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Adolescents Seek Social Information Under Uncertainty

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Adolescence is a period of emerging independence, in which adolescents face difficult decisions, including those that involve risk for health and well-being. Previous research suggests that learning from others might be a prominent strategy of adolescents to inform these difficult decisions. However, there is a gap in the literature that addresses the active role adolescents may have in gaining information about others' behavior (i.e., social information search). Here, we investigated when and how much social information adolescents search before making decisions under risk and ambiguity, using a novel social search paradigm. In this paradigm, adolescents were able to reveal real information about their classmates' choices before deciding on their final choice. Our two experiments suggest that social information search can be broken down in two independent decisions: first the decision to initiate search, followed by the decision to continue search. Several factors motivated initiation of search, including: (a) the difficulty of the choice, (b) uncertainty about the outcome, and (c) the magnitude of the reward at stake. Search took generally longer when adolescents faced information not in line with their initial preference. Finally, we observed that adolescents used the sampled social information to inform their risky-choice behavior. Taken together, these results provide novel insights into the dynamics of peer influence in adolescence and stress the importance of treating adolescents not only as receivers, but as active agents searching for social information.

Keywords: social information search, social learning, risk-taking behavior, uncertainty, adolescence

Supplemental materials: <https://doi.org/10.1037/xge0001299.supp>

Information-seeking is an important aspect of decision-making: Individuals seek information that helps them to better understand the situation they face. For example, before purchasing a new mobile phone or applying for an university, we inform ourselves about the different options. One of our prominent sources of information is our social environment: Here, we learn how to behave by observing others' behavior or opinions (Bandura, 1977). During adolescence, peers become the most prominent source of social information. Adolescents do not only start to spend more time with their peers (Brown & Larson, 2009; Lam et al., 2014; Larson et al., 1996), these peers also exhibit a significant impact on adolescent's behavior, such as risk-taking (e.g., Gardner &

Steinberg, 2005; Riedijk & Harakeh, 2018; Simons-Morton et al., 2005), but also prosocial behavior (e.g., Choukas-Bradley et al., 2015; van Hoorn et al., 2016). Due to the rise of social media platforms, adolescents have gained access to the behavior and opinions of their peers more than ever before (Aillie & McNicol, 2018; Pew Research Center, 2018). It is, therefore, important to understand when and why adolescents use social information. However, most experimental research on peer influence predominantly constructed a social context with the adolescent as passive receiver of social information. Therefore, little is known about the role adolescents play in searching for and selecting social information.

The most common experimental operationalization of peer influence is the response to peer observation (e.g., Cascio et al., 2015; Dekkers et al., 2020; Gardner & Steinberg, 2005; van Hoorn et al., 2016) or the presentation of social information, such as the choice or opinion of a peer (e.g., Blankenstein et al., 2016; Braams et al., 2019; Cohen & Prinstein, 2006; Knoll et al., 2015; Pinho et al., 2021; Reiter et al., 2021; Rodriguez Buritica et al., 2019; Tomova & Pessoa, 2018). However, studies with adults have shown that decision-making also involves active information or advice seeking behavior, for which people use strategies to guide their reliance on social information (Danchin et al., 2004; Glowacki & Molleman, 2017; Morgan et al., 2012). It is likely that adolescents also actively seek information from their peers to inform their decisions. For example, when they consider engaging

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The authors declare no conflict of interest. All data and code supporting the main findings of this study are available from the public repository, accessible via <https://osf.io/wutf8/>.

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in some risky activity, such as trying out drugs or alcohol for the first time. Indeed, adolescents report to use social media for everyday life information seeking, such as getting updates about news, health, fashion or others' opinions (Aillerie & McNicol, 2018), and report to spend a significant amount of time online reading the posts of their peers (Aillerie & McNicol, 2018; Beyens et al., 2020). Understanding the adolescent as an active agent will thus be key to our understanding of peer influence during this critical period. However, it is currently unclear what motivates adolescents to seek social information, how much information they need before deciding, and how this impacts their choices. The current study aimed to address these questions in the context of adolescent's risky decision-making.

We developed a novel social search paradigm to investigate when, and how much, adolescents search for social information (i.e., choices of their peers) prior to decision-making under risk and ambiguity. In this task, participants have the option to gather information about the choices of their peers before they choose between an option with a certain or a variable outcome. The option with a variable outcome is either a risky (i.e., known outcome probability) or an ambiguous option (unknown outcome probability). Search is voluntary, which allows us to investigate when participants search for (a) social information, (b) how much they search, and (c) ultimately how social information impacts choice. Crucially, instead of presenting the choices of fictitious peers (e.g., Choukas-Bradley et al., 2015; Teunissen et al., 2012; Tomova & Pessoa, 2018; van Hoorn et al., 2017), as has been done in most experimental work on peer influence, our paradigm uses social information from adolescents' own social network at school. Thus, adolescents obtain information about the real choices of their classmates, which increases the relevance of the social information and ecological validity of our paradigm.

To understand when and how much social information adolescents seek we built on existing frameworks developed for understanding information search in a nonsocial context (e.g., Hauser et al., 2017; Ratcliff & Smith, 2004). These models assume that initial beliefs are updated with each piece of incoming information in a Bayesian fashion, and that search stops when an evidence threshold is met. Here, search ends when uncertainty is reduced to a prespecified level (Hausmann & Läge, 2008). Evidence from observational learning paradigms suggest that the integration of social information follows a similar Bayesian logic (De Martino et al., 2017; Molleman et al., 2020; Moutoussis et al., 2016; Toelch & Dolan, 2015; Tump et al., 2020). Importantly, in contrast to these existing models, participants do not update initial beliefs in our social search paradigm, but they update their risk preference (Chung et al., 2015; Ciranka & van den Bos, 2019). Previous research already showed that observing the risky decisions of unknown others modulates the risk preference of adults and adolescents (so-called risk contagion; Reiter et al., 2019; Suzuki et al., 2016), as a result of the altered subjective value given to this risky option (Chung et al., 2015).

Based on this framework and social learning theories, we derived several factors that might influence adolescent's search for social information. First, adolescents will initiate search when they are uncertain about what to choose (Hypothesis 1 [H1]). Consistent with this idea, Reiter et al. (2021) showed that higher uncertainty about what to choose, led to more adaptation to others' preferences (fictitious peers) in young adolescents. This uncertainty can stem from multiple sources. For instance, one can be uncertain about what to choose if

there is no clear difference between the expected outcome of the two options. When facing these difficult choices (Glickman et al., 2019) one could benefit from observing the behavior of others (Gino & Moore, 2007; Laland, 2004; Morgan et al., 2012). Thus, more difficult choices will motivate people to search for social information (H1a). In addition, uncertainty about what to choose can also stem from a lack of available information. Incomplete information about the options (i.e., ambiguous vs. risky options) could make people more inclined to search for social information (H1b). Consistent with this notion, van Hoorn et al. (2017) showed that adolescents conformed more to the advice of fictitious peers when the outcome uncertainty of a gamble increased. Second, how much information adolescents' search will depend on the congruency between their initial choice preference and the general direction of the social information (H2). If the sampled information is in line with the initial choice preference of the receiver (i.e., congruent), search will be relatively short. However, if the information is in contrast with one's choice preference (i.e., incongruent), search will be relatively long (Gesiarz et al., 2019; Ratcliff & Smith, 2004). Finally, we expect that adolescents are more likely to change their choice preference the more incongruent information they receive (H3).

To test these hypotheses, our paradigm assessed adolescents' search behavior in two experiments. The first experiment included a sample of 175 adolescents (11–19 years) and examined whether choice difficulty and congruency of social information influenced search behavior. We presented choice dilemmas with different levels of difficulty, defined by the difference in expected value (EV) between the two options (Glickman et al., 2019). We expected that more difficult choices would lead to increased uncertainty and, as a result, increased willingness to search (H1a). In addition, we manipulated the congruency of social information (i.e., relative to participants' initial choice preference), expecting that incongruent information would increase the amount of information searched (H2) and would lead to more shifts in their choice preference (H3). In a second experiment (N = 92, 11–14 years), we examined the impact of ambiguity on search behavior. We expected that ambiguity (i.e., unknown probability), compared to risk (i.e., known probability), would elicit search occurrence more often, with a longer search prior to deciding (H1b). To get a better understanding of the social search process and integration of social information, we formalized and compared multiple computational models of social information search. Lastly, in both experiments, we explored whether tolerance for uncertainty could explain individual differences in social information search.

Experiment 1

This experiment was performed to assess the effect of choice difficulty and incongruency of social information on adolescent's search behavior (i.e., the initiation and amount of information sought). the initiation and amount of social information search. Choices under uncertainty were made in a gambling task, collected in two sessions. Participants and their classmates started with a solo version of the task, to obtain real social information of classmates. Session 2 included a social search paradigm of the gambling task, giving participants the option to view their classmates' choices, before they decided. Finally, we tested whether tolerance for uncertainty could explain individual differences in social information search. This study was preregistered on the Open Science Framework (<https://osf.io/bz2en>). Deviations from the preregistration, regarding the analyses

plan, can be found in [Supplement B3](#) of the online supplement materials.

Method

Participants and Procedure

A sample of 193 participants aged 11–19 years participated in this study, of which 175 participants (55% female, range: 11–19 years; $M_{\text{age}} = 15.09$, $SD_{\text{age}} = 1.63$) completed both sessions and were included in further analyses. Participants were recruited from two Dutch high schools, including the vocational and preuniversity education level of the Dutch school system (see [Supplement B4](#) of the online supplemental materials for more details). Parents (if participants aged < 16 years) and participants provided informed consent and study procedures were approved by the Ethics Review Board (ERB) of the University of Amsterdam (case number 2019-DP-10269).

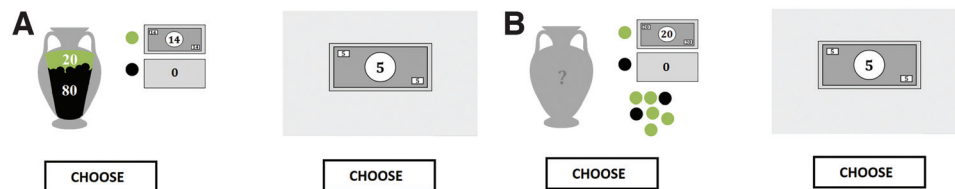
Test sessions took place at school within the classroom and started with a brief oral instruction, after which participants continued individually on a tablet for task and questionnaire administration. The solo version of the gambling task was provided in the first session. Participants were instructed that their solo choices (obtained in Session 1) would be shared with their classmates in Session 2, as social information. After a 3-week interval, the social version of the gambling task was performed in Session 2, followed by a questionnaire. In both versions of the gambling task, participants did not receive any feedback about the outcome of their final choice to minimize a possible learning effect. In total, sessions lasted 50–60 min. Each class received a monetary incentive per session (5 euro per pupil). In addition, participants were instructed that they could gain lottery tickets depending on the outcome of three random trials of the gambling task to incentivize engagement. Post hoc analyses of participants' reaction time (RT) showed no outliers or very short reaction times ($RT > 2 SD$ from the mean RT or $RT < 2000$ ms; see [Supplement A7](#) of the online supplemental materials, not preregistered), suggesting that all participants engaged seriously with the task. Lottery tickets were used in a classroom raffle, for winning an online voucher of 40 euros.

