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Developmental patterns of change in the influence of safe and risky peer choices on risky decision-making

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Abstract
Adolescents take more risks when peers monitor their behavior. However, it is largely unknown how different types of peer influence affect adolescent decision-making. In this study, we investigate how information about previous choices of peers differentially influences decision-making in adolescence and young adulthood. Participants (*N* = 99, age range 12–22) completed an economic choice task in which choice options were systematically varied on levels of risk and ambiguity. On each trial, participants selected between a safer choice (low variability in outcome) and a riskier choice (high variability in outcome). Participants made choices in three conditions: a solo condition in which they made choices with no additional information, a social condition in which they saw choices of supposed peers, and a computer condition in which they saw choices of a computer. Results showed that participants' choices conform to the choices made by the peers, but not a computer. Furthermore, when peers chose the safe option, late adolescents were especially likely to make a safe choice. Conversely, when the peer made a risky choice, late adolescents were least likely to follow choices made by the peer. We did not find evidence for differential influence of social information on decisions depending on their level of risk and ambiguity. These results show that information about previous decisions of peers are a powerful modifier for behavior and that the effect of peers on adolescents' decisions is less ubiquitous and more specific than previously assumed.

1 | INTRODUCTION

Adolescence, the phase of the lifespan between childhood and adulthood, is a period of life associated with wide-ranging social, emotional, and cognitive development. During this time, there are normative changes in social attunement (Blakemore, 2008; Steinberg & Morris, 2001), reward-related motivation (Defoe, Dubas, Figner, & van Aken, 2015), and future oriented thinking (van den Bos, Rodriguez, Schweitzer, & McClure, 2015). One possible manifestation of these complex, co-developing processes is the phenomenon of peer influence on decision-making. A host of data on adolescents' risky behaviors indicates that they are more subject to peer influence when engaging in risk taking behavior in the real world (Eaton et al., 2010). Peer influence on risk taking is an important public health issue, in that risk taking during adolescence can result in both short-term and lifelong negative consequences. One example is the increased crash rate of adolescent drivers with peer passengers compared to driving alone (Simons-Morton, Lerner, & Singer, 2005). The present study aims to expand our understanding of when adolescents are subject to peer influence by testing how information about the previous choices of peers influences adolescent and adult decision-making.

Laboratory research can help reveal the mechanisms of the complex phenomenon of peer influence on adolescent decision-making. It is important to consider that 'peer influence' is a multi-layered phenomenon (Trautmann & Vieider, 2012) that can range from active monitoring by peers (Cascio et al., 2015; Kretsch & Harden, 2014) to subtle manipulations of social norms (Paluck & Shepherd, 2012). For example, previous work has demonstrated that adolescents tend to make riskier decisions when being actively monitored by a peer who

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is in the room (Chein, Albert, O'Brien, Uckert, & Steinberg, 2011) or in a virtual context (Van Hoorn, Van Dijk, Guroglu, & Crone, 2016). Other studies have operationalized peer influence differently such as providing information about how risky peers rated a situation (Knoll, Magis-Weinberg, Speekenbrink, & Blakemore, 2015).

One less understood form of peer influence is receiving information about the decision-making preferences of other peers. This form of peer influence is common in the real world. For instance, after a party an adolescent might decide to drive home after drinking alcohol if they have seen their peers make the same decision in the past. Previous studies using choice information about other participants' decisions showed that choice information from peers is a powerful modifier for behavior (Asch, 1951; Chung, Christopoulos, King-Casas, Ball, & Chiu, 2015; Klucharev, Hytönen, Rijpkema, Smidts, & Fernández, 2009; Welborn et al., 2016; Zaki, Schirmer, & Mitchell, 2011). The design of the current study was based on a study in adults (Chung et al., 2015). In this study, participants changed their choice preference towards more risky choices when other participants had selected the risky option and towards more safe choices when the other participants had selected the safe option. In the current study, we used a similar design to test the influence of decision-making preferences by showing participants the choices of their peers to evaluate whether adolescents are more likely to follow the risk preferences of others.

Like peer influence, decision-making is also composed of several underlying subprocesses. Classic economic decision theory has demonstrated two important factors that predictably bias decisions in adults: risk and ambiguity (Levy, Snell, Nelson, Rustichini, & Glimcher, 2010; Tversky & Kahneman, 1992). When making choices between options with variable outcomes, risk refers to choices with known probabilities of outcomes, whereas in an ambiguous choice the probabilities of outcomes are unknown. Recent studies have investigated whether increased tolerance for risk and/or ambiguity could explain increased engagement in risky behaviors, such as drinking alcohol, in adolescence. Regarding risk tolerance, studies have found mixed results in which some studies find increases in risk tolerance in adolescence (Braams, van Duijvenvoorde, Peper, & Crone, 2015; Powers et al., 2018; van den Bos & Hertwig, 2017), whereas others have not found differences between adolescents and adults (Blankenstein, Crone, van den Bos, & van Duijvenvoorde, 2016; Van Leijenhorst, Westenberg, & Crone, 2008). Three studies so far have compared ambiguity tolerance between adolescents and adults. These studies found that adolescents are more tolerant towards ambiguity than adults (Blankenstein, Peper, Crone, & van Duijvenvoorde, 2017; Tymula et al., 2012; van den Bos & Hertwig, 2017). Previous studies have shown that peer influence can increase risky decision-making (Cascio et al., 2015; Chein et al., 2011).

However, it is currently unknown whether increases in engagement in risky behavior under peer influence are driven by changes in risk tolerance, ambiguity tolerance or both. One possibility is that participants follow choices of others regardless of decision type, that is, risky vs. ambiguous. This could be due to social processes such as conformity. Conformity refers to changes in behavior to match behavior of others (Cialdini & Goldstein, 2004). If conformity is the driving factor of behavioral change we would expect to see participants altering their choices to match the peers' choices, but we would not expect to see differential effects of peer influence on risky and ambiguous choices. Another possibility is that peers selectively alter risk or ambiguity tolerance. Information about peers' risk could selectively influence participants' risk (but not ambiguity) tolerance if information about peers' choices alters explicit expected value computations to be more aligned to the peer's choice. In ambiguous situations, there is less information on which to base a decision since the probabilities of obtaining the rewards are unknown. Potentially, adults and adolescents are influenced through the same mechanisms, but due to the enhanced importance of peers in adolescence, adolescents might value and incorporate the choices of others more than participants of other ages, resulting in higher peer influence in adolescence. The current study investigates developmental changes in effects of information about others' choices on risky decision-making and whether these changes in risky decision-making are driven by changes in risk or ambiguity tolerance. Participants performed a monetary decision-making task in which they made choices between a safer and a more risky option. Choice options were systematically varied on levels of risk and ambiguity. For some decisions, participants received information about the choices of supposed peers of a similar age who had completed the study previously. To isolate the influence of social information on risky and ambiguous decision-making, these trials were compared to a solo condition in which participants made the same decisions but without seeing any information about other participants' choices.

