**Title:** Peer-Mediated Social Signals Alter Risk Tolerance in Teenage Boys Based on How far they are from Their Peers

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## Abstract

During early adolescence, peer influences play a crucial role in shaping learning and decision preferences. When teens observe what their peers are doing, they can learn and change their behavior, especially when they are taking risks. Our study incorporated an economical behavioral task and computational modeling framework to examine whether and how early male adolescents' risk attitudes change when they see information about their peers' choices. We recruited 38 middle school male students aged 12-15 years. The experiment consisted of three sessions: The first session and the third session were designed to evaluate the risk attitude of the participants. In the second session, participants were asked to guess the choices made by their peers, and then the computer gave them feedback on the correctness of their predictions. Each participant was randomly assigned to risk-taking or risk-averse peers. Our results revealed that teenagers who predicted risk-averse peers exhibited significant declines in their risk attitudes during the last session. On the other hand, participants with risk-seeking peers exhibited a significantly higher level of risk attitudes after predicting their peers. The data showed that these peer-biased changes in risk attitudes are proportional to the gap between teens' and their peers' risk perspectives. Results showed that their perspectives aligned closer after receiving the information, and approximately a third of the gap was eliminated. This shift may be part of an adaptive process that involves social integration.

**Keywords**: Adolescence; Social influence; Risk attitude; Social information; Observational learning

## Introduction

Risk-taking behaviors can be seen in a wide range of contexts, from extreme sports and gambling to drug use and unprotected sex. Teenage years are associated with an increased risk-taking behavior (Steinberg, 2008). For instance, when it comes to financial matters, they may experiment with risky investments in the stock market or cryptocurrency without proper guidance. Another example is spending money on expensive electronics, such as smartphones and gaming consoles.

Peer influence is a powerful force in the lives of teenagers particularly in the digital age when they are exposed to social media (Valkenburg et al., 2022). These influences play an important role in how they make decisions. Teenagers often look to their peers for guidance on how to dress, what music to listen to, and how to behave. Influence from peers can be a double-edged sword (Molleman et al., 2022). Positive peer influence can encourage teenagers to make good choices, such as avoiding drugs and alcohol, while negative peer influence can lead teenagers to engage in risky behaviors, such as smoking or skipping school.

Smoking and drinking alcohol are more prevalent among adolescents when they are in the company of peers, and having friends who smoke and drink is a predictor of their substance use (Andrews et al., 2002; Loke & Mak, 2013). In laboratory settings, it has been demonstrated that adolescents engage in more risky behaviors when interacting with peers than when alone (Albert et al., 2013; Blankenstein et al., 2016; Gardner & Steinberg, 2005).

Some studies have found that contextual factors affect whether and how peer presence influences decision-making. Teenagers may commit risky acts in the presence of peers when they believe that it will enhance, protect, or otherwise reinforce their social relationships (Somerville et al., 2019). Evidence from humans and animals suggests that the presence of others may heighten the value of non-social rewards (Lucy Foulkes & Blakemore, 2016). Adolescents are more prone to risky behavior, and they are more susceptible to peer influence, so peer presence should, in theory, have a greater effect on risky behavior among adolescents than among adults (Gardner & Steinberg, 2005). Although adolescents can evaluate the risks and consequences of their behavior, being with peers can cause them to exhibit risk-taking behaviors (Smith et al., 2014).

Observing and learning from others' risk-related decisions can also lead to people changing their risk preferences, which is called the risk contagion effect(A. M. F. Reiter et al., 2019; Suzuki et al., 2016). When the participant follows the decision of his colleague, the degree of contagion is positive. For instance, if a colleague takes a risky investment, the participant will likely act in the same manner. On the other hand, if the partner chooses a risk-averse option, the participant is likely to do the same.

Recent studies have shown the effect of contagion when we have information about others' risk-related choices (Suzuki et al., 2016). Similar to adults, this kind of social stimulus affects adolescents as well (Braams et al., 2021; A. M. F. Reiter et al., 2019). There is a tendency in adolescents to change their behavior to be like their peers. Teenagers can use peers as a source of information and change their behavior through peer-to-peer observations (A. M. F. Reiter et al., 2019). In adolescents, observing peers' gambling choices changes the subjective value of those gambles (Blankenstein et al., 2016). In a recent study on adolescents (Braams et al., 2021), participants viewed the gambling choices of peers in some trials of the experiment. It was found that this observation altered adolescents' subjective values of peer-selected choices. This shift is better captured by a change in risk attitude rather than a change in the simple social bias towards or against the utility of gambling choices (Suzuki et al., 2016).

We designed an experiment to examine how social learning influences risk attitude in early adolescents. Our experimental setting was designed as follows: For the first session (self-phase), participants made a series of choices between a sure option and a risky variable option. The second session (predict session) followed, in which they predicted the choices for the hypothetical participant and immediately received feedback about how accurate their predictions were. Participants performed the self-evaluation phase for a second time in the final session (session three) after the prediction session.

Our analysis is twofold: first, we checked whether attitudes toward risk shift after learning about peers' risk attitudes during our early adolescence (measuring contagion effect). The second step is to formulate participants' risk attitudes after learning about their peers as a function of their baseline risk attitudes and the risk attitudes of their peers. We calculated the relative distance between participants and their peers and represented participants' risk attitudes after seeing their peers as a weighted average of their baseline risk attitude and their peers to determine how much social information is weighted by the adolescents. With the help of this method, we can quantify how individuals integrate their personal risk attitudes with their peers' attitudes in a weighted average model. This method also has recently been applied to studies involving perceptual decision making tasks (Molleman, Kurvers, et al., 2019; Molleman et al., 2020, 2022), in which participants can revise their initial estimates after seeing what another person estimates.

# Method

## Sample

To find the appropriate sample size, we performed a power analysis. For this analysis, we used the effect size of the contagion in risk attitude in a recent study (Effect size: d=0.58) (Suzuki et al., 2016). Given the significance level $\alpha$ = 0.05, and the effect size d= 0.58, an a priori power analysis determined that the total sample size required to ensure a power>0.90 is N=27. We recruited 38 middle school male students aged 12-15 years (Mean age = 13.18 , SD =0.48, median age = 13). Data acquisition was restricted to male participants as discussed in (A. M. F. Reiter et al., 2019) due to differences in pubertal development trajectories between female and male adolescents, as well as evidence of baseline gender differences in risk preferences in females and males (Byrnes, James P and Miller, David C and Schafer, 1999).

Prior to the experiment, participants were requested to fill out a demographic form, wherein they were asked whether they had any recent psychiatric disorders. According to their self-reported responses, none of them had any recent psychiatric diagnosis.

Participants and their parents signed an informed consent form. The research was approved by the SCS Research Ethics Committee of the Institute for research in fundamental Sciences (IPM) (Ref. No. SCS. REC: 1401/60/1/618).

## Procedure and Task

The experiment consisted of three sessions, each session with 35 trials presented to each participant. The first session and the third session were designed to evaluate the risk attitude level of the participants. In these sessions, called the “self-phase,” participants had to choose between accepting and rejecting a gambling offer in each trial. In the task instruction, the participants were told that if they chose to reject the offer, they could take a guaranteed amount of money (30TT[1]). However, if they accepted the offer, they would be able to enter the gamble at the end of the game. The gambling money for all the trials was higher than 30TT because participants would not choose it if it were lower than the guaranteed money (30TT).

The gamble's outcome was not revealed to the participants in each trial to prevent potential influences of reward feedback on their decision-making process. At the end of the experiment, one choice was randomly chosen and implemented as part of the payment procedure (please see Payment Procedure for further details). Considering that participants did not know which trial would be selected, the trials should have been treated equally as though they were the only ones.