Material and Measurements

Gambling Task: Solo Version. Participants were asked to make a series of choices between a safe and a risky option (Blankenstein et al., 2016; van den Bos & Hertwig, 2017). Here, risk taking is defined as choosing the option with the highest outcome variability, which may lead to greater benefits, but may also lead to negative outcomes, at the expense of certainty. The safe option always yielded a gain of 5 points. The risky option was displayed as a vase filled with a mix of green and black marbles, with a total of 100 marbles (see [Figure 1A](#)). Choosing the risky option potentially resulted in a higher reward compared to the safe option, or in winning nothing, depending on whether the computer drew a green or black marble, respectively. Each vase displayed the odds of gaining the higher reward, by showing the full distribution of marbles (*choices under risk*). Ambiguous options included vases of which the distribution of marbles was covered. Instead of showing the full distribution, participants saw a sample of seven marbles from the vase (*choices under ambiguity*; see [Figure 1B](#)). The reward that could be gained from the vases varied between 8, 14, 20, 32 and 50 points. Gain probabilities varied between 10% and 90%. To increase the saliency of the task, participants were instructed that three out of the 48 trials would be randomly selected by the computer for pay out. Participants' choice on these trials were played out, yielding earned points that were converted to lottery tickets.

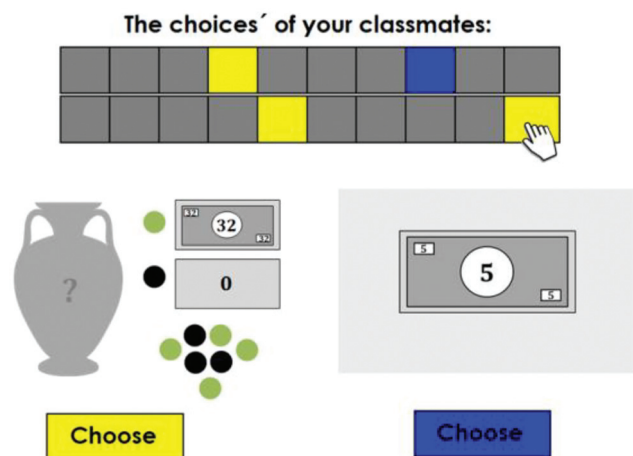
The task consisted of four blocks, including two ambiguous blocks (choices under ambiguity) and two risk blocks (choices under risk). The ambiguous and risk trials were randomly assigned to one of the two blocks for each participant. Participants always started with a risk block, followed by an alternation of the other blocks. This was done to provide the instructions gradually, starting first with the condition including the basic principles. The position (left or right) of the options was randomized between trials to prevent habitual choosing. Solo choices (Session 1) from the participant's classmates were used as social information in Session 2 (see [Figure 2](#)), which was communicated with all participants before the start of the experiment.

Figure 1
Choices Under Risk and Choices Under Ambiguity Within the Gambling Task



Note. This figure illustrates the two types of choice dilemmas within the solo version of the gambling task, with panel A showing an example of the choices under risk trials and panel B showing an example of the choices under ambiguity trials. Within each trial participants choose between a safe option (sure pay-off of 5 points) or a risky option (gambling vase). The risky option resulted in zero points, in case a black ball was drawn, or an amount of 8, 14, 20, 32 or 50 points (this varied per trial), when a green ball was drawn. The probability to gain when choosing the risky option, was based on the distribution of the green and black marbles. This probability was either depicted on the vase by showing the full distribution (choices under risk; panel A) or by showing a sample of 7 marbles from the vase (choices under ambiguity; panel B). See the online article for the color version of this figure.

Figure 2
Outlook of a Trial in the Social Version of the Gambling Task



Note. Figure 2 displays a choice dilemma for which participants could view the choices made by their classmates, for this specific trial. These choices were presented as uncovered boxes in a matrix (social board), which could be revealed by the participant by clicking on a grey box. Revealing blue indicated that the safe option was chosen by one of the classmates; revealing yellow indicated the risky choice was chosen by one of the classmates. This illustrates an example board. In the experiment the number of boxes on the social board depended on the class size. See the online article for the color version of this figure.

Gambling Task: Social Version. In the second session, participants played a modified version of the gambling task. In this version, participants were able to gather social information before they decided between a safe and risky option. Given that the focus of the current study was the effect of congruency and choice difficulty participants were only confronted with the choices under ambiguity in this social version (see Figure 2). The social information consisted of the solo choices of their classmates for that specific decision trial, which were collected in Session 1. Participants decided how much social information they wanted to sample by clicking on the boxes of the social board (inspired by Clark et al., 2006; Hauser et al., 2017); revealing the color blue indicated that a classmate chose the safe option, whereas yellow indicated that the risky option was chosen by their classmate. The length of the social board varied according to the class size of each participant ($M = 20.58$, range = 12–29). Participants were instructed that they were free to reveal as many choices as they wished but were not required to open any of the boxes. There were no explicit sampling costs other than the time and effort involved in opening a box. After the search phase, participants made their final choice. The social version of the task started off with 20 solo trials (see Supplement B1 in the online supplemental materials for trial specifics), eliminating a time lag between participants' solo and social choices. These initial solo choices (Session 2) were used to configure the congruency manipulation. After these solo trials, participants were faced with the same trials again, but with the option to view their classmates' choices. This set of trials resulted in participants choosing the gamble option in 54% of the cases based on their initial preference (see Supplement A2 in the online supplement materials for an inspection of the group-level solo data for this trial set). Moreover, no systematic bias was found between the solo data of

Session 1 and 2 (Pearson's product-moment correlation: $r(173) = .65$, $t = 11.25$, 95% CI [.56, .73], $p < .001$; see Figure S3).

Social Information Manipulation: Congruency. Social information underneath the boxes was selected from the pool of real answers of the participant's classmates to create 10 congruent and 10 incongruent trials. Incongruent boards revealed social information of which the majority was in contrast with participant's initial solo choice (measured at Session 2), whereas congruent boards would present social information in line with participant's initial solo choice (measured at Session 2). The created social boards consisted of incongruent or congruent information as the majority, ranging from 65% to 85%. This range in majority percentage was set to prevent participants from becoming suspicious about the reliability of the social information. The total number of trials were divided over two trial sets, which were matched on EV difference and gamble reward (see Table S7). The matching trial sets were randomly assigned to the congruent or incongruent condition. Next, congruent and incongruent trials were randomly ordered for each participant.

Choice Difficulty. Choice difficulty has been operationalized by varying the differences in EV between the safe and risky choice option. Previous gambling studies indicated that participants take longer to decide when the absolute EV difference between the two options decreases and showed to be more indifferent in their choice preference in these cases (Glickman et al., 2019; Krajbich et al., 2010; Rolls et al., 2008). For each trial in the social version of the gambling task, we estimated the choice difficulty of the specific choice dilemma by calculating the absolute difference in EV, based on the probability (p) and reward (V) associated with each option (see Equation 1 and Equation 2). Thus, higher values for choice difficulty means a lower choice difficulty. For the choices under ambiguity trials, the probability was based on the sample of marbles that participants saw. For the choices under risk, this probability was based on the full distribution of the marbles.

$$U(option) = p * V \quad (1)$$

$$Choice\ difficulty = abs(U\ safe - U\ risk) \quad (2)$$

Tolerance for Uncertainty. Adolescents' tolerance for uncertainty was measured by calculating their attitude toward ambiguity during the solo version of the gambling task. Solo choices from Session 1 were used for modeling participant's choice behavior, as only Session 1 included choices under risk and choices under ambiguity trials, both necessary for estimating one's attitude toward ambiguity. This yielded an ambiguity parameter that was used in subsequent analyses (see Supplement B2 of the online supplemental materials, for a description of the modeling procedure).

Analysis for Modeling Search Behavior

To quantify the search behavior of adolescents, we examined how often participants initiated search (yes or no) and how much social information (i.e., number of boxes opened) they revealed per trial (search length¹). We assumed that a person first decides

¹We also corrected for social board size differences, by taking the relative search length as dependent variable, but this yielded similar results.

whether to search, and then, conditionally on a positive decision, how much to sample. We used a multilevel hurdle model given that this model assumes such a two-step process and is able to deal with excessive proportion of zero values and overdispersion in count data, generated by such a process (Hofstetter et al., 2016; Mullahy, 1986; see also Supplement B3 of the online supplemental materials, not preregistered). The hurdle model followed a two-step sequential fitting procedure. First, in the zero-part of the model, a logistic regression modeled trials in which search did not occur ($Y = 0$) against trials in which search initiation occurred ($Y = 1$, where all values larger than 0 are fixed at 1). This is followed by the truncated count-part of the hurdle model, where the positive count in search (i.e., search length) is modeled with a negative binomial regression, but only for the trials for which participants searched ($Y > 0$). Both processes were modeled on a trial-by-trial level (Level 1) with the R package “GLMMadaptive” (Rizopoulos, 2020), and both parts of the model included a random intercept on the individual level (Level 2). Choice difficulty and ambiguity attitude were added as predictors in both parts of the model to investigate their effect on social information search. Congruency of the revealed social information was only used in the model to predict search length, given that this information was only observed when participants searched.

Within our task, choice difficulty was correlated with the magnitude of the reward of the ambiguous option (Pearson's $r = .71$, $t = 4.23$, 95% CI [.38, .88], $p < .001$). This suggests that the effect of choice difficulty may be partly driven by the reward at stake. Reward magnitude was added to the model to assess the unique effect of choice difficulty on search initiation and search length (not preregistered). Trials on which participants revealed information were post hoc categorized as congruent if the majority of information was similar to the participant's initial choice, and incongruent if the majority was in contrast with participant's initial choice. Trials in which participants revealed no information or

inconclusive information (50% congruent and 50% incongruent) were labeled as an additional condition 0. The model showed absence of multicollinearity (VIF values < 2).

