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In search of the functional base of risk-taking: inexperience and safety

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ABSTRACT

This study is aimed at challenging the notion that risk-taking is based merely on some mechanistic foundation like control deficiencies or process imbalances. We hypothesize that risk-taking has an adaptive function and is an optimal strategy for an agent who (1) has scarce knowledge about the current environment or (2) is in a position in which a potential loss is not threatening. We argue that the two above are related to age which, in turn, may explain association between age and risk-taking commonly reported in the developmental literature. We investigate the possible influence of the age-related variables on the risk propensity in two ways: by inducing rich or scarce knowledge and safe or unsafe position in the experimental environment with task parameters and, simultaneously by examining actual differences between adolescents and adults. The results of two experiments that used a novel compound risk task provide support for the first hypothesis concerning knowledge about the environment. On the other hand, the results falsify the second "safe position" hypothesis. Also, the second experiment reveals that one's status relative to resources can influence risk-taking, but it does so in a way that is different from our initial assumption.

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Introduction

It may seem obvious that taking a selfie with an injured wild bear is a foolish idea (Sharman & Dubey, 2018), but once in a while people engage in actions which have a low chance of a successful outcome and may lead to tragic results. Some risk researchers seem to make the assumption that a risky option, although it might occasionally lead to highly profitable success, is the worse option in the long run (e.g., Institute of Medicine and National Research Council, 2011, compare also definition of risk in Moore & Gullone, 1996: "behavior that involves potential negative consequences [or loss] but balanced in some way by perceived positive consequences [gain]," p. 347).

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These kind of assumptions are mostly made within public health research where risk-taking is identified with undertaking some potentially harmful behavior (e.g., reckless driving, unprotected sex, taking drugs, Gerrard, Gibbons, Benthin, & Hessling, 1996; Reyna & Rivers, 2008; Willoughby, Good, Adachi, Hamza, & Tavernier, 2013; Icenogle et al., 2019). The assumption that taking risk is rather a bad decision is not unanimously accepted in the field of psychology. Many theories originating from the normative approach do not acknowledge this assumption and recognize risk-taking as a strategy which can be equally beneficial as the safe one (most notably von Neumann & Morgenstern, 1953; see also Fischhoff & Kadvany, 2011 for review). Currently, many researchers focusing on neural and hormonal base of risky-behavior and its social correlates share this view and recognize both positive aspects and the functional base of the risk (e.g., Crone, van Duijvenvoorde, & Peper, 2016; Do, Moreira, & Telzer, 2017; Duell & Steinberg, 2019, 2020; Humphreys, Lee, & Tottenham, 2013).

We would like to avoid taking any assumptions about the profitability of the risk. Both the assumption about risk being disadvantageous, proposed in some works coming from the early versions of Dual Systems Model (Steinberg, 2008; see also alternative formulations in Getz & Galvan, 2008 and Luna & Wright, 2016) which assume that adolescents' tendency to take risks arises from (besides heightened reward sensitivity) immature impulse control, as well as the ones stating that risk is constitutionally beneficial if one takes a closer look at it (Fuzzy Trace Theory, Chick & Reyna, 2012; see also Romer, Reyna, & Satterthwaite, 2017).

There are two main reasons for abandoning these assumptions. First, if a person makes a risky (or safe) decision due to their lack of control or an imbalance of opposing processes of any kind, it may constitute an extremely interesting case for clinical or developmental psychology, or in fact any field of psychology which is interested in the mechanism of the decision. But this case provides little, if any, interesting information for psychologists interested in the function of decision making (and risk-taking in particular), since when someone's decision is deemed wrong, it is indeed difficult to determine its underlying function.

Second, the fact that risky behavior is observed along with safe choices and that the same people manifest both of these behaviors in different situations and different people behave differently in similar situations suggests that both risk and safe acts can be optimal, depending on the external (environmental) or internal (personal) state of the agent. Therefore we would like to determine which states of an environment or an agent lead to risky behaviors.

So, what are the features of a situation that make people take more risk? We decided to focus on one group that allegedly risks more—the adolescents. This choice does not imply that we center our attention on the developmental aspect of risk-taking or that we chose to limit our conclusion only to this group. Instead we would like to exploit the fact that, when it comes to risk-taking, adolescents can serve as an epitome of a group that has specific risk-taking patterns and at the same time faces environmental problem quite different to these faced by the adults. So comparing adolescents to adults may highlight the environmental function of risk-taking.

Until recently it was widely recognized that adolescence is a period of increased risk-taking (Boyer, 2006; Burnett, Bault, Coricelli, & Blakemore, 2010; Eisner, 2002). However, recent studies suggest that the difference between adolescents and adults may boil down to more subtle characteristics. It has been shown that adolescents actually take more risks than adults but only in so-called "hot" tasks (i.e., exciting tasks that provide immediate feedback; Figner, Mackinlay, Wilkening, & Weber, 2009; Defoe, Dubas, Figner, & van Aken, 2015), or that they risk more in the domain of gains but not in the domain of losses (Reyna & Ellis, 1994; Weller, Levin, & Denburg, 2011). Some researchers suggest that it is not a higher propensity for risk that is manifested in adolescents' behavior but higher tolerance of ambiguity (Tymula et al., 2012; van den Bos & Hertwig, 2017).

Acknowledging that there is a difference between adolescents and adults in terms of risk-taking, but that the precise nature of this difference is yet to be determined, we may approach explaining this in two manners. First, one can focus on the mechanism which underlies the dissimilarity. Some of the theories (e.g., the Dual Systems Model or the Fuzzy Trace Theory) aim to describe the process that underlies the change in risk-taking that occurs with age. However, although this type of explanation may bring interesting insight into the working of the mind, it only moves the answer further away. For example, if the reason that adolescents have a specific pattern of risk-taking is their weaker cognitive control (Shulman et al., 2016), why do they have weaker control? If we answer this question again using the mechanistic explanation, e.g., by pointing out that development of the lateral prefrontal cortex is not completely finished until early adulthood (Foulkes & Blakemore, 2018), the answer again moves away: why does it take so much time for the prefrontal lobes to fully develop, whereas other parts of the brain mature several years earlier?

Second, one can point out some inherent features of being an adolescent or an adult that make it more (or less) profitable to take risks. If we found any such features, then any of the mechanisms proposed above would be just a means for applying the strategy that is optimal for each of the age groups.

Now, what constitutes the general difference between the situation of adolescent and adults? Two main features attract attention when it comes to possible risk-taking: lack of experience and the more fluid state of adolescents' lives. Surely, one can point out several features which differentiate adolescents and adults, and many of them can be argued to be more or equally important as others, but we claim that these two characteristics are (a) fundamental and primal (in the sense that other differences stem from them) and (b) they seem to describe adolescents in the environment of evolutionary adaptedness as well as in most contemporary cultures (Arnett, 2000; Pasupathi, Staudinger, & Baltes, 2001). The above claim certainly deserves a proper substantiation but such an argument exceeds the subject of this paper so we are ready to take this statement as an assumption.

Adolescents' lack of knowledge about the environment hardly requires argumentation. For all mammals and many other animals, the main function of this stage in life is to gather know-how about living in a given habitat (Bjorklund & Pellecrlnl, 2002; Walsh & Beaver, 2008). As for the inherently indefinite character of the adolescents' status, this may seem less obvious, mainly because status is largely hereditary (Braun & Stuhler, 2018; Clark, 2014). However, even when enjoying a safety net, leaving the nest is always a big step and, despite the fact that there are great differences between adolescents, they all face huge uncertainty about the future in comparison to adults who are on a steady life path most of the time (the differences in stability concern, among others, personality, Roberts & DelVecchio, 2000; vocational interests, Low, Yoon, Roberts, & Rounds, 2005; emotional stability, Larson, Moneta, Richards, & Wilson, 2002; or economic status, Brown & Males, 2011).

