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CHILD DEVELOPMENT

EMPIRICAL ARTICLE

Valence bias in metacontrol of decision making in adolescents and young adults

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Abstract
The development of metacontrol of decision making and its susceptibility to framing effects were investigated in a sample of 201 adolescents and adults in Germany (12–25 years, 111 female, ethnicity not recorded). In a task that dissociates model-free and model-based decision making, outcome magnitude and outcome valence were manipulated. Both adolescents and adults showed metacontrol and metacontrol tended to increase across adolescence. Furthermore, model-based decision making was more pronounced for loss compared to gain frames but there was no evidence that this framing effect differed with age. Thus, the strategic adaptation of decision making continues to develop into young adulthood and for both adolescents and adults, losses increase the motivation to invest cognitive resources into an effortful decision-making strategy.

During adolescence, the ability to engage in more complex decision-making strategies increases (Raab & Hartley, 2019). However, the successful use of a given decision-making strategy does not only depend on the mere ability to engage in it—it also depends on how flexible individuals are in adjusting their reliance on decision-making strategies to changes in internal and external demands. In this study, we ask how the ability for metacontrol of decision making (i.e. the dynamic adaptation of decision-making strategies; Eppinger et al., 2021; Ruel, Devine, et al., 2021) develops from adolescence into young adulthood and whether framing effects differentially affect the flexible usage of decision-making strategies in adolescents as compared to young adults.

To study metacontrol, we draw on previous work that dissociates two major decision-making strategies: model-based and model-free decision making (Daw et al., 2011; Dayan & Niv, 2008). Model-based decision making represents a deliberative, prospective strategy that evaluates different choice options by means of forward planning based on knowledge about the structure of the environment (a cognitive model). In contrast, model-free decision making represents a more reflexive, retrospective strategy that relies on previously experienced action-reward contingencies. Previous developmental research shows that the reliance on model-based decision making (but not model-free decision making) becomes more pronounced from childhood to adulthood (Decker et al., 2016; Potter et al., 2017) and these findings mirror the

Abbreviation: CI credible interval

development of executive functions (Munakata et al., 2012) which model-based decision making is thought to rely on (Otto, Gershman, et al., 2013; Otto et al., 2015).

Due to this reliance on executive functions, model-based decision making is effortful and carries an intrinsic cost (Kool et al., 2010). In return, it can provide higher behavioral flexibility than model-free decision making because dynamic changes in the environment can be accounted for more quickly (Dayan & Niv, 2008). Recent theories of metacontrol have proposed that humans weigh the cost and benefits associated with a decision-making strategy against each other when controlling their reliance on these strategies (Kool et al., 2019; Lieder & Griffiths, 2017). According to this view, the cognitive effort associated with employing model-based decision making needs to be matched by sufficiently high benefits. This is in line with findings demonstrating that adults rely more on model-based decision making when this decision-making strategy leads to greater monetary pay-offs (Kool et al., 2017). Conversely, the engagement in model-based decision making is reduced when the task at hand gets more complex and thus this strategy becomes cognitively more effortful (Bolenz et al., 2019; Eppinger et al., 2017; Kool et al., 2018). Several recent findings suggest that the strategic adaptation of physical and cognitive effort improves from adolescence into adulthood (Insel et al., 2017; Rodman et al., 2020). In line with these results, in the current study we ask whether the metacontrol of decision making improves in a similar way with increasing age.

So far, research on the interplay of model-free and model-based decision-making strategies has almost exclusively focused on decisions in the gain domain. The initial work on the dissociation of model-free and model-based decision making used rewards (vs. omission of rewards) as outcomes to reinforce behavior (e.g., Daw et al., 2011; Gläscher et al., 2010) and the studies on metacontrol applied rewards of varying magnitudes (e.g., Kool et al., 2017, 2018). Studies that also included losses as potential outcomes did not systematically contrast the effects of different outcome framings (Kool et al., 2016) or used a task that has been questioned to elicit metacontrol (Voon et al., 2015; Worbe et al., 2016). This focus on decisions in the gain domain is surprising given behavioral and neuroscientific studies emphasizing the greater impact of prospective losses on the engagement in effortful behavior: Losses carry a higher subjective weight than gains in decisions under risk (Tversky & Kahneman, 1981) and losses have been associated with a greater allocation of cognitive resources (Yechiam & Hochman, 2013). Evidence from neuroscience studies supports the idea of dissociable mechanisms involved in decisions in the gain domain compared to the loss domain. For example, electrophysiological and neuroimaging work points to a unique role of the dorsal anterior cingulate cortex in the processing of monetary loss as well as in mediating effortful behavioral adjustments in response to negative feedback (Fischer & Ullsperger, 2013; Holroyd et al., 2004; Ullsperger et al., 2014). Taken together, these findings suggest that losses may bias the cost-benefit evaluations underlying metacontrol and point to partially dissociable cognitive and neural processes underlying decisions in the gain and loss domain.

