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Jepma, M.; Schaaf, J.V.; Visser, I.; Huizenga, H.M.

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Marieke Jepma *, Jessica V. Schaaf, Ingmar Visser, Hilde M. Huizenga

Department of Psychology, University of Amsterdam, 1012 WX Amsterdam, the Netherlands

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Recent studies that compared effects of pre-learning advice on experience-based learning in adolescents and adults have yielded mixed results. Previous studies on this topic used choice tasks in which age-related differences in advice-related learning bias and exploratory choice behavior are difficult to dissociate. Moreover, these studies did not examine whether effects of advice depend on working memory load. In this preregistered study (in adolescents [13–15 years old] and adults [18–31 years old]), we addressed these issues by factorially combining advice and working memory load manipulations in an estimation task that does not require choices and hence eliminates the influence of known age-related differences in exploration. We found that advice guided participants' initial estimates in both age groups. When advice was correct, this improved estimation performance, especially in adolescents when working memory load was high. When advice was incorrect, it had a longer-lasting effect on adolescents' performance than on adults' performance. In contrast to previous findings in choice tasks, we found no evidence that advice biased learning in either age group. Taken together, our results suggest that learning in an estimation task improves between adolescence and adulthood but that the effects of advice on learning do not differ substantially between adolescents and adults.

* Corresponding author.
E-mail address: m.jepma@uva.nl (M. Jepma).

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Introduction

Adaptive behavior requires people to quickly learn the value of new stimuli and events in their environment. Stimulus–outcome and action–outcome contingencies can be learned through direct personal experience but also via information from others (e.g., instructions, advice). These two means of acquiring knowledge often co-occur, for example, when a friend recommends a specific restaurant after which you visit that restaurant yourself or when you first hear your partner's opinion about his or her family members and then get to know them yourself. In such situations, how does the information you received beforehand influence your own subsequent learning process?

This question is particularly relevant in the context of development. Children and adolescents frequently receive instructions and advice from their parents and teachers, and are highly sensitive to their peers' opinions (especially adolescents) (Albert, Chein, & Steinberg, 2013; Brown & Larson, 2009; Rodman, Powers, & Somerville, 2017), while at the same time learning from their own experiences. There is extensive evidence for developmental changes in experience-based learning in the absence of advice (Christakou et al., 2013; Cohen et al., 2010; Crone, Jennings, & Van der Molen, 2004; Eppinger, Mock, & Kray, 2009; Hauser, Iannaccone, Walitza, Brandeis, & Brem, 2015; Javadi, Schmidt, & Smolka, 2014; Jepma, Schaaf, Visser, & Huizenga, 2020; Palminteri, Kilford, Coricelli, & Blakemore, 2016; van den Bos, Cohen, Kahnt, & Crone, 2012; van Duijvenvoorde, Zanolie, Rombouts, Raijmakers, & Crone, 2008), but if and how the influence of advice on experience-based learning changes across development is still largely unknown (but see Decker, Lourenco, Doll, & Hartley, 2015; Lourenco et al., 2015; Rodriguez Buritica, Heekeren, & van den Bos, 2019). More insight into this topic may help to increase the efficacy of educational programs and public health campaigns aimed at specific age groups.

Previous studies in which adult participants were advised to choose a particular option before starting an instrumental reward learning task found that participants' choices were biased toward the advised option (Biele, Rieskamp, & Gonzalez, 2009; Biele, Rieskamp, Krugel, & Heekeren, 2011; Doll, Hutchison, & Frank, 2011; Doll, Jacobs, Sanfey, & Frank, 2009; Staudinger & Buchel, 2013). Furthermore, this advice-following behavior often persisted over time even if it yielded suboptimal outcomes (Decker et al., 2015; Doll et al., 2009; Staudinger & Buchel, 2013). These findings may reflect several not mutually exclusive effects of advice on experience-based learning. First, advice is likely to affect people's initial expectations, such that positively advised options start out with a higher expected value than non-advised options (Biele et al., 2011; Rodriguez Buritica et al., 2019). Second, advice may bias experience-based learning in two ways. This bias can operate on the expectation-updating process by increasing the learning rate for advice-consistent outcomes relative to advice-inconsistent outcomes (Doll et al., 2009, 2011). Such a "confirmation bias" results in an overvaluation of advised options, which can explain persistent advice following despite contradictory evidence. Alternatively, advice can also bias learning by affecting outcome evaluation. Specifically, a more positive evaluation of outcomes from advised options—which has been referred to as an "outcome bonus"—can produce a persistent overvaluation of these options as well (Biele et al., 2011). Note that although the outcome bonus and confirmation bias mechanisms are conceptually different—affecting the input to the expectation-updating process and the updating process itself, respectively—they bias the learning process in similar ways and hence are difficult to dissociate. Third, people may be more confident about the value of advised options, corresponding to more precise expectations. In a Bayesian framework, more precise expectations, or priors, are updated less in response to prediction errors (i.e., lower learning rates). Thus, instead of *biasing* learning, advice may *suppress*, or slow down, experience-based learning by increasing the precision of expectations (Li, Delgado, & Phelps, 2011).

Importantly, people's choice behavior not only depends on the expected values of advised versus non-advised options but also depends on how these values are translated into choices. A key element of this choice process is the trade-off between exploiting the option with the highest expected value and exploring alternative apparently suboptimal options (Cohen, McClure, & Yu, 2007). If advised options start out with a higher expected value than non-advised options, people with a strong exploitative choice strategy will tend to exclusively choose the advised option, which is beneficial in case of correct advice. In contrast, people with a more exploratory choice strategy will sometimes choose non-advised options as well, which is beneficial in case of incorrect advice because it will facilitate the discovery of other more rewarding choice options. Thus, because people's degree of exploration influences their advice-following behavior, individual differences in advice-driven modulation of learning can be difficult to disentangle from individual differences in exploration. This is especially problematic when studying differences between experimental conditions or groups; if these differ in advice-following behavior, it is hard to determine whether this is due to differences in advice effects on the learning process, differences in exploration, or both.