Results

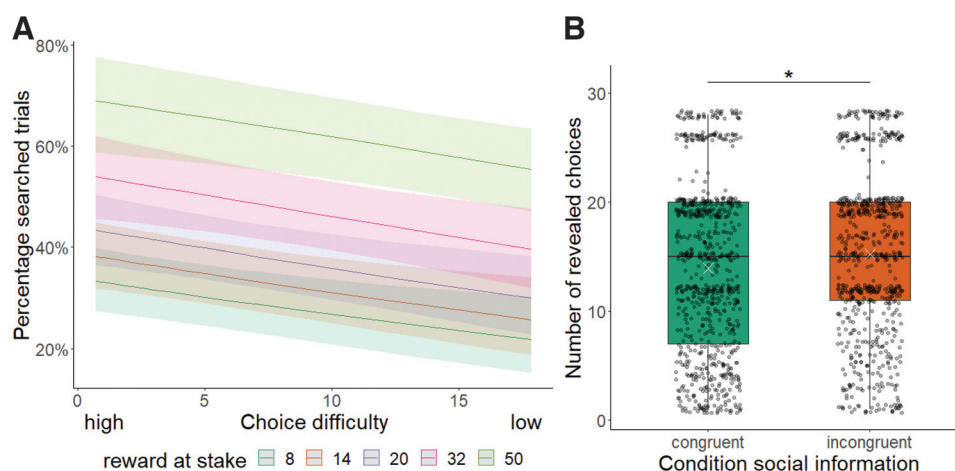
Group Level Search and Social Information Use

From the 177 participants included in the analyses, 14 participants did not search in any trial during the task. Participants who searched in at least one trial ($N = 163$), searched on average in 9.4 trials ($SD = 5.49$) of the 20 trials in total. Mean number of revealed choices for these searched trials was 13.5 ($SD = 6.35$, range = 1–28, equals a mean proportion of .30 [$SD = .4$] from the total social board). As expected, the analysis of adolescent's choice data showed that participants were more likely to change their initial choice when they faced higher levels of incongruent information ($b = .58$, $SE = .06$, 95% CI [.46, .70], $Z = 9.37$, $p < .001$; see Supplement A1 of the online supplemental materials for the analysis), which was higher than the observed base-rate of switching (41% vs. 19%; see Supplement S10 of the online supplemental materials and Figure S9). These switches happened more often from safe to risk than vice versa (see Figure S10), resulting in participants switching to the option with the highest EV in 60% of the switch cases (see Figure S11). Taken together, this indicated that participants were motivated to gather information and, importantly, used this information to inform their decisions.

Predicting Search Initiation and Search Length

In line with our predictions, the results of the hurdle model showed that initiation of search was more likely when choice difficulty increased ($b = .18$, $SE = .06$, OR 95% CI [.06, .29], $p < .01$; see Figure 3). Interestingly, initiation of search also happened more often for trials with a higher reward at stake ($b = -.44$, $SE =$

Figure 3
The Effect of Choice Difficulty, Reward, and Congruency on Search Behavior



Note. Panel A displays the occurrence of search initiation as a function of choice difficulty, for the different rewards (8, 14, 20, 32, 50) associated with the risky option. Panel B displays the number of revealed choices when participants were faced with congruent social information (green bar) or incongruent social information (orange bar). Dots refer to trials. See the online article for the color version of this figure.

* $p < .001$.

Table 1
Hurdle Model Results of Experiment 1

Parameters	Coefficient (SE) zero part ^a	OR [95% CI]	Coefficient (SE) count part ^b	RR [95% CI]
Intercept	0.41 (0.14)**	1.51 [1.15, 1.98]	2.41 (0.05)***	11.12 [10.16, 12.18]
Choice difficulty	0.18 (0.06)**	1.20 [1.07, 1.34]	−0.02 (0.01)	0.98 [0.95, 1.01]
Reward at stake	−0.44 (0.06)***	0.65 [0.57, 0.73]	0.04 (0.01)**	1.05 [1.02, 1.07]
Ambiguity attitude	0.06 (0.14)	1.07 [0.81, 1.41]	0.05 (0.05)	1.05 [0.96, 1.15]
Congruency: incongruent	—	—	0.13 (0.02)***	1.14 [1.09, 1.19]
log θ	2.59			

Note. SE = standard error; CI = confidence interval; OR = odds ratio; RR = rate ratio; θ = dispersion parameter.

^a The zero part of the model predicts nonsearch events. ^b The count part of the model predicts the number of revealed boxes.

** $p < .01$. *** $p < .001$.

.06, OR 95% CI [.57, .73], $p < .001$). Thus, adolescents took the potential reward into account when deciding to search. As expected, search length showed to be dependent on the type of information. That is, adolescents searched longer when faced with incongruent social information, compared to congruent social information ($b = .13$, $SE = .02$, RR 95% CI [1.09, 1.19], $p < .001$; see Figure 3). Choice difficulty did not predict search length ($b = -.02$, $SE = .01$, RR 95% CI [.95, 1.01], $p = .165$), but higher rewards at stake did ($b = .04$, $SE = .01$, RR 95% CI [1.02, 1.07], $p < .001$). Finally, participant's estimated tolerance for ambiguity did not predict search initiation or search length (see Table 1). Upon reviewers' request, we exploratory tested for age-effects by adding age into the hurdle model (see Supplement A6 of the online supplemental materials for results).

Summary

In the social search paradigm, adolescents actively gathered social information and used this information to inform their decisions. In line with our expectations, search initiation was more likely when choice difficulty increased, and search length increased when participants faced social information incongruent with their initial choice. Interestingly, our data also revealed that participants searched more often and longer for choice dilemmas with higher rewards at stake.

Experiment 2

This second experiment was conducted to assess the effect of outcome uncertainty (ambiguity) on social information search, in a new independent sample. In contrast to Experiment 1, social information search was also assessed for *choices under risk* and compared with *choices under ambiguity*. In addition, we assessed whether we could replicate the effects of choice difficulty and reward on social information search. To examine if search behavior is generated by a two-step process, as implied by the hurdle model, and to further examine how factors influence the initiation and amount of search, we expanded our analyses with comparative analyses of computational models. Finally, we included a validated self-reported measure of intolerance for uncertainty instead of the computational derived ambiguity measure used in Experiment 1. A short questionnaire about the social gambling task was included, to get a self-reported measure of their motives to search for information. This study was preregistered on the Open Science Framework (<https://osf.io/6tgs2>). Deviations from the preregistration regarding the data analyses can be found in Supplement B3 of

the online supplemental materials. An overview of the differences between Experiment 1 and 2 and justification can be found in Table S11.

Method

Participants

Another sample of participants was recruited by contacting two Dutch high schools, representing different education levels within the Dutch school system (from vocational to preuniversity; see Supplement B4 of the online supplemental materials for more details), resulting in participation of 22 classrooms. Parental consent was asked for all students below 16 years. Participants also provided their own consent. From the 409 participants, a final sample of 92 participants completed Session 2 as well. The sample completing the experiment was reduced by the unexpected closing of high schools in response to the COVID-19 pandemic. In contrast to Experiment 1, this resulted in a smaller adolescent age range and a 3-month interval between Session 1 and 2 (see also Supplement B5 of the online supplemental materials). Data had been checked for indices of inattention based on participants' RT (see Supplement A7 of the online supplemental materials, not pre-registered). Five participants showed signs of inattention or careless responding ($RT > 2 SD$ from the mean RT or $RT < 2000$ ms). However, results of the reported analyses did not change whether they were included in the analyses or not (see Supplement A7 of the online supplemental materials and Table S5 and S6). Therefore, we decided to retain these participants, leaving a total of 92 participants for data analysis (60% female, range = 11–14 years, $M_{age} = 13.31$, $SD_{age} = 1.06$).

Procedure

Session 1 followed the same procedure as described in Experiment 1, in which participants started with the solo version of the gambling task. The social version of the gambling task was performed after a 3-month interval, at home. This task was followed by a questionnaire asking about participant's motives to search within the gambling task (see Supplement A3 of the online supplemental materials), and by the Tolerance for Uncertainty Scale. Both test sessions lasted 50–60 min. Participant received 5 euros per session with an additional fee depending on their gambling task performance in Session 2, based on three random trials. However, participants only received information about the total number of points they earned at the end of the task, to rule out any learning effect. Additionally, participants were instructed that they could

gain lottery tickets for an online voucher of 40 euros, by playing the gambling task in Session 1 and 2, to incentivize engagement. This study was approved by the ERB of the University of Amsterdam (case number 2019-DP-11427).

Material and Measurements

Gambling Task: Solo Version. Experiment 2 made use of the same task as Experiment 1. Small changes were made in the design of the task to assess the effect of ambiguity. In this experiment the task consisted of three type of trials. Again, *choices under risk* included gamble vases that displayed the odds of winning the higher reward (known distribution) explicitly. The gamble vases in the more uncertain condition (*choices under ambiguity*) revealed incomplete information about the distributions of the green and black marbles, by means of a sample of marbles. In contrast with Experiment 1, *choices under ambiguity* made use of two different samples to induce ambiguity; three marbles out of 100 or 15 marbles out of 100 marbles were shown from the vase. Task conditions (risk trials, 15 marbles trials and three marbles trials) were divided in six blocks, consisting of eight trials each (16 trials per condition). For each participant the first block was fixed on *choices under risk*, as we believed that providing the instructions gradually, and playing, from risk to ambiguity would help in understanding the manipulated ambiguity. The fourth block was also fixed on *choices under risk*, to remind all participants halfway of the difference between risk and ambiguity trials. The other blocks were randomly assigned to the three marbles and 15 marbles condition. At the start of the game, *choices under risk* and *choices under ambiguity* trials were randomly assigned to one of the belonging blocks.

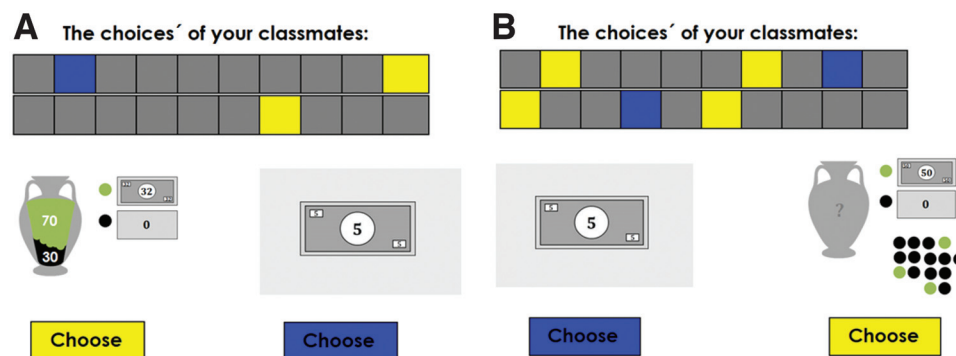
Gambling Task: Social Version. The social version of the gambling task followed the same design as Experiment 1, with some deviations in the conditions and social boards that has been used. The social version of the task now consisted of two conditions, *choices under risk* (see Figure 4A) and *choices under ambiguity* (see Figure 4B), in which participants saw a sample of 15 marbles. Only the trials with a 15-marbles sample were included, as participants did not report

a great difference in the experience of uncertainty between the two levels (15 marbles vs. three marbles) used in the solo version of the game. We believed that including only one uncertainty condition would set a stronger contrast against *choices under risk*. The 15-marbles trials were preferred as these yielded more variations in possible distributions that could be displayed, and therefore could be matched on EV difference and gambling reward with the choices under risk trials. A total of 42 trials (21 *choices under risk*; 21 *choices under ambiguity*) were played in four blocks (10, 10, 11, and 11 trials). *Choices under risk* and *choices under ambiguity* trials were randomly assigned to the four blocks at the start of the game. This set of trials (see Table S9 and Table S10) resulted in participants choosing the gamble option in 54% of the cases based on their own preference (see Supplement A8 of the online supplemental materials for a description of the solo data).