The potential impact of losses on decision making is interesting from a developmental perspective because of several findings that suggest that the neural systems involved in the processing of loss outcomes and the associated behavioral adaptations continue to develop into adolescence (Crone & Steinbeis, 2017; Kelly et al., 2009; Rubia et al., 2006). The question whether adolescents and adults differ in how they attribute subjective weight to losses as compared to gains remains unanswered. Results of a developmental neuroimaging study on loss aversion during descriptive decision making show differences in fronto-striatal activation during decision making between adolescents and adults but no differences in behavioral preferences (Barkley-Levenson et al., 2013). In contrast, results from studies using the Iowa Gambling Task suggest that performance deficits in children and adolescents may result from a disproportionate tendency to shift behavior after receiving loss feedback when compared with young adults (Cassotti et al., 2011). Moreover, there are diverging findings on how learning from relative gains (better-than-expected outcomes) and relative losses (worse-than-expected outcomes) develops from adolescence into adulthood (Nussenbaum & Hartley, 2019). Finally, several studies have reported different developmental trajectories for gains as compared to losses with respect to effects on behavior and neural processing. For example, the neural sensitivity for differences in monetary outcomes follows independent developmental curves during adolescence in gains versus loss contexts (Insel & Somerville, 2018) and adolescents show a stronger asymmetry between gains and losses than adults during probabilistic reinforcement learning (Palminteri et al., 2016).

To summarize, in this study we investigated metacontrol and its susceptibility to gain-loss framing effects across development from adolescence to young adulthood. To do so, we used a sequential decision-making task to dissociate model-free and model-based decision making. In this task, we manipulated the magnitude of monetary outcomes (low stakes vs. high stakes) and outcome valence (gains vs. losses). Both high stakes and the loss framing should increase the benefits of investing resources in a model-based strategy and therefore affect the cost-benefit evaluations that are assumed to guide metacontrol. Specifically, we expected increased reliance on model-based decision making when stakes are high (cf. Kool et al., 2017) and when outcomes are framed as losses. Moreover, we expected that with increasing age, participants would show more overall model-based decision making (cf. Decker et al., 2016) and—based on the findings of improving strategic effort adaptation (Insel et al., 2017; Rodman et al., 2020)—we expected age-related increases in metacontrol of model-based decision making with respect to different stakes conditions. Finally, given evidence for a stronger gain-loss asymmetry in more basic reinforcement-learning processes for adolescents (Palminteri et al., 2016), we expected a more pronounced gain-loss asymmetry in metacontrol for adolescents than for adults.

METHODS

Participants

Ninety-seven adolescents (50 female, M_{age}: 14.5 years, age range: 12–17 years) and 104 adults (61 female, M_{age}: 21.3 years, age range: 18–25 years) took part in this study. We aimed for a larger sample size than previous developmental studies on model-based decision making because of our intention to investigate interaction effects and because we expected generally weaker effects due to the more restricted age range. The target sample size of around 200 participants was determined based on feasibility considerations. No participant was excluded from data analysis. Participants' age followed an approximately uniform distribution within the age range (Figure S1). We compensated participants with 5 € per hour or course credit as a baseline compensation and with an additional performance-dependent bonus payment of 7 cents per 100 points in the sequential decision-making task (range: 3.99 €–5.46 €). All participants and the parents of all underage participants provided written informed consent.

The study was conducted from November 2018 to February 2020. Participants were recruited by advertising the study on university platforms and by sending postal invitations to local families. 100% of the adolescents and 93% of the adults reported German as their first language. Our participants had a relatively high level of education, with 88% of the adults being university students and 73% of the adolescents attending a school type that directly qualifies for entering a university program. Participants self-assessed their socioeconomic status on a 10-point rating scale as above average, with adolescents reporting a mean value of 6.66 (inter-quartile range: [6, 7]) and with adults reporting a mean value of 6.71 (inter-quartile range: [6, 8]).

Procedure

Participants were invited for individual testing sessions in the lab. After filling out a demographic questionnaire, they performed the sequential decision-making task. During the instruction and training phase, an experimenter was present to read the task instruction aloud from the screen and to answer questions. The instruction phase lasted approximately 15 min and the actual task lasted approximately 46 min (plus self-paced breaks between blocks). During testing, the experimenter left the room. Afterward, participants completed a covariate task battery including a cognitive-control task and a risk-preference task as well as questionnaires on impulsivity, cognitive effort investment, and real-world risk taking. Results of these tasks may be reported elsewhere.

Sequential decision-making task

We used a sequential decision-making task (adapted from Kool et al., 2016) to determine reliance on model-free and model-based decision making. In this task, participants make repeated decisions between two spaceships—either between an orange and a turquoise spaceship or between a blue and a green spaceship, with one pair of spaceships being randomly assigned to each trial. Each spaceship deterministically leads to one of two planets where the participants obtain a number of outcomes (see Figure 1a). The number of outcomes available at the planets slowly drifts according to independent Gaussian random walks (with mean 0, standard deviation 2, and reflecting bounds at 0 and 9).

To understand how model-free and model-based decision making differ in this task, consider that a model-free decision-maker makes choices based on an independent reward expectation for each of the four spaceships. In contrast, a model-based decision maker predicts the planet to which a spaceship will lead and uses the reward expectation associated with this planet to guide choices. Crucially, because multiple spaceships lead to one planet, the model-based decision maker can integrate reward expectations over experiences with different spaceships.

To investigate how the framing of outcomes affects model-based decision making, we manipulated the outcome valence across blocks of trials: In some blocks, outcomes were framed as gains ("space treasure") and participants were instructed to maximize reward. In other blocks, outcomes were framed as losses ("antimatter") and participants were instructed to avoid losing. Moreover, similar to previous studies (e.g., Kool et al., 2017), we manipulated how many points were at stake in each trial: In low-stakes trials, participants gained/lost one point for each outcome they had collected and in high-stakes trials participants gained/lost five points for each outcome (Figure 1b).