One can argue that there is no direct link between risk-taking and either of the characteristics of adolescence proposed above; however we would like to point out that there are two other features directly connected with these characteristics whose association with risk-taking we will account for subsequently: exploration and evaluation of rewards.

First, exploration is defined as searching for new and potentially highly profitable actions at the expense of choosing actions which are already known to be profitable. Staying with well-known, relatively good actions and refraining from looking for potentially more profitable ones is exploitation. Clearly, in the exploration—exploitation tradeoff both these strategies in their pure versions are suboptimal. There is no point in a ceaseless search for a better option when the agent does not profit from the result of the search. On the other hand, the first option tried rarely turns out to be the best one, therefore it is wiser to explore a little before one sticks with the chosen action. There is extensive literature regarding the exploration—exploitation problem (e.g., Laureiro-Martínez et al., 2013; Mehlhorn et al., 2015; Steyvers, Lee, & Wagenmakers, 2009), but the general solution to the optimization problem is not known.

There is an evident link between a lack of knowledge about the environment and the tendency to explore. The more extensive the knowledge, the lower the probability of finding another option which is more profitable than the already known ones. So, we expect that agents with less knowledge about the environment (e.g., adolescents) would explore more than agents with more knowledge (e.g., adults).

When it comes to status (understood as one's position with respect to resources), the model of the relationship between the objective value of a reward and the subjective value assigned to the reward by some agent can shed some light on the problem. The first mathematical model of this relationship proposed by Bernoulli (1738/1954) was a logarithmic function. This model implies that the relationship between the objective value of the reward and the subjective value has negative acceleration, which means that the subjective value rises more slowly than the objective value. Bernoulli's formulation entails a constant risk aversion which does not allow for expressing individual differences observed in this domain (Slovic, 1964). An alternative simple model of said relationship is the power utility function: $v(x) = x^{\alpha}$ where $\alpha \in (0, 1]$, x is an objective value, and v is an utility function. The closer α is to 1, the less bent the function line (the less negative the acceleration). When α is significantly smaller than 1, the function line tends to be more horizontal when the rewards increase. In other words, although an individual's valuation of resources increases as the amount of the resource grows, the rate of the increase can change with the amount of the resource. The α represents to what extent the individual's valuation keeps up with the grow of the resource. The lower the α (down to nearly zero) the faster the individual's valuation of the resource fall behind its actual, objective value as it grows.

The power utility function is also an important part of Kahneman and Tversky's (Cumulative) Prospect Theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) which is an influential psychological theory of risk and predicts several effects including subjective probability estimation, transformation of cumulative probabilities, etc. The α parameter of the power utility function shapes Kahneman & Tversky's value function in both gains and losses or only in gains depending on formulation, determining the extent of risk aversion (and possibly risk seeking).

It is argued that the utility function describes a cognitive module that carries out an adaptive task (McDermott, Fowler, & Smirnov, 2008). If someone has almost nothing, any loss can have tragic consequences because it can push the agent over the edge of the minimum necessary for survival. Also, any gain is an asset and the value of the gain is not really important. On the other hand, if one has a lot, the only gains that count are big ones and losses are not that critical. So, it can be expected that individuals who are better-off (e.g., adults) should have larger αs than those in a less safe position (e.g., adolescents).

Finally, let us get to the most central concept of this study: risk. What is risk when stripped of the evaluative connection to specific real-life cases which are usually associated with it in public-health research? This definition of risk, which we take to be uncontroversial (e.g., see Crone et al., 2016; Figner & Weber, 2011; Rosenbaum & Hartley, 2019), was introduced by Rothschild and Stiglitz (1970) and states that it is a measure of variance in the possible outcomes of an action. Assuming that all available actions have equal expected rewards, the riskier the action, the less predictable its eventual outcome. So the risk is a property of an environment and should be distinguished from the risk-taking which is a preference/choice of risky situations.

One can immediately see that risk is an inevitable consequence of exploration. Choosing an option, which can possibly be lucrative but can also appear to be profitless over known, relatively good ones perfectly fits the definition of risk. As regards α (the parameter of the utility function), the matter is a little more complex.

Let us compare two agents, one with large (close to 1) and one with small (close to 0) α, both of which face safe (one sure outcome) and risky (two possible outcomes, low and high) options. The safe reward (s) is bigger than the worse risky reward (r) but smaller than the better risky reward (R). So, $s = r + c$ and $R = r + c + d$ for some positive c and d. Both agents' expected safe reward is s^α and the risky reward value is $\frac{1}{2}(r^\alpha + R^\alpha)$ (making an unnecessary but simplifying assumption about probability $P(r) = P(R) = \frac{1}{2}$). Therefore, the advantage of the risky option over the safe one is $\frac{1}{2}(r^\alpha + R^\alpha) - s^\alpha$. After choosing a scale ($r = 0$ and $R = 1$), we can rewrite this as $\frac{1^\alpha}{2} - c^\alpha$. This is an increasing function of α, meaning that the higher the α, the higher the relative value of the risky option. Figure 1 presents a graphical explanation of the demonstration.

So now let us formulate the hypotheses. Since adolescents have less knowledge about the environment, they are supposedly more exploratory and therefore take more risk than adults. On the other hand, since adolescents have a more fluid status, they should have lower α and therefore take less risks than adults.

Unquestionably, a correlational study would not allow us to draw conclusions about the causal relationship so, we decided to experimentally control both knowledge about some virtual environment and the reward status of the participants We also decided to test both described age groups, therefore we expected that these effects would manifest themselves in the

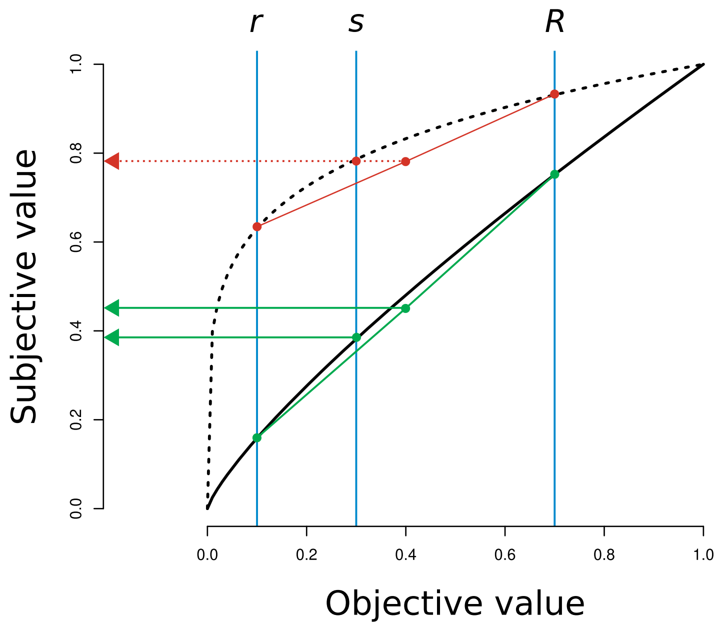

Figure 1. Subjective utility functions for two agents, $\alpha = .2$ (dotted curve) and $\alpha = .8$ (solid curve). Two actions are available: safe action (guaranteed reward of $s = 0.3$) and risky action (50% chance of small reward $r = 0.1$ and 50% chance of high reward $R = 0.7$). For the low α agent, the expected subjective values of both actions are virtually equal (compare the dotted arrows). For the high α agent, the risky option is more profitable (compare the solid arrows).

form of an interaction between age group and manipulation level. For example, in order to manifest low α, this interaction could require both being an adolescent and facing an unstable situation. To test the hypotheses, we constructed a composite risk task which allows us to manipulate and observe all the relevant variables within one procedure.