The size of the social boards was set to reveal a maximum of 20 choices. The social boards, representing the classmates' real choices, were based on a subsample of the classmates' choices to obtain the following ratio of underlying choices: 70:30 (14 out of 20 choices) agreeing to gamble, 50:50 (10 out of 20 choices) agreeing to gamble, or 30:70 (six out of 20 choices) agreeing to gamble. Here, the chosen ratio per trial aligned with the risk preference on group-level (based on the whole sample), and thus, was not anchored to the participant's choice. For a breakdown of the trials and the belonging social boards, see Supplement B6 of the online supplemental materials.

Intolerance for Uncertainty. In contrast to Experiment 1, we assessed adolescent's intolerance for uncertainty with the self-report Intolerance for Uncertainty Scale (IUS, short version; Carleton et al., 2007). This shortened version contains 12 items, which measures one's negative feelings and thoughts about uncertainty (e.g., "uncertainty makes life intolerable"). Wording of some items have been changed to enhance adolescents' compatibility and understanding (Comer et al., 2009). The IUS total scale and both subscales have shown excellent internal reliability (range of $\alpha = .85-.91$; Carleton et al., 2007). The 12-item total score correlates high with the full 27-item version of the IUS ($r = .96$), and showed no reduction

Figure 4
Schematic Representation of Main Elements of the Social Gambling Task



Note. Panel A shows an example trial of the choices under risk condition and panel B shows an example trial of the choices under ambiguity condition. Participants had the option to select between a risky (yellow; left) and a safe option of 5 point (blue; right). The social board depicted the classmates' choices as unopened gray boxes. Clicking on the box revealed a made choice, by uncovering the color yellow (indicating that the classmate chose the risky option) or blue (indicating that the classmate chose the safe option). See the online article for the color version of this figure.

in construct validity (Carleton et al., 2007; McEvoy & Mahoney, 2011).

Analysis for Modeling Search Behavior

Search Initiation and Search Length

To quantify the search behavior of adolescents, we examined how often participants choose to sample choices (initiation of search; yes or no) and how much choices (i.e., boxes) they revealed per trial (search length). Again, a multilevel hurdle model, with random intercept on the individual level, was applied on the search behavior. Initiation to search was modeled by the uncertainty in outcome (choices under risk versus choices under ambiguity), IUS scores, choice difficulty, and by the reward associated with the more risky option. These predictors were also used to model search length in the second stage. We used imputation based on predictive mean matching to account for the missing values on IUS score for three participants. The model met the assumption of no multicollinearity ($VIF < 2$).

Computational Model for Social Search Behavior

To better understand the generative process of social information search and integration, we developed two types of computational models. Unlike the hurdle model, these models can model the sequential nature of the incoming social information. Inspired by previous literature we tested simple sequential sampling models with one decision threshold. This model type assumes a step-by-step updating of the utility of the two options until participant's choice preference reaches a decision threshold (e.g., Chung et al., 2015; Hausmann & Läge, 2008; see Figure 5A). Second, based on the findings of Experiment 1, we tested two-step sequential sampling models with two decision thresholds. These models assume that people first determine to initiate search or not based on the first threshold. Next, during the search process, the utility of the options is updated until the participant reaches a second independent threshold (Figure 5B). All models were further extended to incorporate the effects of ambiguity and reward at stake.

Core Framework Initial Choice Preference. Both types of models relied on the following principle: initiation of search relied on participants' initial choice preference for the risky or safe option (γ) and their threshold (δ ; see Figure 5). We assumed symmetric decision thresholds for the risky and safe option. We calculated participant's initial choice preference per trial (i.e., starting point), based on the expected utility theory and participant's solo choices (Session 1). The subjective utility for the risky and the safe option (U_{risk} and U_{safe}) were determined by multiplying the reward probability and reward outcome of the gambles, taking participant's risk- and ambiguity-attitude into account (Tversky & Kahneman, 1992; see Supplement B2 of the online supplemental materials). Based on these utilities we could calculate the probability that the risky option would be chosen by the participant on that specific trial (see Equation 3).

$$p(risk) = \frac{1}{1 + e^{-\tau(U_{risk} - U_{safe})}} \quad (3)$$

In Equation 3, τ is an estimate of the sensitivity parameter, where smaller values of τ indicate less sensitivity to the difference in expected utility between the safe and risky option. Smaller

values for τ brings p (risk) closer to the .5 indifference point (note that participant-specific τ estimates were derived by fitting participant's solo data; see Supplement B2 of the online supplemental materials for more information about the fitting procedure). At the first step the model determines whether the initial choice preference resulted in search initiation by comparing it to the first threshold (δ). Assuming equal thresholds for risky and safe options, we translated p (risk) to an unitary choice preference value (γ), by the distance from the indifference point (p (risk) = .5):

$$\gamma = abs(p(risk) - 0.5) \quad (4)$$

Core Framework for the Search Process. If the initial choice preference did not exceed the threshold (δ), participants would start sampling social information. In each step the preference for the risky or safe option would be updated based on the revealed choices of others. For the simple sequential model, search would stop when the decision threshold (δ) would be reached, or all 20 boxes were opened. For example, a person with a high value for the decision threshold (δ) indicates that this person needs lots of information before deciding, and thus searches more often. This person would decide without sampling, only when he or she has a very strong choice preference. Within this model, the time it takes to reach the decision threshold depends on the starting point (initial preference) and the magnitude of the update in choice preference based on the social information (weighting parameter θ ; see examples of different starting points in Figure 5A). Larger values for the weighting parameter θ would indicate more sensitivity to social information. In the simple sequential model, search initiation and continuation depended on the same threshold.

In contrast with the simple sequential model, the more complex two-step sequential sample model assumed that participants' search process depended on two thresholds: an initiation threshold for deciding to initiate search (δ) and a decision threshold for deciding to stop search once initiated (λ ; see Figure 5B). Thus, search initiation and search continuation are determined by two separate processes, capturing the same logic as the hurdle model. The decision threshold (λ), determining continuation, was expected to be higher than the initiation threshold ($\lambda > \delta$).

In both models, the probability of initiating search was determined by a hard soft-max function with a fixed temperature function ($\tau = 100$):

$$p(search) = \frac{1}{1 + e^{-100(\delta - \gamma)}} \quad (5)$$

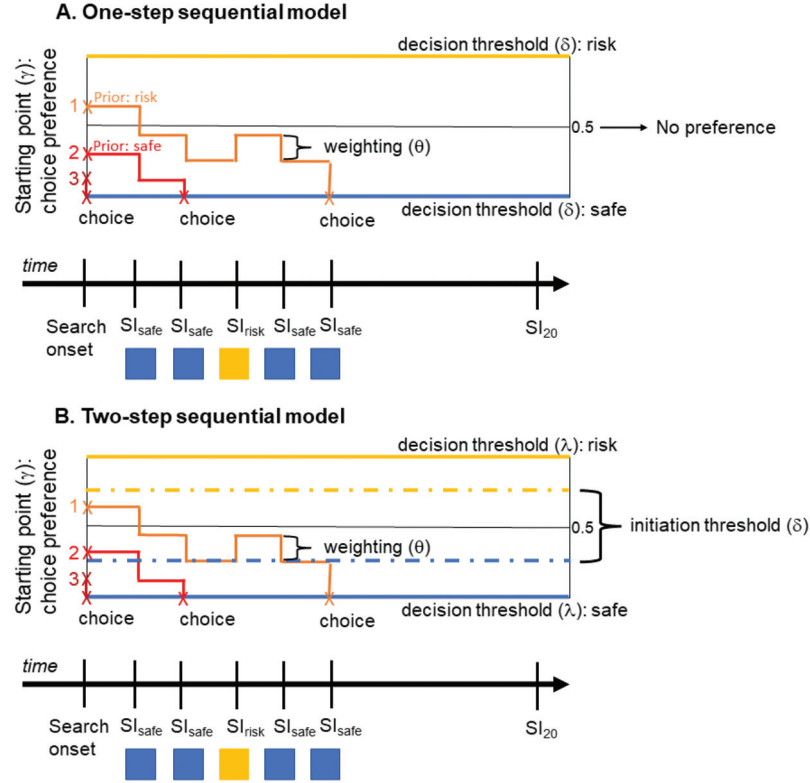
Following previous models of social learning (Chung et al., 2015; Ciranka & van den Bos, 2019), we assumed that, once search was initiated, the utility of each option was updated based on the social information (SI) that was revealed, where magnitude of the update in utility was determined by weighting parameter θ :

$$U_{risk} = U_{risk} + \theta \text{ ;if SI = risk}$$

$$U_{safe} = U_{safe} + \theta \text{ ;if SI = safe}$$

Next, to determine the current choice preference of the participant, $p(risk)$ is updated per Equation 3. The probability that search will

Figure 5
Schematic Scheme of the Proposed One-Sequential (A) and Two-Sequential Model (B)



Note. An overview of the one-step sequential model with one decision threshold (panel A) and the two-step sequential model with two decision thresholds (panel B). In panel A search initiation and search length depend on one singular threshold. In panel B search initiation depends on the initiation threshold and search length on the decision threshold. Case 1, 2 and 3 (dark red, red, and orange lines) displays the path of evidence accumulation for different starting points, until a participant is satisfied with the strength of preference he has reached. In panel A and B, starting with a prior preference for risk (case 1) results in a longer search compared to starting with a prior preference for safe (case 2), based on the incoming information and decision threshold. In panel A, initiation of search occurs for case 3, as the stronger prior preference for safe still does not meet the decision threshold. In panel B, case 3 results in no search as the strength of preference for safe is sufficient, and therefore outside the window for initiation (see initiation threshold δ). See the online article for the color version of this figure.

continue depends on the type of model. For the one-step sequential model this will again be determined by comparing the updated choice preference γ with the δ – threshold (see Equation 5). For the two-sequential model the updated choice preference γ will be compared with decision threshold λ (see Equation 6):

$$p(\text{search}) = \frac{1}{1 + e^{-100(\lambda - \gamma)}} \quad (6)$$

Model Extensions. Based on the results of Experiment 1 and hypotheses of Experiment 2, we included two model extensions. First, an uncertainty parameter was included. Given that both the probability to initiate search and amount of information needed might increase when participants are more uncertain, we hypothesized that uncertainty would directly impact the choice sensitivity parameter. That is, we assume that choice sensitivity

τ is reduced by some factor α when presented with *choices under ambiguity* (simply, $\tau - \alpha$). As noted, reducing τ results in less sensitivity to differences in expected utility, moving $p(\text{risk})$ closer to the no preference point of .5. As a result, this increases $p(\text{search initiation})$, see Equation 5, and the number of steps it takes to reach the second threshold (λ), thus increasing search length. Second, we added a parameter that scaled the first threshold (initiation; δ) by the reward associated with the risky option:

$$\delta = \delta + \pi \left(\frac{\text{reward}}{100} \right) \quad (7)$$

where π is a free parameter that scales the effect of reward on the initiation threshold. Increasing the threshold for higher reward will result in a higher $p(\text{search})$, in line with our behavioral findings.