The task consisted of 480 trials divided into eight blocks of 60 trials. Outcome valence alternated between blocks and participants were informed about the upcoming outcome valence at the beginning of each block. The stakes condition varied between trials in a random order and was cued to participants at the beginning of each trial. More details on the task are reported in Supporting Information.

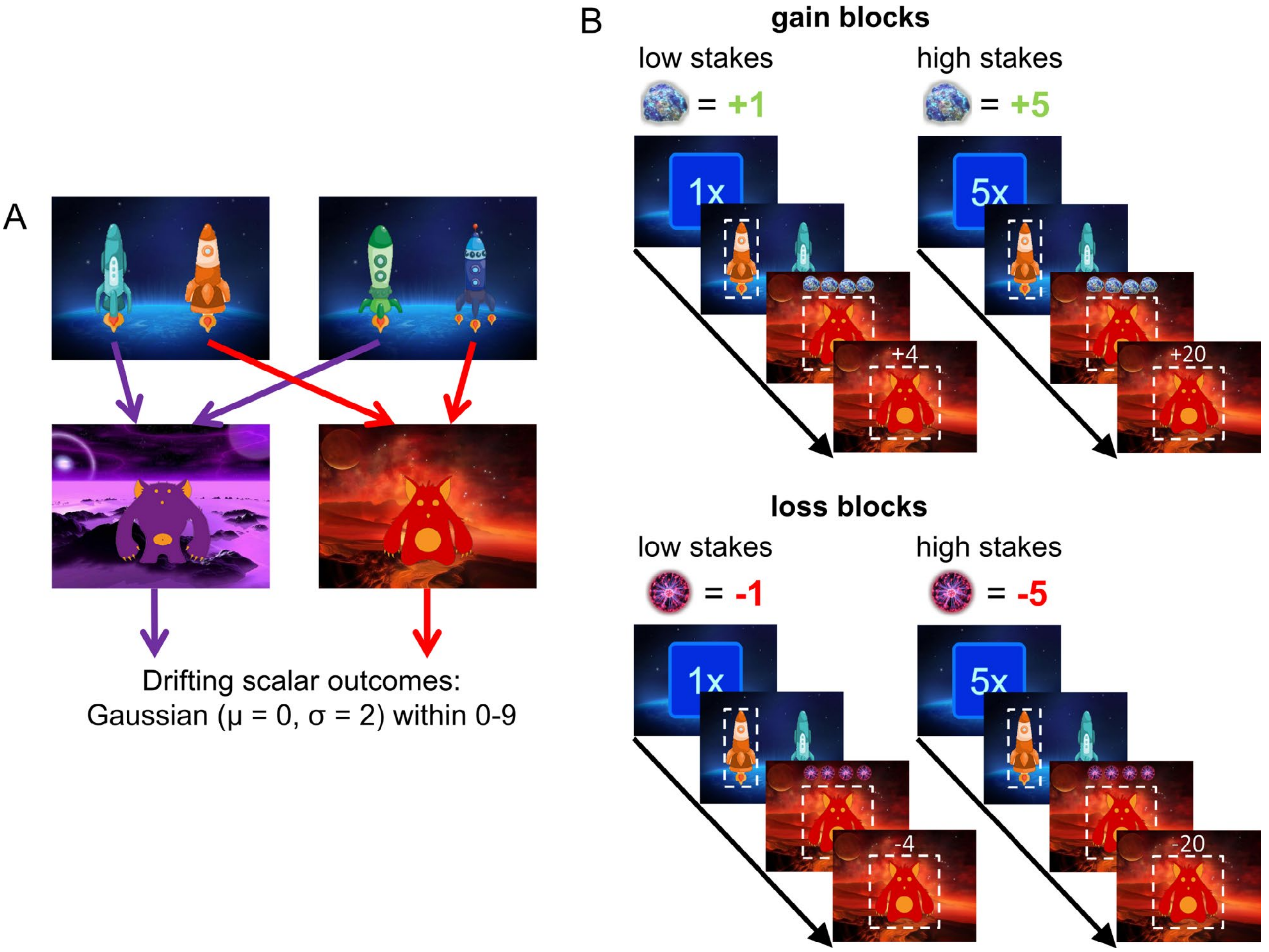

FIGURE 1 Decision-making task. (a) Task transition structure. In every trial, one of two pairs of spaceships is presented. Each spaceship deterministically leads to one of two planets where a number of outcomes is obtained. The number of outcomes available at the two planets drifts over the course of the task. (b) Trial structure. At the beginning of a trial, the stakes condition is cued which determines how the outcomes of this trial are converted into points. During some blocks, outcomes are framed as gains and during the other blocks, outcomes are framed as losses