Experiment 1

Participants

One hundred and ninety participants (101 women and 89 men) took part in the experiment. The sample consisted of two equipotent subsamples: adolescents (age 13–17, mean 15.27, $SD = 0.84$, $N = 95$, 38 women) and adults (age 19–31, mean 24.21, $SD = 1.92$, $N = 95$, 63 women). The adolescents were recruited in schools during parental meetings. The adults were recruited via a public internet advertising platform. In recruitment of adults we controlled the percentage of high school students/graduates (HSG) in order to mach the country HSG percentage ($\approx$45%) and get the adults sample as similar as possible to the sample of adolescents. Both groups were compensated for participation according to their performance in one of the tasks (details below). All participants provided written informed consent. In the case of underage participants, parental consent was also obtained. The results of eight participants (four adolescents) were excluded due to their poor performance in the *n*-back Task ($d' < 1$).

Procedure

The experiment was conducted in a dedicated classroom in the participants' school (adolescents) and in the university laboratory (adults). The participants took part in the procedure one by one and completed two tasks: the Composite Risk Task (CRT, designed by the authors) and the *n*-back Task (Kirchner, 1958). The sole purpose of the *n*-back Task was to control for working memory capacity since we acknowledged that it may play significant role in a task as complex as the CRT. Each participant completed two of four versions of the CRT. There were two levels of familiarity with the virtual environment, labeled "known" and "unknown," and two levels of reward type that were "independent" and "dependent" of performance in the CRT.

In the "known" condition, the participants were provided with some information about the environment in which they would make decisions; in the "unknown" condition, all the information had to be acquired by interactions with the environment. The familiarity manipulation was administered within subjects: every participant completed the CRT task twice, once in each condition in random order. In both of the performances of the CRT, the environment consisted of a different set of objects (see below) in order to minimize possible transfer of knowledge from the environment of the first performance to the second one.

The reward type manipulation ("independent" or "dependent") was administered between subjects, therefore every participant had one type of reward that was randomly assigned for both performances of the CRT. Participants who had an "independent" reward were given a fixed amount of money (about $10 in shopping vouchers) unless they fell in the bottom or top 5% of performances, in which case they obtained an alternative reward (about $5 and $15 respectively). The margin of uncertainty was left in order to motivate the participants to apply an efficient strategy but it was set so thin to make the majority of them certain that despite of possible minor variations in their performance the value of the reward is determined. Participants who had a "dependent" reward were given shopping vouchers whose value was proportional to their performance in the CRT (between about $5 and $15).

The complete procedure was as follows. First, the participants performed CRT training; next they performed the first version of the CRT ("known" or "unknown"). After a short break, they were administered the other version of the CRT; finally they performed the training and the main part of the *n*-back Task.

The composite risk task

The Composite Risk Task was aimed at independently assessing three distinct measures with one task: risk propensity, exploration—exploitation tendency, and α. The rationale for this goal was twofold: First, since the different tasks measuring any of these variables correlate very poorly (Frey, Pedroni, Mata, Rieskamp, & Hertwig, 2017; Mata, Frey, Richter, Schupp, & Hertwig, 2018; Pedroni et al., 2017), we decided to put all three of them in one task to enhance the chance of detection of any possible connections. Second, since we were going to examine the relations between these three variables and to keep the results free from any artifactual relationship, we designed the task in such a way that the measurement of the variables was as independent as possible. There is a tradeoff between independence of these measures and their power to capture any potential relationship between each other. As far as we can see, there is no way to achieve both of these goals simultaneously. If the variables are measured with one integrated task, some level of entanglement between them is inevitable. So we decided to allow for very moderate level of entanglement between the measures (e.g., the decision of terminating the decision phase to some degree depends on the participant's α).

The CRT is a computer task. The goal in this task was to gather as many points as possible by choosing objects (e.g., animals). Each object was linked to some covert distribution of points. In each trial (of 60) two types of decisions were to be made. First (in the object-choosing phase of the trial), choosing the object among all possible ones (see Figure 2). Second (in the decision phase), repeatedly choosing between: (a) the object picked in the first phase, (b) other random object, and (c) terminating the trial (see Figure 3). The decision (a or b) would lead either to earning some points or to loosing all points gathered in the current trial.

In the object-choosing phase, the participant had to choose one of the objects in the set (Three sets of objects were used: animals and foods for the main part of the task, and furniture for training). The chosen object would appear in the decision phase. The object differed in profitability. The profitability of an object can be defined as an expected number of points that the participant receives after choosing this object. A specific mean and variance were assigned to each object, and the payoff values for this object were drawn from normal distribution with this mean and variance. Means for all the objects had an exponential distribution, therefore there was a small chance of finding a very profitable object.

Figure 2. The object-choosing phase of the CRT. Forty objects were available to choose from. In parenthesis next to each object is the number of payoff samples known for this object (the samples would later be visible in the decision phase), so the participant could decide to choose either a known or a new object. Above the button panel are two progress bars: the upper one displays the task progress by showing the number of turns elapsed; the lower one displays the relative number of points gathered by the participant. The number of points is shown in reference to the average performance in the task at the current stage (Experiment 1) or minimal performance which would provide the bigger reward (Experiment 2). The second bar is displayed to help participants assess their performance and optimize their strategy.

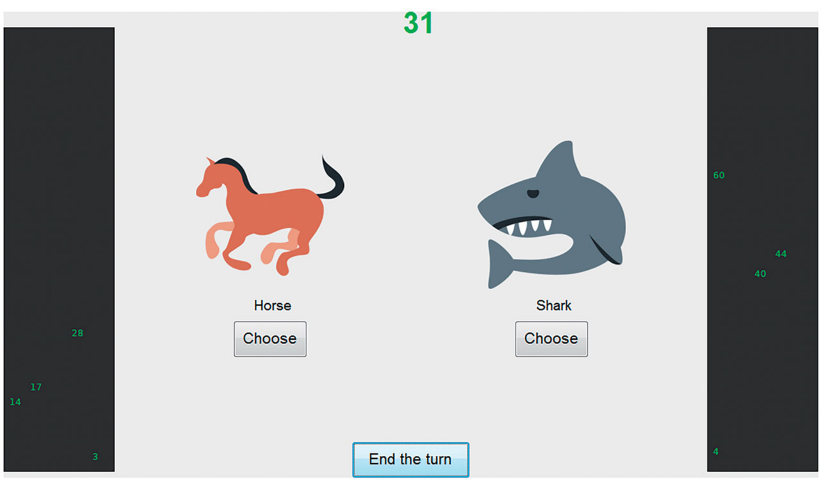

Figure 3. The decision phase of the CRT. The chosen object is on the left side of the screen. On the right side is a randomly chosen object of similar profitability. Next to each of the objects is a plot showing the values of points that have been won so far by choosing this object. There is a "choose" button under each object which, when pressed, has two possible outcomes: winning a random number of points from the object's distribution (75% chance); losing all the points gained in this phase (31 points in this case, as displayed above) and termination of the phase (25% chance). Below is the "end turn" button. Pressing this button results in going to the next object-choosing phase and keeping all the points gathered in this decision phase.

The profitability could be unknown to the participant (if the condition of the task was "unknown" and they had not chosen the object previously) or known (if the condition of the task was "known" or they had chosen the object previously). Thus, the participant could choose objects whose profitability was known to them (exploitation) or choose unknown/less known objects in the hope they would be more profitable (exploration). In the choosing phase, participants could track their performance against the average performance of previous participants (the lower progress bar on Figure 2) so they could adjust their strategy according to the current performance.