In total, this resulted in two types of models (one-step sequential and two-step sequential) with three variations (simple and two extensions). Models were fit on the behavioral data of the social version of the gambling task, of which both the search behavior as well as the final choices of the participants were modeled. All models were informed on participant's initial choice preference, based on the solo data of the gambling task (see Supplement B2 of the online supplemental materials). Five participants were excluded from the analyses, as their prior choice preferences could not be calculated due incomplete solo data ($N = 87$, 60% female, $M_{\text{age}} = 13.31$, $SD_{\text{age}} = 1.05$).

Model Fitting. Model fitting was based on the maximum likelihood estimation (MLE). We used 50 combinations of starting points for each parameter, to avoid local minima. These were driven from an uniform distribution within the following parameter bounds: δ and $\lambda = [.01, .6]$, $\theta = [.01, .5]$, $\tau = [.001, 5]$, $\alpha = [.001, 1]$, and reward = [.000001, 2]. Model parameters were estimated using the L-BFGS-B method (Byrd et al., 1995). For model comparison, we computed the Bayesian information criterion (BIC), summed across all participants. The best fitting model was selected on the lowest BIC value. We checked the robustness and predictions of the best fitting model with model recovery (see online Supplement A5 and <https://osf.io/wutf8/>, for code and data).

Results

Group Level Search and Use of Information

Out of the 92 participants, 16 participants did not search during the task. Participants who searched in at least one trial ($N = 77$), searched on average in 7.5 trials ($SD = 6.13$) of 42 trials in total. Mean number of revealed choices for these searched trials was 14.0 ($SD = 5.53$, range = 1–20). As expected, and in line with the results of Experiment 1, the analyses of adolescent's choices showed that adolescents

informed their decisions by the revealed social information ($b = .45$, $SE = .05$, 95% CI [.36, .54], $Z = 9.88$, $p < .001$; see Supplement A3 of the online supplemental materials for the analysis).

Predicting Search Initiation and Search Length

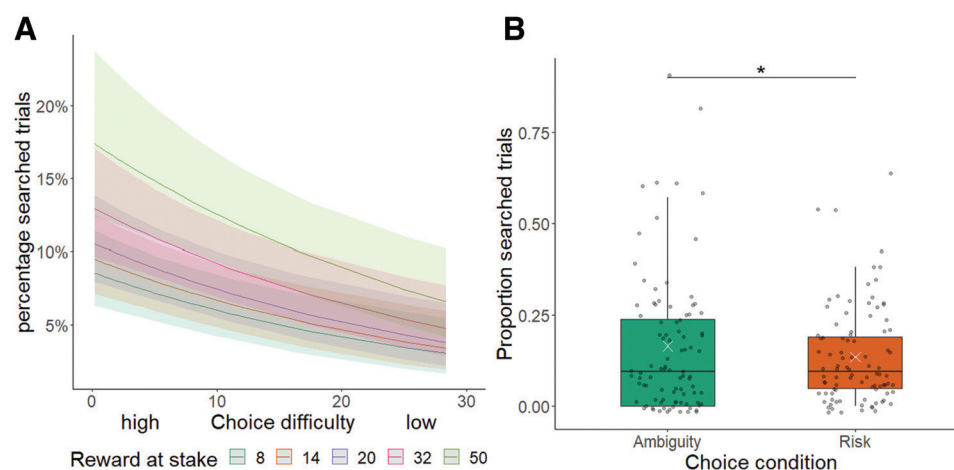
The results showed that participants were more likely to initiate search for choices under ambiguity compared to choices under risk (prediction no search: $b_{\text{risk}} = .27$, $SE = .10$, OR 95% CI [1.08, 1.59], $p < .01$; see Figure 6, Table 2). No effect of ambiguity was found on search length ($b = -.01$, $SE = .05$, RR 95% CI [.90, 1.08], $p = .79$). Confirming the results from Experiment 1, search initiation was more likely for trials with increasing choice difficulty, reflected by smaller EV differences between the two choice options (no search prediction: $b = .24$, $SE = .06$, 95% CI [1.12, 1.44], $p < .001$). However, more difficult choices did not increase search length prior to deciding ($b = -.05$, $SE = .03$, RR 95% CI [.90, 1.01], $p = .13$). Moreover, search initiation did increase for higher rewards at stake (no search prediction: $b = -.28$, $SE = .06$, OR 95% CI [.68, .85], $p < .001$; see Figure 6). In contrast to Experiment 1, reward had no effect on search length ($b = .04$, $SE = .03$, RR 95% CI [.98, 1.09], $p = .19$). Self-reported IUS did not explain the initiation nor the length of search ($b = -.00$, $SE = .02$, OR 95% CI [.97, 1.03], $p = .99$; $b = -.01$, $SE = .01$, RR 95% CI [.98, 1.00], $p = .21$; see Supplement A4 of the online supplemental materials for discussion).

The exit questions, asking about participant's motives to view their classmates' choices showed that the majority of participants revealed information because they felt uncertain (see Supplement A4 of the online supplemental materials for the questionnaire items and results).

Computational Model for Social Search Behavior

Model comparison, based on the model its search and choice predictions, indicated that the set of models with two thresholds

Figure 6
Effect of Choice Difficulty, Reward, and Ambiguity on Search Initiation



Note. Panel A displays the effect of choice difficulty on search initiation, separated for each reward value at stake (8, 14, 20, 32, 50). Panel B displays the effect of increased outcome uncertainty. Here, choices under risk are compared with choices under ambiguity. Gray semitransparent dots refer to data points on participant level. See the online article for the color version of this figure.

* $p < .01$.

Table 2
Hurdle Model Results of Experiment 2

Parameters	Coefficient (<i>SE</i>) zero part	OR [95% CI]	Coefficient (<i>SE</i>) count part	RR [95% CI]
Intercept	2.13 (0.16)***	8.41 [6.10, 11.61]	2.58 (0.06)***	13.23 [11.65, 15.02]
Choice difficulty	0.24 (0.06)***	1.27 [1.12, 1.44]	−0.05 (0.03)	0.96 [0.90, 1.01]
Reward at stake	−0.28 (0.06)***	0.76 [0.68, 0.85]	0.04 (0.03)	1.04 [0.98, 1.09]
Condition: Risk	0.27 (0.10)**	1.31 [1.08, 1.59]	−0.01 (0.05)	0.99 [0.90, 1.08]
IUS	−0.00 (0.02)	1.00 [0.97, 1.03]	−0.01 (0.01)	0.99 [0.98, 1.00]
Log θ	1.57			

Note. The zero part of the model predicts nonsearch events. *SE* = standard error; CI = confidence interval; OR = odds ratio; RR = rate ratio; θ = dispersion parameter; IUS = Tolerance for Uncertainty Scale.

** $p < .01$. *** $p < .001$.

outperformed the model with one threshold for search initiation and search length (see Table 3). This suggests that participants indeed made two, somewhat independent, decisions: adolescents showed to have a decision threshold for the initiation of search and a different decision threshold for stopping search (reflecting the amount of social information needed). Including an uncertainty parameter improved model fit for both types of models, suggesting that uncertainty about the underlying probability indeed reduced participants' certainty about which option they preferred. Furthermore, adding a parameter for the reward at stake, which modulated the certainty threshold, further improved model fit (see Table 3 and Supplement A5 of the online supplemental materials for model recovery results). Thus, increasing the potential gains associated with the risky option increased the probability to initiate search. Model results of the two-step sequential model showed that the first threshold ($\delta_M = .035$), to initiate search, was much smaller than the second decision threshold ($\lambda_M = .418$), for continuing search.

Based on the mixed findings about adolescent's tendency to integrate safe information more often than risky information (Braams et al., 2019; Reiter et al., 2019), we allowed the model to differentiate in the weighting parameter θ for risk and safe information. Post hoc analyses showed that including a different weighting for risky and safe information improved the two-sequential model with an uncertainty and reward parameter even further ($\text{BIC}_{\text{search process}} = 10400.98$; see Supplement A9 of the online supplemental materials for more detail). The median *relative* difference between these parameters was equal to zero (paired-samples Wilcoxon test: $V = 1756$; $p = .76$). However, a one-sample Wilcoxon signed rank test showed that the median of

the *absolute* difference between the estimated weighting parameters was greater than zero (median = .30, $V = 3655$; $p > .001$). This suggests that some adolescents put more weight on risky information, and others more on safe information, but this does not support a structural bias towards risk (Reiter et al., 2019) or safe (Braams et al., 2019) information. However, note that our study was not optimized to assess the weight given to risky or safe information.

Summary

Comparable to Experiment 1, Experiment 2 showed that participants were more likely to initiate search for more difficult choices and higher rewards at stake. As predicted, participants searched more often for choices under ambiguity than choices under risk. Choice difficulty, reward and uncertainty had no effect on the number of revealed choices, prior to deciding. Computational modeling indicated that social search is generated by a two-step decision process: one that determines initiation of search and one that determines how much information is needed. In addition, model comparison confirmed that uncertainty and higher rewards at stake increased search behavior for social information.