Reinforcement-learning model

To analyze how reliance on model-based decision making differed between experimental conditions and across development, we used a hierarchical Bayesian version of an established reinforcement-learning model (Daw et al., 2011; Kool et al., 2016; Otto, Raio, et al., 2013). The hierarchical modeling approach is in line with recent recommendations to improve parameter reliability due to partial pooling of parameter estimates in hierarchical models (Brown et al., 2020). The model computes both model-free and model-based reward expectations for the different spaceships in parallel. Model-free reward expectations are based on a temporal difference learning algorithm that updates reward expectations according to reward prediction errors (i.e., the difference between expected and actually experienced reward). Model-based reward expectations are computed by integrating the transition structure of the task with the reward expected at the different planets. To model choice behavior, model-free and model-based reward expectations are fed into a softmax function that maps reward expectations to choice probabilities. Here, model-free and model-based reward expectations are weighted by two independent model parameters: a model-free and a model-based weight. These weights represent how strongly choices are guided by each of the two strategies. Note that while more conventional formulations of the reinforcement-learning model (Daw et al., 2011; Kool et al., 2017) use a single weighting parameter that reflects the relative influence of model-based versus model-free decision making, the formulation we used here is algebraically equivalent (Otto, Raio, et al., 2013) but comes with less bounded parameters which facilitates hierarchical model-fitting. In the current implementation, model-free and model-based weights independently reflect how consistent choices are with the corresponding strategy, where a weight of 0 indexes that a strategy has no effect on decision making.

In our analyses, we focused on the model-based and model-free weight parameters that reflect the degree to which choices are guided by model-based and model-free decision making (see Table S1 for a summary of other model parameters and supplemental results for a more detailed analysis of other model parameters). We used two variants of the reinforcement-learning model, a developmental model and a non-developmental model. In the developmental model, model-based weights were regressed on stakes condition, valence condition (using effects-coding for both categorical variables), participants' age (scaled to range from 0 to 1), and all two-way and three-way interactions. This allows to test how model-based weights and the effects of the experimental conditions change across development. For the sake of model simplicity and because we do not have specific hypotheses about nonlinear developmental trajectories, we did not include quadratic age effects in the model. In the developmental model, the coefficients of the categorical variables (stakes condition, valence condition) represent the effects for when the continuous variable is 0. Due to rescaling of participants' age, the coefficients of the categorical variables thus correspond to the effects of the categorical variables for participants at the lower end of the age range. For estimating the main effects of the categorical variables (i.e., pooled effects across all participants regardless of age), we also fit a non-developmental model, in which model-based weights are only regressed on stakes condition, valence condition, and their interaction (thus omitting age as a predictor variable). If not explicitly stated differently, we will report results from the developmental model for all regression weights that relate to age and from the non-developmental model otherwise. Note that while the models already incorporate the variables stakes condition, valence condition, and age as regressors, this structure measures but does not enforce any effect of these variables and every effect could in principle be estimated as being non-existent. More details on the reinforcement-learning model, a parameter recovery analysis and a posterior predictive check are reported in Supporting Information.

Distributions of all model parameters were estimated in a hierarchical manner using Stan (Stan Development Team, 2018). When presenting group-level parameters, we report means and 95% credible intervals (CIs) of the marginal distributions. CI are computed as the [.025, .975] percentile interval and can be interpreted as including the true value of the parameter of interest with a probability of 95%. When presenting participant-level parameters, we report means of the marginal participant-level distributions.

Behavioral proxies of model-based decision making

To better understand the effect of model-based decision making on task behavior, we investigated two proxies of model-based decision making: task performance and stay probabilities. Task performance was assessed as the difference between outcomes obtained in a trial and the average number of outcomes available at the two planets (before applying the stakes multiplication). Thus, this performance metric reflects how much more outcomes a participant had obtained than it would have been expected by a random decision maker. Importantly, more model-based behavior leads to better outcomes in this task (see Supporting Information).

For the stay probability analysis, we followed the reasoning of Kool et al. (2017) that a model-based decision maker should be more likely to stay with the same goal (i.e., travel to the same planet) after a better-than-expected outcome (a positive second-stage reward prediction error) in the preceding trial than after a worse-than-expected outcome (a negative second-stage reward prediction error). The effect of reward prediction error on subsequent choice behavior should be less pronounced for a model-free decision maker because model-free decision making relies on separate reward expectations for each spaceship and thus the immediately preceding trial can only have an effect if both trials share the same starting state and the same spaceships are re-encountered. Thus, a stronger effect of reward prediction error on stay probabilities can be seen as reflective of more model-based decision making. Reward prediction errors were obtained from the computational model by using the mean of the participant-level parameter distributions and were added as continuous predictor in the analysis.

We analyzed both metrics (task performance and stay probabilities) with hierarchical regression models using the R package brms (Bürkner, 2017). Similar to the computational modeling approach, we fit separate models including or excluding age as a predictor variable and report results from the developmental model (including age) only where effects relate to age.

RESULTS

We will first report confirmatory analyses of model-based weights that directly test our hypotheses. Thereafter, we also report several more exploratory analyses that investigate how model-based decision making is reflected in task performance and stay behavior and whether the reliance on model-free decision making is affected by age and the experimental conditions in a similar way to model-based decision making.