In the decision phase, the selected object was paired with another random object of comparable profitability and this pair was displayed on the screen. The participant had to choose one of the two objects. Each choice could result in winning a random number of points which would be added to the overall sum of the points at the end of the decision phase. The profitability of the objects were not explicitly given to participants, but they could estimate it on the basis of previous payoffs. All the preceding payoffs were plotted next to the picture of the object in the decision phase. In the "unknown" condition, participants only had information from decisions they had actually made; in the "known" condition, every object was given five samples of payoffs drawn from their specific distribution at the beginning of the task.

In the decision phase participants could choose any of the two objects any number of times. Each successful choice would lead to the number of points gathered in the phase being incremented (and one sample added to the set of known samples of the chosen object). However, every decision had 25% risk of failing, in which case all points gained in the current phase were lost and the phase ended. Additionally, at any moment a participant could pass and end the current phase, thus keeping all the points gathered in it.

Three measures were taken in the CRT: (a) risk-taking, (b) exploration—exploitation tendency, and (c) utility function parameter α. The measure of risk-taking was the expected number of times the participant chose one of the objects in the decision phase before they ended the phase. This measure is very similar to those used in the widely applied family of risk tasks (including Devil's Task, Slovic, 1966; Balloon Analogue Risk Task, Lejuez et al., 2002; Columbia Card Task, Figner et al., 2009). Unfortunately, this task family has a great limitation when it comes to estimating the number of steps that a participant is willing to take toward the risk of failing (e.g., the number of cards revealed in the hot version of the Columbia Card Task). If a participant skips further steps and the trial is ended successfully, the number of steps is indeed equal to the one intended by them and is an adequate measure of the participant's risk propensity. However, when the trial fails and is ended abruptly, we do not know how many further steps the participant had intended to take.

There are three simple ways of dealing with this problem: One is to ignore the aforementioned bias altogether (e.g., Buelow, 2015); second is to remove the possibility of failing (almost) entirely while trying to keep the participant convinced that the danger is real (e.g., Figner et al., 2009); the third is to work around the problem by taking into consideration only the successful (not failed) trials. As the flaws of these three methods are evident, we applied a completely different approach. We estimated the intended number of steps in each turn, taking into account actions observed in both failed and successful trials. We assumed a hidden variable (intended number of steps) which can either manifest directly in successful trials or is forcibly decreased in unsuccessful trials. A detailed description of the graphical model used to estimate the risk propensity as well as the evidence that the three described methods are flawed is provided in Supplementary Material A.

There is a significant difference between the family of Risk-taking tasks mentioned above and CRT. In the former the reward from each step is constant so their sum at stake is a linear function of the number of steps already taken. Whereas in the CTR the reward value is randomly drawn from certain distribution which is different for each object. So, unlike in the other tasks, in the CRT a participants may find themselves in very different situations regarding both the number of points gathered up to a certain trial and the possible reward they can get if they choose another draw. But it should be noted that the participants are not arbitrarily nor randomly placed in the choice situation. The number of the points accumulated depends on the expected reward value of the chosen object and the latter in turn depends on the participants knowledge of the profitability of the available objects. So, although the expected value of the reward and the number of accumulated points are in fact probabilistic, they are greatly determined by participant's knowledge on the environment, making the risk decision highly comparable between trials and participants.

The tendency to explore was assessed on the basis of the decisions made in the object-choosing phase. The measure of exploration was simply either the number of objects the participant had already chosen up to a given trial (in analyses of unaggregated data), or the number of objects the participant chose during the whole task (in analyses of aggregated data). In all statistical analyses that included exploration as a variable, we controlled for the mean observed payoff from the most profitable object found because we assumed that if someone had already found a very profitable object, they would show less exploratory behavior. There is an alternative measure of exploration which takes into account the knowledge about chosen option.

It is based on the number of probes from the distribution available for the chosen object. Since such a measure is highly correlated with the one based on number of chosen objects ($r = .81$) we decided to use the simpler of these two and the one that is not confounded with the measure of the risk propensity.

Utility function parameter α was estimated for each participant with graphical modeling using Markov chain Monte Carlo sampling on the basis of decisions made in the decision phase. Given the history of an object's payoffs, α, and the power utility model of the subjective value, we were able to estimate the relative probability of choice for each of the two available objects. Thus, knowing the actual decision, we used Bayesian parameter estimation to determine the probability distribution of α for each participant (for details, see Supplementary Material A).

Additionally, the performance was measured in order to vary the compensation given to participants since the relationship between performance level in the CRT and the value of the financial reward was one of the key manipulations in the experiment. The measure of performance was the number of points gathered in both completions of the CRT.

The n-back task

The *n*-back Task required participants to follow a series of consonants displayed one by one on a screen. Every time the currently presented letter was the same as the one presented n letters earlier (for some given n), the participant had to react by pressing the space key. Beside the signals (letters consistent with letters n steps earlier) and noise (letters different from any recent letter), lures were also presented. These were letters that were the same as the ones presented $n+1$ or $n-1$ (for $n>1$) earlier. Participants were instructed not to react to the lures.

The task consisted of two blocks ($n=1$ and $n=2$) lasting 100 and 200 seconds (one stimulus per second) and was preceded by short training ($n=1$) with feedback after each reaction or omission. In the main part of the task the feedback was not given.

The measure in this task was d' (a measure that takes into account the proportions of both hits and false alarms based on signal detection theory). Due to the ceiling effect in the $n=1$ block, we included only results from the $n=2$ block.

Results

The unaggregated results were analyzed whenever possible. In other cases, the results were averaged over participants. Repeated measures ANOVA,

Table 1. Correlation matrix and descriptive statistics of variables used in experiment 1.

	Risk (u)	Risk (k)	Explor. (u)	Explor. (k)	α	d'
Reward type [dependent]	.18*	0	−.12	−.13	.05	.11
Age group [adults]	−.27***	−.29***	−.03	.03	−.04	.15*
Gender [male]	.12	.18*	−.2**	−.15*	.05	−.01
Risk-taking (unknown)		.73***	0	−.08	−.12	−.05
Risk-taking (known)			−.04	−.04	-.2**	−.08
Exploration (unknown)				.64***	−.34***	−.23**
Exploration (known)					−.45***	−.17*
α						.15*
Mean	3.52	3.42	26.15	26.09	.58	2.35
SD	0.78	0.58	9	8.43	.23	0.61
Range	[2.2, 6.2]	[2.24, 5.66]	[5, 40]	[3, 40]	[.2, .97]	[1.03, 4.16]

Note: For dichotomous variables the alternative (non zero) value is given in square brackets. In cases of two continuous variables the Pearson correlation coefficient was computed, in cases of one continuous and one dichotomous variable the point-biserial correlation was computed $^*p < .05$, $^{**}p < .01$, $^{***}p < .001$

linear models or mixed linear models (using the “lme4” package, Bates, Mächler, Bolker, & Walker, 2015 for the R software environment, R Core Team, 2021, when the random effects occurred) were fitted to the data. Whenever the variables estimated in Bayesian models were used as predictors the models were fit using maximal likelihood function. The mediation was analyzed with the “mediation” package for R (Tingley, Yamamoto, Hirose, Keele, & Imai, 2014). Table 1 presents correlation matrix and descriptive statistics of variables used in the analysis.