While we replicate several findings reported in Experiment 1, there is also a discrepancy in the frequency of search between Experiment 1 and 2. In Experiment 2 participants searched less frequently, and a greater percentage of adolescents refrained from sampling social information. It might be that this discrepancy has to do with the shift from collecting data at schools (Experiment 1) to collecting data online (Experiment 2). Adolescents might have felt less engaged and attentive during this online session

Table 3
Model Comparison Based on the Search and Choice Behavior Performance

Computational models	<i>df</i>	BIC search behavior	BIC search and choice behavior
At chance model	0	16216.87	21282.39
One-step sequential models			
Simple model	2	29014.31	33982.96
Extended model: ambiguity	3	24803.63	29496.63
Extended model: ambiguity and reward	4	23074.13	27598.95
Two-step sequential models			
Simple model	3	12433.97	17506.74
Extended model: ambiguity	4	11385.43	15920.26
Extended model: ambiguity and reward	5	11161.13	15676.33

Note. Rerun of the models yielded the same ranking in model fit (BIC values deviated with a maximum of .2% from the reported values). At chance model is included as reference point for performance. BIC = Bayesian information criterion.

(Francavilla et al., 2019). Nonetheless, this experiment shows that the factors influencing search are independent of this mean level shift in search behavior.

Discussion

During adolescence peers are known to have significant influence on adolescent's choices. The heightened prevalence of risk-taking behavior and social sensitivity in adolescents has led to ample attention to peer influence in this specific group. This is not surprising given that choices made during adolescence may impact the developmental trajectory and have long term consequences (Crone & Dahl, 2012; Dahl et al., 2018). Yet, most research so far has constructed peer influence as the passive reception of information. Therefore, little is known about the active role of adolescents in gaining social information. Our novel social search paradigm enabled us to investigate when and how much adolescents search for social information (i.e., choices of their own classmates) in two experiments. In contrast to most social influence studies, participants were able to observe the choices of their own classmates, instead of fictitious or unknown peers. The results of both experiments showed that initiation of search increased when choice difficulty increased (H1a), and the reward at stake was higher. In addition, Experiment 2 showed that adolescents initiated search more often for choices under ambiguity compared to those under risk (H1b). Moreover, Experiment 1 revealed that being confronted with incongruent social information led to more search for social information prior to deciding, compared to congruent information (H2). As expected, the revealed social information also influenced the final choice of the adolescent (H3). Finally, computational modeling indicated that the search process followed a two-step procedure in which the adolescent first decides to initiate search, followed by an independent decision about the length of search. In sum, both studies showed that adolescents actively searched for social information from their classmates and used this to inform their decisions.

Integration of the Findings

Our results support our line of reasoning that peer influence in adolescence does not purely arise from peer pressure or confrontation with other's behavior, but also exists due the motivation of adolescents to observe and learn from their peers. Importantly, we give some insights into the factors that contribute to the increased motivation to observe others, which lead to adopting others' choices. As expected, choice difficulty and uncertainty about the outcome motivated adolescents to view the choices of their classmates. These results are in line with adolescents' self-reports about their motives to see other's choices. Indeed, more than half of the adolescents reported that they were interested in the choices of their classmates because they felt uncertain about what to choose. This is also in line with a small set of adolescent studies, which showed that people will be more open to social influence when they are uncertain (Moutoussis et al., 2016; Reiter et al., 2021; van Hoorn et al., 2017). Thus, social search can be seen as an adaptive process, since it allows adolescents to reduce uncertainty by informing their choices by peer behavior (Ciranka & van den Bos, 2021; Laland, 2004; Morgan et al., 2012), which provides a novel perspective on social influence.

In Experiment 1, we also found that adolescents searched more often when they faced high reward at stake, which was replicated in Experiment 2. This result is in line with the increased willingness of late adolescents and adults to learn about the probability of high reward, by drawing more samples for high reward at stake, compared with low reward (Hau et al., 2008). It also supports the work of (Davidow et al., 2018) who showed that high-reward values motivated late adolescents to increase effort and cognitive control, leading to more goal-directed behavior. These findings suggest that adolescents felt more motivated to perform optimally on choices leading to potential high reward, and show that high reward could lead to better informed decisions, depending on the expertise of the consulted social source. Our experiments showed that the positive effect of reward on search length was not significant in Experiment 2. This discrepancy might result from the fact that the decision to continue search is also dependent on the revealed information by the participant on that specific timepoint. Due to the exogenous stochasticity in which information is revealed and ordered, there is quite some trial variance, which makes the data on search length much more uncertain compared with search initiation, and thus harder to detect small effects. In addition, a true small effect would be harder to detect in the smaller sample of Experiment 2, where search length was also generally shorter. Taken together, we believe that for this specific effect we did not have adequate power to replicate the effect and thus currently conclude that there is simply no strong evidence for the effect of reward on search length. In sum, these results imply that adolescents would be more likely to inform their decisions by observing the behavior of their peers when an important (i.e., high reward) decision needs to be made, or when they feel uncertain. Future research could investigate how high reward could promote evidence-based decisions in this age group.

Next, our results indicate that the quantity of revealed social information by adolescents depends on the type of social information they encounter. Adolescents searched longer when they encountered choices of their peers that were not in line with their initial preference. This is in line with Gesiarz et al. (2019) who addressed evidence-accumulation as valence-dependent: the belief participants hold influenced the amount of nonsocial information they required. Importantly, our choice analyses also indicated that facing incongruent information made adolescents change their initial choice. This is in line with our theoretical and computational model, which assumed that preferences are updated in the direction of the social information, until a certain decision threshold is met.

Our experiment allowed us to study the factors that contribute to the initiation and continuation of search in adolescence, and exploratory analyses strongly suggest that adolescents also use the revealed social information to adjust their choices. There are multiple potential reasons why adolescents use social information, which are related to the distinction between informational and normative influence (Deutsch & Gerard, 1955; Toelch & Dolan, 2015). First, adolescents may believe that observing the choices of others might help them to make more optimal choices, and thus maximize a higher payoff. Although information of another person in this task reveals little about the optimality of either choice, it may be that seeing a majority choosing risk is interpreted as "wisdom of the crowd" (Surowiecki, 2004). Our exploratory analyses showed that participants benefited economically from following peers' choices

in Experiment 1, as they shifted more often to the option with the highest EV (i.e., the risky option). However, besides economic gains, individuals may also gain social benefits from information sampling. Adolescents are known to specifically put value on belonging to their peer group, and one very effective way of strengthening your connections with the group is to conform to its behavior. Thus, the social information may also be used to reap to social benefits of conforming to the group, and may even push adolescents to make, what they believe are, suboptimal choices. While we were able to assess the effect of the sampled social information to some extent, we are not able to disentangle the motives driving adolescents to conform to social information. Future studies may help disentangle these informational and normative motives by including additional measures such as self-reports (e.g., risk perception) or experimental conditions where participants can choose between social and nonsocial information (cf. Glowacki & Molleman, 2017).

Finally, several insights follow from our computational modeling analyses. First, our findings showed that adolescents' search behavior was best described by a two-step sequential process: first the decision whether to search for social information, followed by the decision on how much information to sample. These computational results converge with our hurdle model that indicated that different factors predict whether someone starts sampling and how long they continue, supporting the idea of two separate decisions. Moreover, the threshold to initiate search was much stricter than the decision threshold used to decide to continue search. This indicates that most participants only initiated search when they were relatively uncertain, but once they started searching, they continued until they reached a strong preference for one of the options. This suggests that the decision to initiate search is qualitatively different from the subsequent decision to search for more information, and that searching for social information generally results in more certain choices. Lastly, computational modeling supported the role of outcome uncertainty (ambiguity) and reward in search initiation and provided more insight in the potential underlying mechanism: outcome uncertainty made adolescents more indifferent about their choice (i.e., risk preference closer to .5), whereas high reward increased adolescents' need for certainty before deciding. This computational framework might help to understand the sources of developmental differences in social information use. For instance, it could help to distinguish between the motivation to initiate search and the motivation to obtain more information, when assessing developmental differences in the use of social information. Moreover, this computation framework might fine-tune current models on information sampling behavior in general, as the current findings for social information might reflect general search processes for nonsocial information as well.

Limitations and Future Directions

Our study showed large individual differences in search initiation and search length, which were not linked to adolescents' self-reported and estimated tolerance for uncertainty. Individual differences in search might be better explained by age. Reiter et al. (2021) previously showed that uncertainty in one's choice preference declined across adolescence, together with a decline in copying others' choices. Moreover, based on reported age differences in sensitivity to peer influence in observational paradigms (e.g., Knoll et al., 2015; Smith

et al., 2015; Steinberg & Monahan, 2007), one might expect that age is also linked to differences in social information search. Our exploratory age-analyses do not support age-related differences in social search behavior across adolescence. However, these analyses should be interpreted with caution, and future research with a more appropriate design (e.g., a more balanced and extended age range, including children and adults) should investigate whether age differences exist. In addition, our study cannot make claims about the specificity of our findings for adolescents. We show that adolescents choose to observe the behavior of others when the ambiguity, difficulty, or reward at stake of a decision increases, a strategy that is likely to be employed by adults as well (Gino & Moore, 2007; Laland, 2004; Ma et al., 2020). Future research should include an adult group to confirm whether adults are likely to employ these search strategies as well.

Moreover, it would be interesting to investigate how adolescents' search strategies for social information are related to their search strategies in a nonsocial context. Search behavior for nonsocial information has been studied in adolescents using different types of experimental designs with mixed findings. The study of van den Bos and Hertwig (2017) suggests that adolescents search less for objective information compared with adults and children, while another recent study showed that adolescents searched more information compared with adults (Niebaum et al., 2022). In contrast, Somerville et al. (2017) did not find quantitative differences in exploration behavior, but qualitative differences between adolescents and adults. Contrasting the search behavior for social information with the search behavior for objective information might yield interesting developmental findings on how adolescents and adults inform their decisions. Along these lines, one should consider the social reputational (Ma et al., 2020) and effort costs (Niebaum et al., 2022) that sampling might have.

A next step, which would extend the ecological validity of our findings and move toward developing a more comprehensive idea of factors eliciting social information use, would be to assess this social search paradigm in other (risk) domains, including more real-life decisions. Previous research has shown that peer influence is not limited to risk-taking but occurs in a wide variety of domains such as eating habits and prosocial behavior (e.g., Romero et al., 2009; van Hoorn et al., 2016). For instance, we believe that existing tasks, such as the public goods game or the risk-perception task, can be easily adapted to this social search paradigm, making this paradigm widely applicable to examine social search across different contexts. The domain-specific nature of our experiment could also explain why, in both experiments, a subsample did not search at all. This group of adolescents might not feel uncertain within this specific context or they are careless about their performance on the gambling task, leading to a lack of motivation to see others' choices. Situations in which observing others' behavior (i.e., social information search) serve to increase one chance of being accepted or liked instead of the need to be right, might motivate adolescents even more to search for social information, compared with this paradigm.