With regard to developmental changes, several studies have shown that children and adolescents make more exploratory choices than adults in both the absence and presence of advice (Christakou et al., 2013; Decker et al., 2015; Javadi et al., 2014; Jepma et al., 2020; Rodriguez Buritica et al., 2019; Spear, 2000). To our knowledge, three previous studies have examined how incorrect advice (Decker et al., 2015; Lourenco et al., 2015) and correct advice (Rodriguez Buritica et al., 2019) affect subsequent learning and decision making in different age groups. One study found that choices of children and adolescents were driven more by the actual experienced outcomes and less by incorrect advice than choices of young adults (Decker et al., 2015). Computational models applied to the choice data from this study provided evidence for a confirmation bias in learning in adults but not in learning in children and adolescents. The second study, using an incorrect-advice manipulation in a more cognitively demanding task—including four stimulus pairs and two advised stimuli—did not find an overall advice-related bias in either adolescents or young adults (the authors did not test children) and found no differences between these age groups (Lourenco et al., 2015). The third study showed that correct advice had a stronger effect on the initial expected values in adolescents than in children and young adults but found no age-related differences in advice effects on the subsequent learning process (Rodriguez Buritica et al., 2019). Thus, the three previous developmental studies that examined advice effects on experience-based learning yielded mixed results. Together, their findings suggest that whether and how effects of pre-learning advice differ between adolescents and adults may depend on the accuracy of the advice as well as on the cognitive load of the task.

Of the three developmental studies reviewed above, two studies used computational models to infer the learning and decision mechanisms underlying participants' choice behavior (Decker et al., 2015; Rodriguez Buritica et al., 2019). Importantly, in addition to age-related changes in the effects of advice on the learning process (Decker et al., 2015) and on initial expectations (Rodriguez Buritica et al., 2019), the model-based analyses from both these studies revealed a higher degree of choice randomness (or exploration) in children and adolescents as compared with adults. Although the computational models used in these studies are designed to tease apart learning and choice mechanisms, the model parameters that control these two mechanisms often trade off against each other to some extent (Daw, 2011). Such parameter trade-offs are also present in models that include advice effects on learning (see Supplemental Text 1 and Supplemental Fig. 1 in the online supplementary material for simulation results), which is problematic when interpreting differences in estimated advice effects between groups of participants if these groups also differ in choice randomness or exploration.

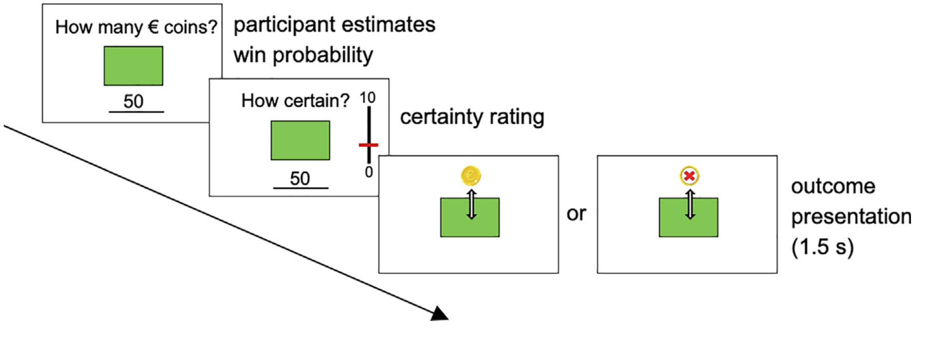

Fig. 1. Outline of a trial in the Set Size 1 version of the task.

The current study

The aim of the current study was to study potential age-related differences in advice effects on learning unconfounded by age-related differences in exploration. To this end, we tested adolescents aged 12 to 15 years (from the second year of high school) and adults aged 18 to 31 years (the two age groups were matched with regard to educational level) on a learning task that does not involve choices but requires participants to explicitly estimate the value of stimuli based on sequentially observed outcomes. Thus, this task directly measures the expectation-updating process unconfounded by exploration. Specifically, during our task, participants repeatedly estimated the value (operationalized as the probability of winning) of a stimulus. Following each estimate, participants observed one binary outcome (win or no-win outcome), after which they could update their estimate. Participants also rated their certainty in each estimate. Whereas studies using instrumental learning tasks typically infer participants' learning rate and trial-by-trial changes in expected value from choice data, our task provides a direct measure of these variables (also see Method).

We examined effects of correct and incorrect advice about stimuli's win probability—received from an alleged same-aged peer prior to the first observation—on estimation accuracy and certainty ratings. Then, to shed more light on *how* advice affects estimation performance and whether this differs between adolescents and adults, we examined the effects of advice on participants' initial estimates and on their learning rates. In the analysis on learning rate, we specifically examined evidence for (age-related differences in) a confirmation bias. Finally, we reasoned that the impact of advice may be stronger in more demanding learning tasks such as those with a high working memory load. Furthermore, given that working memory function and its underlying neural circuitry continue to mature into late adolescence (Geier, Garver, Terwilliger, & Luna, 2009; Huizinga, Dolan, & van der Molen, 2006; Kwon, Reiss, & Menon, 2002; Luna, 2009; McAuley & White, 2011), this dependence on working memory load may be stronger for adolescents than for adults. To test these ideas, we also varied the working memory load of the learning task—by manipulating the number of stimuli that participants learned about concurrently (i.e., the set size)—and tested for the effect of set size, and its interaction with age group, in all our analyses.

Method

Preregistration

We preregistered our main research questions, analyses, and exclusion criteria using AsPredicted (http://aspredicted.org/blind.php?x=cp9rd4). Non-preregistered analyses are treated as exploratory and are reported in the supplementary material.

Participants

In total, 103 young adults (age range = 18–31 years; 58% female) and 163 adolescents (age range = 12–15 years; 65% female) participated in the study. Adults were students or former students at Dutch universities or colleges of higher professional education. Adolescents were in the second year of high school of the Dutch school system (pre-university or higher general secondary education); hence, the vast majority of adolescents were 13 or 14 years old, with a few exceptions being 12 or 15 years old. Adult participants received 5 euros or course credits, plus a variable bonus of 1 to 3 euros, for their participation. Adolescent participants received 5 chocolate coins, plus a variable bonus of 1 to 3 chocolate coins, for their participation. Adult participants provided written informed consent. Primary caretakers of the adolescent participants were informed about the experiment and had the opportunity to refuse the participation of their children (passive consent). All procedures were approved by the local ethics committee.

In total, 32 adolescents and 5 adults did not complete the task because of technical problems (interruptions of the task, which was run online, mostly due to unstable internet connections at the schools where the adolescents were tested). Of the remaining participants, 11 adolescents and 10 adults were excluded prior to analysis because they reported a history of psychiatric or neurological disorders and/or use of alcohol or recreational drugs on the test day. This left us with data from 120 adolescents (3 12-year-olds, 81 13-year-olds, 35 14-year-olds, and 1 15-year-old; 67% female) and 88 adults (M_{age} = 22.1 years, *SD* = 3.2, range = 18–31; 60% female).