As in recent developmental studies (Blankenstein et al., 2016; L van Leijenhorst, 2006; Shad, 2011; Van Den Bos & Hertwig, 2017), we used wheels of fortune to visualize gambles. For each gambling offer, the chances of winning and the amount of money the participants could earn were shown on a pie chart, and they were asked to accept or reject the offer using the right and left arrow keys on the keyboard. The pie chart shown to the participants consisted of a blue area showing the probability of winning, and inside the blue area, they could see the amount of gambling money. Please refer to the Supplementary material file (Supplemental Information on the Task and the Experimental Procedure) and Figure S.1 for details regarding the payoffs and probabilities of the gambles in the task.

[1] TT: Thousand Iranian Tomans, at the time of the experiment, 1$ was equal to 4.2TT

This type of stimulus is frequently used in developmental research to illustrate probability to adolescents who have recently begun to grasp the concept of probability (Fig. 1a).

To identify the misleading data of inattentive participants, two trials were included in each self-session with a 100 percent chance of winning. The amount of reward offered by risk-free gambles is higher than the sure payoff. Accordingly, economic rationality dictates that participants should always prefer the risk-free gamble to the sure option regardless of their risk attitude. If a participant rejected both trials, that data was considered invalid.In the second session, known as the "prediction phase," the second round of 35 trials was run. During this session, the participants were asked to predict the choices made by their peers, and then the computer would give them feedback on the correctness of their predictions (Fig. 1b). Throughout the instruction, they were informed that one of their peers had played the game before, and their data was recorded. In reality, the data shown to the participants were generated by a computer algorithm (please see Supplementary material: Computational Model of decision making under risk section for details of algorithm)

and exhibited two patterns of risk-taking or risk-averse behavior. Each participant was randomly assigned to one of these patterns, assuming that it was the data from their peers and trying to guess the pattern and predict their answer. During the experiment, none of the participants doubted that the peer choices were real. The simulated risk-seeker peers averagely chose gambles in 80% of trials (SD=3%, range 77%–86%)), whereas the simulated risk-averse peers averagely chose gambles in 19% of trials (SD=2.5%, range 14%–23%).

Before starting the actual experiment, the participants went through a training phase where they experienced three trials similar to the self-phase of the experiment and three trials similar to the prediction phase. Then, they proceeded to the actual experiment. To avoid tiredness and its possible effects on participants' choices, the participants were allowed to rest a while between the sessions and then continue the game by pressing a random key. This was reminded to them after they finished each session.

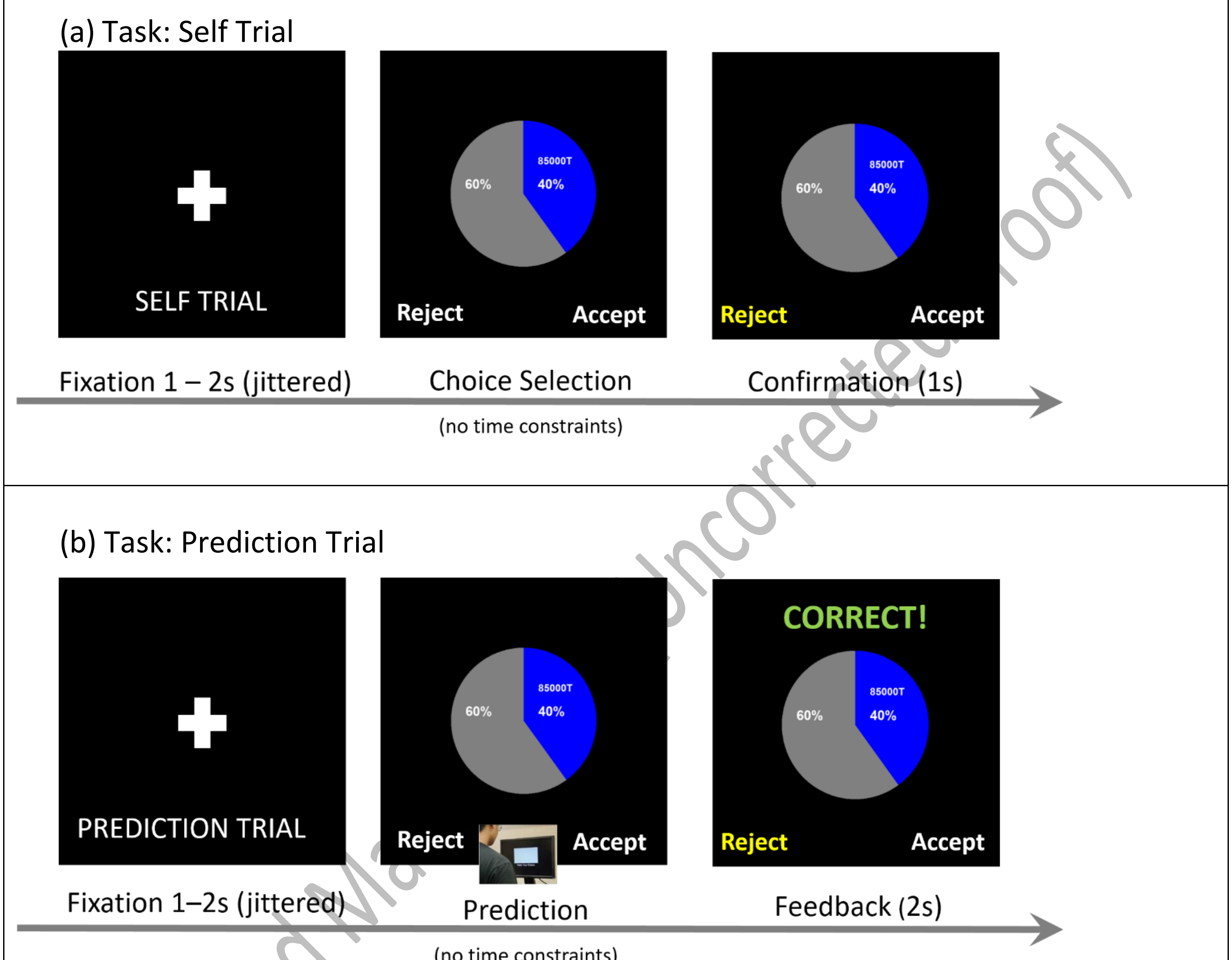



**Fig. 1**. Experimental Task. (a) Each trial in Self-Session begins with a jittered fixation between 1-2 seconds, which contains a cross sign and the word "SELF TRIAL" at the bottom. Thereafter, a gambling wheel appears and participants are given the opportunity to accept or reject a gamble without regard to time constraints. Participants who accept the gamble can bet for the specified amount of money; otherwise, they may take a guaranteed amount of money (30TT; TT stands for Thousand Iranian Tomans; at the time of the experiment, one US dollar was equivalent to 4.2TT). The reward probability and magnitude of the gamble are presented as a pie chart. The blue area indicates the probability, and the numbers inside the blue area represent the magnitude. When the left/right arrow key is pressed, the participant's choice is highlighted in yellow for one second.

(b) In the Prediction session, each trial begins with a jittered fixation lasting between 1-2 seconds, which is accompanied by a cross sign in the center of the screen and the word "Prediction TRIAL" at the bottom. Following this, a gambling wheel appears, with a picture of the peer displayed at the bottom of the pie chart. Afterward, the participant makes a prediction concerning whether the displayed gamble was accepted or rejected by the peer. When the participant provides his prediction, it is highlighted in yellow, and feedback appears at the top of the screen. Upon correctly predicting, the word "CORRECT!" is displayed in green for two seconds and upon incorrectly predicting, the word "WRONG! " appeared in red for two seconds.

The peer image is from (Suzuki et al., 2016). This picture was taken from the back, which minimizes the effect of peer appearance.

