The Rational Adolescent: Strategic Information Processing during Decision Making Revealed by Eye Tracking

Youngbin Kwak[1], John W. Payne[5], Andrew L. Cohen[1] and Scott A. Huettel[2,3,4]

[1] Department of Psychological and Brain Sciences, University of Massachusetts, Amherst, MA, USA, 01003

[2]Center for Cognitive Neuroscience, Duke University, Durham, NC, USA, 27708

[3]Duke Center for Interdisciplinary Decision Sciences, Duke University, Durham, NC, USA, 27708

[4]Department of Psychology and Neuroscience, Duke University, Durham, NC, USA, 27708

[5]The Fuqua School of Business, Duke University, Durham, NC, USA, 27708

Please direct all correspondence to:

Scott A. Huettel, Duke University, Center for Cognitive Neuroscience, B203 LSRC Building, Research Dr., Box 90999, Durham, North Carolina, USA 27708-0999

Phone: 1-919-668-5286

Fax: 1-919-681-0815

Email: scott.huettel@duke.edu

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Abstract

Adolescence is often viewed as a time of irrational, risky decision-making – despite adolescents' competence in other cognitive domains. In this study, we examined the strategies used by adolescents (N=30) and young adults (N=47) to resolve complex, multi-outcome economic gambles. Compared to adults, adolescents were more likely to make conservative, loss-minimizing choices consistent with economic models. Eye-tracking data showed that prior to decisions, adolescents acquired more information in a more thorough manner; that is, they engaged in a more analytic processing strategy indicative of trade-offs between decision variables. In contrast, young adults' decisions were more consistent with heuristics that simplified the decision problem, at the expense of analytic precision. Collectively, these results demonstrate a counter-intuitive developmental transition in economic decision making: adolescents' decisions are more consistent with rational-choice models, while young adults more readily engage task-appropriate heuristics.

1. Introduction

Adolescence is commonly characterized as a period of unhealthy decision making; for example, adolescents are disproportionally likely to engage in risky behaviors such as reckless driving and abuse of addictive substances (Benthin, Slovic, & Severson, 1993; Parsons, Siegel, & Cousins, 1997; Viner et al., 2012). In recent years, much work has been done in cognitive and developmental neuroscience to explain the underlying mechanisms of adolescent decision making (for reviews see Blakemore & Robbins, 2012; Casey, Jones, & Somerville, 2011). The canonical model in the current scientific literature contends that adolescents make poor decisions because of a transient imbalance between a late-developing cognitive control system and an early-developing affect/reward system (Casey, Getz, & Galvan, 2008; Somerville, Jones, & Casey, 2010; Steinberg, 2005, 2010). Specifically, it is argued, development of the affect/reward system outpaces that of prefrontal cortex regions supporting cognitive control, driving adolescents to potentially engage in riskier, reward-seeking behavior.

Laboratory studies of decision making have typically tested predictions of the imbalance model through paradigms that directly contrast a safe option with a risky but higher-value option (i.e., something with higher expected value but also higher variance) (Burnett, Bault, Coricelli, & Blakemore, 2010; Harbaugh, Krause, & Vesterlund, 2002; Paulsen, Platt, Huettel, & Brannon, 2011). These paradigms can uncover tradeoffs between decision variables, such as whether decision-makers seek to minimize potential losses or maximize potential gains. However, such approaches can miss a critical aspect of decision making: the strategies by which an individual simplifies complex decision problems into something more manageable.

Strategic components of decision making have become a primary focus of decision science research in adult participants (Camerer, 2003; Gigerenzer & Goldstein, 1996; Payne, Bettman, & Johnson, 1988). Evidence shows that when faced with a complex decision space, people typically adopt one of many heuristic strategies to simplify the problem, excluding some information and prioritizing other information. The specific strategy to be adopted depends on the structure of the decision problem and the cognitive limitations of the individual (Simon, 1955). Importantly, heuristics support many forms of adaptive decision making – and decision performance can improve dramatically as people learn to apply the right heuristic in the right context (Johnson & Weber, 2009). Supporting this notion, older adults show greater reliance on heuristics during complex decision making to compensate for their reduced cognitive capacity (Peters, Finucane, MacGregor, & Slovic, 2000).

Much less is known about whether and how adolescents use heuristics in their economic decisions. One intriguing perspective from studies of reasoning and judgment argues that children and adolescents use heuristics less frequently than adults (Klaczynski, 2004; Reyna & Adam, 2003; Reyna & Farley, 2006), in part because of an inability to recognize contexts in which heuristics would apply. Maturation of cognitive abilities associated with the developing prefrontal cortex (Blakemore & Robbins, 2012; Casey, Jones, & Somerville, 2011) may be particularly critical for processes of pattern recognition and strategy selection (Venkatraman, Payne, Bettman, Luce, & Huettel, 2009). This leads to the strong but counterintuitive predictions that adolescents (compared to adults) exhibit *increased* consistency with rational-choice models of economic decisions and *decreased* use of simplifying heuristics.

In the current study, we used a complex economic gambling task that places rational-choice models and heuristics into opposition (Payne, 2005; Venkatraman, et al., 2009; Venkatraman, Payne, & Huettel, 2014) (Fig. 1), while using eye-tracking measures to uncover the pattern of information processing that leads to a given decision (Glockner & Herbold, 2011; Johnson, Schulte-Mecklenbeck, & Willemsen, 2008; Krajbich, Armel, & Rangel, 2010). Specifically, when faced with decisions between pairs of gambles that contain a distribution of monetary gains and losses, adult participants reliably adopt overall *probability maximizing* choices in which they ignore the magnitudes of each potential gain and loss, instead focusing on the overall probability of winning compared to losing (Payne, 2005). Such choices are inconsistent with the predictions of traditional models of economic choice, including both expected utility (EU) maximization (Bernoulli, 1954; von Neumann & Morgenstern, 1944) and cumulative prospect theory (CPT, Tversky & Kahneman, 1992).

[Insert Figure 1 about here]

Choices, by themselves, can only provide partial and indirect evidence for heuristic use. Much stronger evidence could come from examination of the processes leading to choice – specifically, patterns of information acquisition and how that information is integrated into a decision. Using eye-tracking data, we characterized how the specific information acquired for a given gamble predicts choices, and how information acquisition and integration changes across time and decision contexts (Payne, et al., 1988). By combining choice data with multiple measures of information acquisition behavior, as revealed through eye-tracking, our results provide strong support for a revised perspective on the development of economic decision making: from rational, analytic processing in adolescence to flexible, heuristic-based processing in young adulthood.