In addition, we preregistered to exclude participants who used negative learning rates (i.e., reduced their estimated win probability after a win outcome or increased their estimated win probability after a no-win outcome) on more than 30% of the trials because this behavior is indicative of poor task understanding or the use of a gambler's fallacy-like strategy (see the first Results section and Discussion). Note that this exclusion criterion does not consider *when* the trials with negative learning rates occurred (but see Supplemental Text 2 for an analysis on this issue). Based on this criterion, we excluded 49 adolescents and 8 adults. Thus, the remaining sample consisted of 71 adolescents (36 and 35 in the Set Size 1 and Set Size 2 versions, respectively; 47 13-year-olds, 23 14-year-olds, and 1 15-year-old; 64% female) and 80 adults (39 and 41 in the Set Size 1 and Set Size 2 versions, respectively; M_{age} = 22.3 years, range = 18–31; 65% female).

As preregistered, we performed our analyses on this final sample. However, we also repeated the analyses on estimation accuracy without excluding participants according to our gambler's fallacy criterion. These analyses are reported in Supplemental Text 2; we summarize their results here. Including participants with a gambler's fallacy-like strategy resulted in stronger effects of age group on overall estimation performance. This can be explained by the fact that many more adolescents than adults used this maladaptive strategy; hence, including these participants impaired average estimation accuracy more in the adolescent group. Including these participants did not change the Age Group $\times$ Advice interaction or the Age Group $\times$ Advice $\times$ Set Size interaction, suggesting that the effects of advice did not differ substantially between the adolescents who did use a gambler's fallacy-like strategy and those who did not.

General procedure

Adolescent participants were tested in a classroom or computer room at their high school in groups of approximately 20. Adult participants were tested in a computer room at the university in groups of 2 to 5 (we did not test the adults in larger groups for practical reasons). At least one experimenter was always present in the testing room as well. Participants performed the experiment individually on a laptop or PC. Before starting the probabilistic learning task, participants were informed about the task structure and procedure by means of computerized instructions and performed a practice block (without advice). In the instructions, participants were encouraged to raise their hand and (softly) ask the experimenter for clarification if they did not understand the instructions or had questions about the task. At the end of the test session—which lasted 30 to 45 min—participants were debriefed about the aim of the experiment and were informed that the advice they had received did not actually come from other participants but rather had been preprogrammed by the experimenters.

Probabilistic learning task

In this task, participants observed sequences of binary outcomes—win and no-win outcomes. Before each new observation, participants estimated the probability of a win outcome and rated how certain they were about this estimate (Fig. 1). To make the estimation of probabilities more intuitive, we embedded the task in a cover story according to which the outcomes were coins that were drawn from specific boxes displayed on a computer screen. We instructed participants that each box contained 100 coins, which consisted of a mixture of euro coins (win outcomes; depicted as coins with a euro sign) and fake coins (no-win outcomes; depicted as coins with a cross). The proportion of euro coins was unknown, but on each trial one coin was drawn from a box and was revealed to participants. Participants were also instructed that after a coin was drawn, it was returned to the box and all coins were shuffled for the next trial. Unbeknownst to participants, the percentage of euro coins drawn from a specific box was always 25%, 50%, or 75%.

Participants won 1 point each time a euro coin was drawn but not when a fake coin was drawn. We instructed participants that their total number of points won would be translated into a bonus to be received at the end of the test session (in reality, this bonus was 1 euro and 1 chocolate coin for each adult and adolescent, respectively). Participants were also instructed that they could not influence the proportion of win outcomes. To incentivize estimation accuracy, participants earned a second bonus—0, 1, or 2 euros or chocolate coins for adults and adolescents, respectively—depending on how close their estimates were to the actual proportion of win outcomes.

Trial outline

At the start of each trial, participants estimated the number of euro coins inside the current box—because each box contained 100 coins, this corresponds to the overall win probability for the current box multiplied by 100—by typing a number on the keyboard (self-paced). Participants' estimate appeared underneath the (relevant) box, and participants confirmed their estimate by pressing the Enter key. If the typed number was not in the range of 0 to 100, an error message appeared and participants needed to change their answer to a number from 0 to 100 before they could continue. Participants then rated their certainty about this estimate on a vertical scale from 0 to 10 with lower and upper anchors of *completely uncertain* and *completely certain,* respectively, using the mouse (self-paced). Next, 700 ms later, one coin was revealed inside the box and then moved up (outside the box) and down (back inside the box), as if it was drawn from the box and then returned. This coin-drawing animation took 1.5 s, after which the next trial started and participants could update their estimate.

Actual win probabilities

Participants estimated the win probabilities of 10 different boxes—each with a unique color—and observed 16 draws per box. For a given box, one, two, or three of every four draws was a euro coin corresponding to win probabilities of .25, .50, or .75. Within each series of four draws, the order of euro and fake coin draws was random. Thus, although participants were instructed that outcomes were sampled completely random with replacement, the actual sampling was random without replacement within each series of four outcomes. This was done to prevent differences in actual experienced win probabilities between participants. Note that participants were asked to estimate the *overall* number of euro coins inside the current box, not the probability that the *next* draw would be a euro coin. Therefore, in the unlikely case that participants detected the pseudorandom nature of the sampling procedure, this should not affect the optimal estimation strategy (e.g., a gambler's fallacy-like strategy would still be maladaptive).

Advice manipulation

Participants learned about six boxes—with win probabilities of .25, .50, and .75—in the absence of advice. For two other boxes, participants received incorrect advice. The actual win probability for both these boxes was .50, but the advised win probabilities were .31–.40 (too low) and .61–.70 (too high) for one box each. These two incorrect-advice conditions are well-suited to test for a confirmation bias in learning (see the "Analysis" section). Finally, we included two boxes for which participants received correct advice. The win probabilities of these boxes were .25 and .75, and the (correctly) advised win probabilities were .21–.30 and .71–.80, respectively. Note that we did not aim to directly compare the incorrect- and correct-advice conditions (which differed in actual win probability) with each other. Instead, in our analyses on estimation accuracy and certainty ratings, we analyzed these two advice conditions separately, comparing each with the corresponding no-advice condition (with identical actual win probability).

We instructed participants that the advice came from same-aged peers—other participants who previously completed the same task at another high school or university. For the boxes paired with advice, an advice message was shown on the screen before the first outcome from that box was sampled. This message contained the name of the alleged advisor (Lisa, Anna, Daan, or Sem) and the number of euro coins inside that box according to this advisor. The message remained on the screen throughout the entire learning process for that box, such that it could not be forgotten and did not tax working memory. A different advisor was introduced for each advice block, so all participants encountered each of the four alleged advisors once. To increase the credibility of the advice manipulation, participants were also asked to advise a future participant about the proportion of euro coins themselves following some of the blocks. They could select one of the following advice options: 0–10, 11–20, 21–30, 31–40, 41–50, 51–60, 61–70, 71–80, 81–90, or 91–100 euro coins.