Choices of supposed peers were manipulated to sometimes select the safer option and sometimes select the risky option. Importantly, participants were never instructed to follow the choice of the other participant or the computer; thus any changes from baseline can be inferred to result from the spontaneous use of that information by the participant. We hypothesized that adolescents would be more likely to follow choice preferences from peers and that adolescents would be especially likely to follow others' risky choices. Furthermore, we expected that peer influence would be

RESEARCH HIGHLIGHTS

- We investigated developmental changes in the impact of peers' choices on risky and ambiguous choices.
- Social information is a more powerful modifier than computer-generated information.
- Adolescents are most influenced by safe decisions of others, and this age group was least influenced by risky decisions of others.
- We show that the effect of peer on adolescents' decisions is less ubiquitous and more specific than previously assumed.

more prominent in certain decision contexts. Based on previous work (Chung et al., 2015) we hypothesized that social information will change risk preferences and that social information would be an especially strong modifier for behavior in ambiguous choice situations. In ambiguous choice situations there is less information to guide decision-making. We expected that extra information, in this case information about others' choices, could therefore be utilized more by participants. Lastly, we aimed to disentangle the influence of a social agent's choices in particular from the availability of information more generally, so we included a third condition in which participants saw choices of a non-social agent (i.e. a computer). Altogether, this study will shed light on developmental changes in the interaction between social information and different aspects of a complex decision-making process. Understanding these complex interactions will allow us to better understand adolescent risky decision-making.

2 | METHODS

2.1 | Participants

One hundred and fourteen participants between 12–22 years old participated in the study. Eleven participants were excluded because they made less than 5% or more than 95% risky choices (M_{age} = 19.3, $Range_{age}$ = 13.7–22.4), meaning that they did not scale their choices to reflect differences in probability of winning the high amount of money (see task design). Six participants were excluded from analyses because they did not believe that the supposed peers were real people (M_{age} = 19.8, $Range_{age}$ = 18.0–22.4). Two participants were excluded based on both criteria, meaning that the total number of excluded participants was 15. The total sample for analyses contained 99 participants (47 males), M_{age} = 17.1, $Range_{age}$ = 12.1–22.7). A chi-squared test did not indicate a difference in sex distribution across age ($\chi^2(10) = 6.56$, p = 0.765 (note that age was binned per year for this analysis, see Supplemental Figure 1). All data were checked for outliers. When appropriate, robust analyses were run if possible, which downweight the influence of extreme scores and therefore provide a more stable estimation of parameters. As there are no robust alternatives for nonlinear mixed effects models, participants who changed their choices more than 3 standard deviations of the mean were excluded for the social information conditions. This resulted in exclusion of one additional participant in the social safe condition and one additional participant in the social risky condition. Note that these participants' data were included for the other conditions.

Since no prior work has investigated developmental changes in social influence it was not possible to use effect sizes of prior work in a power analysis to determine sample size a priori. However, the sample size for the current study was chosen based on a task previously used in an adult sample (Chung et al., 2015). In this study participants saw risky and safe choices of others. Based on effect sizes of changes in behavior in this study (following towards a risky choice: Cohen's d = .75; Following towards a safe choice: Cohen's d = 1.0; see Chung et al., 2015) we would need 16 subjects to reach 80% power at α error probability $p < 0.05$ in an adult sample based on the smaller effect size of the two. However, in the current study the main analysis of interest is not a paired t test, but a non-linear mixed effects model to detect age-related changes. Furthermore, we included an ambiguity manipulation and we were interested in an interaction between age, social condition, ambiguity, and risk. We doubled the original sample size to account for the addition of the ambiguity factor and again doubled the sample size to ensure sufficient representation of participants across age. Therefore, we collected usable data from at least four times the number of participants resulting from the power analysis. As this was an estimation of minimal needed power, we opted to acquire additional data until we acquired approximately 100 usable participants.

The total duration of the session was 2 hours. Participants were paid $20 for participation and received additional bonus money. Participants believed that bonus money was related to performance on the task, whereas in actuality all participants received $5 bonus money at the end of the task. Recruitment was performed in the Boston-Cambridge area using an online recruitment platform and a participant database. Care was taken to match the adult sample to the community sample of minors by recruiting members of the general public and limiting the number of Harvard undergraduate students in the adult sample. In the adult sample the total percentage of Harvard undergraduate students was 35%. Adult participants provided informed consent; parent permission and participant assent were obtained for minors. This study was approved by the Committee on the Use of Human Subjects at Harvard University.

2.2 | Task

2.2.1 | Social manipulation

Participants were led to believe that in the social condition they would see choices of previous participants, which were actually experimentally manipulated to depict certain profiles of risk preference. Before the start of the task, participants rated 15 pictures of similar aged and gender matched individuals. Participants rated these individuals on seven different questions assessing dimensions such as niceness, friendliness and popularity (see Supplementary Materials for details). Ratings were made on a continuous scale with anchors 'not at all' and 'extremely'. Participants indicated their rating with a slider on the scale. Participants were told that these people were previous participants in the study and to make it believable that we took a picture of previous participants, the experimenter also took a picture of the participant. To ensure that participants saw choices of those individuals that they were most interested in, participants were asked to select three individuals for whom they would see choices in the task. Selected individuals received higher ratings on each of the seven different dimensions, that is, attractiveness, possibility of becoming friends, niceness, popularity, similarity, whether the participant thought the other person was more attractive and whether the participant thought the other person was more popular, than non-chosen individuals (see Supplementary Materials).We then randomly assigned each of these peers to three decision-making types: a risky peer, a safe peer and a neutral peer. The 'Neutral peer' made 50% risky choices and 50% safe choices. We intended to show 75% risky choices for the 'Risky peer' and 75% safe choices for the 'Safe peer'. However, due to a technical error 69 participants saw 77% risky choices for the 'Risky peer', and 76% safe choices for the 'Safe peer'. Note that despite the slight difference in which peer made the choices, in total all participants saw 50% of social information trials where a hypothetical peer endorses the risky choice, and 50% where a hypothetical peer endorses a safer choice.

Peers' choices appeared intermixed during the social block, and were analyzed for trial-by-trial adaptation of the participants' risk preferences to match the risky or safe choices of the peer. The analysis targets shifts in choices at the level of individual trials, not based on whether the participant shifted their choice toward the individual peer who tended to make mostly risky or mostly safe choices. Participants were fully debriefed about the social manipulation at the end of the session.