2. Materials and Methods

2.1. Participants

Data were collected from 47 young adults (16 males; age range = 18-30 years, *M* = 22 years, *SD* = 3 years) and 30 adolescents (12 males; age range = 10-16 years, *M* = 13 years, *SD* = 2 years) from the Durham, NC community. Young adults provided informed consent and parental consent and child assent was provided for the adolescents, under a protocol approved by the Duke University Institutional Review Board.

The experiment was embedded within a testing session in which adults and adolescents were paid at a base rate of $12 and $10, respectively, for their participation.

In addition, participants were paid for one trial, randomly selected from all trials, in which their selected gamble was played out. A linear function was used to convert the gamble amount (expressed in points) to the final monetary payment, as indicated in the task description below. To equate motivation across the two age groups, the conversion was undisclosed to the participants until after the experiment. After conversion, the bonus was between \$0 and \$5.

2.2. Multi-outcome risky gambling task.

On each trial, the participant was presented with a set of gambles displayed as a 3×3 grid of values (see Fig. 1a, b). The rows of the grid represented the three different gamble alternatives. Alternative names were provided as “J”, “K”, or “L” in the leftmost column, indicating the button to be pressed to select that alternative. The remaining columns represented the three gamble attributes (i.e., the three possible outcomes scored as points). The points ranged between -50 to 75. Each outcome was associated with an equal probability. Outcome probabilities (0.33) were provided in the top row of the matrix.

There were two primary types of trials: structured (40 trials; Fig. 1a) and random (40 trials; Fig. 1b). The gamble alternatives in the structured trials were generated from a base gamble with one large gain outcome (range: 35 ~ 50), one large loss outcome (range: -50 ~ -35), and a third intermediate outcome that was either 0 or a small loss. To create the three gamble alternatives, a positive value was added to the highest, intermediate, or lowest outcome of the base gamble to create the gain maximizing (Gmax), probability of winning maximizing (Pmax), and loss minimizing (Lmin) alternatives, respectively. Adding a positive value to the intermediate outcome makes two out of three outcomes to be positive for Pmax compared to only one out of three positive outcome for Gmax and Lmin options. Thus, the Pmax option maximizes the overall probability of winning (i.e., gaining points) within a particular trial. Note that Pmax does not necessarily maximize the reward amount (see Payne, 2005, for detailed descriptions). Also note that all three alternatives have the same expected value (EV). Traditional rational-choice economic models would predict that participants would either show indifference between the gambles, given the matched EV, or show a bias toward Lmin due to loss aversion (Kahneman & Tversky, 1984). A bias toward Pmax choices provides evidence for use of a probability-maximizing heuristic.

In contrast to the structured trials in which the gamble alternative were constructed from a base gamble using a predefined logic, the random trials were generated with outcome values randomly sampled from Gaussian normal distributions. The only constraint was to match the expected values across the three gamble alternatives within a trial. The mean and the standard deviation of the EVs were also set to be comparable between structured and random trials. Likewise, the minimum and maximum values of the gamble outcomes were approximately matched between the two trial types. Because the outcome values of the random trials are randomly sampled and not specifically constructed, no Gmax, Pmax, and Lmin gambles are defined. Including random trials allows us to reduce the predictability of the gambles throughout the task. If only structured trials were included, it may be easier for the participants to become aware of the fixed pattern of outcome values, which may lead them to a fixed visual information-processing pattern. By including random trials we made the gamble structures more ambiguous, which allows visual search patterns to be less fixed encouraging more valid eye movements. The random trials also serve as a different decision environment from the structured trials as the gambles show a distinctive composition of outcome values. We compared eye movement patterns across the two trial types in the two age groups to determine whether decision environment differentially influences information-processing behavior in adolescence.

For both structured and random trials, the gamble alternatives were randomly ordered and the maximum and minimum outcomes were presented in the left and right value columns, respectively. Participants selected a gamble by pressing "J", "K", or "L" on a keyboard. To ensure that participants were engaged in the task, five check trials were included in which one gamble stochastically dominated the other two. The dominating option had the largest outcome values in all three columns of the stimulus table shown in Figure 1. To familiarize the participant with the task environment, the first two trials (one structure and one random trial) were practice trials.

2.3. Procedure

All study participants completed the same 87 multi-outcome risky gambling trials: 40 structured trials, 40 random trials, 5 check trials, and 2 practice trials. To assess general cognitive competence, following the gambling task, adolescent participants completed the matrix reasoning subtest of the Wechsler Abbreviated Scale of Intelligence (WASI, Wechsler, 1999). Task stimuli were presented using Psychtoolbox in MATLAB. A Tobii T60 eye tracking system (Tobii Technology Inc., sampling rate: 60 Hz) collected fixation data. Trials were self-paced, with a 1.5s inter-trial interval.

2.4. Eye tracking measures

Eye tracking data were used to examine decision processes associated with the pre-decision stage (i.e., the time period after the information was presented, but before a decision was registered). For the majority of eye tracking data analyses, we only included the structured trials. This is because relating the eye movement patterns to information processing, particularly associated with the use of heuristics in this task, is only possible when the Pwin, Gmax and Lmin options are defined. Eye tracking data from the random trials were only included in the analysis to compare performance changes across decision environment in adolescents and adults.

We focused primarily on the following dependent variables derived within a trial. Three measures assessed the total amount of information searched: (a) the total number of fixations (fixations longer than 40 ms within a cell of the matrix were considered valid acquisitions), (b) total time spent on a trial (response time, RT), and (c) average time spent per fixation. Three additional measures assessed the selectivity of information search: the proportion of time spent fixating the (d) maximum, (e) intermediate, and (f) minimum outcomes of a gamble. We also assessed the breadth of information searched: (g) the number of unique outcomes fixated (out of 9 from the 3×3 grid of possible gamble outcomes). As a final measure we examined the sequence of processing by calculating (h) the Payne Index (PI; Payne, 1976), defined as the normalized difference between the number of alternative-based transitions (i.e., row-wise, RW, eye movements between the different outcomes of the same gamble) and attribute-based transitions (i.e., column-wise, CW, eye movements that compare different gambles on the same outcome). Any fixation transition from one cell to another within a row was considered a valid RW shift and any fixation transition from one cell to another within a column was considered a valid CW shift. Other fixation patterns were not used in the PI calculation. The following formula was used to calculate PI:

$$PI = \frac{\#\ of\ RW - \#\ of\ CW}{\#\ of\ RW + \#\ of\ CW}$$

(see Fig. 1a for an example of a RW and CW acquisition pattern). A higher PI would indicate decision strategy that is more likely to involve within-gamble processing (e.g., determining the EV for each gamble), which is more likely to be consistent with compensatory models like EU maximization. In summary, we calculated measures of the amount of processing, selectivity in processing, and sequence of processing. As shown in prior work (e.g. Payne, et al., 1988; Venkatraman, et al., 2014) this multiple measures approach can provide unique insights into decision strategy use.