Set size manipulation

To manipulate the working-memory load of the estimation task, we varied the number of boxes that participants learned about in parallel between participants. Half of the participants in each age group learned about one box at a time (Set Size 1 version); they completed 10 experimental blocks (one box per block), and in each block they observed a sequence of 16 draws from the same box. The other half of the participants learned concurrently about two different boxes (Set Size 2 version); they completed five experimental blocks in which two boxes were presented at the left and right sides of the screen, and in each block they observed 16 draws from each of these two boxes (i.e., 32 draws per block in total). Thus, the number of boxes and the number of learning trials per box were identical for the two set size versions. We constrained the order of draws from the two boxes in the Set Size 2 version, such that participants never observed more than two draws from the same box in a row. On each trial, the currently relevant box was indicated by means of a frame.

Table 1 summarizes the actual and advised win probabilities per block in each set size version. In the Set Size 2 version, advice was received for one of the two boxes (in four blocks) or for none of the boxes (in one block). When advice was received, this was specifically directed toward one of the boxes; for clarity, the advice was displayed next to the relevant box and the color of that box was mentioned in the advice message. The two boxes with win probability .50 and incorrect advice were each paired with a no-advice box with win probability .75, such that the learning conditions for these boxes were identical except for the advice. The two boxes with correct advice (win probabilities .25 and .75) were paired with a no-advice box of another win probability (.75 and .25, respectively). Finally, the Set Size 2 version included one block with two no-advice boxes with win probabilities .50 and .75, respectively. The blocks were completed in random order with one restriction, namely that the first advice participants received was always correct. We used this restriction because it has been shown that initial advice-confirming experience potentiates the influence of subsequent incorrect advice (Staudinger & Buchel, 2013).

Computation of trial-specific learning rate

We defined the prediction error ($\widehat{\delta}$) on each trial t as the difference between the outcome (win and no-win outcomes were coded as 1 and 0, respectively) and the participant's estimate (divided by 100 to reflect estimated win probability): $\widehat{\delta}_t = \text{Outcome}_t - (\text{Estimate}_t/100)$. Consequently, we estimated the trial-specific learning rate ($\widehat{\alpha}$) as the change in estimated win probability of a given box across two successive trials, namely trial t and trial $t+1$, divided by the prediction error on trial t: $\widehat{\alpha}_t = (\text{Estimate}_{t+1} - \text{Estimate}_t)/\widehat{\delta}_t$. Note that this corresponds to the definition of learning rate according to standard reinforcement learning models (Sutton & Barto, 1998).

Analysis

Multilevel regression analyses

We performed a series of preregistered multilevel regression analyses on trial-specific estimation accuracy (operationalized as absolute estimation error, i.e., |estimated − actual win probability|), certainty ratings,[1] initial estimates, and learning rate ($\widehat{\alpha}$) using the *nlme* package in R (Pinheiro, Bates, DebRoy, & Sarkar, 2019). Random intercepts and slopes (separately for each age group and set size version) were modeled in all analyses, covariances between random effects were fixed to 0, and correlation between error terms across trials was considered by specifying first-order autoregression. If a model failed to converge, only random intercepts were estimated.

Unless indicated otherwise, we included trial (linear and quadratic effects modeled as two continuous mean-centered, regressors), advice condition, and outcome (in the analysis on learning rate only)

[1] The analyses on certainty are reported in Supplemental Text 5 because they are not of primary importance to the conclusions of this study.

Table 1
Overview of the different conditions in each set size version of the task.

Set Size 1 Actual win probability	Advised win probability	Number of blocks
.50	no advice	2
.25	no advice	2
.75	no advice	2
.50	.31–.40 (too low)	1
.50	.61–.70 (too high)	1
.25	.21–.30 (correct)	1
.75	.71–.80 (correct)	1
Set Size 2		
Actual win probabilities	Advised win probabilities	Number of blocks
.50/.75	no advice/no advice	1
.50/.75	.31–.40 (too low)/no advice	1
.50/.75	.61–.70 (too high)/no advice	1
.25/.75	no advice/.71–.80 (correct)	1
.25/.75	.21–.30 (correct)/no advice	1

as within-participants variables. How advice condition was modeled depended on the particular question under study. In the analyses on the effects of correct advice on estimation accuracy and certainty, we contrasted the correct-advice and no-advice conditions (with identical win probability). In the analyses on the effects of incorrect advice on estimation accuracy and certainty, we contrasted the incorrect-advice and no-advice conditions (with identical win probability). In the analysis on the effects of advice on initial estimates, we included all correct- and incorrect-advice conditions and modeled the linear effect of the advised win probability (whether or not advice was correct was irrelevant because the initial estimate was made before any outcomes had been observed). In the analysis on the effects of advice on learning rate in which we tested for a confirmation bias, we contrasted the too-high versus too-low advice conditions (i.e., the two incorrect-advice conditions). Age group (adults vs. adolescents) and set size version (1 vs. 2) were included as between-participants variables in all analyses.

In the analysis on learning rate, we excluded the last trial for each stimulus, and trials on which the prediction error ($\widehat{\delta}$) was 0 (<1% of all trials), because learning rate could not be computed on those trials. In addition, we excluded trials on which the learning rate exceeded the 99th percentile or was lower than the 1st percentile (calculated separately for each age group and set size version using all conditions) because these extreme learning rates likely reflected typing errors (e.g., when a participant accidentally typed "3″ instead of "73").

Non-preregistered, exploratory, analyses

In addition to the preregistered analyses, we performed exploratory analyses to examine (a) the prevalence and effects of a gambler's fallacy-like strategy (Supplemental Text 2), (b) potential age-related differences within our adult group (Supplemental Text 3), (c) whether advice suppressed (instead of biased) learning rate (Supplemental Text 4), and (d) the relationships between self-reported certainty and learning rate (Supplemental Text 6). Results from these exploratory analyses are summarized in the main text and fully described in the supplementary material.

Computational modeling

To examine the latent processes that may underlie the observed advice effects, we applied a series of computational learning models (beta-binomial models) to the estimation data for the stimuli with win probability .50 that were paired with no advice, too low advice, and too high advice, using a hierarchical Bayesian approach. We compared several model versions that assumed no advice effects or effects of advice on the initial estimates and/or update rates. Model recovery results indicate that our modeling procedure could accurately distinguish the advice effects implemented in our different models (Supplemental Text 7C). A complete description of the different models and modeling methods can be found in Supplemental Text 7A.

Results

A gambler's fallacy-like strategy is more prevalent in adolescents than in adults

A substantial subset of the participants we tested (41% of the adolescents and 9% of the adults after exclusion due to technical problems, history of psychiatric/neurological disorders, or alcohol/drug use) used negative learning rates on more than 30% of the trials—one of our preregistered exclusion criteria. Thus, these participants often reduced their estimated win probability after a win outcome and increased their estimated win probability after a no-win outcome, suggesting the use of a gambler's fallacy-like strategy instead of a learning strategy (see Discussion).