2.2.2 | Trial structure

On each trial, participants viewed two lotteries that varied in risk and ambiguity over trials, and chose their preferred lottery. Lotteries were represented graphically as bars with the colors of the bars representing the chance of winning different amounts (see Figure 1). Trials started with a 1s onset screen showing 'New Round' followed by a display of the two lotteries. After 6s the participant could indicate their choice (free response) after which their choice was displayed for 2s. In total, the task consisted of 300 trials, 60 per condition (see below).

In each trial, both lotteries had the same probability of winning, but the amount of money that could be won with each lottery varied systematically. Within each pair, for one of the lotteries the amounts of money were less different, hereafter referred to as the 'safer' option (lower outcome variability), and for the other lottery the amounts were more different, hereafter referred to as the 'risky' option (greater outcome variability). High and low amounts were based on Chung et al. (2015) and divided by 10 to make the amounts that could be won on each trial more appropriate for a developmental population. For the safer options, the difference between the high and low amount varied from \$0.06 to \$1.01, and for the risky options, the difference between the high and low amount varied from \$3.63 to \$5.51. The probability of winning the high amount of money varied between 40% to 90% with increments of 10% (see Figure 1).

For some trials, part of the bar was occluded, introducing ambiguity. Levels of ambiguity varied between 0% and 80% with increments of 20% (see Figure 1). In total there were eight different counterbalanced trial presentations. Probabilities of winning the high amount were presented in either blue or red, the location of the high and low amount were presented on the top or bottom of the bar, and safer and risky choices were presented on either the left or right side of the screen. Counterbalance was assigned between subjects, that is, participants were assigned to one trial presentation and this was held consistent throughout the task.

2.2.3 | Conditions

The task was composed of three blocks. In the solo block, participants made choices and did not see any other information, which was used to quantify baseline risk preferences. During the social block, participants saw the supposed previous choices of other participants while making their choices. Trials in the social block displayed a name and a picture of one other (supposed) participant along with a green rectangle above his or her selection (see Figure 2). Choices of the peers (i.e. risky peer, safe peer and the neutral peer) were presented intermixed in the social block. During the computer block, participants saw the random choices of a computer serving as a comparison condition in which additional information about another choice was available but devoid of a social target. In the computer block, the screen displayed the choice of the computer (denoted by a computer icon), which randomly selected one of the lotteries. The computer's choice was displayed above the bars and was indicated by a green rectangle.

In total this resulted in five conditions: solo, computer safe, computer risky, social safe and social risky. The order of the blocks (solo, social, computer) was fully counterbalanced between subjects, achieved by randomly assigning participants to one of six counterbalanced block orders. A chi-square test did not support the possibility that counterbalance orders was dependent on age ($\chi^2(70)$ = 70.18, p = 0.47).

2.2.4 | Raven progressive matrices

To exclude the possibility that differences in non-verbal fluid intelligence drove choice behavior, participants completed a nine-item abbreviated version of the Raven Standard Progressive Matrices Test. Selection of items was based on Bilker et al. (2012). Data were missing for one participant.

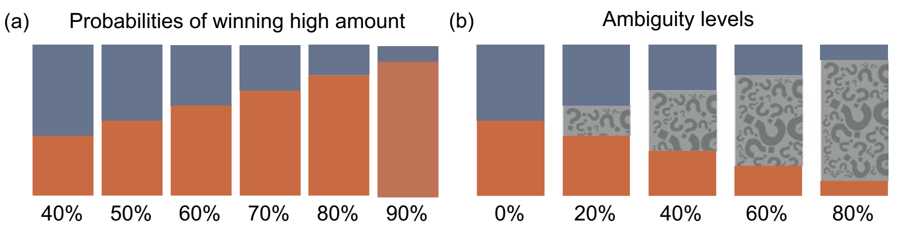

FIGURE 1 Display of the different probability levels (panel a) and ambiguity levels (panel b) used in the task. In the task all ambiguity levels could be paired with all probability levels

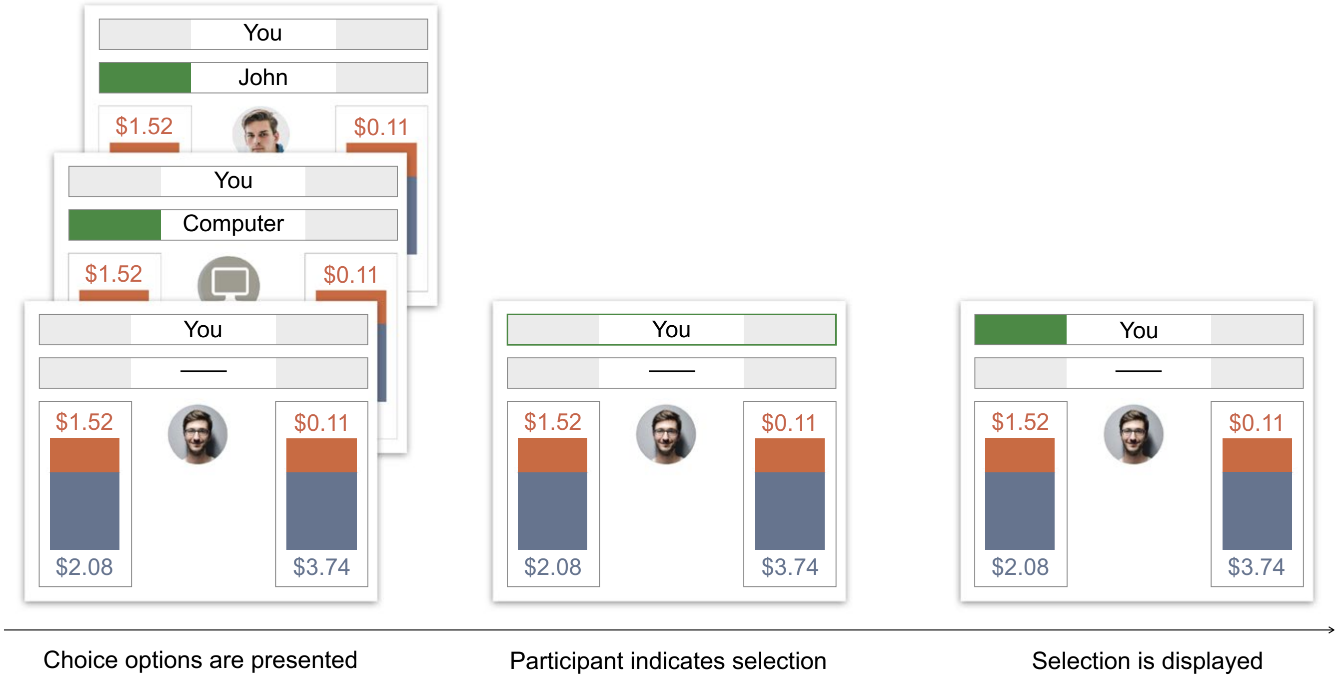

FIGURE 2 Task design. Trials started with a screen showing 'New Round' (not displayed). Participants were then presented with a screen on which they could see the choice options. In the social condition, participants saw a picture of the other person and the choice of the other person, displayed as a green bar over the selection. Other people were the same gender and age category as the participants. The example displays an 18–22-year-old male. In the computer condition, participants saw a computer icon and the word 'computer' along with the selection. After 6 seconds, the selection activated (denoted by green outline) and the participant indicated their own selection (self-paced). Trials ended with a 2-second display of their choice, denoted in green above the selection