Exploration, familiarity, and age group

A linear mixed model with random intercepts was fitted to the unaggregated data to predict the exploration. The predictors were familiarity, reward-type, age group (adolescents or adults), and all possible interactions between these variables as fixed effects. Moreover, gender, order of the performance of the CRT (first or second), *n*-back’s d', maximum mean payoff, and the logarithm of the trial were controlled for. The logarithm of the trial was used instead of the plain value due to the nonlinear shape of the relation between the trial and the exploration: if the logarithm was dropped, the distribution of the residuals demonstrated the unsatisfactory fit of the model. The model showed adequate fit (no correlation between the fitted values and the residuals, $r_\varepsilon = .0045,\ p = .52$; the variance of residuals was homogeneous, as demonstrated by Levene’s test, $F[1, 20106] = 0.013,\ p = .91$). The normality of the residuals did not need to be tested due to the large sample (see Lumley, Diehr, Emerson, & Chen, 2002 for argument).

There was a main effect of familiarity ($M_k = 19.4$, $M_u = 19.06$, $F[1, 19990.2] = 29.4,\ p < .001$) as well as the interaction between familiarity and age group ($F[1, 19994.6] = 104.2,\ p < .001$, see Figure 4), but no main effect of age group ($F[1, 176.7] = 0.7,\ p = .39$). There was also a significant effect of reward type ($M_i = 19.77, M_d = 18.7$) and interaction between reward and both familiarity and age group (the full ANOVA table is

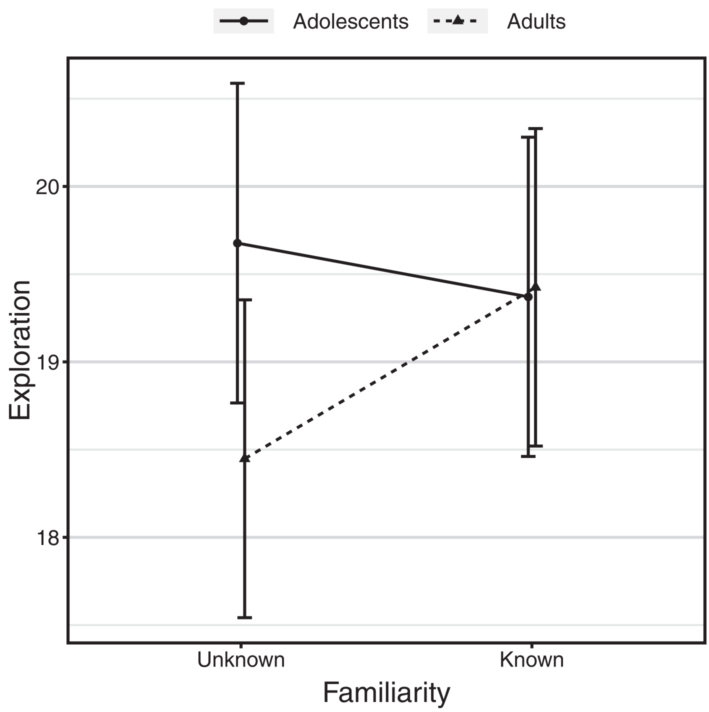

Figure 4. Effect on exploration of the interaction between the familiarity of the CRT environment and age group. The vertical bars indicate 95% confidence intervals.

presented in Supplementary Material B, Table B3, marginal $R^2 = .59$, conditional $R^2 = .79$).

Parameter α, reward type, and age group

In order to predict α, whose single value was calculated from all trials, a linear model was fitted to data aggregated over participants. The predictors were reward type, age group (adolescents or adults) and interaction between these variables. Moreover gender, *n*-back's d', group-relative age (difference between the age and the group mean), and preference for the option selected in the object-choosing phase (see Supplementary Material A for details) were controlled for. The model showed adequate fit (no correlation between the fitted values and the residuals, $r_\varepsilon = 0$, $p > .999$; the variance of residuals was homogeneous, $F[1, 180] = 0.75$, $p = .39$). the normality of the residuals, as demonstrated by the Shapiro-Wilk test ($W = .95, p < .001$), was not great but visual examination of the residuals' distribution revealed that the deviations from normality were negligible.

There was no main effect of reward type ($F[1, 174] = 0.4$, $p = .53$) nor age group ($F[1, 174] = 0.24$, $p = .62$), but we observed interaction between

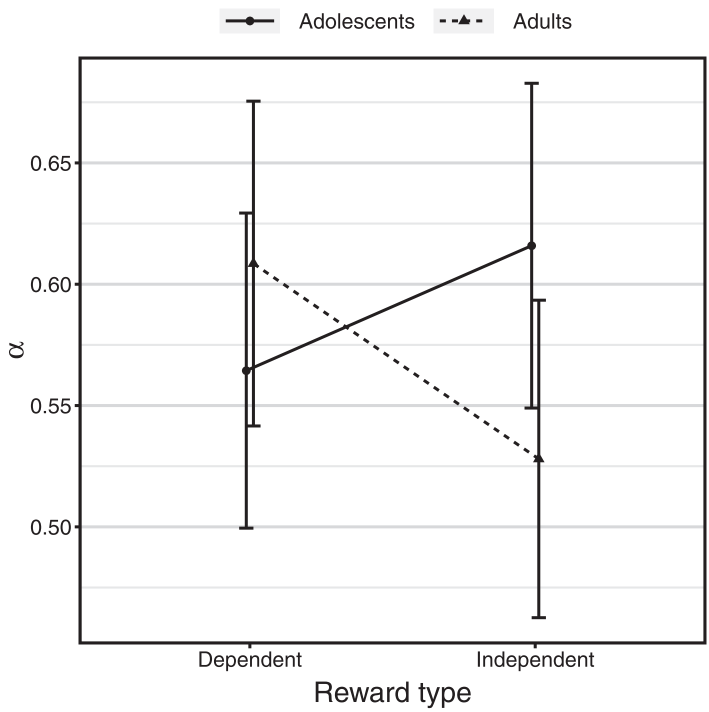

Figure 5. Effect of interaction between reward type and age group on α. The vertical bars indicate 95% confidence intervals.

these variables ($F[1, 174] = 3.96$, $p = .048$, see Figure 5, $R^2 = .045$). The full ANOVA table is presented in Supplementary Material B (Table B4).

Risk-taking, familiarity, and reward type

Subsequently, we examined the influence of the two experimental manipulations on risk propensity. A multi-way repeated measures ANOVA was used instead of a mixed linear model because the model failed to achieve a satisfactory fit. Otherwise, the residuals of the ANOVA were normally distributed ($W = 1$, $p = .71$) and the variance of the dependent variable was homogeneous across groups ($F[31, 332] = 1.35$, $p = .11$). The predictors were familiarity, reward type, and age group. We also controlled for gender, preference for the selected option, *n*-back's d', order of the performance of the CRT, and group-relative age. We found that adolescents risked more than adults ($M_a = 3.65$, $M_A = 3.29$, $F[1, 173] = 16.55$, $p < .001$), and in the unknown condition participants risked more than in the known one ($M_u = 3.52$, $M_k = 3.42$, $F[1, 177] = 7.46$, $p = .007$). There was also an interaction between familiarity of the environment and reward type ($F[1.177] = 15.01$, $p < .001$, $\eta^2 = .16$; see Figure B8 in Supplementary Material B). The full ANOVA table is presented in Supplementary Material B (Table B5). The reward type had no influence on risk-taking ($p = .13$).