## Payment Procedure

The reward calculation process consisted of two parts: one for self-trials and one for prediction trials. The payment process for self-sessions went like this: The computer randomly selected one trial from session 1 and session 3 and displayed it along with the participant's choice. Participants who accepted the offer on that trial were required to provide a number between 1 and 100. Depending on the chances of winning in that gambling offer, a given percent of these numbers were marked as "win," and the rest were labeled "lose." If the bet numbers given by participants were labeled as "win," they won the offer and received their reward. Participants who chose not to accept the offer on the selected trial were also given a certain amount of 30TT.

The computer also randomly selected one of the trials for the prediction session. An additional 30TT was awarded if the participant's prediction on that trial was correct. Based on the protocols for an experiment involving early adolescents, we are unable to pay cash directly to the participants. Accordingly, we summed up each participant's scores over the course of the experiment and awarded him a prize equal to the sum of those scores.

## Statistical analyses

There were two different measures used to assess risk attitude (model-based and model-free methods). To derive a parameter representing the participant's risk attitude based on our model-based method, we fitted an exponential utility function to the participants' choices. Detailed information on exponential utility functions and model fitting can be found in the online Supplementary Material. A model-free measure of participants' risk preferences is the proportion of gambles accepted in comparison with the (hypothetical) proportion acceptable to a risk-neutral agent (A. M. F. Reiter et al., 2019; Suzuki et al., 2016). A risk-neutral agent chooses whether or not to gamble by comparing the expected reward of the gamble (the probability times the magnitude of the reward) with the value of a safe option.

In the prediction trials, participants predicted the choices that the peer made and immediately received feedback on the correctness of their predictions. The performance in prediction could be interpreted as a way to assess how well participants had learned about their peers' behaviors. We measured the percentage of correct guesses as participants' performance in the prediction phase.

We divided the prediction session which consisted of 35 trials into four parts: Train trials, Early trials, Middle trials, and Late trials. This allowed us to gain a deeper understanding of participants' prediction behavior. The first five trials constitute the Train part, and the remaining parts each consist of 10 trials. We assumed performance at prediction as being significantly free of chance if the proportion of correct predictions is larger than the specified threshold.

To calculate this threshold, we employed the method introduced by Steffens et al. (Steffens et al., 2020). We left the first five trials (Train trials) and calculated the threshold by the remaining 30 trials. Therefore, in this setting, if the observed performance is greater than 63.3% then the performance could be assumed as being significantly free of chance (see Table 2 in (Steffens et al., 2020)).

Seven participants were excluded from the final analysis out of the initial 38 participants. One participant was removed due to providing an incorrect answer on the risk-free trials, indicating that he was not paying attention to the task procedure. Two further participants were excluded due to their prediction performance falling below the chance threshold in the prediction session, suggesting that they did not learn their peers' choices efficiently. Additionally, following a model-based analysis, it was determined that four participants made the majority of their decisions randomly, and thus their data was removed from further analysis. Ultimately, the data from the remaining 31 participants was used for the analysis.

Data were analyzed using MATLAB (2017; The Mathworks, Natick, MA). We used “Statistics and Machine Learning Toolbox Functions” for common statistical analysis such as Pearson’s linear correlation and t-test. Also, to construct the linear models, we used the "fitglm" and "lsqlin" functions. We employed the maximum likelihood method to extract risk attitudes. For this purpose, choices of every self-session were fitted using the “fmincon” function with the SQP search algorithm. To determine the sample size for the current study, we conducted power analysis in G*power software (version 3.1) (Faul et al., 2007)

## Results

Firstly, we assessed the participants’ risk attitudes at baseline. That is their attitude toward risk before being exposed to social influence (please refer to the Method and Fig. 1 for information regarding the study design). This was accomplished by fitting a computational model of decision-making under risk to the choice data collected from each participant in the first session (see online Supplementary material).

Contrary to previous studies on adolescence (Blankenstein et al., 2016; A. M. F. Reiter et al., 2019; Tymula et al., 2012), risk aversion did not seem to be a common characteristic among the sample

(Fig. S3). Based on the computational model, participants' risk attitudes in session 1 ($\rho_{s1}$) ranged between 0.84 and 1.20 ($\rho_{s1}$: mean = 1.01, SD = 0.10, median = 0.99), reflecting a broad range of risk aversion and risk-taking behaviors. There are roughly equal proportions of risk-seekers and risk-averse participants in the sample (14 participants were risk-seekers ($\rho_{s1}$>1), 16 were risk-averse ($\rho_{s1}$<1), and one was risk-neutral ($\rho_{s1}$=1)). Furthermore, participants who predicted and observed risk-averse peers have no distinct baseline risk attitudes from those who predicted and observed risk-seeking peers (two-sample t-test, t = -0.1, df=29, p = 0.92).

Participants showed high performance during the prediction phase, which indicates that they successfully learned their peers' risk behavior (mean = 82%, SD=8, range = 63%-97%) (Fig. S4). The data from the two participants with unsatisfactory prediction performance were not taken into account. This is because their prediction performance was lower than the chance threshold (63.3%) in the prediction session.

A prediction session with 35 uninterrupted trials was conceptually divided into four parts. At the start, participants were not familiar with the data and therefore their performance was below the chance threshold. However, as the session went on, they started to identify patterns and make more accurate predictions. This was likely due to the fact that they had more time to become familiar with the data and the patterns that emerged from it, allowing them to better understand the data and make more accurate predictions.

Despite performing below chance in the first five trials (Train trias), the subsequent ten trials (Early trials) showed remarkable progress. (Performance in the Early part: M =80%, SD=14%, t= 6.68 , df=30, p<$10^{-5}$). On average, the Early part performance was 11% higher than the Train part. After that, the average proportion of correct predictions remains above 80% (Middle and Late parts). It ensured that the quality of prediction remained in the acceptable range until the end of the prediction phase despite potential factors such as lack of attention (see Method: Statistical Analysis).

In line with previous studies (Braams et al., 2019, 2021; Suzuki et al., 2016), we expected that participants made riskier choices after predicting and observing the choices of risk-seeking peers, and fewer risky choices when the peers are risk-averse.

Participants who predicted risk-averse peers (15 participants) selected the risky option, on average, in 55.4% of trials in session 1 (SD= 17.8, range =28-97) and 46.7% of trials in session 3(SD=16.4, range =22-77). This result shows that after predicting risk-averse peers, participants selected gambling options significantly less than before (paired t-test: t=-2.17, df=14, p=0.04). On the other side participants who predicted risk-taker peers (16 participants) selected the risky option, on average, on 56.4% of trials in session 1(SD= 17.7, range =31-88) and 68.9% of trials in session 3(SD= 16.6, range =40-94), indicating that after predicting risk-seeking peers they selected risky options significantly more than before (paired t-test : t=4.45, df=15, p=4*$10^{-4}$ ; Fig. 2a).