2.3 | Procedure

Participants were tested in a quiet room. After consenting, participants received an explanation about the task and were led through guided practice with the experimenter to ensure that each participant understood the task. Comprehension of the probabilities and ambiguity was confirmed during the practice by the experimenter. Participants then completed the task. After the task participants filled out the Raven short. The session ended with debriefing and payment. A funnel debrief was used to assess whether participants believed that the choices were made by other previous participants. In the debriefing interview, participants were first asked to describe how they made choices and whether they paid attention to the choices of others. If participants indicated that they did not pay attention to the choices of others we asked them if there was a specific reason why they did not pay attention to those choices. If participants said they did not believe that the choices were made by other people, they were excluded from analysis, see Participants section for more details.

2.4 | Data analysis

The goal of the study was to identify how risky and ambiguous choice behavior are influenced by social information and to investigate how the influence of social information changes over development. The dependent variable in all mixed effects models was choice on the trial-by-trial level. Risky choices were coded as 1 and safer choices as 0. Choice data in the solo condition were inspected for normality. Choice data ranged between 5% and 90% average risky choice. The average percent risky choice in the solo condition was 33%.

We included risk and ambiguity level of the lottery to test how these variables influenced percent risky choice. Within pairs of choice options on a given trial, we define the riskier option as the one with higher outcome variability (greater range between winning and losing amounts; Levy et al., 2010; Tymula et al., 2012). We then computed the expected value for each choice option and subtracted the risky from the safe expected value as a predictor of choice. For example, if for the risky option the chance of winning \$3.72 was 60% and the chance of winning \$0.11 was 40%, the expected value for this option was (0.6*\$3.72) + (.4*\$0.11) = \$2.27. If for the safe option the chance of winning \$2.44 was 60% and the chance of winning \$2.30 was 40%, the expected value of this option was (0.6*\$2.44) + (0.4*\$2.30) = \$2.38. In this example, the expected value difference would be \$−0.11, indicating that based on expected value the safe option would be the mathematically optimal choice. These values were entered into analyses; representing the difference in expected value would be required to shift participants away from the safe choice, a proxy for risk aversion.

Expected value differences ranged between −\$0.41 and \$2.35, with negative values indicating that the safe choice was more mathematically advantageous and positive values indicating the risky choice was more advantageous. These values were skewed positively to provoke participants to overcome natural risk aversion, consistent with prior work. Ambiguity level of the choice was included as a continuous variable and could take values of 0%, 20%, 40%, 60% and 80%. Interactions between age, expected value difference and ambiguity were tested to investigate whether expected value difference and ambiguity differentially affected choice behavior for the different ages. Lastly, interactions between condition, age, expected value and ambiguity were tested to investigate whether the magnitude of change in the influence conditions was differentially dependent on expected value difference and ambiguity for the different ages.

To test how different sources of information affect choice behavior, we included conditions in which participants were informed about choices of a computer and previous choices of participants. Before testing mixed effects models, we performed a repeated measures ANOVA to test whether participants changed their average percentage risky choices in the information conditions, independent of any other factors such as risk level, ambiguity level and age. In the repeated measures ANOVA we included factors 'condition' with levels 'social and computer' and the factor 'others' choice' with levels 'risky' and 'safer'. If the ANOVA was significant, we followed up using paired *t* tests to determine which conditions were significantly different from solo. In the mixed effects models we then aimed to parse out which factors were related to changes in risky choice. In the mixed effects models, condition was included in the models as a factor with levels solo, social risky, social safe, computer risky, computer safe. In all models in which condition was included, the solo category served as the reference category. Any significant effects for condition can therefore be interpreted as a difference between the condition of interest and the solo condition. To test whether magnitude of change in risky choice was different with age we tested for condition by age interactions. A significant interaction would mean that the magnitude of change in percent risky choice is stronger for some ages than for others.

To test for developmental effects, we included age in the models as a predictor. To detect different age-related patterns of change, we included predictors for linear and quadratic (adolescent-peaking) age. Models with a quadratic predictor of age also included the linear predictor for age. These age terms were not collinear (r = 0). Significant linear effects would indicate a continuous increase or decrease over age. Based on previous literature (Braams et al., 2015; Defoe et al., 2015) we hypothesized quadratic effects of age. The age range of our sample (12–22 years) was chosen such that significant quadratic effects of age would indicate effects that show highest or lowest values in late adolescence.

We used non-linear mixed effects models to determine best fitting models to the data. All models were fitted with full information maximum likelihood estimation. Model fitting was performed using R (R Core Team, 2014) and package lme4 (Bates, Mächler, Bolker, & Walker, 2015). As choice on the trial-by-trial level is a dichotomous variable, logistic regressions were used. A model with an interaction between the linear and quadratic predictor for age and condition and an interaction between expected value difference and ambiguity would be modeled as follows:

$$\begin{aligned}&\text{model} < -\text{glmer(choice} \sim \text{poly(Age,2,raw} = \text{TRUE)} * \text{Condition} + \\ &\text{Ambiguity} * \text{EVDifference} + (1|\text{participantID}), \text{data} = \\ &\text{data, family} = \text{binomial, control} = \text{glmerControl (optimizer} \\ &= \text{'bobyqa'), nAGQ} = 10)\end{aligned}$$

Models were compared based on the Akaike Information Criterion (AIC; Akaike, 1974). AIC is a goodness of fit parameter that takes into account the number of parameters. Lower AIC values indicate better model fit. All reported parameters for best fitting models are unstandardized. Improvement of model fit was compared against a null model in which a fixed and random intercept were included, but no predictors of interest. Log likelihood ratio tests were employed to formally test improvement of model fit for nested models.

3 | RESULTS

The aim of the current study was to investigate how information about peer choice changes risky decision-making across age. The results are built up in three steps. We first fitted non-linear mixed effects models on the solo condition to establish baseline choice behavior. We then tested whether the information conditions (i.e. social and computer) change risky decision-making. In the last step we investigated developmental effects of social information.