Risk-taking, exploration and α

Again, the ANOVA was used, but exploration and α were used as the predictors instead of the familiarity and reward type. The residuals were normally distributed ($W=1$, $p = .97$) and the variance of the dependent variable was homogeneous across groups ($F[7,356] = 1.19$, $p = .31$). As above the ANOVA revealed that adolescents risked more than adults ($F[1,169] = 18.21$, $p < .001$),. Also the participants who explored more risked more ($F[1,177] = 4.11$, $p = .044$), and participants with higher alpha also risked more ($F[1,169] = 4.13$, $p = .017$). There was an interaction between exploration and α ($F[1,177] = 5.78$, $p = .017$, $\eta^2 = .2$, see Supplemental material B for Figure B9 and the full ANOVA table B6).

Mediation between experimental manipulation and risk-taking

We tested if the exploration mediated the influence of the familiarity of the environment and age group on risk taking. The model-based inference was used. The controlled variables were reward type, gender, order of the CRT performance, n-back's d', maximum mean payoff, and the logarithm of the trial. The tendency to explore mediated 1.9% (95%CI= $[1\%, 3\%]$, $p < .001$) of the influence of the familiarity on the risk-taking. The mediation of α between the type of reward and the risk-taking was not tested because we did not observe a statistically significant relation between the two latter variables.

Experiment 2

Rationale

The results of the first experiment do not allow the conclusion that risk-taking is determined by the volatility of one's status. Participants who were quite sure about their reward (compensation independent of performance) did not differ in risk propensity from those who had to strive to get higher compensation. However, aside from the effect in question being too weak to detect or nonexistent, there is another possible explanation of the lack for the observed effect: The dependent reward condition required better performance in order to achieve high or at least not low reward, but neither of the pure strategies (risky and safe) had higher expected efficiency than the other one. Therefore, it can be expected that some of the participants tried to cope with the unstable condition by behaving more safely (avoiding the risk of losing the small but sure earned amount of points), while others behaved more riskily (risking to earn more points); so there was no observable tendency.

In the second experiment, we decided to change the assumption concerning the difference between adolescents and adults in terms of status.

It might be more justified in the light of our knowledge about the environment of evolutionary adaptedness to assume not only that adolescents' success more strongly depends on their action, but also that on the verge of growing up they are below the threshold of survival and unless they fight their way above the threshold they will not be able to compete with their peers. So, in the second experiment we introduced two reward conditions: "easy" and "difficult." In the former condition (reflecting adults' position) the average performance was sufficient to gain a bigger reward. In the "difficult" condition (reflecting adolescents' position), one needed to strive to achieve the higher reward.

In the second experiment, in order to simplify the experimental plan and focus on the manipulation, we included only the adults.

Participants

Seventy-seven adult participants (32 men and 45 women) took part in the experiment. The mean age was 23.91 (20–28, $SD = 1.76$). Similarly as in experiment 1, participants were recruited via a public internet advertising platform and they provided written informed consent. Participants were compensated according to their performance in one of the tasks (details below).

Procedure

The experiment was conducted in the university laboratory. The participants took part in the procedure one by one and performed the same tasks as in experiment 1: the CRT and the *n*-back Task. The CRT was conducted in two versions: "easy" and "difficult." The manipulation was administered between subjects. The participants were paid (in shopping vouchers) one of two rewards: low (about \$7) or high (about \$19), based on their performance in the CRT. In the "easy" condition, the threshold for the high reward was set low, so 80% of the participants were able to get it, while in the "difficult" condition, where the threshold was set higher, only 20% got it.

During all the CRT, participants could track their performance against the exemplary performance, which would, if matched, lead to the high reward (lower progress bar in Figure 2). The same three variables were measured in the CRT as in experiment 1: risk propensity, exploration—exploitation tendency, and α. After the CRT, participants performed the *n*-back task with training similarly as in experiment 1. Results from four participants were excluded due to their poor performance in the *n*-back Task ($d' < 1$).

Results

Table 2 presents correlation matrix and descriptive statistics of variables used in the analysis.

A linear model was fitted to data aggregated over participants to predict the logarithm of α. The predictor was the reward condition. Gender, n-back's d', age, and preference for the selected option were controlled for. The dependent variable was logarithmized due to its skewness ($\gamma_1 = 0.62$ before and $\gamma_1 = 0.16$ after logarithmization). Before the logarithmization the residuals were not normally distributed, while after the intervention the model had a good fit (the fitted values were not correlated with the residuals, $r_\varepsilon = 0$, $p > .999$; residuals were homogeneous, $F[1, 71] = 1.97$, $p = .17$, and normally distributed, $W = .98$, $p = .24$). The logarithm of α did not depended on the reward condition ($p = .9$, $R^2 = 0$). the full ANOVA table is presented in Supplementary Material B (Table B7).

Secondly a linear model was fitted to predict risk propensity. The predictor was again the reward condition. Gender, n-back's d', age, exploration, and preference for the selected option were also controlled for. The model had a good fit (the fitted values were not correlated with the residuals $r_\varepsilon = 0$, $p > .999$; the residuals were homogeneous, $F[1, 71] = 1.63, p = .21$, and normally distributed, $W = .98$, $p = .46$). In the easy condition, participants risked less ($M_e = 3.36$) than in the difficult condition ($M_d = 4.01$, $F[1, 66] = 12.12$, $p < .001$, $R^2 = .15$). The full ANOVA table is presented in Supplementary Material B (Table B8).

Third, a linear model was fitted to predict risk propensity again. The model was similar as in step two, but instead of the reward condition the predictor was the logarithm of α. The fitted values were not correlated with the residuals ($r_\varepsilon = 0$, $p > .999$) and were normally distributed ($W = .97$, $p = .23$). The risk-taking did not depend on the logarithm of α ($p = .14$). The full ANOVA table is presented in Supplementary Material B (Table B9).

Table 2. Correlation matrix and descriptive statistics of variables used in experiment 2.

	Risk-Taking	Exploration	log α	d'
Reward condition [difficult]	.38***	.02	−.02	.03
Gender [male]	.4	−.15	.07	.07
Age	.12	.01	−.09	.05
Risk-taking		.2	−.18	.06
Exploration			−.35**	−.06
log α				0
Mean	3.71	27.85	−.76	2.48
SD	0.83	9.88	0.26	0.65
Range	[2.23, 5.75]	[3, 40]	[−1.28, −0.26]	[1.04, 4.08]

Note: For dichotomous variables the alternative (non zero) value is given in square brackets. In cases of two continuous variables the Pearson correlation coefficient was computed, in cases of one continuous and one dichotomous variable the point-biserial correlation was computed *$p < .05$, **$p < .01$, ***$p < .001$

The logarithmized α did not mediate the influence of the reward condition on risk propensity (proportion mediated 0%, 95% CI= $[-13\%, 12\%]$, $p = .91$).

Discussion

Of our two hypotheses concerning (a) knowledge of the environment and exploration and (b) safe status and utility function parameter α, the first was confirmed in the first experiment while the second was not. Moreover, the second experiment provided further indirect falsification for the second hypothesis.

There was a main effect of familiarity on exploration. This sheer effect would suggest that people explore more in known environments but the observed interaction with age group must be considered in the interpretation. We observed the expected interaction between age group and familiarity in influence on exploration. It turned out that when in an uncharted land it takes being young at heart to start exploring. In other words, an unknown environment exposes adolescents' higher tendency to exploration.

Both of these factors (adolescent age and lack of knowledge about an environment) are conducive to risk-taking. We expected such a result and asked a further question: is the increase in risk-taking a direct effect of age and knowledge, or do these factors influence risk propensity through increased exploration? The mediation analysis supports the latter hypothesis. Exploration is at least partially responsible for the rise in risk-taking in adolescents and in an unknown environment. The low value of the proportion mediated may suggest that the mediation effect is negligible, but it should be noted that in the case of the imperfect measure of the mediator, the mediation effect is always underestimated (see le Cessie, Debeij, Rosendaal, Cannegieter, & Vandenbroucke, 2012, for proof).