Development of model-based decision making

Across conditions, model-based weights increased with age (b_{age} = .21, CI [.12, .30]). Separate analyses showed

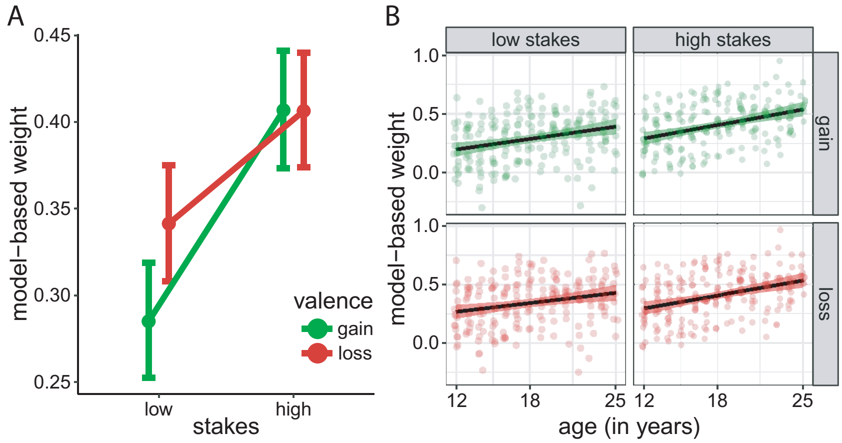

FIGURE 2 Metacontrol of model-based decision making and its development across adolescence. (a) Mean model-based weights across all participants. Error bars represent Bayesian 95% credible intervals. (b) Model-based weights in all experimental conditions as a function of age. The shaded areas represent 95% credible intervals. Points represent means of the participant-level distributions from the developmental model (jittered along the *x*-axis)

age-related increases in model-based weights for all experimental conditions (Figure 2b; $b_{\text{age(low, gain)}} = .19$, CI [.09, .30]; $b_{\text{age(high, gain)}} = .25$, CI [.15, .35]; $b_{\text{age(low, loss)}} = .16$, CI [.06, .26]; $b_{\text{age(high, loss)}} = .24$, CI [.13, .34]). These findings suggest that model-based decision making continues to develop across adolescence. To establish whether developmental changes in model-based decision making might be confounded by age differences in sustained attention, we restricted the computational analysis to the first two blocks (120 trials). This analysis showed a similar increase in model-based weights with age as the one reported above ($b_{\text{age}} = .24$, CI [.14, .34]), suggesting that the age effect is evident early in the task and not simply a consequence of older participants being better able to sustain attention across the experiment.

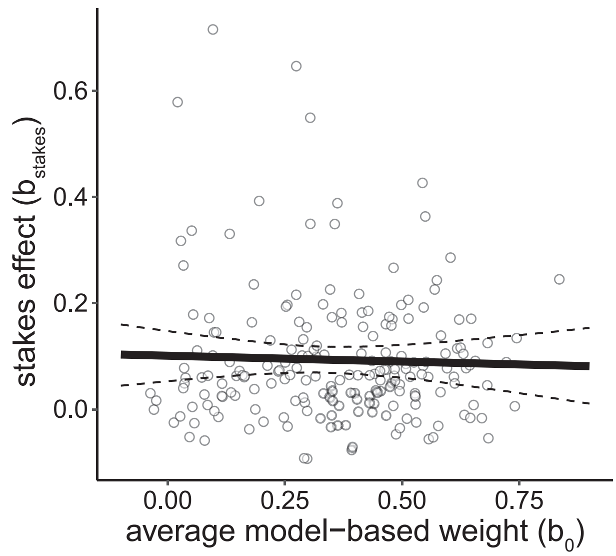

FIGURE 3 Relationship between average model-based weight and stakes effect. Dashed lines indicate 95% credible interval. Points represent means of participant-level distributions

Stakes-based metacontrol

Effects of stakes manipulation

Across all participants, we found increased model-based weights for high-stakes trials compared to low-stakes trials ($b_{\text{stakes}} = .09$, CI [.07, .12]; Figure 2a). Consistent with previous non-developmental studies (e.g., Kool et al., 2017), this indicates that participants showed stakes-based metacontrol, that is, they adapted their reliance on model-based decision making to the different stakes conditions. Separate analyses for adolescents and adults showed stakes-based metacontrol in both age groups (see Table S2; Figure S2).

Note that some participants show negative model-based and model-free weights, especially in low-stakes trials (cf. Figures 2b and 6b). While there is a higher uncertainty for individual parameter estimates, this could indicate that sometimes participants deliberately chose the option with the lower reward expectation to strategically explore this option when stakes were low.

Developmental differences

In the developmental model, we found a positive slope for the stakes effect ($b_{\text{stakes}} = .06$, CI [.02, .10], cf. Figure S3) reflecting a reliable effect of stakes for participants at the lower end of the age range. These results indicate that 12-year-old participants already showed metacontrol of model-based decision making. To investigate whether stakes-based metacontrol changes across adolescence, we analyzed stakes