3.1 | Choice behavior in the solo condition

Before testing effects in the information conditions, we first determined the best fitting model for the solo condition. This analysis informs base attitudes towards risk and ambiguity across age. Model fitting was performed in two steps. We predicted that the difference between the expected values for the safer and risky options and the ambiguity of the lotteries would modulate participant choices. Therefore, we fitted models including predictors representing the difference in expected value between the safer and risky lotteries, and ambiguity of the lotteries. We compared a null model with a fixed and random intercept against four alternative models: (i) fixed main effect of expected value difference, (ii) fixed main effect of ambiguity, (iii) a fixed main effect of expected value difference and fixed main effect of ambiguity, and (iv) a fixed main effect of expected value, fixed main effect of ambiguity and an interaction effect between expected value difference and ambiguity. Results showed that a model with an interaction effect between expected value difference and ambiguity of the choice best described the choice data in the solo condition (see Table 1 for model fit and parameter estimates).

After determination of the best fitting model (EV difference * Ambiguity) we added age to this model to investigate improvement

TABLE 1 Effective degrees of freedom (*df*) and AIC values for models with expected value difference and ambiguity for the solo condition

	Model	df	AIC	Log lik.	
Step 1					
Null model (fixed and random intercept only)	1	2	6627		
EV difference	2	3	5688	1 vs. 2	$p < 0.001$
Ambiguity	3	3	6025	1 vs. 3	$p < 0.001$
EV difference + ambiguity	4	4	4945	3 vs. 4	$p < 0.001$
EV difference* ambiguity	5	5	4649*	4 vs. 5	$p < 0.001$
Step 2					
Age^1 + EV difference* ambiguity	6	6	4648		
Age^2 + EV difference* ambiguity	7	7	4650	6 vs. 7	$p=0.581$
Age^{1*} EV difference* ambiguity	8	9	4642	7 vs. 8	$p=0.003$
Age^{2*} EV difference* ambiguity	9	13	4633*	8 vs. 9	$p=0.002$

Note. Preferred models (indicated by *) were selected based on AIC values. EV difference refers to the difference in expected value for the safer and the risky option. Age^1 refers to the linear predictor of age, Age^2 refers to the quadratic predictor of age. Note that for the models with a quadratic age term the linear age term was always included as well. Models with interaction effects also included a main effect for these factors. Log lik refers to a log likelihood ratio test.

of model fit. Four additional models were fitted. All four additional models included the interaction between expected value and ambiguity. In addition to this interaction, two models included a main effect of age: (i) one model with only a linear fixed main effect for age, and (ii) one model with both a linear and a quadratic fixed main effect for age. Two models included both a main effect and an interaction effect of age: (iii) one model included a fixed main effect of the linear age and an interaction between the linear fixed effect of age, expected value difference and ambiguity, and lastly (iv) one model included a fixed linear main effect of age, a fixed quadratic main effect of age and interactions between the linear predictor of age, expected value difference and ambiguity, and the quadratic predictor of age, expected value difference and ambiguity.

Model comparison showed that model iv with an interaction effect between the quadratic predictor for age, expected value difference and ambiguity was the best fitting model (see Table 1, Table 2 and Figure 3). In this model, there was a significant linear main effect of age showing that risky choice decreased with age. Furthermore, there were main effects of expected value difference and ambiguity. The main effect of expected value difference showed that participants were increasingly more likely to select the risky option as the expected value difference between the safe and risky option increased. This effect was in the expected direction since for choice pairs with a higher expected value difference, the risky choice was the mathematically more optimal choice. The main effect of ambiguity showed that participants were less likely to select the risky option as ambiguity of the choice increased. This is in line with ambiguity aversion.

The three-way interaction between age, expected value difference and ambiguity indicated that the interaction between expected value difference and ambiguity changed with age. Visual inspection of the two-way interaction between expected value difference and ambiguity indicated that participants discriminated more between mathematically optimal (i.e. higher expected value) and less optimal choices as ambiguity decreased. In other words, when ambiguity was high, participants refrained from choosing the risky option even when this was mathematically the more optimal decision. When ambiguity was low, participants chose the risky option more often when this was the mathematically more optimal choice. The three-way interaction indicated that expected value difference and ambiguity differentially interacted with age. Visual inspection of the plots in Figure 3 showed that risky choice decreased over age, except for the condition where ambiguity was low and the risky option was the mathematically optimal choice. In this case, there was no change in percent risky choice across age. Note that although a model with a quadratic predictor for age fit the data best, the quadratic predictor for age was not significant. This shows that the quadratic predictor explains some amount of meaningful variance, but does not itself reach significance. In this case we interpret the significant age terms, which in this case was a linear interaction with age. The plots in Figure 3 therefore depict the linear effects of age.

3.2 | Choice behavior in the information conditions

To evaluate the influence of the social- and computer-delivered information, we first tested whether participants' average percentage of risky choice changed as a factor of the information conditions. A repeated measures ANOVA was performed with percent risky choice as the dependent variable and condition (social vs. computer) and others' choice (risky vs. safe) as the manipulated variables. Percent risky choice was aggregated per participant and per condition. This analysis

TABLE 2 Parameter estimates for all parameters in the best fitting model for the solo condition

	Variance	B	Std error	z	p
Random effect					
Intercept	2.77		1.67		
Fixed effects					
Intercept		−2.58	0.32	−8.10	<0.001***
Age^1		−0.17	0.06	−2.69	0.007**
Age^2		0.03	0.02	1.10	0.270
EV difference		3.33	0.18	18.60	<0.001***
Ambiguity		−0.77	0.36	−2.13	0.033*
Age^1* EV difference		0.12	0.03	3.83	<0.001***
Age^2* EV difference		−0.04	0.01	−2.92	0.003**
Age^1* Ambiguity		0.09	0.07	1.41	0.159
Age^2* Ambiguity		0.02	0.03	0.80	0.425
EV difference* Ambiguity		−3.76	0.34	−11.16	<0.001***
Age^1* EV difference* Ambiguity		−0.20	0.06	−3.23	0.001**
Age^2* EV difference* Ambiguity		0.03	0.02	1.42	0.156

Asterisks indicate significance at $p < 0.05$ (*), $p < 0.01$ (**) and $p < 0.001$ (***).

revealed a significant interaction between condition (social vs. computer) and others' choice (risky vs. safer) ($F(1, 292) = 9.48$, $p = 0.002$). We then followed up this interaction with post-hoc t tests to evaluate whether each condition differed from the baseline solo condition. A significant difference would indicate that choices in that condition were significantly altered based on the information manipulation.

When participants saw that the other participant made a safer choice, participants were more likely to also choose the safer option relative to their baseline choice (i.e. when no social information was visible) ($t(97) = -2.561$, $p = 0.011$). The opposite was true for the risky condition. When participants saw that the other participant chose the risky option they were more likely to also choose the risky option, significant at a trend level ($t(97) = 1.94$, $p = 0.055$), relative to their baseline choice when no social information was visible. Choice behavior was not significantly different from the solo condition when participants viewed the choices of a computer, either when the computer chose the safer option ($t(98) = 0.24$, $p = 0.81$) or the risky option ($t(98) = 0.02$, $p = 0.97$) (see Figure 4).