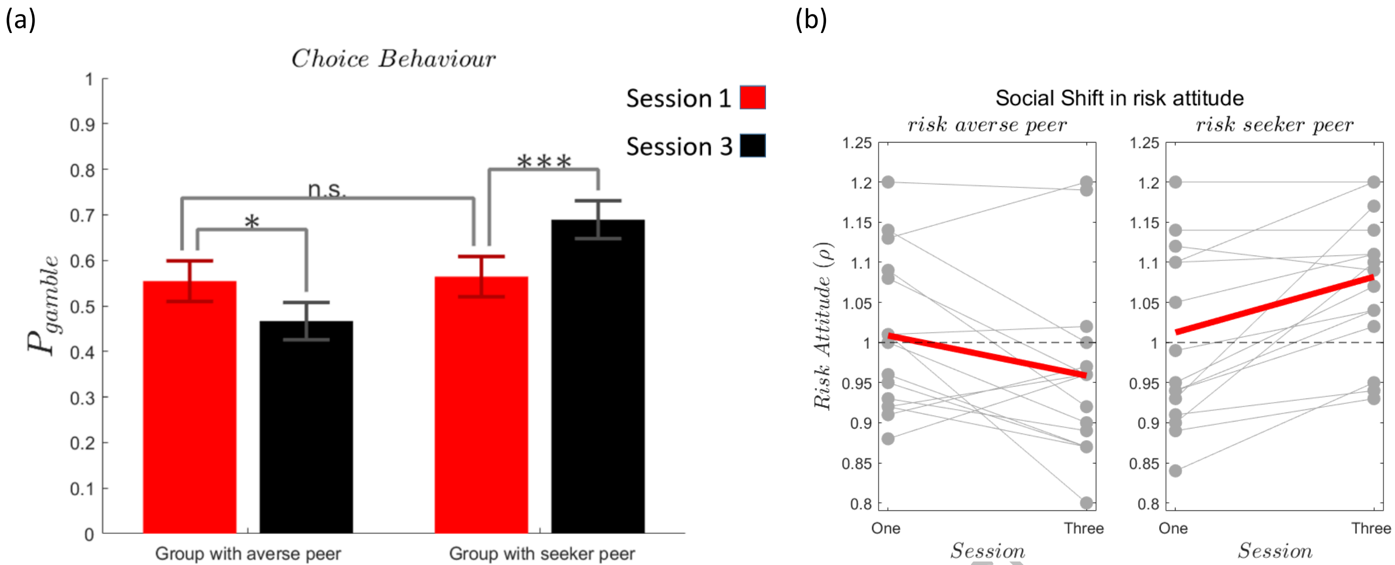



**Fig. 2**. (a) Choice behavior. The bars compare gambling rates in session 1 and session 3 (red bars for session 1 and black bars for session 3). Participants are split into two groups based on their peers (aversive peers: two left bars and seeking peers: two right bars). * p<0.05, ** p<0.01, *** p<0.001, and "n.s." means not significant as the p > 0.05 in the t-test.

(b) Social shift in risk attitude: Comparing participants' risk attitudes $\rho$ in sessions one and three. Participants with risk-averse peers are on the left panel, and participants with risk seekers are on the right. The gray lines show how each participant's risk attitude changed. Each group's average shift is shown in red lines. As can be seen, the red line for the risk-averse peer group has a negative slope. Conversely, the red line for the risk-seeking peer group has a positive slope.

For both groups, Fig. 2b compares the participants' attitudes before (session 1) and after (session 3) the prediction session. As determined by the paired t-test, participants who predicted risk-averse peers in session 2, exhibited significant declines in their risk attitudes during session 3 (mean of changes= -0.05, SD=0.09, t=-2.13, df= 14, p=0.04). On the other hand, participants with risk-seeking peers exhibited a significantly higher level of risk attitudes in session 3 (mean of changes=0.07, SD=0.07, t=3.72, df=15, p=0.002).

As a way to gain additional insight into participants' behavior, we measured the degree of contagion, which is prevalent in similar studies (A. M. F. Reiter et al., 2019; Suzuki et al., 2016).

Contagion occurs when someone conforms to his peer and quantitatively it can be expressed as follows (Suzuki et al., 2016):

$$\text{Contagion } (\Delta) = \begin{cases} \rho_{s1} - \rho_{s3}; \text{ risk-averse peer} \\ \rho_{s3} - \rho_{s1}; \text{ risk-seeking peer} \end{cases} \tag{Eq. 1}$$

Fig. 3a summarizes risk contagion within the sample. Among the majority of participants, the risk contagion value falls above the zero line. The risk contagion effect was found to be significantly positive among our participants (one-sample t-test against zero: $\Delta_{\text{all}}$= 0.06, SD=0.08, t = 4.08, df= 30, p =$3 \times 10^{-4}$). On average, our adolescents adapt their risky behavior after observing their peers' risk behavior.

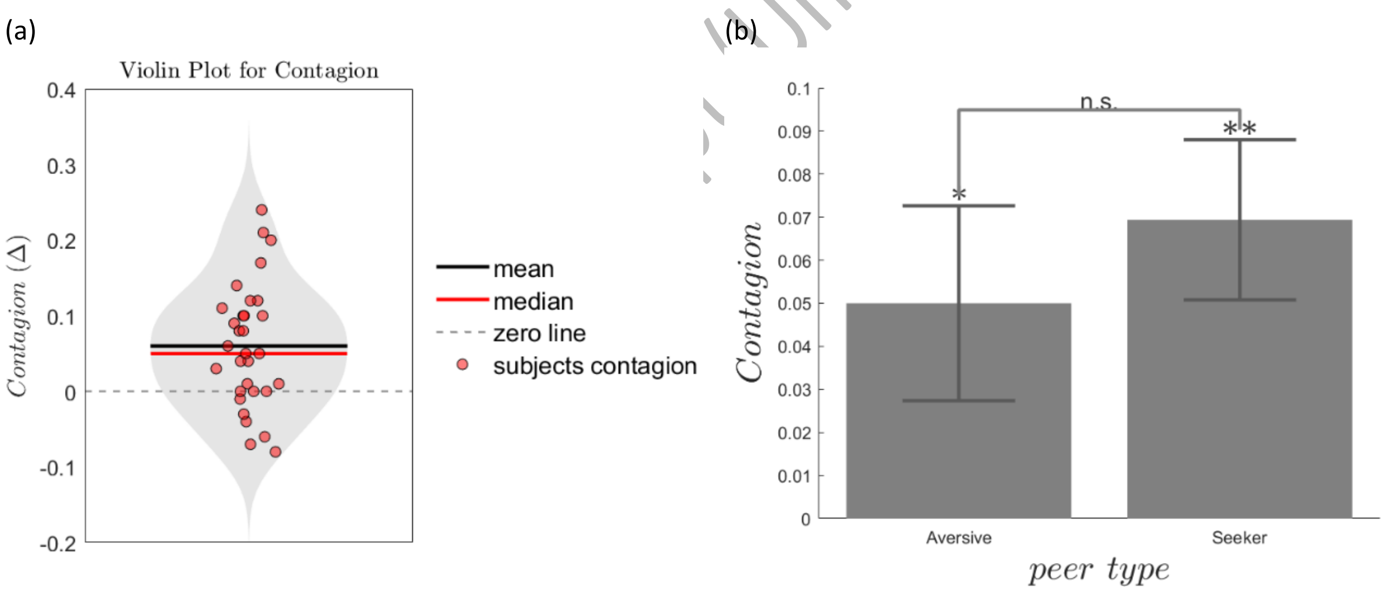



**Fig. 3. (a)** The violin plot illustrates the degree of contagion among participants. The positive values indicate that the participant is moving in accordance with his peers, and the negative values indicate that the participant is moving in the opposite direction. (b) Contagion based on the peers' type. Both groups' contagion is significantly positive. * p<0.05, ** p<0.01, *** p<0.001, and "n.s." means not significant as the p > 0.05 in the t-test.

Fig. 3b illustrates the degree of contagion based on the peer's risk attitude (aversive or seeking). Both groups were significantly affected by the contagion effect (Group with aversive peers:

t=2.14, p=0.04; Group with seeker peers: t=3.7, p=0.002). As can be seen in Fig. 3b, the average contagion effect for the group with the risk-seeking peer was stronger than the group with a risk-averse peer ($\Delta_{\text{aversive-peer}}$=0.05 and $\Delta_{\text{seeker-peer}}$=0.07). However, a two-sample t-test between the two groups revealed no significant differences in the size of contagion (t=-0.65, df=29, p= 0.52). Further analysis revealed that the degree of contagion was not significantly correlated with the proportion of correct predictions in session 2 (P=0.19), implying that the contagion was not primarily triggered by predicting the peers' choices.