We performed non-preregistered and thus exploratory analyses to test whether and how (a) this behavior differed between the two age groups and set size versions, (b) this behavior changed over the course of the task, (c) estimation accuracy differed between the participants who showed this behavior and those who did not, and (d) excluding participants who showed this behavior affected age-related effects on estimation accuracy. These analyses are reported in Supplemental Text 2. Importantly, the prevalence of a gambler's fallacy-like strategy was higher in adolescents than in adults but was independent of working memory load (Supplemental Text 2). Furthermore, in both age groups, estimation accuracy was worse for the participants who used a gambler's fallacy-like strategy than for the participants who did not, confirming that this strategy was maladaptive (Supplemental Text 2). As preregistered, participants who showed gambler's fallacy-like behavior were excluded from further analysis.

Estimation error in the correct-advice versus no-advice conditions (win probability is .25 or .75)

In this analysis, we examined absolute estimation error in the correct-advice and no-advice conditions (in which the win probability was .25 or .75) (Fig. 2A) and tested for effects of trial, advice, age group, and set size. The statistics for all fixed effects are reported in Supplemental Table 1; here we focus on the age-related effects. Although both age groups became more accurate as more outcomes were observed (i.e., they learned), estimation error decreased slower in the adolescents [i.e., adolescents learned slower; Age Group × Trial–Linear interaction, $t(147) = 2.3$, $p = .02$]. In both age groups, estimation error was lower when correct advice was present, especially during early trials (in the beginning of learning). Finally, there was an Age Group × Set Size × Advice interaction, $t(147) = 2.9$, $p = .004$, reflecting that adolescents benefited more from correct advice than adults, in particular when the working memory load was high. Put differently, the impaired performance in adolescents relative to adults was most apparent in the absence of correct advice, in particular when the working memory load was high.

Estimation error in the incorrect-advice versus no-advice conditions (win probability is .50)

We performed the same analysis on absolute estimation error in the *incorrect*-advice and no-advice conditions in which the actual win probability was .50 (Fig. 2B). The statistics for all fixed effects are reported in Supplemental Table 2; here we focus again on the age-related effects. Estimation error was overall larger in the adolescents than in the adults [main effect of age group, $t(147) = 2.2$, $p = .03$]. The only other age-related effect was an Age Group × Advice × Trial–Linear interaction, $t(147) = 3.6$, $p < .001$, reflecting that estimation accuracy was affected by the incorrect advice relatively longer in the adolescents than in the adults. There were no significant interactions between age group and set size (Supplemental Table 2).

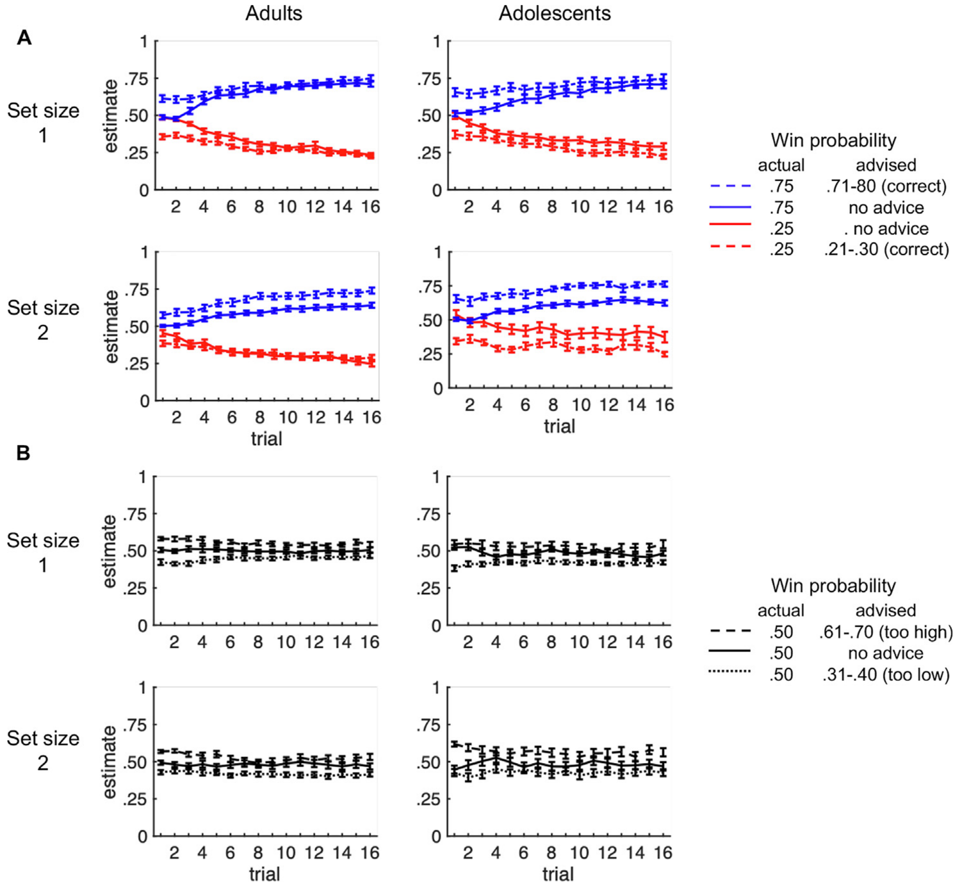

Fig. 2. Mean estimated win probability as a function of trial, actual and advised win probability, age group, and set size for the correct-advice and no-advice conditions with win probabilities .25 and .75 (A) and the incorrect-advice and no-advice conditions with win probability .50 (B). Error bars indicate standard errors.