In this study, we can combine data across these measures to evaluate age-related changes from a compensatory strategy to a heuristic strategy. For example, a compensatory strategy (compared to a heuristic strategy) would be associated with a larger number of fixations, longer fixation durations, less selective processing across different outcomes, a larger number of unique cells fixated, and a higher PI (more gamble-based processing) – along with increased consistency in behavior between the structured and unstructured gamble presentation formats. Use of a heuristic strategy, in contrast, would generate an opposite pattern of results.

3. Results

We excluded participants from further analysis if their eye-tracking data were missing more than 33% of recorded time points (e.g., because of system problems, head movements, or inability to determine gaze position) or if they selected the dominating alternative on fewer than 4 of the 5 check trials. Out of 47 adults, 12 were excluded based on missing eye-tracking data and 2 were excluded based on check trials. Out of 30 adolescents, 3 were excluded based on missing eye-tracking data and 7 were excluded based on check trials. The final sample for data analysis contained 33 young adults (70%) and 20 adolescents (66%). The check and practice trials were not included in the analysis.

Because Gmax, PMax, and Lmin options are only defined in the structured trials, the random trials were not included in analyses of behavior or eye tracking data related to those trials. IBM SPSS ver 21.0 (IBM Corp.) was used for all data analyses. When computing tests for repeated measures data, the Huynh–Feldt epsilon (Huynh & Feldt, 1970) was used to determine whether data met the assumption of sphericity (Σ>0.75). In cases where the sphericity assumption was not met, the *F* statistic was evaluated for significance using the Huynh–Feldt adjusted degrees of freedom. Levene's test (Levene, 1961) was used to determine whether the assumption of equal variance was met for *t* tests, and adjusted degrees of freedoms were used in case of unequal variance.

3.1. Preliminary analyses

To determine whether the initial comprehension of the task environment was equivalent for the two age groups, we compared the mean response times of the practice trials across adolescents and adults and found no significant difference ($t(51) = 0.79$, $p = 0.43$) suggesting comparable understanding of the task. To ensure that all the participants included in the analyses were similarly engaged in the task, we compared performance on the 5 check trials across age groups. No significant difference was found in the number of dominating options chosen ($t(51) = 0.31$, $p = 0.76$, average % correct for adolescents: 95 %, average % correct for adults: 96%), suggesting that both groups were equally engaged in the task. To determine whether the included and excluded participants show differences in choice pattern, we compared the proportion of Pmax alternatives selected across the included and excluded participants within each age group. No significant difference was found in either the adults ($t(33) = 0.02$, $p = 0.99$) or the adolescents ($t(25) = 0.2$, $p = 0.84$).

3.2 Choice data

Overall choice behavior is shown in Fig. 2a. Consistent with previous findings (Payne, 2005; Venkatraman, et al., 2009), there is a tendency towards the Pmax alternative in both age groups, which indicates that maximizing the overall probability of winning is the most preferred option for both age groups. The next preferred alternative for both groups was to minimize the worst loss (Lmin). This result is consistent with loss aversion as a general behavioral property (Kahneman & Tversky, 1984). Adolescents chose the Pmax alternative significantly less ($t(51) = 2.93$, $p = 0.005$, $d = 0.82$), and the Lmin alternative significantly more ($t(26.28) = -3.18$, $p = 0.004$, $d = -1.24$), than young adults. No significant differences were found in Gmax choices ($t(47.73) = 0.53$, $p > 0.5$), which were much less frequently chosen. These results indicate that, although maximizing the overall probability of winning was the most prevalent choice across age groups, adolescents adopted this particular heuristic less often and chose to minimize the worst loss more often than the adults.

[Insert Figure 2 about here]

3.3. Correlation between choice behavior and eye tracking measures

While choice data provides insight into strategy use, the correlations between the eye-tracking measures and choice behavior provide insight into the relationship between the decision-making process and choice. To start with an overall view of this relationship, Table 1 provides these correlations collapsed across both age groups. Significant correlations were found between a number of process measures and choice. The significant correlations between the proportions of time spent viewing the maximum, middle, and minimum outcome values and the probability of selecting the Gmax, Pmax, and Lmin alternatives, respectively, validate the approach of using eye tracking to measure decision processes. In particular, the data show that greater information processing in the unique cell for a particular alternative (e.g., the cell with the minimum loss, for the Lmin option) tends to precede choices of that alternative.

[Insert Table 1 about here]

The negative relationships between the Pmax choice and the process measures (e.g., total number of fixations) are consistent with the use of a heuristic strategy. That is, on trials where there were fewer eye movements and less information acquisition, participants were more likely to choose the Pmax alternative. Conversely, the positive relationships between the probability of selecting the Lmin alternative and the process measures are consistent with traditional compensatory models of choice; they imply that more thorough and comprehensive information processing resulted in the selection of the conservative, loss-minimizing alternative. The results of the correlation analyses give support for our interpretation of the age group comparison of the eye tracking data presented below.

3.4. Age group difference in process measures

The eye tracking data revealed significant age group differences in the amount, selectivity, and pattern of information processing. The amount of processing was examined by the total number of fixations and the amount of time spent viewing each information item. Adolescents made more fixations ($t(51) = 3.16$, $p = 0.003$, $d = 0.88$, Fig. 3a), spent more time viewing the gamble alternatives (RT, $t(26.42) = 4.12$, $p < 0.0001$, $d = 1.61$, Fig. 3b), and spent more time on each fixation (RT/number of fixations, $t(27.99) = 4.87$, $p < 0.0001$, $d = 1.84$, Fig. 3c) suggesting a greater amount of information processing in adolescents. Adolescents also viewed more unique outcomes before making a decision ($t(50.99) = 3.89$, $p < 0.0001$, $d = 1.09$, Fig. 3d).

Selectivity of information processing was examined by comparing the proportion of time spent looking at the maximum, middle and minimum outcomes (Fig. 2b). Across age groups, there was a significant difference in time spent viewing the middle ($t(50.99) = 3.99$, $p < 0.0001$, $d = 1.12$) and minimum ($t(51) = 2.15$, $p = 0.037$, $d = 0.6$) outcomes, but not the maximum outcome ($t(51) = -1.35$, $p > 0.1$). Adolescents viewed the middle outcome less and the minimum outcome more than young adults. The overall pattern from visual inspection of figure 2b showed that adolescents spent time more equivalently across the three possible outcomes. Put another way, adolescents spread their attention more evenly across the three outcomes than the young adults.