We observed that as early adolescents observe peers who make risk-seeking /risk-averse choices, their risk attitudes will increase/decrease respectively. Here we assessed whether the size of this social shift could be predicted by the difference between a participant's risk attitude and that of their peer (social distance). Employing the formulation used in (Molleman, Kurvers, et al., 2019; Molleman et al., 2022), the social distance is calculated by comparing the baseline risk attitude of a participant with that of his peer:

$$social\ distance = \rho_{peer} - \rho_{s1} \qquad \text{(Eq. 2)}$$

There is a strong correlation between this social shift ($\rho_{s3} - \rho_{s1}$) and the distance between the participant and his peer, (Pearson correlation, r=0.71, P<0.001; Fig. 4a). The result shows that we can linearly relate the social shift to the social distance as follows:

$$(\rho_{s3} - \rho_{s1}) \propto (\rho_{peer} - \rho_{s1}) \qquad \text{(Eq. 3)}$$

We fitted a generalized linear regression model to our data ($y \sim 1 + x$: $x = \rho_o - \rho_{s1}$ and $y = \rho_{s3} - \rho_{s1}$), which revealed that the intercept was not significant (intercept = 0.01; p-value = 0.43). As a result, our model no longer includes the intercept:

$$\rho_{s3} - \rho_{s1} = w * (\rho_{peer} - \rho_{s1}) \; or \; w = \frac{\rho_{s3} - \rho_{s1}}{\rho_{peer} - \rho_{s1}} \quad \text{(Eq. 4)}$$

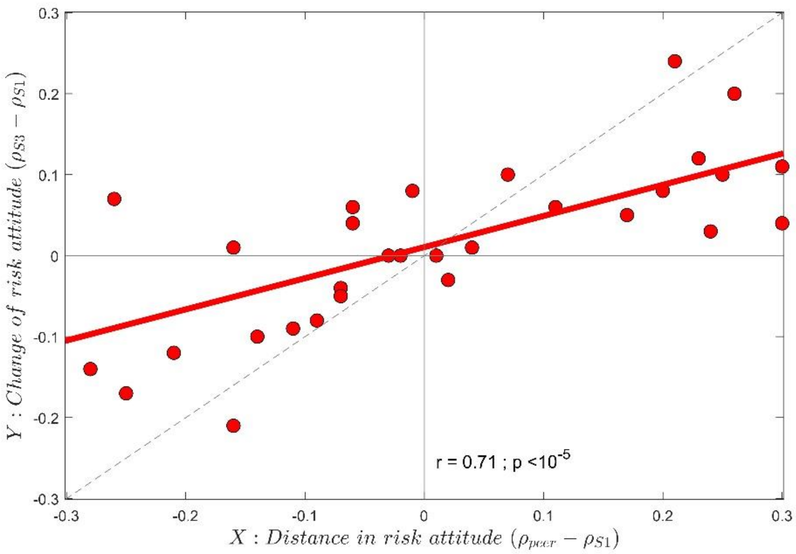
There is an alternative way to arrange Eq. 4 where participants' risk attitudes after observing peers ($\rho_{s3}$) can be represented as a weighting average of their baseline risk attitudes ($\rho_{s1}$) and their peers' risk attitude ($\rho_{peer}$).

$$\rho_{s3} = w * \rho_{peer} + (1 - w) * \rho_{s1} \quad \text{(Eq. 5)}$$

In Eq. 4 and Eq. 5, $w$ (social weight) represents how much weight a peer has in a participant's view. The participant's risk attitude after interaction lies somewhere between that of his peer and that of himself before the interaction. Fig. 4b illustrates how $\rho_{s3}$ may vary depending on the amount of $w$. The higher $w$, the more similar the participant will become to his peer after acquiring social information. Participants with $w$ = 0 do not change according to social information, whereas those with $w$ = 1 conform fully to their peers' behaviors. Participants who give the same weight to their own strategy and that of their peers are represented by $w = 1/2$.

Assuming $\rho_{s1}$ and $\rho_{peer}$ form a convex combination, we fitted the model suggested in Eq. 5 to the entire data set. Consequently, $w$ was estimated to be 0.38. We also calculated $w$ using the model-free estimation of risk attitude (see Method: Statistical Analysis). The value of $w$ was 0.33, which is approximately comparable to the value determined by the model-based approach. Taking the entire sample data into consideration, the results of the model-based and model-free approaches indicate that the social weight (w) lies between 0.3 and 0.4.

(a)




(b)

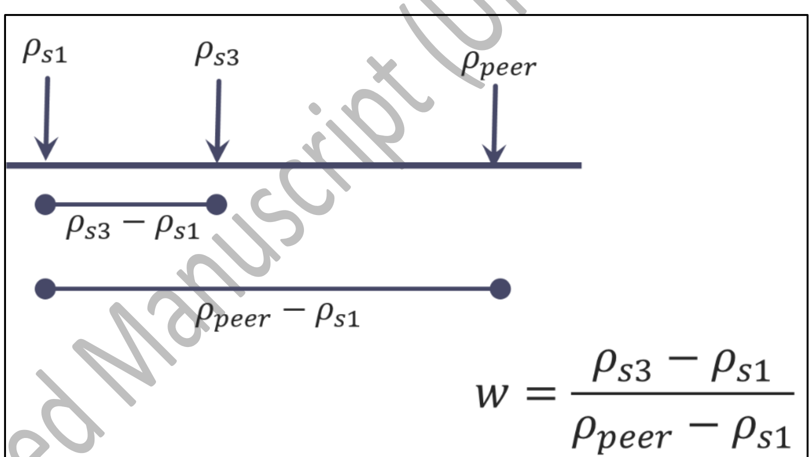



**Fig. 4. (a)** Correlation between social shift and social distance. The social shift is measured by the change in risk attitude between sessions 1 and 3 ($\rho_{s3} - \rho_{s1}$). A participant's social distance from his peer is defined as the difference between their risk attitudes ($\rho_{peer} - \rho_{s1}$). The identity line is depicted by a gray dashed line. In the graph, the red line represents the regression line that fits the data. (b) we define social information weight (w) as the adjustment from $\rho_{s1}$ to $\rho_{s3}$ as a fraction of the distance between $\rho_{peer}$ and $\rho_{s1}$

## Discussion

In the present study, by combining an economical behavioral task with a computational modeling approach, we investigated how information in the social context influences risky behavior among early male teenagers. In accordance with the literature, we demonstrated that boys' risk attitudes shift when they become aware of their peers' choices. We observed the risk contagion effect in teenagers as adolescents' risk attitudes increase/decrease when they observe peers making risk-seeking/risk-averse choices. After learning about their peers, participants' risk attitudes were formed based on their own baseline risk attitudes as well as their peers' risk attitudes. Results showed that peer-biased shifts in risk attitudes correlate with the risk perspective gap between teenagers and their peers.

We confirmed previous studies (Blankenstein et al., 2016; Braams et al., 2021; A. M. F. Reiter et al., 2019; Suzuki et al., 2016), indicating that attitudes toward risk change after observing and learning about peers' risk attitudes during early adolescence. Consistent with these results, one incorporates information obtained from observing others into his decision-making process. We found that adolescents displayed significant changes toward their peers. Our findings line up with a recent study that showed the risk contagion effect happened more in early adolescents, whereas older adolescents put more emphasis on their own preferences and beliefs (Molleman et al., 2022). It is possible that early adolescents may have a less clear understanding of what is right and wrong (A. M. F. Reiter et al., 2019), while older adolescents may be less uncertain of these values (Morgan et al., 2012). It is possible that the reported developmental trends in susceptibility to social influence are due to the decrease in randomness in decision-making as we age (Rodriguez Buritica et al., 2019). We checked for and excluded participants who made most of their choices randomly (See Method: Statistical Analysis).