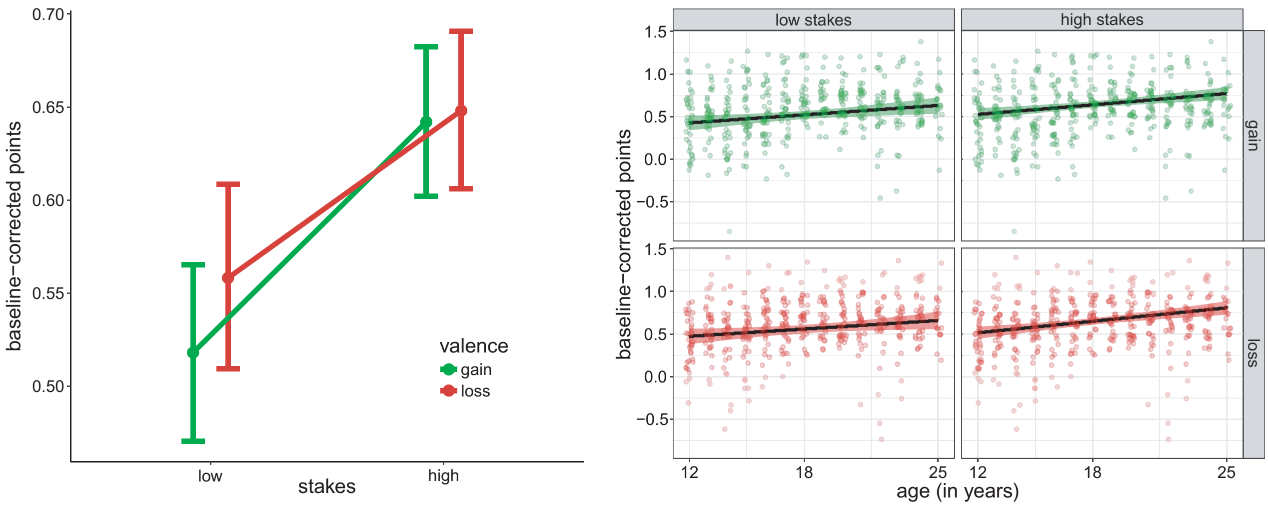

FIGURE 4 Task performance (baseline-corrected points) and its development across adolescence. (a) Mean task performance across all participants. Error bars represent Bayesian 95% credible intervals. (b) Task performance in all experimental conditions as a function of age. The shaded areas represent 95% credible intervals. Points represent means of the participant-level distributions from the developmental model (jittered along the *x*-axis)

effects as a function of age. We found moderate evidence that the stakes effect increased with age ($b_{\text{age} \times \text{stakes}}$ = .07, CI [−.01, .15], 94.9% of the posterior mass above 0) indicating that metacontrol tended to increase with age (Note that the framework of Bayesian statistics allows for interpreting evidence in a gradual manner without dichotomizing cut-off values, cf. Kruschke, 2010). Furthermore, separate analyses for gain and loss blocks showed moderate evidence for age-related increases in stakes effects for both valence conditions ($b_{\text{age} \times \text{stakes(gain)}}$ = .06, CI [−.03, .15], 88.4% of the posterior mass above 0; $b_{\text{age} \times \text{stakes(loss)}}$ = .08, CI [−.02, .17], 94.2% of the posterior mass above 0).

As metacontrol could be related to the ability to engage in model-based decision making (i.e., younger participants could show less metacontrol because they are generally more constrained in their ability to engage in model-based decision making), we analyzed if higher overall reliance on model-based decision making correlated with metacontrol. Our results show that there was no or at most only a small positive correlation between mean model-based weights and stakes effects (r = −.03, CI [−.20, .13], 35.8% of the posterior mass above 0; Figure 3). This suggests that increases in metacontrol do not necessarily result from a greater ability to engage in model-based decision making.

Valence bias in metacontrol

Effects of valence manipulation

Across all participants, we found higher model-based weights in loss blocks compared to gain blocks (b_{valence} = −.03, CI [−.05, −.01]; Figure 2). This indicates that participants relied more on model-based decision making when outcomes were framed as losses than when outcomes were framed as gains. Moreover, we found an interaction of stakes condition and valence condition ($b_{\text{stakes} \times \text{valence}}$ = .06, CI [.03, .09]), indicating that the effect of outcome valence differed between low-stakes trials and high-stakes trials. While we found increased model-based weights in loss blocks compared to gain blocks for low-stakes trials ($b_{\text{valence(low)}}$ = −.06, CI [−.08, −.03]), we did not find evidence for a valence effect for high-stakes trials ($b_{\text{valence(high)}}$ = .00, CI [−.02, .02]). Thus, loss-induced increases of model-based decision making were particularly pronounced in trials with low stakes. Separate analyses for adolescents and adults indicated interactions of stakes condition and valence condition in both age groups (see Table S2; Figure S2).

Developmental differences

In order to examine developmental differences in how gains and losses affect model-based decision making, we analyzed the effect of outcome valence as well as the interaction of stakes condition and valence condition as a function of age. We did not find evidence for an age-related change in the effect of outcome valence on model-based weights ($b_{\text{age} \times \text{valence}}$ = .02, CI [−.03, .07], 82.0% of the posterior mass above 0). Moreover, there was no evidence for an age-related change in the interaction of stakes condition and valence condition ($b_{\text{age} \times \text{stakes} \times \text{valence}}$ = −.02, CI [−.11, .08], 34.3% of the posterior mass below 0). Thus, our results do not provide evidence for developmental differences in the asymmetry of gains and losses with respect to metacontrol of decision making. However, it should be noted that the uncertainty around these effects does likewise not allow to completely rule out any potential for developmental effects on these cognitive processes.

Task performance

Effects of experimental manipulations

Task performance was higher in high-stakes trials compared to low-stakes trials (b_{stakes} = .11, CI [.07, .14], Figure 4). This is in line with increased model-based decision making in high-stakes trials compared to low-stakes trials. There was moderate evidence for increased task performance in loss blocks compared to gain blocks ($b_{valence}$ = −.02, CI [−.05, .01], 92.2% of the posterior mass below 0) but we did not find evidence that the valence effect differed as a function of stakes condition ($b_{stakes \times valence}$ = .03, CI [−.04, .11], 80.1% of the posterior mass above 0).