Otherwise, the interaction between age group and reward type in the influence on α, as observed in the first experiment, was different than expected (neither the dependent reward decreased adolescents' α compared to adults nor the independent reward increased adults' one compared to adolescents). Together with the lack of influence of reward type on risk-taking, this renders the second hypothesis false.

The results of the second experiment are congruent with the results of the first one on this subject. There was no main effect of condition on α and as a consequence there was no mediation of α between the condition and the risk-taking. The main effect of the condition on risk-taking did not corroborate the hypothesis; however, this effect additionally allowed us to falsify the hypothesis because it proved that the form of the reward policy does have an impact on risk-taking but not in the way we expected it to in the first experiment. In the second experiment, we applied manipulation based on Risk Sensitivity Theory (Kacelnik & Bateson, 1996; McNamara & Houston, 1992), according to which an agent takes risky behavior only when the minimal level of performance is difficult to achieve using a safe strategy. As expected by both the Risk Sensitivity Theory and our rational analysis, in the easy condition the participants risked less than in the difficult one, where achieving the high reward level was quite a challenge.

So, where do these results leave us regarding our theoretical assumptions? Although it is difficult to identify and evaluate patterns in psychological data gathered at such a high level of behavior, we think we are in position to conclude that risk-taking (especially in adolescents) can largely be boiled down to the task of finding profitable actions in an unknown environment. On the other hand, in contrast to our expectations, although the reward policy influences the risk propensity, a direct connection between subjective utility function and risk-taking cannot be observed in the results.

There might be two reasons for this: first, having a volatile or stable position may not induce having low or high α; second, high α may not increase risk propensity. Both of these possibilities were directly tested in the first experiment. It appeared that risk propensity was related to α, while α depended neither on reward type nor age group. So, as could be expected based on the proof provided in the introduction, we are probably safe to conclude that there is a close connection between α and risk-taking but the young age or insecure position do not decrease the value of α.

In the second experiment, no relation was found between the condition and α nor between α and risk propensity. This result is not surprising since the status manipulation in this experiment was of a different kind than in the first one. In the first experiment, the foundation for the hypothetical relation between reward policy and risk-taking was Subjective Utility Theory/Prospect Theory. In these theories, the connection between status and a change in the subjective evaluation of an objective reward has an adaptive justification. Moreover, there is a direct link between the change in the subjective valuation and the risk-taking. In the second experiment, the manipulation was based on Risk Sensitivity Theory, which links status to the risk propensity but does not assume any intermediary constructs like α.

There are two main limitations to the study which may narrow the scope of possible conclusions. First, as it was stated earlier, the high level psychological constructs, such as risk propensity, correlate poorly when measured with different tasks, questionnaires, or observations. This, on one hand, makes the possible effects weak and difficult to detect. On the other hand, it raises a question about what we really talk about in psychology, when we talk about risk (or any other construct) since there is no possibility for consistent and general measurement. Second, which follows from the above, any task that aims at jointly measure several high level characteristics of the subjects, faces the problem of entanglement: the measured behaviors are, to some extent, involved in many processes determined by the task and, in consequence, observed effects may be biased.

The learning from this study, concerning any future similar experiments applies to both theoretical and practical aspects of the studied problem. Is in possible to find a one common theoretical background for different risk-taking theories which seem to simultaneously apply to observed behavior? Is it possible to construct one integrated platform for observation and measurement characteristics involved in this behavior? Is it possible to integrate the mathematical/statistical tools used for the assessments of these characteristics (like using one instead of several graphical models)? Any follow-up study Will have to answer these question in order to overcome the shortcomings mentioned above.

To draw final conclusions, the findings of this study are threefold. First, it provides an argument that risk-taking, although it sometimes may stem from a lack of control or an imbalance of some kind, can have an adaptive function. Second, especially in adolescent age, its function is the search for unknown and possibly profitable options, namely exploration. Third, although the utility function parameter α is closely related to risk-taking, the stability of the status (economical or any resource-related) does not influence risk-taking through the α parameter. The characteristics of adolescents' risk-taking do not come from their status characteristics.

The results leave us with follow-up questions concerning risk-taking. If it is not status that influences α, what does α depend on? Hence, what are the possible features of an agent or an environment that may affect risk-taking through α?

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Ethical approval

The Ethics Committee of Pedagogical University of Kraków provided approval (number 16/11/2017) for both of the reported experiments.

Disclosure statement

The authors report there are no competing interests to declare.

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Data availability statement

The data that support the findings of this study are openly available in OSF.IO at doi.org/10.17605/OSF.IO/FXPS5.

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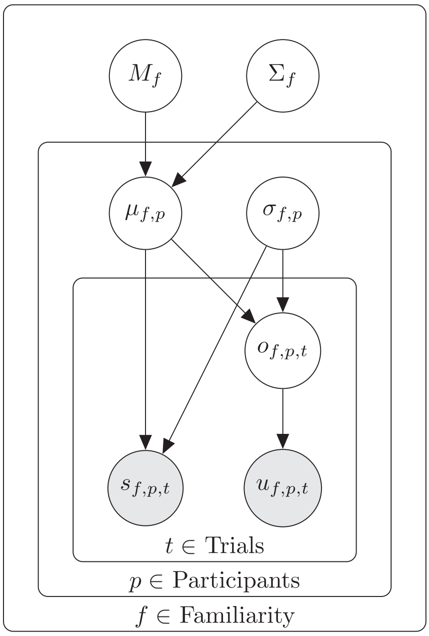
Appendix A

A.1 Estimation of risk propensity

In the CRT, as in many similar risk tasks (e.g., the hot version of the Columbia Card Task), the participant is asked in every trial (in the decision phase) to take a chosen number of steps. Each step leads to an increase in the possible reward value but also increases the risk of failure, which results in loss of the entire reward. The average number of steps taken can be used as an assessment of a participant's risk propensity. When the trial ends successfully, the taken number of steps directly reflects the risk propensity (possibly with some random error). However, when the participant fails and the trial ends abruptly, all we know is that the chosen number of steps was larger than the actual number taken in this trial. There are three straightforward ways of dealing with this problem: (a) Ignore the bias, i.e., average the number of steps taken in successful and unsuccessful trials. This method hardly solves the problem. (b) Remove the possibility of failing entirely or greatly reduce it while trying to keep the participant convinced that the danger is real. In this way, researchers would not deal with failed trials, while participants allegedly would behave in the same way as in the unaltered task. In such a case, one certainly cannot know to what extent the participants' representation of the task is based on the given, false description (that the danger is real) and to what extent this representation is based on the experience of the actual task. (c) Include in the results only the successful trials. This method undoubtedly results in a biased measure because one can expect positive correlation between the number of steps the participant intends to take and the probability of failing in this task.

We applied a different approach. To estimate the average desired number of trials we used a graphical model. This model includes a hidden variable (μ) which determines the number of steps that the participant is willing to take in both successful and unsuccessful trials. In successful trials, the actual number of steps taken is close to the intended number, while in failed trials the actual number of steps is obviously lower. This model is presented in Figure A1.