Participants typically look more often at the choice they ultimately select (e.g., Krajbich, et al., 2010) and at outcome values that are specific to a particular option (e.g., the minimum value for the Lmin option; Venkatraman, et al., 2014). Thus, we also determined the proportion of time spent looking at the three outcome categories (i.e., max, mid, min) given the choice made in that trial (i.e., Gmax, Pmax, Lmin; Supplementary Fig. 1). Both age groups showed a greater proportion of fixations on the outcome value that characterized the final choice made. That is for trials with Gmax choices, proportion of fixation time was the greatest on maximum outcome ($F(2,68) = 4.04$, $p = 0.022$, $\eta^2 = 0.11$) and for trials with Pmax choices, fixation proportion was the greatest on middle outcome ($F(2,104) = 36.98$, $p < 0.0001$, $\eta^2 = 0.43$). No such effect was found for Lmin choices however ($F(2,90) = 0.24$, $p > 0.5$). No significant age group by choice by outcome value interaction was found ($F(4,124) = 0.77$, $p = 0.55$), suggesting no group difference in this pattern.

The pattern of information processing considering the sequence that information items were processed was examined using Payne Index. Adolescents showed a greater tendency to scan different attributes within a gamble (i.e., the Payne Index was more positive, $t(50.99) = 2.64$, $p = 0.011$, $d = 0.74$, Fig. 3e) compared to adults, suggesting greater focus on EVs in adolescents .

[Insert Figure 3 about here]

3.5. Dynamics of information processing across and within trials

The change in process measures over the course of the experiment was also compared across age groups. The experiment trials were divided into quartiles and performance was compared within each quartile and across age groups. Only the process measures showing significant age-group-by-time interactions are reported. Significant interaction age group by quartile interaction was found in the number of unique outcomes fixated ($F(3,153) = 4.97$, $p = 0.003$, $\eta^2 = 0.03$) (Fig. 4). While the number of fixated items decreased as the experiment progressed in both groups, this decrease was much more pronounced for the adults. To test for a linear trend across time, a follow-up linear contrast was examined. Over time, there was a significant linear decrease in the number of unique outcomes fixated for adults ($F(1,32) = 39.34$, $p < 0.0001$, $\eta^2 = 0.16$), but not adolescents ($F(1.80,34.14) = 2.005$, $p > 0.1$). These results demonstrate that the adults adjusted their information processing strategy over time (i.e., considered less information), while the adolescents did not change their processing behavior over time.

[Insert Figure 4 about here]

The question of age-related processing differences can also be addressed by examining how processing changes as a function of time *within* a trial. Each trial was divided into four phases, based on the total number of fixations for each trial in each individual. For example, on a trial with 20 fixations, fixations 1-5, 6-10, 11-15, and 16-20 would be in phases 1, 2, 3, and 4, respectively. The proportion of fixations on each gamble alternative (Lmin, Pmax, and Gmax across the four phases for each age group is shown in Fig. 5. A heuristic strategy, such as searching for and selecting the Pmax option, would appear as an increasing preference for viewing a particular option, e.g., Pmax. That is, processing would be more likely to stop once the preferred alternative type was located. A compensatory decision-maker would be much more likely to process information from all alternatives before deciding. The data show a three-way age group × alternative × quartile interaction (F(6,306) = 2.182, p = 0.045, η^2 = 0.04).

To interpret this interaction, first consider the adults (Fig. 5a). As the trials progressed, there was increased attention to the Pmax alternative and decreased attention to both the Gmax and Lmin alternatives. Although adolescents were still more likely to view the Pmax alternative, the proportion of fixations on the three alternatives remained much more egalitarian throughout the trial (Fig. 5b). The proportion of fixations on the Lmin and Gmax alternatives didn't show a significant decline until the last phase. These results imply that, while adults adopt a heuristic strategy from early on in a trial, adolescents' behavior is much more consistent with a compensatory strategy.

[Insert Figure 5 about here]

We also looked at how – given the choice made in the trial – fixation proportion on each gamble option changed across time (Supplementary Fig. 2). Towards the end of a trial, both groups made preferential fixations to the option matching their final choice. However adults showed selective preference to the ‘to-be-chosen’ option from even earlier on compared to adolescents regardless of final choice. This was particularly significant for trials with Pmax choices as shown by significant age group x alternative x quartile interaction ($F(6,306) = 3.50$, $p = 0.002$, $\eta^2 = 0.06$). This suggests that the more exploratory fixation pattern of adolescents within a trial (Fig. 5) is characteristic of their information processing regardless of final choice.

3.6. Change in decision processes across different task contexts

The structured trials, on which the Gmax, Pmax, and Lmin alternatives were available, and the random trials, on which these alternatives were not available, can be viewed as different decision environments. To determine how the decision process changes across different decision environments, eye tracking measures were compared across both age group and trial type. Only significant interactions are reported. Significant age group by trial type (structured vs. random) interactions were found in time per fixation ($F(1,51) = 4.84$, $p = 0.032$, $\eta^2 = 0.003$) and the number of unique outcomes fixated ($F(1,51) = 4.99$, $p = 0.03$, $\eta^2 = 0.003$). A post-hoc paired t-test showed that, whereas more unique outcomes were fixated on random trials than on structured trials ($t(32) = 3.11$, $p = 0.004$, $d = 1.10$) in adults, no significant difference across decision environment was found in adolescents. No significant results were found in the post-hoc t-test with time per fixation. These results suggest that while the structure of the decision problem influenced adults' eye tracking behavior, adolescents show little to no difference between the structured and unstructured environments. That is, whereas the adolescents seemed to treat both decisions contexts equivalently, adults recognized trials on which a Pmax option was available (the structured trials) and adjusted their strategy accordingly (i.e., they used fewer fixations).

3.7. Heuristic use and cognitive capacity

A correlation between the proportion of Pmax choice and the measure of cognitive ability would indicate that the use of heuristics is associated with cognitive capacity. WASI scores were collected from 29 out of 30 adolescents. There was a significant positive relationship between Pmax choice and WASI score ($r(27) = 0.38$, $p = 0.045$, $d = 0.82$), demonstrating that adolescents with higher cognitive capacity were more likely to select the Pmax option, which in turn suggests greater heuristic use. This relationship was marginally significant when age was included as a covariate ($r(26) = 0.37$, $p = 0.054$, $d = 0.80$). Thus, adolescents with a more adult-like cognitive capacity demonstrated performance consistent with a greater reliance on heuristics.