Developmental differences

In the developmental model, we found a positive intercept (b_0 = .49, CI [.43, .54]) reflecting the grand mean of task performance for participants at the lower end of the age range. This indicates that even our youngest participants were able to perform the task above chance level. Task performance increased with age (b_{age} = .23, CI [.13, .33]) but there was only limited evidence that the stakes effect on task performance increased with age ($b_{stakes \times age}$ = .07, CI [−.05, .19], 88.6% of the posterior mass above 0).

To rule out developmental differences in sustained attention, we regressed task performance against trial number and age (cf. Figure S4). This analysis revealed higher performance with later trials (b_{trial} = .13, CI [.05, .21]) for participants at the lower end of the age range and we did not find evidence that this effect differed with age ($b_{trial \times age}$ = −.03, CI [−.18, .12], 63.9% of the posterior mass below 0). This suggests that across the entire age range, participants were able to sustain attention throughout the task.

Stay probabilities

Effects of experimental manipulations

Participants were more likely to stay with the same goal following a better-than-expected outcome compared to a worse-than-expected outcome (b_{RPE} = .24, CI [.22, .26]). This effect was stronger on high-stakes trials than on low-stakes trials ($b_{RPE \times stakes}$ = .03, CI [.02, .05], Figure 5). These findings are consistent with the results of the computational analysis and point to increased model-based control on high-stakes trials (see also Kool et al., 2017). Moreover, the effect of better-than-expected outcomes was larger in loss blocks compared to gain blocks ($b_{RPE \times valence}$ = −.02, CI [−.04, −.01]). Again, this is in line with the finding of increased model-based control in loss blocks in the computational analysis. We did not find evidence that high-stakes trials affected the impact of better-than-expected outcomes differentially for gain and loss blocks ($b_{RPE \times stake \times valence}$ = −.01, CI [−.04, .02], 81.6% of the posterior mass below 0).

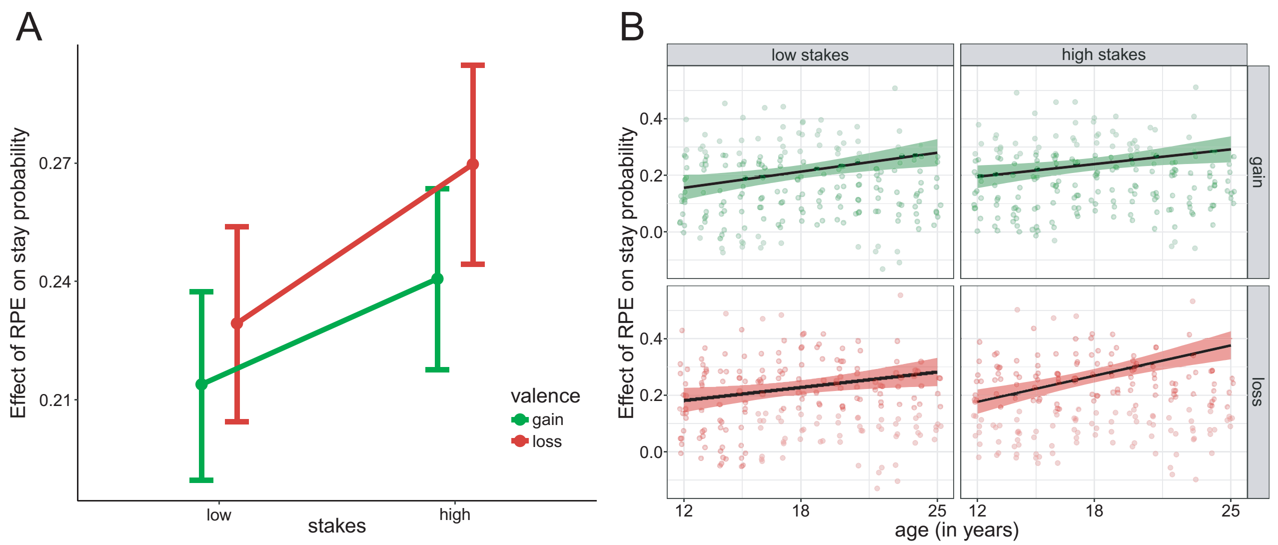

FIGURE 5 Effect of reward prediction errors on stay probability and its development across adolescence. (a) Mean effect of reward prediction errors across all participants. Error bars represent Bayesian 95% credible intervals. (b) Effect of reward prediction errors in all experimental conditions as a function of age. The shaded areas represent 95% credible intervals. Points represent means of the participant-level distributions from the developmental model (jittered along the *x*-axis)

Developmental differences

The effect of better-than-expected outcomes on stay probabilities increased with age ($b_{\mathrm{RPE} \times \mathrm{age}}$ = .13, CI [.07, .19]) and there was moderate evidence that the difference in the effect of better-than-expected outcomes between low-stakes and high-stakes trials became more pronounced with age ($b_{\mathrm{RPE} \times \mathrm{stakes} \times \mathrm{age}}$ = .04, CI [−.02, .09], 91.7% of the posterior mass above 0). To summarize, the findings for the two proxies of model-based decision making seem to support the major conclusions derived from the computational modeling approach.

Model-free decision making

Effects of experimental manipulations

To provide a complete account of developmental differences in decision-making strategies, we also analyzed the reliance on model-free decision making (Figure 6). Model-free weights increased in high-stakes trials compared to low-stakes trials (b_{stakes} = .03, CI [.01, .04]). Additional analyses suggest that the *relative* influence of model-based and model-free decision making did not change across stakes conditions (see Supporting Information). Model-free weights were larger in gain blocks compared to loss blocks, contrasting the valence effect on model-based weights (b_{valence} = .04, CI [.02, .05]). There was no evidence that the valence effect differed between high-stakes and low-stakes trials ($b_{\mathrm{stakes} \times \mathrm{valence}}$ = .01, CI [−.02, .04], 80.2% of the posterior mass above 0).