Lastly, the impact of social information on adolescents' search and choice stresses the importance of investigating which (social) sources adolescents consult to inform their decisions. However, little is known about who adolescents actively observe or turn to for advice. For example, previous research identified popular peers as influential (e.g., Choukas-Bradley et al., 2015; Teunissen et al., 2012), who are more likely to engage in risky behavior such as smoking and alcohol use (e.g., Hawke & Rieger, 2013; Valente et al., 2005). In the current

experiment, following risk-seeking peers may result in higher economic payoffs, given that it was more likely that adolescents followed risky advice that pointed to higher expected value. However, it may strongly depend on the context if following advice from risk-taking peers have a negative impact (e.g., taking health risks). Our social search paradigm can be easily adapted by revealing the identity of the peer's classmates on the social board. Investigating who adolescents observe in a free-sampling paradigm, and how this depends on their own social status, would give insight into who adolescents view as important source for information. Along these lines, it would be interesting to see if (anti-) conformity is more likely for certain type of peers.

Conclusion

This study proposed a new experimental and ecological valid paradigm for studying adolescents' social information use. This paradigm was able to investigate when and how much social information adolescents seek, next to the integration of social information on their subsequent decision-making. Our study provided evidence for the active role of adolescents in observing and imitating others. We showed that choice difficulty, high reward at stake, and outcome uncertainty motivated adolescents to seek social information within their social network. This suggests that search for social information was driven by plausible and rational motives within this gambling task. These factors provide a starting point for promoting positive, safe, and well-informed decisions among adolescents. We encourage new research to focus on adolescent's active role and motivation for requiring social information, under normative and informational domains. This will lead to a better understanding of how peers impact adolescents' decisions, by means of the *when* and *who* question, and eventually helps adolescents to become more socially smart.

Context Paragraph

In our, and others' experimental work it has been shown that peer influence plays a major role in the behavior of adolescents, including their tendency to take risks. Previous literature often viewed peer influence as undesirable and involuntarily (e.g., peer pressure) and portrayed the adolescent as a passive receiver of social information. However, peer influence is also driven by the motivation of adolescents to observe and learn from others (e.g., when choosing a new school or trying out drugs for the first time). The way adolescents seek information might have a great impact on their future behavior. For example, consulting daredevil peers would stimulate risk-taking behavior, while risk-averse peers would refrain you from such behavior. Our study focused on the adolescent as an active agent, to provide new insights about when and why they seek and adopt social information. This knowledge will improve our understanding of peer influence during this crucial life stage. Awareness among adolescents about when and who they observe to guide their behavior, will help in fostering adaptive strategies for social information use.

References

Aillerie, K., & McNicol, S. (2018). Are social networking sites information sources? Informational purposes of high-school students in using SNSs.

- Journal of Librarianship and Information Science*, 50(1), 103–114. <https://doi.org/10.1177/0961000616631612>
- Bandura, A. (1977). *Social learning theory*. Prentice Hall.
- Beyens, I., Loes Pouwels, J., Van Driel, I. I., Keijsers, L., & Valkenburg, P. M. (2020). The effect of social media on well-being differs from adolescent to adolescent. *Scientific Reports*, 10(1), Article 10763. <https://doi.org/10.1038/s41598-020-67727-7>
- Blankenstein, N. E., Crone, E. A., van den Bos, W., & van Duijvenvoorde, A. C. K. (2016). Dealing with uncertainty: Testing risk- and ambiguity-attitude across adolescence. *Developmental Neuropsychology*, 41(1–2), 77–92. <https://doi.org/10.1080/87565641.2016.1158265>
- Braams, B. R., Davidow, J. Y., & Somerville, L. H. (2019). Developmental patterns of change in the influence of safe and risky peer choices on risky decision-making. *Developmental Science*, 22(1), Article e12717. <https://doi.org/10.1111/desc.12717>
- Brown, B. B., & Larson, J. (2009). Peer relationships in adolescence. In R. M. Lerner & L. Steinberg (Eds.), *Handbook of adolescent psychology* (pp. 74–103). John Wiley & Sons Inc. <https://doi.org/10.1002/9780470479193.adlpsy002004>
- Byrd, R. H., Lu, P., Nocedal, J., & Zhu, C. (1995). A limited memory algorithm for bound constrained optimization. *SIAM Journal on Scientific Computing*, 16(5), 1190–1208. <https://doi.org/10.1137/0916069>
- Carleton, R. N., Norton, M. A. P. J., & Asmundson, G. J. G. (2007). Fearing the unknown: A short version of the Intolerance of Uncertainty Scale. *Journal of Anxiety Disorders*, 21(1), 105–117. <https://doi.org/10.1016/j.janxdis.2006.03.014>
- Cascio, C. N., Carp, J., O'Donnell, M. B., Tinney, F. J., Bingham, C. R., Shope, J. T., Ouimet, M. C., Pradhan, A. K., Simons-Morton, B. G., & Falk, E. B. (2015). Buffering social influence: Neural correlates of response inhibition predict driving safety in the presence of a peer. *Journal of Cognitive Neuroscience*, 27(1), 83–95. https://doi.org/10.1162/jocn_a_00693
- Choukas-Bradley, S., Giletta, M., Cohen, G. L., & Prinstein, M. J. (2015). Peer influence, peer status, and prosocial behavior: An experimental investigation of peer socialization of adolescents' intentions to volunteer. *Journal of Youth and Adolescence*, 44(12), 2197–2210. <https://doi.org/10.1007/s10964-015-0373-2>
- Chung, D., Christopoulos, G. I., King-Casas, B., Ball, S. B., & Chiu, P. H. (2015). Social signals of safety and risk confer utility and have asymmetric effects on observers' choices. *Nature Neuroscience*, 18(6), 912–916. <https://doi.org/10.1038/nn.4022>
- Ciranka, S., & van den Bos, W. (2019). Social influence in adolescent decision-making: A formal framework. *Frontiers in Psychology*, 10, Article 1915. <https://doi.org/10.3389/fpsyg.2019.01915>
- Ciranka, S., & van den Bos, W. (2021). Adolescent risk-taking in the context of exploration and social influence. *Developmental Review*, 61, Article 100979. <https://doi.org/10.1016/j.dr.2021.100979>
- Clark, L., Robbins, T. W., Ersche, K. D., & Sahakian, B. J. (2006). Reflection impulsivity in current and former substance users. *Biological Psychiatry*, 60(5), 515–522. <https://doi.org/10.1016/j.biopsych.2005.11.007>
- Cohen, G. L., & Prinstein, M. J. (2006). Peer contagion of aggression and health risk behavior among adolescent males: An experimental investigation of effects on public conduct and private attitudes. *Child Development*, 77(4), 967–983. <https://doi.org/10.1111/j.1467-8624.2006.00913.x>
- Comer, J. S., Roy, A. K., Furr, J. M., Gotimer, K., Beidas, R. S., Dugas, M. J., & Kendall, P. C. (2009). The intolerance of uncertainty scale for children: A psychometric evaluation. *Psychological Assessment*, 21(3), 402–411. <https://doi.org/10.1037/a0016719>
- Crone, E. A., & Dahl, R. E. (2012). Understanding adolescence as a period of social-affective engagement and goal flexibility. *Nature Reviews Neuroscience*, 13(9), 636–650. <https://doi.org/10.1038/nrn3313>
- Dahl, R. E., Allen, N. B., Wilbrecht, L., & Suleiman, A. B. (2018). Importance of investing in adolescence from a developmental science perspective. *Nature*, 554(7693), 441–450. <https://doi.org/10.1038/nature25770>