Risk contagion may be explained by a reward-sensitive motivational state induced by peers, which increases teenagers' likelihood of engaging in risky behavior (A. M. F. Reiter et al., 2019). A recent meta-analysis on 59 fMRI studies of decision-making under risk in adolescents showed that adolescents compared to adults were associated more with the right LPFC when selecting safe choices and associated more with the left insula and bilateral dorsal striatum when selecting risky choices. However, adults were associated with the right mid-dACC more so than adolescents when selecting risky choices, which can be interpreted by applying major developmental theories of decision-making under risk, including the dual-systems model (cognitive control and emotional arousal) and another theory emphasizing changes in cognitive strategies with development (van Duijvenvoorde et al., 2022; Zhang, 2022).

In adolescents, brain areas associated with cognitive control were less strongly recruited than in adults, but activity in the cognitive control system did not vary according to social context. Thus, adolescents may involve an imbalance between cognitive and affective systems (Chein et al., 2011; Steinberg, 2008). Although these studies suggest peer effects on adolescents' decision-making are associated with impulsive behavior and enhanced reward-related activity, some results of the RT analysis contradict these findings (A. M. F. Reiter et al., 2019; Van Hoorn et al., 2017). Based on their results, peer presence (Van Hoorn et al., 2017) and social information (A. M. F. Reiter et al., 2019) did not simply facilitate decision-making, which is inconsistent with an impulsive reaction to risky peer behavior. According to these studies, risk contagion among teenagers involves a deliberate, socially motivated process. In support of this notion, the risk contagion effect has been demonstrated to modulate the neural representation of risk in the caudate through its connectivity with the dlPFC, a region specifically involved in deliberative, goal-directed decision-making and action planning in adults (Suzuki et al., 2016).

A common belief about teens being more risk-prone might suggest that teens being influenced by risk-seeking peers, not risk-averse peers (Loke & Mak, 2013; World Health Organization (Geneva); Regional Committee, 2012) leading to conformity in that direction. Studies in this area, seems to indicate that risk contagion in adolescents is specific to interacting with risk-seeking peers, not risk-averse peers (Chein et al., 2011; A. M. F. Reiter et al., 2019). Or at least, teens who observed risk-seeking peers shifted more than teens who observed risk-averse peers. There are, however, some teens who have pronounced risk-averse preferences (Braams et al., 2021; Chein et al., 2011) and it turns out nearly half of our sample was risk-averse. Moreover, our results revealed that in spite of a stronger contagion effect for the group with a risk-seeking peer, the size was not significantly different. Taking into account the findings of our study, we conclude that risk contagion in early adolescents is a bidirectional effect that does not solely trigger risk-seeking activities but can also help prevent risky behavior.

In addition, as we explored in more detail, we found that social differences in risk attitudes were positively correlated with peer-biased risk contagion. Teens' risk attitudes change proportionally to the gap between their peers and their own, with about 30-40% of the gap vanishing when they learn about their peers' choices. Susceptibility to peer influence appears to be an adaptive process that is associated with a greater sense of interpersonal connection. Interestingly, in real life, social information may also impact individuals based on their position in their social network.

An analysis of a large sample of participants showed that their behavior changed about 1/3 of the distance towards the observed social information after receiving advice (Molleman, Kurvers, et al., 2019). Another recent study conducted on adolescents aged 11 to 15 years, based on a simple estimation task, demonstrated that social information has a strong effect on behavior. In this task, the average adjustment when observing a peer was 43% (Molleman, Kanngiesser, et al., 2019).

The relationship between social integration and real-life behavior in the domain of risk is yet to be investigated. Peers impact almost all aspects of adolescents' lives, from taste in music and clothing, to the more serious, such as the use of illicit drugs or engaging in unprotected sex (Loke & Mak, 2013; Steinberg, 2008). Thus, understanding social influences on adolescent risk-taking behavior is valuable for preventing maladaptive behaviors and disease (A. Reiter et al., 2017; World Health Organization (Geneva); Regional Committee, 2012). Long-term, running with the wrong crowd can adversely affect people's health, education, social and economic success, and general well-being (World Health Organization (Geneva); Regional Committee, 2012). Recent studies, however, indicates that peers may also promote prosocial behavior and reduce risk taking (Ahmed et al., 2020; Chierchia et al., 2020; Molleman et al., 2022). The results of a recent study suggest that children and adolescents are more likely to be positively influenced by peers in the domain of prosocial decision-making than older individuals (L Foulkes et al., 2018). However, more research is needed in this area. It would be useful to examine how peer relationships affect learning and decision-making within social networks in future studies. Understanding how peers promote and shape positive behavior requires understanding how behavior, social learning, and network formation interact.

Because of budgetary constraints, we were limited to a sample size of 38 participants, but our power analysis revealed that this was sufficient to draw conclusions about the overall dataset. However, the sample size of 15-16 used for in-group analysis may not be adequate for generalizations. Nonetheless, the results of each group can still provide valuable insights that can be used to explore risk contagion further. In addition, studies similar to ours have conducted intra-group or auxiliary analyses using a small sample size; for example, (Suzuki et al., 2016) utilized a total sample size of 24, with some of the auxiliary analyses conducted on 12 participants.

Lastly, like most studies in this field, (Braams et al., 2021; Suzuki et al., 2016; Van Hoorn et al., 2017), we restricted our sample to male participants. The purpose of this was to avoid the confounding effect of baseline differences in risk-taking that might be associated with differences in pubertal trajectory between boys and girls. In future studies, both sexes' life span samples should be included to determine whether the findings generalize.

As a topic for future research, it is theoretically interesting to investigate the integration of information from different sources when parents and peers exert opposing influences. It is also interesting to study how individuals' confidence in their own judgment influences how they use social information. As a final point, longitudinal and cross-sectional studies can also provide insight into the origins and development of social learning.

# Conclusion

Our study shed new light on the use of social information by adolescents in making risky decisions. Peer-provided social information was highly used by adolescents. The data showed that these peer-biased changes in risk attitudes are proportional to the gap between teenagers' and their peers' risk perspectives. According to the results, their perspectives began to align closer after receiving the information, and approximately 30-40 percent of the gap was eliminated. A difference in teens' risk attitudes before they communicate does not appear to be causally correlated with social risk contagion. However, it is possible to argue that this shift is part of an adaptive process involving social integration.

# Data availability

All data and code supporting the findings of this study are available from the public repository, accessible via https://github.com/ahtehranisafa/adolescents-social-weight

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# Supplementary material

Supplemental Information on the Task and the Experimental Procedure

The gambles are represented by two parameters $p$ and $r$, where $p$ is the probability of receiving the reward and $r$ is the amount of that reward. Reward probabilities $p$ were 0.3, 0.4, and 0.5. Note that we do not use small probabilities ($p$ < 0.3), so distortion of the subjective probability proposed in Prospect Theory (Tversky & Kahneman, 1992) does not play a crucial role. $p$ and $r$ are systematically varied to decouple the expected value of the reward from its mathematical variance. The sure payoff had a fixed value of 30TT. We set the gambles such that the risk-neutral participants choose gambling in nearly half of the trials (see Fig S.1).