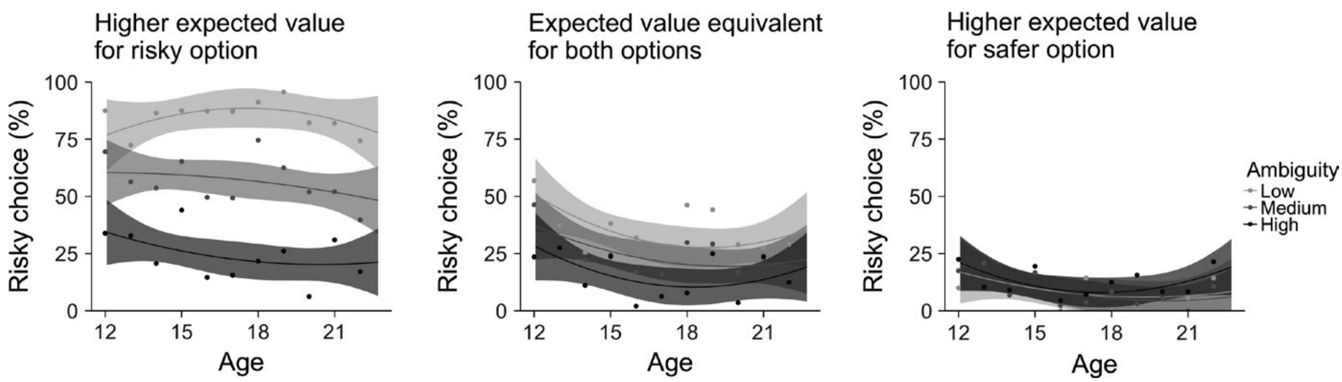

FIGURE 3 Visualization of the three-way interaction between the quadratic predictor of age, expected value difference and ambiguity in the solo condition. For visualization purposes expected value difference is divided into three groups: higher expected value for the risky option (EV difference >1), expected value equivalent for both options (EV difference between 1 and 0), higher expected value for the safer option (EV difference <0). Ambiguity is divided into high ambiguity (60% and 80% ambiguity), medium ambiguity (20% and 40% ambiguity) and no ambiguity (0% ambiguity). Dots represent raw data averaged per age year. These plots show that participants distinguished between expected value when ambiguity was low. When ambiguity was high, participants selected the safe option on the majority of the trials. Note that although the quadratic regressor of age is displayed for transparency, only the linear term in this model is significant. This indicates that the curvature of the predicted model fit is not significantly different across age, but the slope is

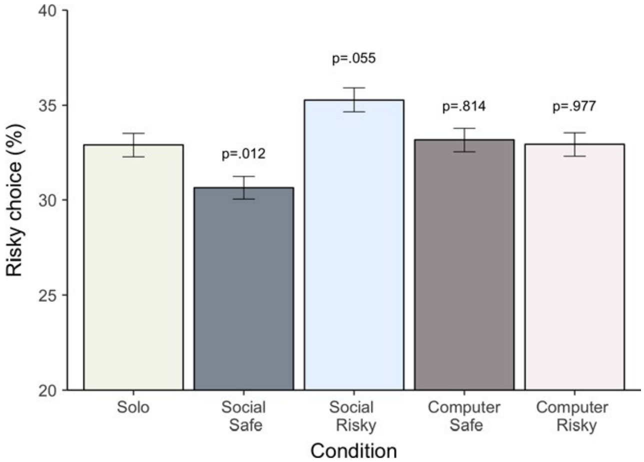

FIGURE 4 Percent risky choice per condition. *P*-values indicate difference between each condition and the solo condition. Error bars represent standard error of the mean. Compared to the solo condition in which participants did not see any additional information, participants were more likely to select the safe option when they saw that the other participant selected the safe option and to select the risky option when they saw that the other participant selected the risky option. When participants viewed the choices of a computer, they did not alter their choices

TABLE 3 Effective degrees of freedom (*df*) and AIC values for models with expected value difference and ambiguity for the social information condition model

Predictors	Model	*df*	AIC	Log lik	
Step 1					
EV difference* Ambiguity	1	5	13531		
Condition + EV difference* Ambiguity	2	7	13485*	1 vs 2	$p<0.001$
Condition* EV difference* Ambiguity	3	13	13493	2 vs 3	$p=0.675$
Step 2					
Age¹* Condition + EV difference* Ambiguity	4	10	13480	2 vs 4	$p=0.016$
Age²* Condition + EV difference* Ambiguity	5	13	13476*	4 vs 5	$p=0.015$

Note. Preferred models (indicated by *) were selected based on AIC values. EV difference refers to the difference in expected value for the safer and the risky option. Age¹ refers to the linear predictor of age, Age² refers to the quadratic predictor of age. Note that for the models with a quadratic age term the linear age term was always included as well. Models with interaction effects also included a main effect for these factors. Log lik refers to a log likelihood ratio test.

3.3 | Developmental patterns of social information use

We performed model fitting to test developmental patterns of percentage choices for the risky option in the social information condition. We did not test for developmental effects in the computer condition, because previous analyses showed that there were no changes in percentage risky choice in the computer conditions. However, for completeness we do report analyses for the computer condition in Supplementary Tables 1–6. We fitted models with predictors for expected value difference, ambiguity, condition and age. Model fitting started with the best fitting model for the solo condition, that is, the model with an interaction between expected value difference and ambiguity. To test whether social information changed percentage risky choice, we included condition (i.e. solo, social risky, social safe) in the model. Solo served as the reference category and, as such, any significant effect of the social risky and/or social safe conditions would indicate that percent risky choice changed due to social information. In the first step, two additional models were compared against the base model with just an interaction between expected value difference and ambiguity: (i) a model with a main effect of condition and an interaction between expected value difference and ambiguity, and (ii) a model with a three-way interaction between condition, expected value difference, and ambiguity. Model fit comparisons showed that the model with a main effect of social information condition and an interaction effect between expected value difference and ambiguity fit best (see Table 3).

In the second step, we included age in the model. We tested for interaction effects of linear and quadratic predictors of age and condition. A significant interaction between age and condition would indicate that the change in risky choice for a condition changes with age. Main effects of age were included in the model. A main effect of age would indicate average developmental patterns over both conditions and were not tested separately as we were specifically interested in how changes in risky choice changed over age in the social information conditions in comparison to the solo condition. We tested two additional models: (i) a model with an interaction between the linear predictor of age and condition, and (ii) a model with interactions between the linear and quadratic predictors of age, and condition. Model comparison showed that inclusion of both a quadratic and a linear age term improved model fit. The best fitting model was a model with an interaction between social information condition and age and an interaction between ambiguity and expected value difference (see Table 3). The best fitting model included no interactions between age and ambiguity or age and expected value difference. This means that the effect of social information across age is similar for all levels of ambiguity and expected value difference.