4. Discussion

Collectively, our results indicate that adolescent decision making – as expressed in choices between complex risky gambles – is relatively more consistent with economic models than the decision making of young adults. Converging evidence from choice behavior and eye tracking supported this claim. First, relative to adults, adolescents showed less tendency to make choices consistent with the probability maximizing heuristic and more tendency to make choices consistent with compensatory economic models (Payne, 2005). Second, adolescents demonstrated more thorough pre-decisional information processing as shown by greater number of fixations on most of the information items and longer time spent on each item. Third, adolescents' pattern of fixations was more evenly distributed across different gamble options, compared to adults. Fourth, unlike adults, adolescents did not show a systematic reduction in the number of fixations per trial (i.e., amount of information acquired) as the experiment progressed.

Taken together, these results suggest that adolescents' choices and eye-tracking behavior were more closely matched to the predictions of canonical models of choice (e.g., CPT, Tversky & Kahneman, 1992) than were the behavior of young adults. Adolescents' pre-decisional processing was more likely than adults to involve a compensatory strategy of integrating information across outcomes and probabilities, and adolescents' choice behavior implied greater loss aversion (Kahneman & Tversky, 1984). This counterintuitive result – that of the "rational adolescent" – could be successfully distinguished from an age difference in choice *preferences* because of our use of complex mixed gambles and the measurement of eye-tracking behavior.

Previous research on the development of decision strategies show that while children and adolescents can adopt heuristics used by adults (see for review, Jacobs & Klaczynski, 2002), there is an age-related progression in heuristic use. Several studies show that there is a greater tendency of relying on compensatory strategies in younger children, with increasing use of heuristics towards adulthood (Davidson, 1991; GreganPaxton & John, 1997; Mata, von Helversen, & Rieskamp, 2011). Our results parallel these previous reports showing reduced reliance on Pmax heuristics supported by both choice and process data in adolescents compared to young adults. Thus, these results are inconsistent with traditional theories of cognitive development that predict that decision making changes from being intuitive (heuristic) to computational (compensatory) in the processing of decision information (Bjorklund, 1989; Siegler, 1991). The age-related changes in our data are, however, in line with psychological models like fuzzy-trace theory (Reyna & Adam, 2003; Reyna & Farley, 2006), which posits that mature decision making stems from simple gist-based mental representations of choices ("fuzzy traces"), not from detailed quantitative representations ("verbatim traces"). Interestingly, our results show that relying more on compensatory and quantitative strategies led the adolescents to more loss-minimizing choices. This result implies that, when faced with a complex decision environment, adolescent choices are more likely to be based on classic economic reasoning relative to adults. This conclusion is contrary to what most previous studies have found with simple two-option gambles. Our findings suggest that, depending on the characteristics of decision problems, adolescents can make more rational decisions than adults.

Our results also indicate that the commonly accepted irrationality in adolescence during economic decisions reflects the immature use of heuristics. We found a correlation between an adolescent's pattern of information gathering and cognitive capacity – particularly the non-verbal abstract reasoning as indexed by WASI matrix reasoning – such that adolescents with higher abstract reasoning were more adult-like in their use of heuristics. This result parallels previous studies showing associations between heuristics use and cognitive capacity during tasks of analytic thinking and judgment in developing children (Fischhoff, 2008; Morsanyi & Handley, 2008). With developing cognitive skills, children and adolescents learn to adopt proper heuristics in decisions. Although this may not necessarily indicate greater economic rationality, it may imply a more adaptive behavior as fast and frugal strategic processing of information is essential when facing complex decision environments (Gigerenzer & Goldstein, 1996). It is of note, however, that the task we used as a measure of cognitive competence was the matrix reasoning from WASI, a task that in itself requires use of heuristics and pattern recognition. Thus the correlation between WASI score and Pmax choice may have been artificially inflated by similarities in task demand.

One alternative interpretation for some of our results could be that adolescents are not adopting rational, compensatory strategies, but are instead less certain about their decisions. Our task is a highly unfamiliar one, which may decrease confidence and increase uncertainty. This uncertainty may lead adolescents to behave more cautiously – to revisit already processed information and to thoroughly search all information – akin to the observed eye-tracking pattern. Similarly adolescents may need to spend more time and effort to acquire the same amount and quality of information. The seemingly inefficient processing pattern can also be interpreted as immature cognitive capacity to understand the task structure.

We note that our conclusions draw on a broad set of measures that converge on a single conclusion. For example, adolescents showed both a greater number of fixations and longer time spent per fixation – as well as a higher Payne index, which describes the degree to which expected value is being considered. Importantly, these measures are independent of each other (i.e., a trial could have only a few fixations but still have a high Payne Index). Together, these measures lead to the inference that the longer time and effort adolescents are putting into information processing reflects their greater sensitivity to outcome values and probabilities. In fact, recent evidence shows that adolescents are more sensitive to EVs than adults as shown by both behavior and also in neural responses (Barkley-Levenson, & Galvan, 2014).

In summary, the current study shows that when faced with a complex gamble involving multiple decision variables, adolescents adopt an approach that is more consistent with a rational, compensatory strategy than adults. Choice was also related to cognitive capacity, which is still undergoing development in adolescents, such that more adult-like cognitive capacity was associated with more adult-like decision behavior. Based on our data we propose that, for economic decision making, the transition from adolescence to adulthood does not reflect increased rationality but instead an increased ability to apply simplifying heuristics to complex decision scenarios. This conclusion points to a potential reconciliation between two highly visible (and contradictory) theoretical perspectives: imbalance models that contend that differential maturation of reward and control circuitry leads to irrational, impulsive behavior during adolescence (Steinberg, 2004, 2007), and gist-based models that contend that risky choices by adolescents reflect a systematic (but rational) overvaluing of potential rewards compared to potential harms (Reyna & Adam, 2003; Reyna & Farley, 2006). Our results point to novel directions for designing intervention approaches for risky behavior in adolescence. Successful interventions might not necessarily simplify a decision problem to a simple rule for behavior, but instead appeal to the adolescent mind's rationality by unveiling the full set of positive and negative outcomes inherent in complex, real-life decisions.

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Table 1. Relationship between choice and eye tracking (ET) process measures.

ET Measures	Choice					
	Lmin		Pmax		Gmax	
	r	*p*	*r*	*p*	*r*	*p*
% of time on middle outcome	-0.54	<0.0001	0.65	<0.0001	-0.27	0.049
% of time on maximum outcome	-0.2	>0.1	-0.14	>0.1	0.55	<0.0001
% of time on minimum outcome	0.71	< 0.0001	-0.53	<0.0001	-0.2	>0.1
Total number of fixations	0.3	0.029	-0.31	0.024	0.06	>0.1
Response time	0.37	0.007	-0.37	0.006	0.07	>0.1
Time spent per fixation	0.33	0.016	-0.34	0.013	0.07	>0.1
# of unique outcomes fixated	0.35	0.01	-0.2	0.152	-0.21	>0.1

Figure Captions

Figure 1. Examples of structured (a) and random (b) trials from the gambling task. The rows are different gamble alternatives. The columns are potential gamble outcomes. In structure trials, a gamble alternative maximizes possible gain (Gmax, response key “J”), maximizes the probability of positive (i.e. winning) outcomes (Pmax, “K”), or minimizes possible loss (Lmin, “L”). The top row displays the (rounded) probability of each outcome. In random trials, the three gamble alternative types are not defined. The red arrow in (a) depicts row-wise data acquisition (RW) and the blue arrow depicts the column-wise data acquisition (CW) used for calculating Payne Index.