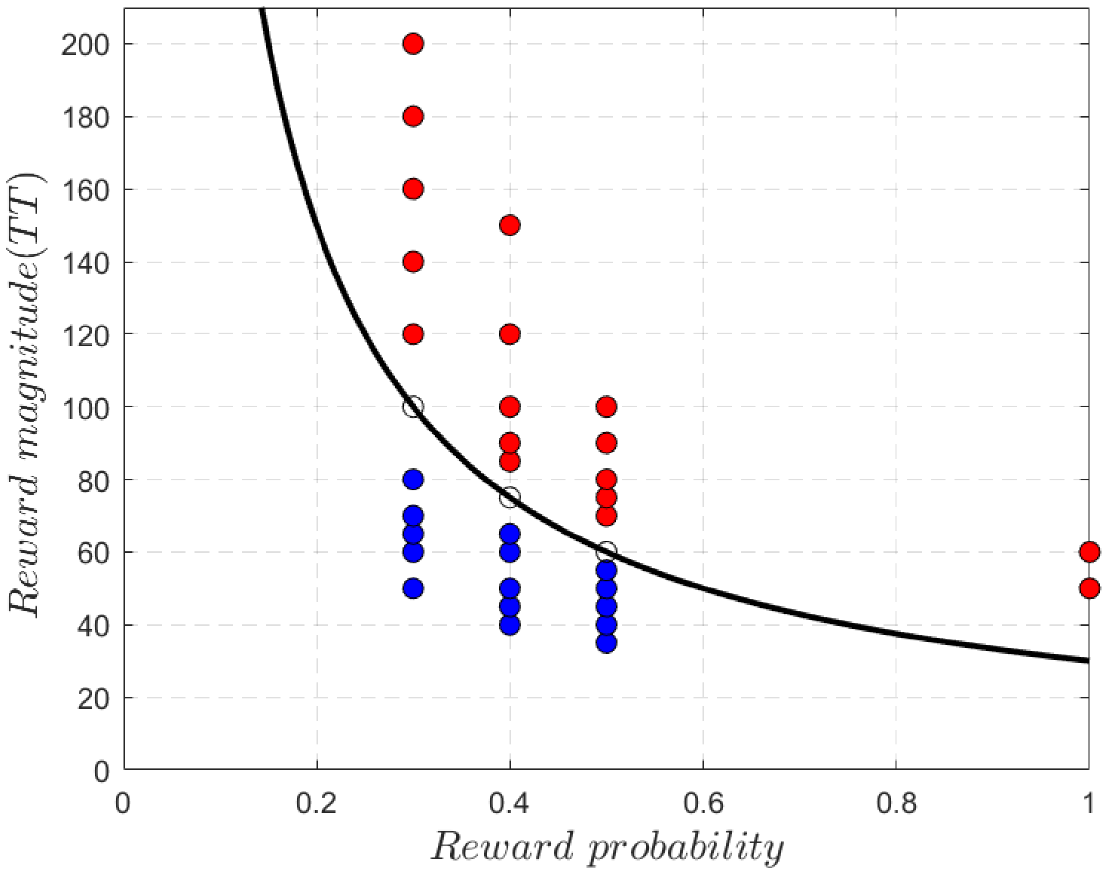


**Fig. S1**. Set of 35 gambles which were presented in each self-session. These gambles were also used to simulate agents' choices during prediction sessions. Each point represents a unique gamble, which is distinguished from others by its probability and the magnitude of its reward. A red color code represents gambles that risk-neutral individuals would accept, and a blue color code represents gambles that risk-neutral individuals would reject. Under a risk-neutral attitude, the solid black homographic graph illustrates a curve of indifference, where the gamble is as valuable as the sure option (30TT). Those points on the indifference curve remain unfilled, showing that risk-neutral individuals have no preference for those options. Two distinct points appear on the right side of the plot, which correspond to two risk-free gambles used in this experiment (reward probability is one, magnitude is 50TT and 60TT). As a matter of fact, at the time of the experiment, 1$ was equal to 4.2TT in terms of currency. ( TT: Thousand Iranian Tomans)



Computational Model of decision making under risk

In our study, participants' attitudes toward risk were estimated through the widely used computational framework (Blankenstein et al., 2016; Braams et al., 2021; Levy et al., 2010;

Tymula et al., 2012). The power utility function(Bernoulli, 1954) is used to model the subjective value of a risky option:

$$U_{Risky}(r,p) = p\, r^{\rho} \qquad \text{Eq. (S.1)}$$

$\rho$ represents the risk attitude of the participants. $\rho$ is less and greater than 1 if he is risk-averse and risk-taker, respectively. $\rho$=1 indicates risk neutrality. The following Softmax function was employed to model the probabilistic nature of choice in the model of behavior Eq. (S.2). Based on the difference between the expected utility of the two options, the Softmax function calculates the probability that a decision-maker will choose the gambling option(Ciranka & van den Bos, 2019).

$$\Pr(chose\ risky\ gamble) = \frac{1}{1 + \mathrm{e}^{-\beta * (U_{risky} - U_{sure})}} \qquad \text{Eq. (S.2)}$$

In Eq. (S.2), $\beta$ is a non-negative free parameter that models the degree to which the choice probability relates to the utility difference. As $\beta$ becomes smaller, choices become more random. It should be noted that this risk attitude estimation method is highly consistent with other commonly used model-based and model-free methods (Suzuki et al., 2016).

We set lower and upper bounds on the risk attitude $\rho$ such that the estimated risk attitude always falls between 0.8 and 1.2. This range was found based on a computer simulation procedure. We simulated subjects with a variety of risk attitude characteristics. 100 simulations were run for each value of $\rho$. For all simulations, $\beta$ is set to 5. Fig S.2 illustrates the probability of accepting the gamble for various values of $\rho$. Based on the simulations, subjects with a risk attitude of less than 0.8 rejected gambling, and subjects with a risk attitude greater than 1.2 chose gambles in over 90% of the trials. Therefore, risk attitudes greater than 1.2 and smaller than 0.8 results in a low variation in choice patterns. After fixing this range, we feed the behavioral data into the optimization algorithm.