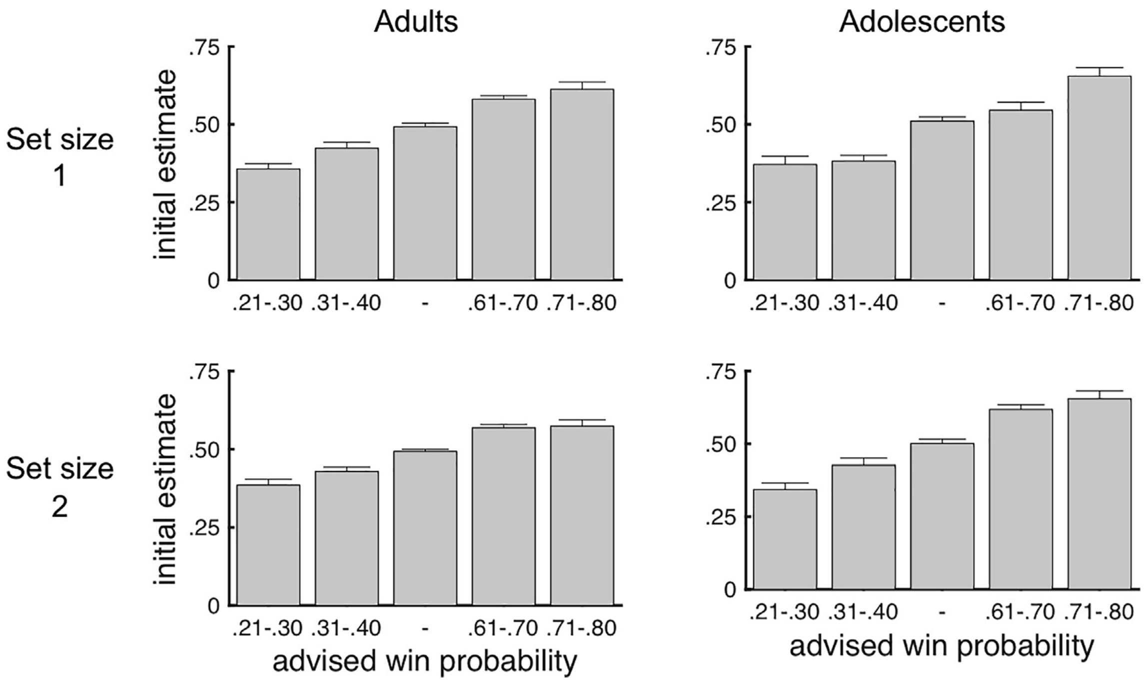

Fig. 3. Mean estimated win probability on Trial 1 as a function of advised win probability, age group, and set size. The middle bar is the no-advice condition. Error bars indicate standard errors.

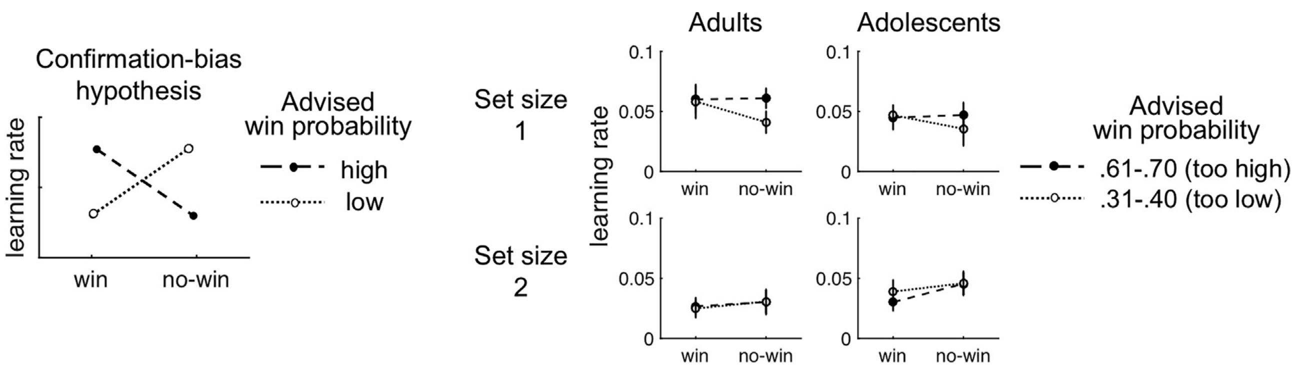

Fig. 4. Learning rate for stimuli with win probability .50 as a function of outcome (win vs. no win) and advised win probability (too high vs. too low) predicted by the confirmation bias hypothesis (left panel) and observed in each age group and set size version (right panel). Error bars indicate standard errors. See Supplemental Fig. 4 for the trial-specific learning rates in all conditions.

A comparison of adolescents, 18- to 21-year-olds, and 22- to 31-year-olds

Some previous studies found that resistance to peer influence (Gardner & Steinberg, 2005) and working memory function (Kwon et al., 2002; McAuley & White, 2011) continue to develop until early adulthood (early 20s). Therefore, it is possible that the effects of advice and set size differed between the younger and older adults within our adult group. To test this idea, we repeated the analyses on estimation error described above, but this time (a) comparing the younger adults (18–21 years old) and older adults (22–31 years old) with each other and (b) comparing each of these two adult groups with the adolescent group in separate analyses. These non-preregistered and hence exploratory analyses are reported in Supplemental Text 3 and Supplemental Fig. 3. To summarize their results, we found some evidence that estimation performance continues to improve during early adulthood, in particular when correct advice is not available and working memory load is high. In addition, the results suggest that susceptibility to incorrect advice decreases between adolescence and early adulthood but does not decrease further after 18 years of age.

The analyses on estimation error indicate that (a) correct advice improved estimation performance, especially in the adolescents when working memory load was high, and (b) incorrect advice had a longer-lasting effect on the adolescents' estimation performance than on that of the adults. To shed more light on *how* advice affected performance in the two age groups, we next examined the effects of advice on participants' initial estimates (i.e., priors) and learning rates.

Advice guides initial estimates in both adolescents and adults

In this analysis, we examined the effects of advised win probability, age group, and set size on participants' initial estimates (on trial 1 before any outcome had been observed). Because the four advice levels used in our task were .21–.30, .31–.40, .61.–.70, and .71–.80, the distance between the second and third advice levels was three times as large as that between the first and second levels and that between the third and fourth levels. Therefore, we coded the four advice levels as −2.5, −1.5, 1.5, 2.5 (i.e., linear effect of advised win probability).

Initial win probability estimates increased as a function of the advised win probability, $t(147) = 11.5$, $p < .001$ (Fig. 3), and this effect did not interact with age group or set size (*ps* > .06). Thus, participants used the advice to guide their initial estimates, but this effect did not differ between the adolescents and adults.

Advice does not bias learning in either adolescents or adults

We next examined evidence for a confirmation bias in learning, that is, stronger updating when new evidence is consistent than when it is inconsistent with received advice. In our task, a confirmation bias would be reflected in higher learning rates for win outcomes than for no-win outcomes when the advised win probability is high and in higher learning rates for no-win outcomes than for win outcomes when the advised win probability is low. In other words, a confirmation bias would produce an interaction between advised win probability (high vs. low) and outcome (win vs. no-win outcome) on learning rate (Fig. 4, left panel). To test this prediction, we focused our learning rate analysis on the stimuli with win probability .50 that were paired with either too-low advice (.31–.40) or too-high advice (.61–70). These stimuli are well-suited to test for a confirmation bias because their advised win probabilities are in opposite directions from the true win probability, but they are otherwise identical and contain an equal number of win and no-win outcomes. Our effects of interest in this analysis were the Advice (too low vs. too high) × Outcome (win vs. no win) interaction and the higher-order interactions with age group, set size, and trial. Therefore, we modeled the effects of outcome, advice, age group, set size, and trial as well as all interactions.