Further inspection of the significance of each predictor in the best fitting model showed that the two-way interaction between the quadratic predictor of age and condition was significant (see Table 4 and Figure 5). Visualization of the model fit showed that when another participant chose the risky option, the participants between approximately 15 and 17 years old were least likely to select the risky option. Visualization of model fit for the condition in which the other participant chose the safer option showed that the effect of social information was strongest for participants between approximately 15 and 18 years old for this condition (see Table 4 and Figure 5).

TABLE 4 Parameter estimates for all parameters in the best fitting model for the social information condition models

	Variance	B	Std error	z	p
Random effect					
Intercept	2.46		1.57		
Fixed effects					
Intercept		−2.30	0.26	−8.85	<0.001***
Social safe		−0.09	0.05	−1.83	0.068
Social risky		0.01	0.02	0.65	0.518
Age^1		−0.38	0.09	−4.40	<0.001***
Age^2		0.06	0.08	0.76	0.449
Ambiguity		−0.59	0.13	−4.59	<0.001***
EV difference		2.88	0.06	46.04	<0.001***
Social safe* Age^1		0.04	0.02	2.37	0.018**
Social safe* Age^2		0.02	0.01	2.93	0.003**
Social risky* Age^1		0.01	0.02	0.33	0.738
Social risky* Age^2		0.01	0.01	2.05	0.041*
EV diff* Ambiguity		−3.41	0.12	−28.48	<0.001***

Note. Asterisks indicate significance at $p < 0.05$ (*); $p < 0.01$ (**); and $p < 0.001$ (***).

3.4 | Raven progressive matrices

To test whether average percentage of risky choice in the solo condition was related to non-verbal fluid intelligence we performed regression analyses with number of correct items on the Raven test (non-verbal fluid intelligence). The average number of items correct was 6.1 (*SD* = 2.07). Due to outliers in the data, robust regressions were run. As expected, number of correct items was positively related to age (B = 0.26, $t(96) = 4.3$, $p < 0.001$). However, we did not observe evidence that the average percentage of risky choice in the solo condition was related to number of correct items on the Raven progressive matrices (B = −1.45, $t(96) = -1.57$, $p = 0.127$). This suggests that there is no evidence that percent risky choice on the lottery task is related to non-verbal fluid intelligence.

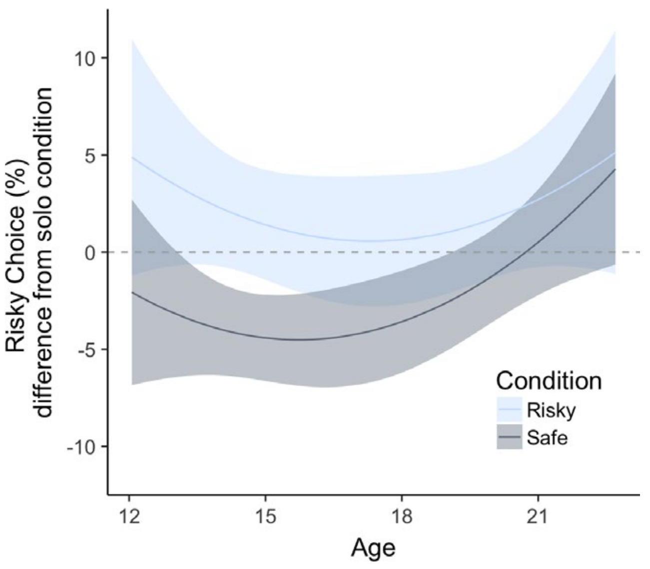

FIGURE 5 Representation of best fitting models for the change in percent risky choice in the condition in which participants saw a risky choice from a previous participant and the condition in which participants saw a safe choice from a previous participant. Change is plotted against the solo condition. Values above zero indicate an increase in percent risky choices and values below zero indicate an increase in percent safe choices. Lines represent predicted data fit by the favored model (see Table 4) and bands represent 95% confidence intervals. The fit lines show that adolescents were most influenced by safe decisions of the other participant, and that this age group was least influenced by risky decisions of the other participant

4 | DISCUSSION

In this study, we investigated how social information influences risky and ambiguous choices in adolescence. We used an economic decision-making approach in which participants made choices between safer and more risky lotteries. Lotteries were systematically varied on levels of risk and ambiguity. To test how information about choice preferences of others influenced decision-making, participants could sometimes see choices of supposed others. Specificity of social information was tested by inclusion of a computer condition. Results showed that in the social information condition, participants followed the choices of the other participants both toward risk and toward safety. Analyses testing for changes in this tendency across adolescence showed that late adolescents were least likely to follow a risky choice and that this age group was most likely to follow the safe choice of another participant. Participants only changed their behavior when they saw choice information of a social agent, as we observed no evidence that participants changed their choices based on the random choice of a computer. Together, these results suggest that information about others' choices is a powerful modifier for behavior and that this information is used differently across adolescence and early adulthood.

4.1 | Developmental patterns of risky and ambiguous choice

We started by determining the baseline choice preferences of participants across age. Results showed that when participants made choices without external information, their choices were influenced by both the risk and ambiguity levels of the choice options. As expected, participants were more likely to choose the risky option when the risky option was increasingly advantageous (i.e. as the expected value difference increased). This indicates that participants understood the concept of expected value and that expected value differences between the choice options guided their decisions. Participants were less likely to choose the risky option when the ambiguity of the choice increased. This is in line with prior work showing that adults exhibit ambiguity aversion in risky choice situations (Levy et al., 2010). Together, these findings show that participants took the expected value and the ambiguity of the choice into account in a rational manner, to decide when to opt in to a risky choice.