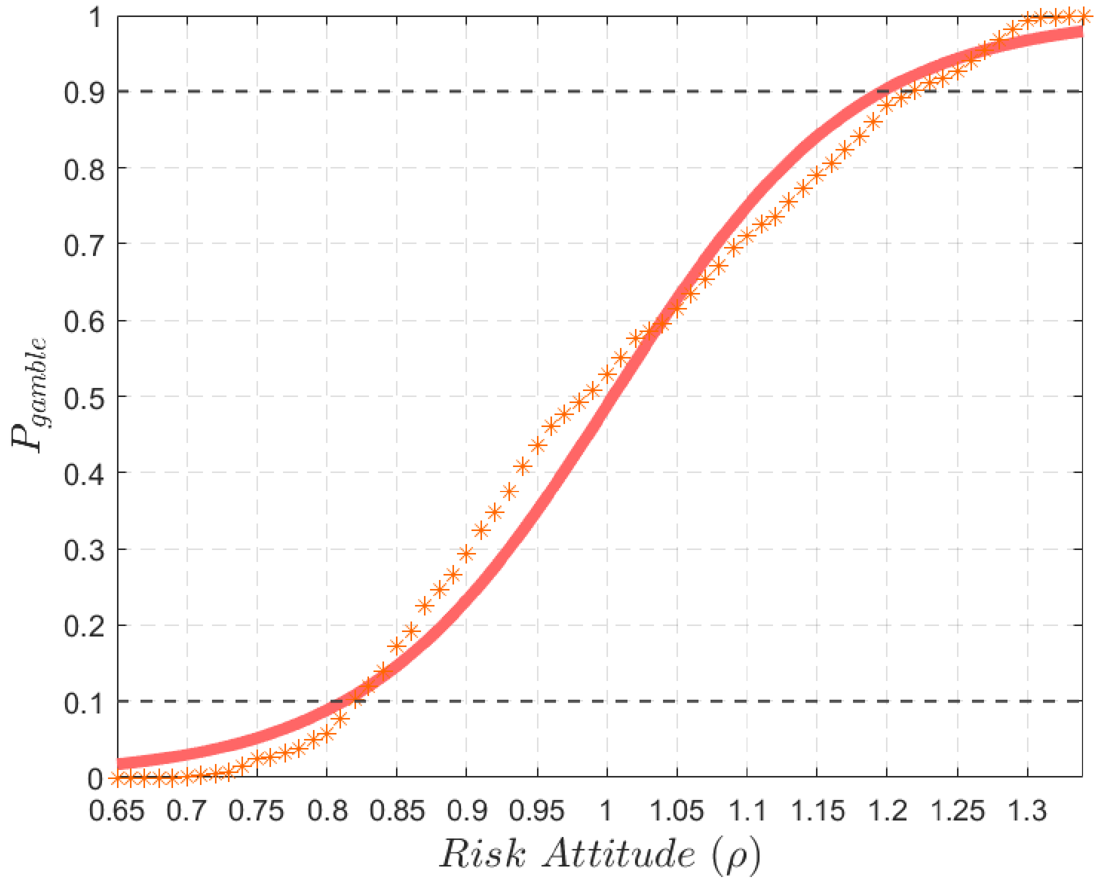


**Fig. S2**. The acceptance rate of gambling by artificial agents in terms of risk attitude ($\rho$). In each simulation run, the proportion of trials in which artificial agents with a preset risk attitude chose the gambling option over the sure option is recorded. We repeated 100 simulations for each risk attitude value. Each star (*) represents the average of these simulations. As per behavioral psychology, the psychometric function (red line) treats gambling probability as a function of risk attitude. This was achieved by fitting the Logit function to star points using the MATLAB function 'glmfit'.



To ensure the reliability of estimation, we simulated choices under different risk attitudes. We used the same set of gambling options and the same number of trials as in the original experiment. These choices were re-fitted based on our computational model. The recovery procedure appears to be highly accurate as can be seen in Table S.1

**Table S.1** recovery of risk attitude parameter

| $\rho$ | $\hat{\rho}$ |
|---|---|
| 0.81 | 0.80 |
| 0.85 | 0.84 |
| 0.89 | 0.90 |
| 0.93 | 0.93 |
| 0.97 | 0.97 |
| 1.01 | 1.03 |
| 1.05 | 1.03 |
| 1.09 | 1.08 |
| 1.13 | 1.11 |
| 1.17 | 1.18 |

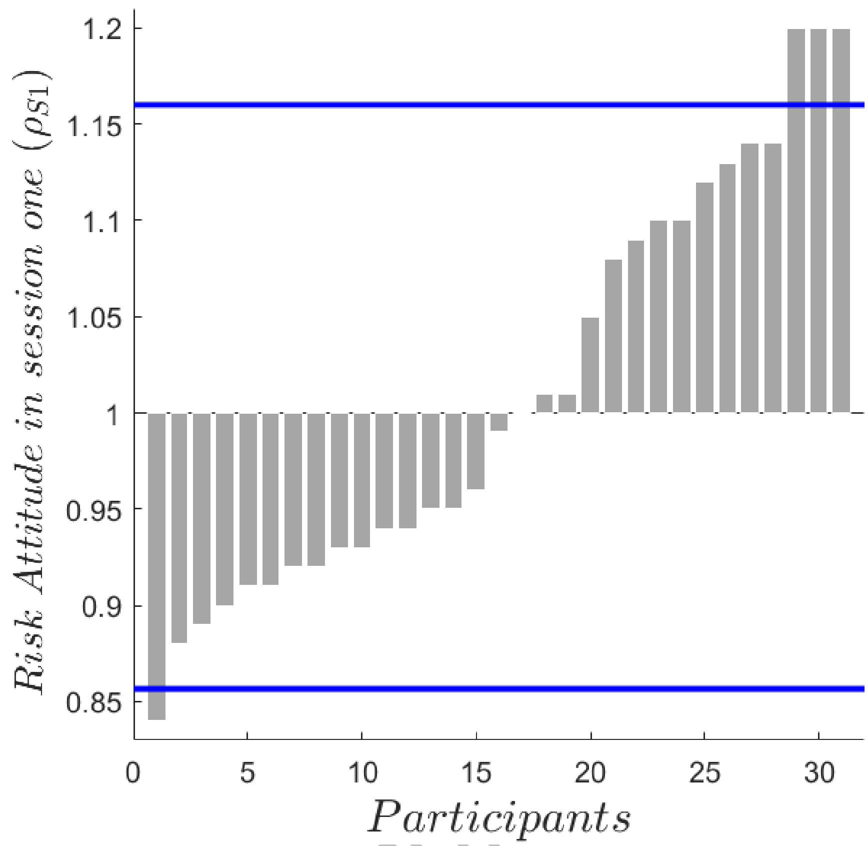


**Fig. S3**. Overview of baseline risk attitudes. Bars show participants' estimated risk attitudes in session one before predicting their peers' decisions. The values above/below one indicate risk-seeking/risk-aversive behaviors, respectively.

Blue lines show the average risk attitude of risk-seeking and risk-averse peers separately. For simulated risk-seeking peers, $\rho$ was 0.86 (SD=0.01), while for simulated risk-averse peers $\rho$ was 1.16 (SD=0.01).

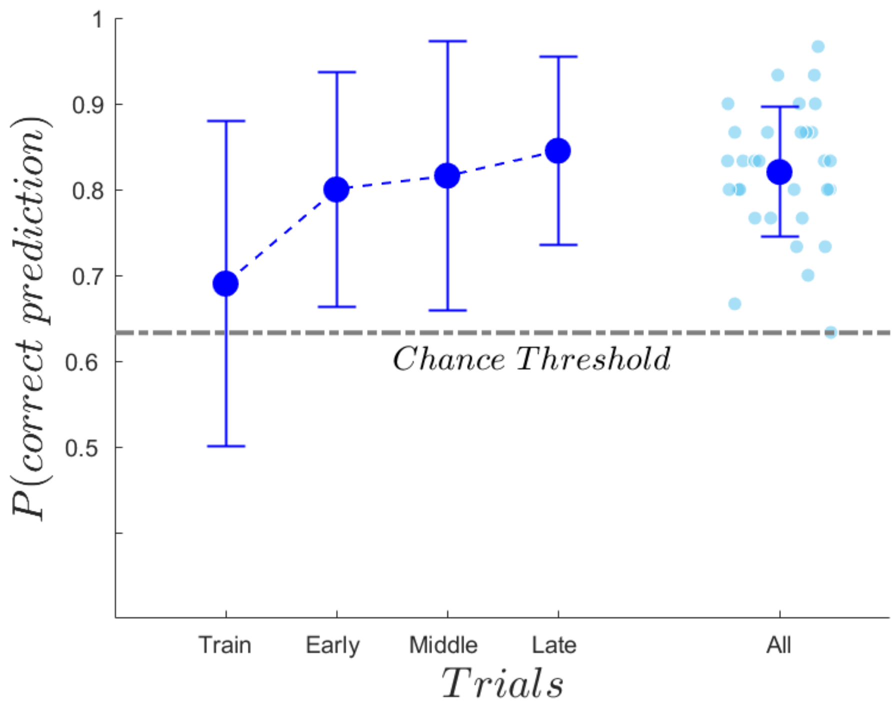


**Fig. S4**. Performance in the prediction session. The graph shows the proportion of correct predictions over time in Predict trials (session two). For each interval, the points represent the average correct prediction (and the error bars represent the standard deviation). The graph on the right shows performance for all trials. The dots on the right graph show the performance of each participant separately.

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