There were no main or interaction effects of advice and outcome (*ps* > .20) (Fig. 4, right panel) and no higher-order interactions with age group, set size, or trial (all *ps* > .15). This implies that a confirmation bias was absent and that there were no differential effects of age group or set size either. Thus, advice did not result in a confirmation bias in learning in either the adults or adolescents, regardless of working memory load.

Advice suppresses learning rate during early trials in adolescents and adults

Finally, in a non-preregistered and hence exploratory analysis, we examined whether advice *suppressed* learning rate regardless of the outcome. In this analysis, we included all advice conditions and contrasted the advice (correct and incorrect combined) and the no-advice conditions. This analysis is reported in Supplemental Text 3 and Supplemental Fig. 3. To summarize its main results, advice suppressed learning rate during early trials, especially when working memory load was low. This suppressive effect of advice on learning rate did not differ between the adolescents and adults. In addition, this analysis revealed that the adults used overall higher learning rates than the adolescents.

Computational modeling results

Our modeling results corroborate the results from the regression analyses described above but do not yield substantial additional insights. Therefore, we report the modeling results in the supplementary material (Supplemental Text 7B and Supplemental Figs. 8–12) and provide a short summary here.

The estimation data for both age groups and set size versions was best explained by a model in which both initial estimates and update rates varied across the no-advice, too-high advice, and too-low advice conditions. However, for the Set Size 1 version, there was no significant difference between this model and the (second-best) model in which advice affected only the initial estimates. Supplemental Fig. 9 illustrates the fit of the winning model per age group and set size version. Parameter estimates indicated that (a) initial win probability estimates were adjusted in the direction of the advice in both age groups and set size versions (corroborating the results shown in Fig. 3) and (b) update rates were higher in the absence of advice than in the presence of either too-low or too-high advice, but only for the Set Size 1 version (in both age groups). This last finding corroborates the finding described in the previous section that advice suppressed the learning rate during early trials, especially when working memory load was low (note that our models assumed constant update rates and hence could not specifically capture advice effects during early trials).

Discussion

Previous studies have investigated effects of advice on experience-based learning using instrumental learning tasks, which involve repeated choices between two or more stimuli (Biele et al., 2011; Decker et al., 2015; Doll et al., 2009; Lourenco et al., 2015; Rodriguez Buritica et al., 2019). In these tasks, both exploratory choice behavior and advice-related modulation of the learning process can influence advice following, which makes developmental differences in these two processes difficult to disentangle. To isolate advice effects on the learning process, and to examine how these effects differ as a function of age and working memory load, we combined advice manipulations with a learning task that does not involve choices but directly measures the expectation-updating process that is the basis of reinforcement learning models.

To summarize our results, many participants—41% of the adolescents and 9% of the adults—used a gambler's fallacy-like strategy instead of a conventional learning strategy. After excluding those participants, we found that adolescents learned slower than adults, especially when working memory load was high. However, we found no prominent differences between the effects of advice in adolescents and those in adults. First, advice directed participants' initial estimates in both age groups, which improved estimation performance when the advice was correct. Second, advice did not produce a confirmation bias in learning in either age group. In addition, our exploratory analyses suggested that advice suppressed learning during early trials in both age groups. Below, we discuss these findings in more detail.

Gambler's fallacy is more prevalent in adolescents than in adults

A substantial proportion of the participants, especially in the adolescent group, frequently adjusted their win probability estimate downward after a win outcome and upward after a no-win outcome, suggestive of a gambler's fallacy (i.e., the belief that if something happened more often in the past, it will happen less often in the future) (Jarvik, 1951). The use of a gambler's fallacy-like strategy, instead of a conventional learning strategy, was clearly maladaptive, as illustrated by the larger estimation error in the participants who showed this behavior. Importantly, participants in our task estimated the proportion of euro coins inside the current box (which corresponds to the *overall* win probability), not the *next* outcome. Therefore, the use of a gambler's fallacy would be maladaptive even if participants detected our semi-random sampling procedure (actual sampling was random without replacement for every series of four trials, such that each box's win frequency was stable throughout the task). That many participants showed this behavior is in line with findings from a recent study in which adult participants estimated probabilities of aversive outcomes; in that study, 18% of the participants were excluded for following a gambler's fallacy-like strategy (Wise, Michely, Dayan, & Dolan, 2019).

Our finding that this behavior was more prevalent in adolescents is consistent with previous findings that susceptibility to the gambler's fallacy decreases between childhood and young adulthood (Fischbein & Schnarch, 1997; Klaczynski, 2001). Furthermore, it stresses the importance of taking this fallacy into consideration when studying experience-based learning of outcome probabilities in developmental samples. In instrumental learning tasks, a gambler's fallacy would manifest as win–switch and lose–stay behaviors (switches to another choice option after a positive outcome and repetition of the same choice after a negative outcome), which would impair performance in tasks with stable outcome contingencies. Thus, it is an interesting question whether increased use of gambler's fallacy strategies in children and adolescents, relative to adults, may have contributed to previous findings of worse learning performance in younger age groups.

Future studies could also focus on *why* this fallacy is more common prior to adulthood. In our study, one possibility is that many adolescents falsely assumed that the sampled outcomes were removed from the box. However, we explicitly instructed participants that each outcome was returned into its box, and this was also illustrated on the screen on each trial. It could be that the adolescents paid less attention to these instructions and animations and therefore were more likely to misunderstand the task structure. Alternatively, the gambler's fallacy may reflect a deep-rooted, possibly implicit bias that affects participants' estimates despite a correct task understanding. If this is the case, our findings suggest that the impact of this bias decreases between adolescence and adulthood. To dissociate these possible causes of gambler's fallacy-like behaviors, the use of comprehension questions prior to the task would be a valuable addition for future studies.

Developmental differences in susceptibility to advice

After excluding the participants who showed a gambler's fallacy-like strategy, we found no salient differences between the effects of advice in adults and those in adolescents. Advice directed initial estimates and suppressed learning rate during early trials in both age groups, and neither age group showed a confirmation bias. Because the current task isolated learning from exploration, the lack of prominent age-dependent advice effects tentatively suggests that differential effects of advice in adolescents and adults found in previous instrumental learning tasks (Decker et al., 2015; Rodriguez Buritica et al., 2019) may have been driven in large part by age-related differences in exploration. Future studies directly comparing the effects of advice manipulations in estimation and choice versions of otherwise identical learning tasks, administered to the same participants, are clearly needed to test this hypothesis.