We then investigated how risky choice changed with age. We found no changes in risk tolerance across age. Although this seems surprising at first since adolescents are generally thought to take more risks than adults in the real world and therefore one might expect that adolescents also take more risks than adults in the laboratory, the literature on developmental patterns of risky decision-making in the laboratory shows mixed results. Some studies have found increased risky decision-making in adolescence (Braams et al., 2015; Chein et al., 2011; Powers et al., 2018) whereas other studies do not find differences (Blankenstein et al., 2016; Van Leijenhorst et al., 2008). Adolescent increases in risk taking behavior in the real world are not only driven by the analysis of objective risk in a situation. Ambiguity tolerance could also lead individuals toward risky choices, in that they are more willing to opt in to a decision in which the values of possible outcomes are highly divergent, but their probabilities are unknown. In the current study, we used an economic decision-making task in which we were able to distinguish between risk and ambiguity tolerance. Three other studies have taken a similar approach. When ambiguous choices were part of the experimental context, only one study found evidence for increased risk tolerance in adolescence (van den Bos & Hertwig, 2017) and two of these studies did not find increased risk tolerance in adolescence (Blankenstein et al., 2016; Tymula et al., 2012). Possibly when explicit ambiguity is introduced into the choices, this is a factor that steers adolescents away from taking more risk in the pure risky, that is, non-ambiguous, choices. Future work should systematically test choice behavior under different types of ambiguity to better understand in which situations adolescents and adults take risk and which underlying mechanism gives rise to this behavior.

Previous work investigating developmental patterns of ambiguity tolerance found increased ambiguity tolerance in adolescence (Blankenstein et al., 2016; Tymula et al., 2012; van den Bos & Hertwig, 2017). Furthermore, there was a relationship between ambiguity tolerance and real-life risky decision-making (van den Bos & Hertwig, 2017). Unexpectedly and not in line with our hypothesis, in the current study we did not find increased ambiguity tolerance in adolescence. One difference between our study and the three studies that previously investigated ambiguity tolerance across age is that in the current study ambiguity was manipulated between trials, but within a trial ambiguity was held constant. Therefore, our task does not directly give participants the option of selecting between an ambiguous and a non-ambiguous choice because both choice options were equivalently ambiguous. In all previous studies there was a safe, sure option, and an ambiguous option. When making decisions with equal amounts of ambiguity, adolescents did not display differences in ambiguity tolerance. Possibly in these situations, the focus could shift more to the difference in expected value, that is, riskiness, of the choices and not on the ambiguity. Future work could further test whether there is a shift in attention to the riskiness of the choice options when both options are ambiguous. If so, this could have implications for the type of risky decisions adolescents are susceptible to in real life.

4.2 | Developmental patterns of social information use

To test how social information moderated risky choice behavior, we included a condition in which participants were informed about choices of a peer. In the current study, results from the social information condition showed that participants followed both risky and safe choices of peers. These results replicate previous work showing influence of choice information in an adult sample (Chung et al., 2015). Following the choice of others was not due to blind following of the choice that was on the screen, since participants did not alter their choices when they viewed choices of a computer, showing that participants distinguished between different sources of information and that social information is more persuasive than randomly generated information. This is in line with previous work using a non-social reference condition (Fareri, Niznikiewicz, Lee, & Delgado, 2012; Moretti, Dragone, & di Pellegrino, 2009).

The key tests of the current study concerned developmental changes in effects of information on others' previous choice. Analysis of developmental effects in the social information condition showed differential patterns of age for risky and safe peer choices. When the other participant made a risky choice, late adolescent participants in the sample were least likely to follow this choice. This result was contrary to what we expected based on previous work showing adolescent increases in risky decision-making in a peer context (Cascio et al., 2015; Chein et al., 2011; Gardner & Steinberg, 2005; Smith, Chein, & Steinberg, 2014).

A key difference between the current study and previous work is the type of peer influence manipulation. In particular, active peer monitoring and peer encouragement of risky behavior appear to be motivators for changes towards more risky behavior (Centifanti, Modecki, MacLellan, & Gowling, 2016; Reynolds, MacPherson, Schwartz, Fox, & Lejuez, 2014). When considering the underlying processes that could differ between peer influence manipulations, there could be several possible mechanisms that are less active in the present social manipulation relative to those that include peers who actively monitor the choices. In the current study, we presented information about the previous choices of peers; participants did not receive feedback about their choices and the peer did not observe their choices. Thus, in the present study participants likely lacked social motivation for changes in behavior whereas active peer monitoring could bring forward more explicit motivations to self-present as risky (Cohen & Prinstein, 2006; Mayeux, Sandstrom, & Cillessen, 2008).

When the other participant made a safe choice, mid-to-late adolescents were most likely to follow this choice. Most previous work has focused on how peers influence decisions towards making more risky decisions and therefore this finding might seem surprising at first. However, some studies that have looked at peer influence towards more safe decisions have shown that adolescents also conform towards safer decisions when a peer exhibits safer norms (Cascio et al., 2015; Knoll, Leung, Foulkes, & Blakemore, 2017). Similarly to risky decision-making, the situations in which peers can move decisions towards safety is dependent on the type of peer influence and the type of decisions. It could be that adolescents take information about safer choices of their peers into account more when the peer is not around (Knoll et al., 2017). Risky decision-making such as risky driving or underage drinking are often reputation enhancing for adolescents (Ellis et al., 2012); maybe, safer decisions are not status enhancing or give great social benefit to the adolescent. Possibly, when the peer is not around to judge or monitor them, they are more likely to follow the safe choice. This could indicate that choices towards safer decisions and towards more risky decisions are dependent on different mechanisms.

The present findings, when integrated with the existing literature, suggest that changes in real-life risky decision-making in adolescence could be driven by social motivations, and as a result adolescents are more willing to follow peers toward safety when they are not being actively monitored whereas they are more willing to follow peers toward risk when they are being monitored (and therefore could enjoy the reputational status-enhancing effect of risky choice). More research will be required to resolve these possibilities.

Lastly, the magnitude of social influence was not dependent on the properties of the different choice options, as there were no interactions between risk level and ambiguity level of the choices. We expected that for choices in which the ambiguity was higher, social influence would also be higher as participants were expected to use others' choices as information for their own choice. However, social influence appears to be equivalent across choice features. Future work could investigate whether other types of peer influence interact with ambiguity level.

4.3 | Limitations

The current study used an economic decision-making approach to investigate risky decision-making. While this approach allows us to systematically manipulate choice options and thus allows for high experimental control, this is at the cost of reduced ecological validity. Choices in the real world are seldom repeated and represented in simple numerical values as is required for laboratory tasks, which may have reduced the excitement for participants. Furthermore, although great care was taken to ensure the validity of the peer manipulation, the peers were described as unknown individuals with whom the participant would not have contact. To investigate how real peers influence behavior, future studies could use risk preferences of actual peers. Lastly, to investigate how risky behavior changes over time and to better distinguish between individual differences and developmental effects, participants should be followed longitudinally.

4.4 | Conclusion

Taken together, the results of this study show that social influence is a powerful modifier for behavior across age. The current study revealed that information about previous choices of peers differentially influenced adolescents' decision-making towards safe and risky choices. Adolescents were most influenced by safe choices of their peers, and least influenced by risky choices of their peers. These results show that the effect of peers on adolescents' decisions is less ubiquitous and more specific than previously assumed.

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CONFLICT OF INTEREST

The authors declare no competing financial interests.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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