
*COV Across Low-Risk Balloons	Total Points Earned	.290	.084	3.09	.02	−.17
COV Across High-Risk Balloons	Total Points Earned	.271	.074	2.67	.13	−.14
COV Across All Balloons	MAI	.304	.092	3.42	.228	−.12
COV Across Low-Risk Balloons	MAI	.314	.098	3.67	.14	−.15
COV Across High-Risk Balloons	MAI	.304	.093	3.43	.16	−.12
Global ECF	COV	.455	.207	.183	.001	−.44
Global ECF	MAI	.323	.104	.078	.10	.20

Note. ECF = Executive control function. COV = Coefficient of Variation of adjusted inflations during the BART. MAI = Mean Adjusted Inflations.

* = Significant at $p < .05$.