Figure 2. Differences in choice and selectivity of information processing between the age groups: (a) Proportion of choices that maximize gain (Gmax), maximize the probability of winning (Pmax), and minimize loss (Lmin) for adolescents and adults. (b) Proportion of time spent fixating on the maximum (Max), middle (Mid), and minimum (Min) outcomes for adolescents and young adults. Error bars indicate standard error.

Figure 3. Differences in eye tracking process measures between adolescents and adults: (a) number of fixations, (b) response time, (c) time spent per fixation, (d) number of unique outcomes fixated, and (e) the Payne index (PI). Error bars indicate standard error.

Figure 4. Change in information processing over time across the experiment. Error bars indicate standard error.

Figure 5. Dynamics of information processing within a trial for adults (a) and adolescents (b). Error bars indicate standard error.

Table(s)

Table 1. Relationship between choice and eye tracking (ET) process measures.

ET Measures	Choice					
	Lmin		Pmax		Gmax	
	r	*p*	*r*	*p*	*r*	*p*
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# of unique outcomes fixated	0.35	0.01	-0.2	0.152	-0.21	>0.1

Figure(s)

a.

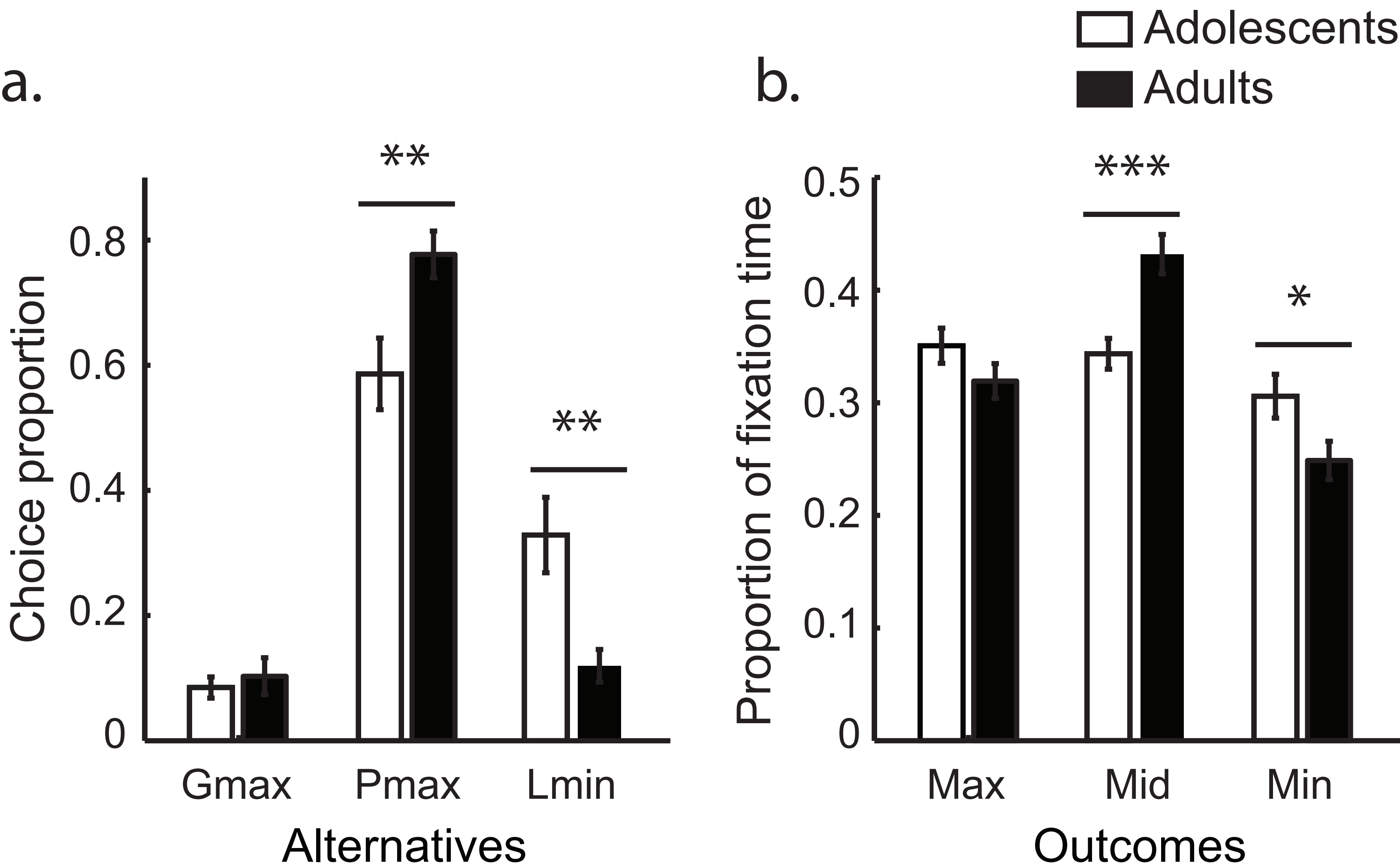
	0.33	0.33	0.33
J	15	-1	-7
K	10	4	-7
L	10	-1	-2

b.