However, we found some subtle differences between the two age groups. Adolescents' estimation performance was affected longer by incorrect advice, which may be explained by the overall lower learning rates in the adolescents. The adolescents also performed somewhat more poorly than the adults, and this age difference was largest when correct advice was not available and working memory load was high (Set Size 2). Thus, adolescents were more affected by a higher working memory load than adults, but the presence of correct advice counteracted this age effect. It is possible that the load of the Set Size 2 task exceeded the adolescents' working memory capacity but not that of the adults, which caused the adolescents to rely more on explicitly available information (in this case advice).

Consistent with this idea, there is substantial evidence that executive functions such as working memory continue to mature until late adolescence or even early adulthood, which is thought to reflect the late functional and structural maturation of the prefrontal cortex (Casey, Jones, & Hare, 2008; Giedd et al., 1999; Larsen & Luna, 2018). Alternatively, it is also possible that the adults were better able to use associative learning or episodic memory processes to compensate for working memory limitations and therefore were less dependent on the advice (Bornstein & Norman, 2017; Master et al., 2020; Selmeczy, Fandakova, Grimm, Bunge, & Ghetti, 2019). Disentangling the developmental trajectories of associative learning and different types of memory, and their respective contributions to learning performance, are important objectives for future studies (Master et al., 2020).

Effects of advice on learning in estimation versus choice tasks

Previous studies that investigated advice effects in instrumental learning tasks using computational models have provided evidence for a confirmation bias in learning (or, similarly, for an outcome bonus for advised options) (Biele et al., 2011; Doll et al., 2009). Moreover, adults were found to show a stronger confirmation bias than children and adolescents (Decker et al., 2015). In our estimation task, however, we found no evidence for a confirmation bias in either age group. As mentioned earlier, this discrepancy between our findings and those of previous studies may reflect a trade-off between parameters capturing advice-related learning bias and exploratory choice behavior in model-based analyses of instrumental learning studies. Another possibility is that advice biases learning when people learn from the outcomes of their own choices—perhaps to justify their choices for the advised options or because advice following is intrinsically rewarding—but not when learning from passively observed outcomes. In addition, in instrumental learning tasks, it suffices to estimate the *relative* win probabilities of several choice options, whereas estimation tasks require participants to estimate *exact* win probabilities. This arguably results in more explicit probability computations in estimation tasks, which could reduce people's susceptibility to learning biases.

Instead of biasing learning, our exploratory analysis revealed that advice suppressed learning during initial trials, and this was particularly apparent when working memory load was low. Specifically, in the absence of advice, learning rates were highest at the beginning of learning and then decreased over time, whereas learning rates started off at a lower value and therefore decreased less over time when advice was present. This suggests that advice rendered participants less willing to update their estimates in response to the first observed outcomes. At a neurobiological level, this may be explained by an advice-related suppression of brain systems that mediate experience-based learning. Consistent with this idea, the availability of (predominantly) correct information about reward contingencies in instrumental learning tasks has been shown to suppress outcome-evoked responses in regions involved in stimulus evaluation and learning such as the ventral striatum and ventromedial prefrontal cortex (Biele et al., 2011; Li et al., 2011). Whether advice also suppresses learning-related brain activity in passive learning tasks (without choices), such as the current task, remains to be tested in future research.

Limitations and future directions

A limitation of our study is that we examined effects of incorrect advice only when the actual win probability was .50, and the discrepancy between the actual and incorrectly advised win probabilities was relatively small. Because participants' initial estimates were around .50, we found no clear evidence of learning for the stimuli win probability of .50 in the absence of advice, making it more difficult to detect advice effects. Therefore, an incorrect-advice manipulation for stimuli with win probabilities other than .50 (e.g., actual win probability = .25 or .75 and advised win probability = .50 vs. no advice) or more extreme incorrect advice manipulations (e.g., actual win probability = .25 and advised win probability = .75 vs. no advice) would be useful additions. We did not include such conditions because we wanted to keep the task duration limited and for at least half of the advice to be correct (to promote its trustworthiness), but including such conditions in future work could potentially reveal learning biases that remained unnoticed in the current study. Another limitation of the current study is that, for practical reasons (the schools we collaborated with did not allow monetary payments to be paid to the adolescents), the adolescent participants were incentivized with chocolate, whereas the adults were incentivized with actual money, and it cannot be excluded that this influenced the results. In addition, we focused on 12- to 15-year-old adolescents (the vast majority were 13 or 14 years old) and young adults. For a more complete understanding of the developmental trajectory of advice-related effects on learning, and its dependence on working memory load, future studies need to test participants from a wider age range and to examine (linear and nonlinear) age effects on a continuous scale.

Another point that remained unaddressed in the current study is that people's sensitivity to advice may differ depending on their relationship to the advisor (e.g., whether advice is receive from a friend, a teacher, or a nonhuman agent) (Goodyear et al., 2016; Lourenco et al., 2015). This could be explored using adapted versions of our paradigm in which the identity of the (alleged) advisor is varied. Interestingly, a previous study found that incorrect peer advice did not affect adolescents' or young adults' choices in an instrumental learning task, whereas incorrect advice from an older adult did bias the choices of both age groups (Lourenco et al., 2015). This finding suggests that, at least in the context of specific cognitive tasks, advice is more powerful when it comes from older adults, possibly because older adults are assumed to have more general expertise. Indeed, people typically value and use expert advice more than novice advice (Luan, Sorkin, & Itzkowitz, 2004; Meshi, Biele, Korn, & Heekeren, 2012; Suen, Brown, Morck, & Silverstone, 2014). In our study, participants received advice from alleged same-age peers who previously participated in the experiment. Thus, like the participants themselves, the advisors could be considered novices on the task at hand. It is likely that advice from experts on this task would result in stronger advice effects, possibly including a confirmation bias in learning. The effects of advisor expertise on experience-based learning, and potential changes in these effects across development, remain to be tested in future studies.

Conclusions

We showed that in a passive learning task, advice directs initial estimates and suppresses early learning in both adults and adolescents but does not bias learning in either age group. Combined with previous findings from instrumental learning studies, our results point to important differences in the effects of advice on learning in passive (estimation) and active (instrumental) learning tasks. Furthermore, they suggest that developmental differences in susceptibility to pre-learning advice are less salient when learning is based on passively observed outcomes as compared with actively acquired ones. Thus, taking the learning context into account may increase our understanding of how and when advice shapes learning.

Data availability statement

Data and analysis codes are available on the Open Science Framework (https://osf.io/w4phf)

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jecp.2021.105230.

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