- Danchin, É., Giraldeau, L. A., Valone, T. J., & Wagner, R. H. (2004). Public information: From nosy neighbors to cultural evolution. *Science*, 305(5683), 487–491. <https://doi.org/10.1126/science.1098254>
- Davidow, J. Y., Insel, C., & Somerville, L. H. (2018). Adolescent development of value-guided goal pursuit. *Trends in Cognitive Sciences*, 22(8), 725–736. <https://doi.org/10.1016/j.tics.2018.05.003>
- De Martino, B., Bobadilla-Suarez, S., Nouguchi, T., Sharot, T., & Love, B. C. (2017). Social information is integrated into value and confidence judgments according to its reliability. *The Journal of Neuroscience*, 37(25), 6066–6074. <https://doi.org/10.1523/JNEUROSCI.3880-16.2017>
- Dekkers, T. J., Popma, A., Sonuga-Barke, E. J. S., Oldenhof, H., Bexkens, A., Jansen, B. R. J., & Huizenga, H. M. (2020). Risk taking by adolescents with attention-deficit/hyperactivity disorder (ADHD): A behavioral and psychophysiological investigation of peer influence. *Journal of Abnormal Child Psychology*, 48(9), 1129–1141. <https://doi.org/10.1007/s10802-020-00666-z>
- Deutsch, M., & Gerard, H. B. (1955). A study of normative and informational social influences upon individual judgement. *Journal of Abnormal Psychology*, 51(3), 629–636. <https://doi.org/10.1037/h0046408>
- Francavilla, N. M., Meade, A. W., & Young, A. L. (2019). Social interaction and internet-based surveys: Examining the effects of virtual and in-person proctors on careless response. *Applied Psychology*, 68(2), 223–249. <https://doi.org/10.1111/apps.12159>
- Gardner, M., & Steinberg, L. (2005). Peer influence on risk taking, risk preference, and risky decision making in adolescence and adulthood: An experimental study. *Developmental Psychology*, 41(4), 625–635. <https://doi.org/10.1037/0012-1649.41.4.625>
- Gesiarz, F., Cahill, D., & Sharot, T. (2019). Evidence accumulation is biased by motivation: A computational account. *PLoS Computational Biology*, 15(6), Article e1007089. <https://doi.org/10.1371/journal.pcbi.1007089>
- Gino, F., & Moore, D. A. (2007). Effects of task difficulty on use of advice. *Journal of Behavioral Decision Making*, 20(1), 21–35. <https://doi.org/10.1002/bdm.539>
- Glickman, M., Shari, O., Levy, D. J., Niebur, E., Stuphorn, V., & Usher, M. (2019). The formation of preference in risky choice. *PLoS Computational Biology*, 15(8), Article e1007201. <https://doi.org/10.1371/journal.pcbi.1007201>
- Glowacki, L., & Molleman, L. (2017). Subsistence styles shape human social learning strategies. *Nature Human Behaviour*. Advance online publication. <https://doi.org/10.1038/s41562-017-0098>
- Hau, R., Pleskac, T. J., Kiefer, J., & Hertwig, R. (2008). The description-experience gap in risky choice: The role of sample size and experienced probabilities. *Journal of Behavioral Decision Making*, 21(5), 493–518. <https://doi.org/10.1002/bdm.598>
- Hauser, T. U., Moutoussis, M., Dayan, P., & Dolan, R. J. (2017). Increased decision thresholds trigger extended information gathering across the compulsivity spectrum. *Translational Psychiatry*, 7(12), Article 1296. <https://doi.org/10.1038/s41398-017-0040-3>
- Hauser, T. U., Moutoussis, M., Iannaccone, R., Brem, S., Walitza, S., Drechsler, R., Dayan, P., & Dolan, R. J. (2017). Increased decision thresholds enhance information gathering performance in juvenile obsessive-compulsive disorder (OCD). *PLoS Computational Biology*, 13(4), Article e1005440. <https://doi.org/10.1371/journal.pcbi.1005440>
- Hausmann, D., & Läge, D. (2008). Sequential evidence accumulation in decision making: The individual desired level of confidence can explain the extent of information acquisition. *Judgment and Decision Making*, 3(3), 229–243. <https://doi.org/10.5167/uzh-6226>
- Hawke, S., & Rieger, E. (2013). Popularity, likeability, and risk-taking in middle adolescence. *Health*, 05(06), 41–52. <https://doi.org/10.4236/health.2013.56A3007>
- Hofstetter, H., Dusseldorp, E., Zeileis, A., & Schuller, A. A. (2016). Modeling caries experience: Advantages of the use of the hurdle model. *Caries Research*, 50(6), 517–526. <https://doi.org/10.1159/000448197>
- Knoll, L. J., Magis-Weinberg, L., Speekenbrink, M., & Blakemore, S. J. (2015). Social influence on risk perception during adolescence. *Psychological Science*, 26(5), 583–592. <https://doi.org/10.1177/0956797615569578>
- Krajich, I., Armel, C., & Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience*, 13(10), 1292–1298. <https://doi.org/10.1038/nn.2635>
- Laland, K. N. (2004). Social learning strategies. *Learning and Behavior*, 32, (1), 4–14. <https://doi.org/10.3758/BF03196002>
- Lam, C. B., McHale, S. M., & Crouter, A. C. (2014). Time with peers from middle childhood to late adolescence: Developmental course and adjustment correlates. *Child Development*, 85(4), 1677–1693. <https://doi.org/10.1111/cdev.12235>
- Larson, R. W., Moneta, G., Richards, M. H., Holmbeck, G., & Duckett, E. (1996). Changes in adolescents' daily interactions with their families from ages 10 to 18: Disengagement and transformation. *Developmental Psychology*, 32(4), 744–754. <https://doi.org/10.1037/0012-1649.32.4.744>
- Ma, I., Sanfey, A. G., & Ma, W. J. (2020). The social cost of gathering information for trust decisions. *Scientific Reports*, 10(1), Article 14073. <https://doi.org/10.1038/s41598-020-69766-6>
- McEvoy, P. M., & Mahoney, A. E. J. (2011). Achieving certainty about the structure of intolerance of uncertainty in a treatment-seeking sample with anxiety and depression. *Journal of Anxiety Disorders*, 25(1), 112–122. <https://doi.org/10.1016/j.janxdis.2010.08.010>
- Molleman, L., Tump, A. N., Gradassi, A., Herzog, S., Jayles, B., Kurvers, R. H. J. M., & van den Bos, W. (2020). Strategies for integrating disparate social information. *Proceedings of the Royal Society B: Biological Sciences*, 287(1939), Article 20202413. <https://doi.org/10.1098/rspb.2020.2413>
- Morgan, T. J. H., Rendell, L. E., Ehn, M., Hoppitt, W., & Laland, K. N. (2012). The evolutionary basis of human social learning. *Proceedings of the Royal Society B: Biological Sciences*, 279(1729), 653–662. <https://doi.org/10.1098/rspb.2011.1172>
- Moutoussis, M., Dolan, R. J., & Dayan, P. (2016). How people use social information to find out what to want in the paradigmatic case of intertemporal preferences. *PLoS Computational Biology*, 12(7), Article e1004965. <https://doi.org/10.1371/journal.pcbi.1004965>
- Mullahy, J. (1986). Specification and testing of some modified count data models. *Journal of Econometrics*, 33(3), 341–365. [https://doi.org/10.1016/0304-4076\(86\)90002-3](https://doi.org/10.1016/0304-4076(86)90002-3)
- Niebaum, J. C., Kramer, A. W., Huizenga, H. M., & van den Bos, W. (2022). Adolescents sample more information prior to decisions than adults when effort costs increase. *Developmental Psychology*. Advance online publication. <https://doi.org/10.1037/dev0001397>
- Pew Research Center. (2018). *Teens, Social Media & Technology 2018*. Pew Research Center: Internet, Science & Tech. www.pewresearch.org/internet/2018/05/31/teens-social-media-technology-2018/
- Pinho, A. D. S., Molleman, L., Braams, B. R., & van den Bos, W. (2021). Majority and popularity effects on norm formation in adolescence. *Scientific Reports*, 11(1), Article 12884. <https://doi.org/10.1038/s41598-021-92482-8>
- Ratcliff, R., & Smith, P. L. (2004). A comparison of sequential sampling models for two-choice reaction time. *Psychological Review*, 111(2), 333–367. <https://doi.org/10.1037/0033-295X.111.2.333>
- Reiter, A. M. F., Moutoussis, M., Vanes, L., Kievit, R., Bullmore, E. T., Goodyer, I. M., Fonagy, P., Jones, P. B., & Dolan, R. J. (2021). Preference uncertainty accounts for developmental effects on susceptibility to peer influence in adolescence. *Nature Communications*, 12(1), Article 3823. <https://doi.org/10.1038/s41467-021-23671-2>
- Reiter, A. M. F., Suzuki, S., O'Doherty, J. P., Li, S.-C., & Eppinger, B. (2019). Risk contagion by peers affects learning and decision-making in adolescents. *Journal of Experimental Psychology: General*, 148(9), 1494–1504. <https://doi.org/10.1037/xge0000512>
- Riedijk, L., & Harakeh, Z. (2018). Imitating the risky decision-making of peers: An experimental study among emerging adults. *Emerging Adulthood*, 6(4), 255–265. <https://doi.org/10.1177/2167696817722918>

- Rizopoulos, D. (2020). GLMMadaptive: Generalized Linear Mixed Models using Adaptive Gaussian Quadrature (R package version 0.7-0). <https://CRAN.Rproject.org/package=GLMMadaptive>
- Rodriguez Buritica, J. M., Hecker, H. R., & van den Bos, W. (2019). The computational basis of following advice in adolescents. *Journal of Experimental Child Psychology*, 180, 39–54. <https://doi.org/10.1016/j.jecp.2018.11.019>
- Rolls, E. T., McCabe, C., & Redoute, J. (2008). Expected value, reward outcome, and temporal difference error representations in a probabilistic decision task. *Cerebral Cortex*, 18(3), 652–663. <https://doi.org/10.1093/cercor/bhm097>
- Romero, N. D., Epstein, L. H., & Salvy, S. J. (2009). Peer modeling influences girls' snack intake. *Journal of the American Dietetic Association*, 109(1), 133–136. <https://doi.org/10.1016/j.jada.2008.10.005>
- Simons-Morton, B., Lerner, N., & Singer, J. (2005). The observed effects of teenage passengers on the risky driving behavior of teenage drivers. *Accident; Analysis and Prevention*, 37(6), 973–982. <https://doi.org/10.1016/j.aap.2005.04.014>
- Smith, A. R., Steinberg, L., Strang, N., & Chein, J. (2015). Age differences in the impact of peers on adolescents' and adults' neural response to reward. *Developmental Cognitive Neuroscience*, 11, 75–82. <https://doi.org/10.1016/j.dcn.2014.08.010>
- Somerville, L. H., Sasse, S. F., Garrad, M. C., Drysdale, A. T., Abi Akar, N., Insel, C., & Wilson, R. C. (2017). Charting the expansion of strategic exploratory behavior during adolescence. *Journal of Experimental Psychology: General*, 146(2), 155–164. <https://doi.org/10.1037/xge0000250>
- Steinberg, L., & Monahan, K. C. (2007). Age differences in resistance to peer influence. *Developmental Psychology*, 43(6), 1531–1543. <https://doi.org/10.1037/0012-1649.43.6.1531>
- Surowiecki, J. (2004). *The wisdom of crowds: Why the many are smarter than the few and how collective wisdom shapes business, economies, societies, and nations*. Little, Brown.
- Suzuki, S., Jensen, E. L. S., Bossaerts, P., & O'Doherty, J. P. (2016). Behavioral contagion during learning about another agent's risk-preferences acts on the neural representation of decision-risk. *Proceedings of the National Academy of Sciences of the United States of America*, 113(14), 3755–3760. <https://doi.org/10.1073/pnas.1600092113>
- Teunissen, H. A., Spijkerman, R., Prinstein, M. J., Cohen, G. L., Engels, R. C. M. E., & Scholte, R. H. J. (2012). Adolescents' conformity to their peers' pro-alcohol and anti-alcohol norms: The power of popularity. *Alcoholism, Clinical and Experimental Research*, 36(7), 1257–1267. <https://doi.org/10.1111/j.1530-0277.2011.01728.x>
- Toelch, U., & Dolan, R. J. (2015). Informational and normative influences in conformity from a neurocomputational perspective. *Trends in Cognitive Sciences*, 19(10), 579–589. <https://doi.org/10.1016/j.tics.2015.07.007>
- Tomova, L., & Pessoa, L. (2018). Information about peer choices shapes human risky decision-making. *Scientific Reports*, 8(1), Article 5129. <https://doi.org/10.1038/s41598-018-23455-7>
- Tump, A. N., Pleskac, T. J., & Kurvers, R. H. J. M. (2020). Wise or mad crowds? The cognitive mechanisms underlying information cascades. *Science Advances*, 6(29), Article eabb0266. <https://doi.org/10.1126/sciadv.abb0266>
- Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, 5(4), 297–323. <https://doi.org/10.1007/BF00122574>
- Valente, T. W., Unger, J. B., & Johnson, C. A. (2005). Do popular students smoke? The association between popularity and smoking among middle school students. *Journal of Adolescent Health*, 37(4), 323–329. <https://doi.org/10.1016/j.jadohealth.2004.10.016>
- van den Bos, W., & Hertwig, R. (2017). Adolescents display distinctive tolerance to ambiguity and to uncertainty during risky decision making. *Scientific Reports*, 7(1), Article 40962. <https://doi.org/10.1038/srep40962>
- van Hoorn, J., Crone, E. A., & Van Leijenhorst, L. (2017). Hanging out with the right crowd: Peer influence on risk-taking behavior in adolescence. *Journal of Research on Adolescence*, 27(1), 189–200. <https://doi.org/10.1111/jora.12265>
- van Hoorn, J., van Dijk, E., Meuwese, R., Rieffe, C., & Crone, E. A. (2016). Peer influence on prosocial behavior in adolescence. *Journal of Research on Adolescence*, 26(1), 90–100. <https://doi.org/10.1111/jora.12173>

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