	0.33	0.33	0.33
J	6	4	-4
K	12	1	-7
L	21	2	-17

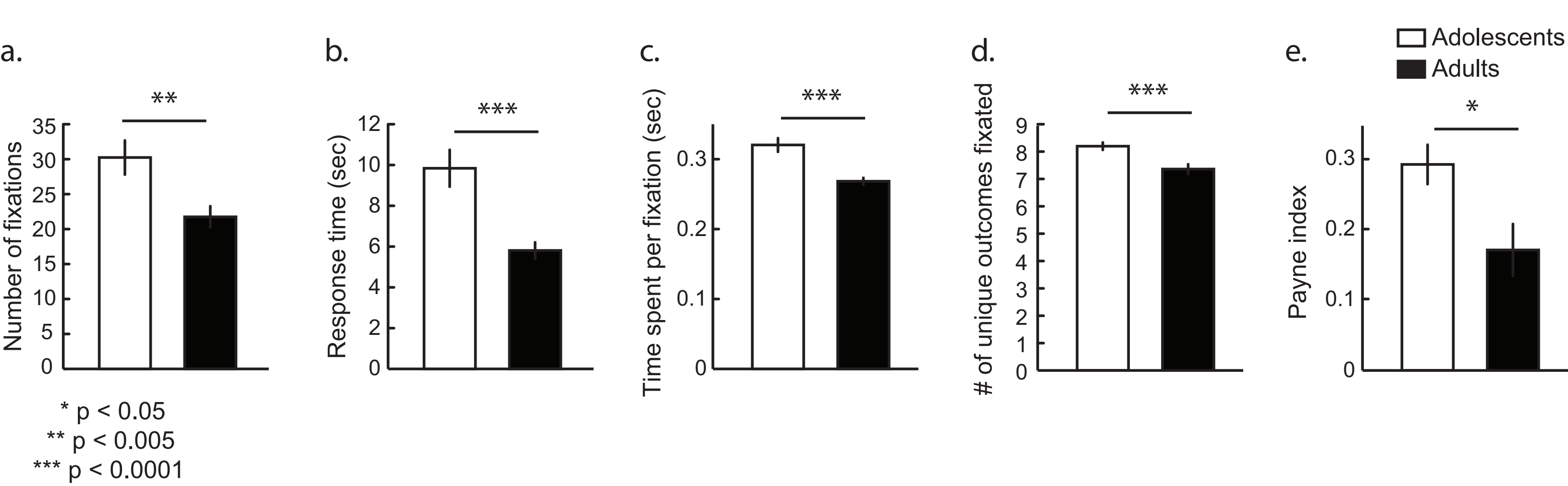
*Payne Index (PI) = (# of RW - # of CW) / (# of RW + # of CW)

Figure(s)



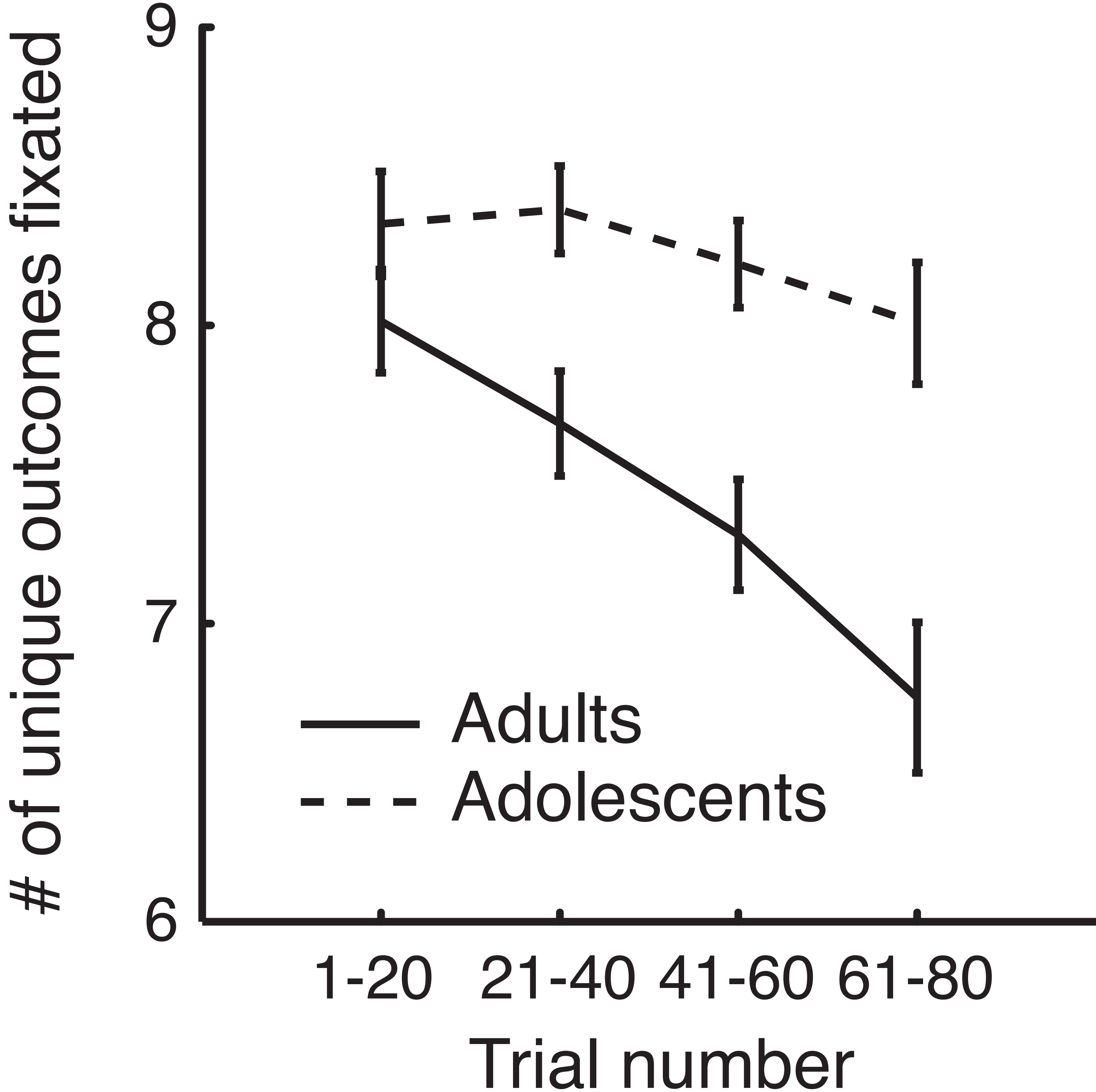
* p < 0.05
** p < 0.01
*** p < 0.0001

Figure(s)