We made a weak assumption that the individual's risk propensities are neither equal for all the participants nor completely independent of each other. Specifically we assumed that in the general population the risk propensity has some normal-like distribution (more precisely—an expnormal distribution since the risk propensity can not be lower than zero) with mean M and standard deviation Σ. The prior for M is a standard exponential



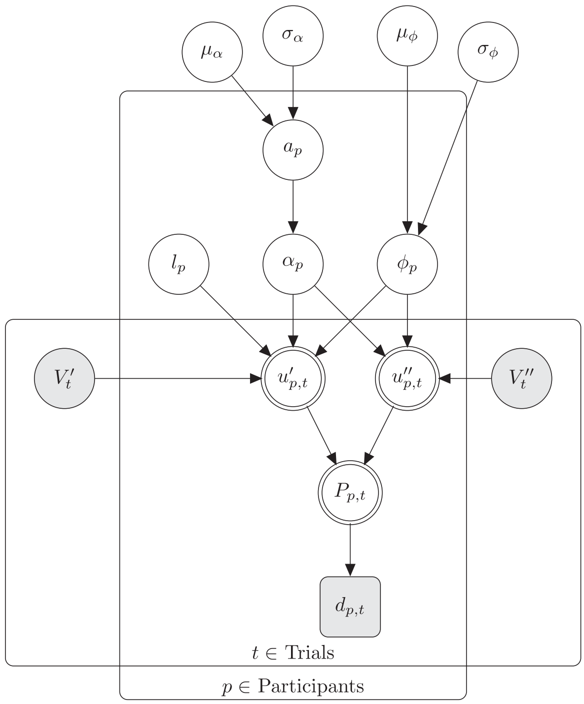
$$
\begin{aligned}
&M_f \sim \exp(1)\\
&\Sigma_f \sim U(0, 10)\\
&\mu_{f,p} \sim \exp N(M_f, \Sigma_f)\\
&\sigma_{f,p} \sim U(0, 100000)\\
&o_{f,p} \sim N(\mu_{f,p}, \sigma_{f,p})\\
&s_{f,p,t} \sim N(\mu_{f,p}, \sigma_{f,p})\\
&u_{f,p,t} \sim P(o_{f,p})
\end{aligned}
$$

Figure A1. Diagram of the graphical model used to estimate participants' risk propensity. Distribution symbols are: exp – exponential, *U* – uniform, exp *N* – expnormal, *N* – normal, and *P* – distribution of possible desired values of steps, given *o* steps taken before failure (see text for details).

distribution because it is a typical uninformative prior for a non negative value which is expected to be rather small. The prior for Σ is an uniform distribution over the range $[0, 10]$ because we do not expect any specific value but a value greater than 10 would be extremely improbable. The familiarity level is supposed to determine the risk propensity so both M and Σ were estimated separately for both familiarity conditions. In the manner of hierarchical modeling we assumed that individual participant's p risk propensity (μ) in a given familiarity condition (f) comes from this expnormal distribution.

The participant's risk propensity in the given familiarity condition manifests in every trial (t) as the number of draws. However the number of draws depends on whether the trial was successful or not. In a successful trial the observed number of draws s is close to the participant's risk propensity (It has a normal distribution with mean μ and participant's specific risk propensity standard deviation σ. The prior for sigma is an uniform distribution over the range $[0, 10000]$ because we expected nothing about its value). In an unsuccessful trial we introduce a desired number of draws o which is similar to number of draws observed in a successful trials but which, conversely, is a latent variable since it is not observed.

What is observed in the unsuccessful trials is an actual number of draws u. The actual number of draws is lower than the desired number of draws because in the unsuccessful trials the drawing process is interrupted by the unsuccessful draw. So the actual number of draws depends on the desired number of draws and comes from the specific probability distribution (P) described below. We used a separate variable o for the hidden desired number of steps in the unsuccessful trials in order to be able to employ the "zeros trick" (Ntzoufras, 2009), which is necessary to use the specific probability distribution (P).



$$
\begin{aligned}
&\mu_\alpha \sim N(0,1)\\
&\sigma_\alpha \sim U(0,10)\\
&\mu_\phi \sim U(-2.3,1.61)\\
&\sigma_\phi \sim U(0,1.13)\\
&a_p \sim N(\mu_\alpha,\sigma_\alpha)\\
&\alpha_p \sim \Theta^{-1}(a_p)\\
&l_p \sim \exp(1)\\
&\phi_p \sim N(\mu_\phi,\sigma_\phi)\\
&u'_{p,t} \leftarrow \exp(M(V_t'^{\alpha_p})\phi_p)l_p\\
&u''_{p,t} \leftarrow \exp(M(V_t''^{\alpha_p})\phi_p)\\
&P_{p,t} \leftarrow \frac{u'_{p,t}}{u'_{p,t}+u''_{p,t}}\\
&d_{p,t} \sim \mathrm{Bern}(P_{p,t})
\end{aligned}
$$

Figure A2. Diagram of the graphical model used to estimate participants' α. Distribution symbols are N – normal, U – uniform, exp – exponential, and Bern – Bernoulli. Θ^{-1} denoted the inverse cumulative distribution function of the standard normal distribution. M denotes mean function.

The distribution $P(x, o)$ provides the probability that the failure occurred in the xth step if a participant intended to take o steps. The assumptions are that $0<x \leq o$, $m \in \mathbb{R}$, and that the probability of failure in each step is equal (25%) and independent of the number of steps taken. Thus, the probability of failure in the xth step equals $\frac{3}{4}^{x-1}$ (given that the failure occurred). So, the distribution P takes the form:

$$P(x,o) = \frac{\frac{3}{4}^{x-1}}{\int_1^o \frac{3}{4}^{i-1} di}.$$

A.2 Estimation of the utility function parameter α

The graphical model for α is based on the model described in Nilsson, Rieskamp, and Wagenmakers' work (2011), which provides a great analysis of the problem of estimating the prospect theory parameter with hierarchical Bayesian modeling. The model is presented in Figure A2.

Again, in the manner of hierarchical paradigm we assumed that participants' α and ϕ (a sensitivity parameter in the Luce choice rule which controls how much the model's choices are determined by the difference between options' values) come from distributions determined by parameters common for a general population. The inverse cumulative distribution function of the standard normal distribution was applied to auxiliary variable a in order to obtain α (see Nilsson, Rieskamp, & Wagenmakers, 2011, for details). Both a and ϕ were drawn from normal distribution with respective means (μ_α and μ_ϕ) and standard deviations (σ_α and σ_ϕ). The prior distributions for the means and standard deviations were based on those used by Nilsson et al. (2011).

The l parameter (specific for each participant) quantifies how much the option chosen in the choosing phase (left) is more attractive to the participant than the random option paired with the chosen one (right, see Figure 3). The prior for l was an exponential distribution which is a typical uninformative prior for small positive values.

Three intermediate values (u', u'', and P) are deterministically computed from α, ϕ, and two observed vectors V' and V''. These vectors are composed of sets of past values returned by each of the two objects available in the decision phase. The values are provided to the participants in the form of a plot (see Figure 3). The parameter P is a probability of choosing the left object based on the Luce choice rule and is computed using two variables (u' and u''). The utility of the left, selected (u') and right, matched (u'') option is quantified as the mean known value returned by the option (V) to the power of a multiplied by the sensitivity parameter (ϕ) passed to the exponential function. The utility of the left option (u') is also multiplied by $1 + l$ to reflect the participant's preference for the object selected in the choosing phase. The final preference of the left object (P) is the relative utility of the object ($u'/(u' + u'')$). The formulas for u and for P together constitute the Luce choice rule. Finally, the decision (d) is expected to come from the Bernoulli distribution given P.

Both models were fitted using JAGS (Plummer, 2003). For every model, 100,000 probes were sampled in each of the three chains. The first half of the samples were discarded as burn-in. The remaining 50,000 were thinned by 50 to obtain 1000 samples for each chain. The point estimation of the parameters were means of their posterior values. The convergence of the MCMC chains was good for both models (verified by visual inspection and examination of the $\hat{R}$ statistic).