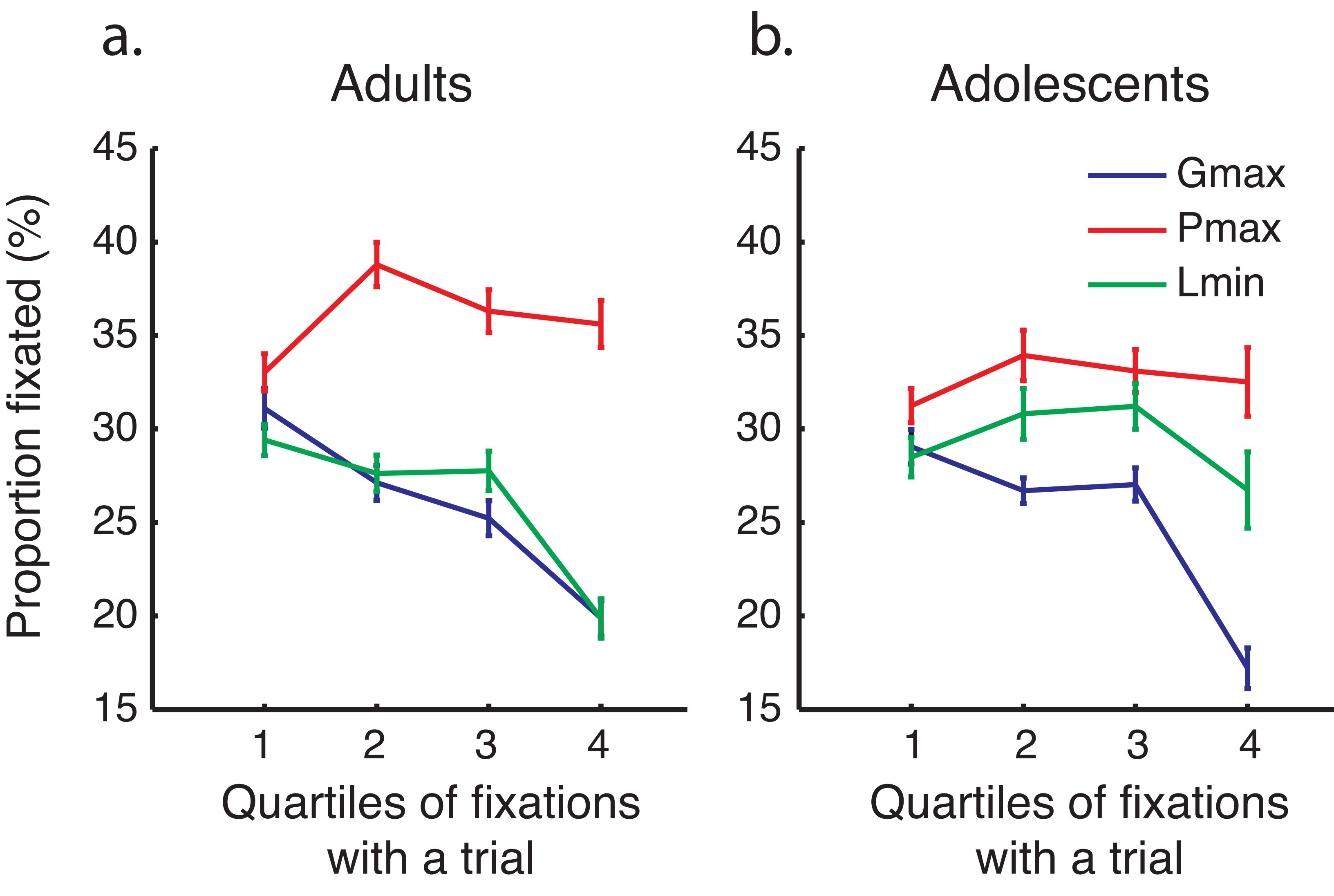
a.
b.
c.
d.
e.
Adolescents
Adults
**
***
***
***
*
Number of fixations
0
5
10
15
20
25
30
35
Response time (sec)
0
2
4
6
8
10
12
Time spent per fixation (sec)
0
0.1
0.2
0.3
# of unique outcomes fixated
0
1
2
3
4
5
6
7
8
9
Payne index
0
0.1
0.2
0.3
* p < 0.05
** p < 0.005
*** p < 0.0001

Figure(s)



9
8
7
6
# of unique outcomes fixated
1-20
21-40
41-60
61-80
Trial number
Adults
Adolescents

Figure(s)



a.
Adults
b.
Adolescents
Proportion fixated (%)
45
40
35
30
25
20
15
1
2
3
4
Quartiles of fixations
with a trial
Gmax
Pmax
Lmin

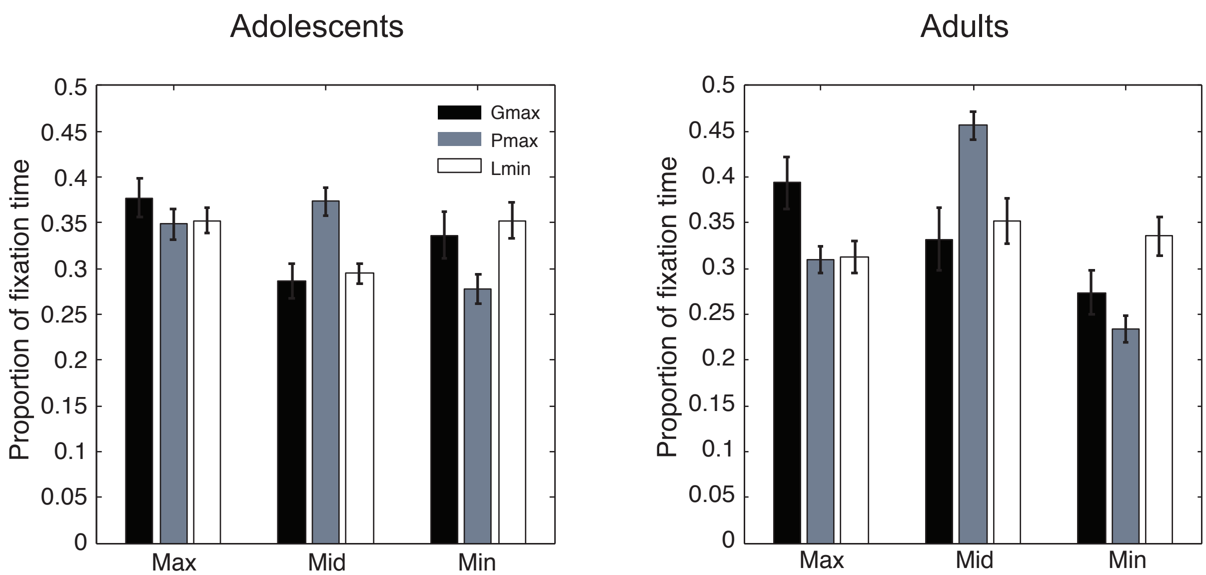
Supplementary Matierals

Supplementary Figure Legend

Supplementary Figure 1. Proportion of time spent fixating on the maximum (Max), middle (Mid), and minimum (Min) outcomes given final choice made in a trial in adolescents and adults. Each bar color represents the choice made in a trial. Error bars indicate standard error.

Supplementary Figure 2. Dynamics of information processing within a trial for adolescents (left column) and adults (right column) give final choice made in a trial (as shown below each plot). Each line color represents the fixated option. Error bars indicate standard error.

Supplementary Figure 1.



Supplementary Figure 2.