Developmental differences

There was no evidence that model-free weights differed with age (b_{age} = −.01, CI [−.06, .04], 65.7% of the posterior mass below 0) and additional analyses suggest that the relative influence of model-based decision making compared to model-free decision making became more pronounced with age (see Supporting Information). The effect of stakes on model-free weights increased with age ($b_{\mathrm{stakes} \times \mathrm{age}}$ = .05, CI [.002, .09]), showing that older participants more strongly adapted this decision-making strategy to the different stakes conditions. There was no evidence for age-related changes in the valence effect on model-free weights ($b_{\mathrm{valence} \times \mathrm{age}}$ = .01, CI [−.04, .05], 60.3% of the posterior mass above 0) and moderate evidence for an age-related change in the interaction of stakes and valence ($b_{\mathrm{stakes} \times \mathrm{valence} \times \mathrm{age}}$ = .08, CI [−.02, .17], 94.2% of the posterior mass above 0).

DISCUSSION

In this study, we investigated the development of metacontrol of decision making across adolescence. Specifically, we asked how metacontrol of model-based decision making toward different stakes changes from adolescence into young adulthood and whether metacontrol in adolescents and adults is differentially sensitive to framing effects. Model-based decision making improved with age and we found moderate evidence that metacontrol of model-based decision making improves with age. Our results also show that metacontrol of decision making is sensitive to outcome valence: the reliance on model-based decision making increases when outcomes are framed as losses compared to when outcomes are framed as gains. However, we do not find evidence for developmental differences in this valence bias.

Development of model-based decision making

The reliance on model-based decision making increased across adolescence. This was evident in the model-based weights derived from the computational analysis and in two proxies of model-based decision making, task performance and the effect of better-than-expected rewards on stay probabilities. Our finding is consistent with the results of previous work that has shown an age-related increase in model-based decision making from childhood (age 8 years) to young adulthood (Decker et al., 2016; Potter et al., 2017). Going beyond these findings, we observe developmental differences in model-based decision making in a more constrained age range (between 12 and 25 years). Thus, the current data suggest that model-based decision making is a slowly developing capacity that continues to mature into early adulthood. A recent longitudinal study found consistent developmental effects in a similar age range (Vaghi et al., 2020). Future research should investigate the potential neurobiological mechanisms underlying the protracted development of model-based decision making. Targets for such developmental neuroscience approaches could be electrophysiological markers of model-based decision making (Eppinger et al., 2017; Ruel, Bolenz, et al., 2021) or areas such as the prefrontal cortex and hippocampus (Calabro et al., 2020; Casey et al., 2005; Daugherty et al., 2016; Selmeczy et al., 2019) that have been implicated in model-based decision making as well as in the learning and consolidation of state transition structures (Gläscher et al., 2010; Huang et al., 2020; Smittenaar et al., 2013; Vikbladh et al., 2019).

We do not find developmental differences in the reliance on model-free decision making. which is consistent with previous findings (Decker et al., 2016). This indicates that the age-related changes in model-based decision making do not simply reflect a general increase

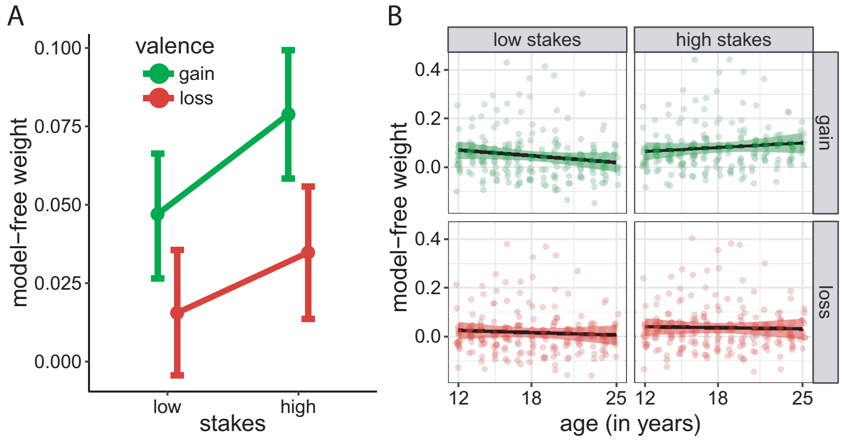

FIGURE 6 Metacontrol of model-free decision making and its development across adolescence. (a) Mean model-free weights across all participants. Error bars represent Bayesian 95% credible intervals. (b) Model-free weights in all experimental conditions as a function of age. The shaded areas represent 95% credible intervals. Points represent means of the participant-level distributions from the developmental model (jittered along the *x*-axis)

in reward-seeking behavior. Instead, the relative reliance on model-based versus model-free decision making increases with age which is also supported by a model using relative model-based weights as in a more conventional formulation of the reinforcement-learning model (Daw et al. (2011; see Supporting Information).

Development of stakes-based metacontrol

Both adolescents and adults showed stakes-based metacontrol, that is they adapted their reliance on model-based decision making toward the different stakes conditions. This was observed in the model-based weights derived from the computational modeling analysis as well as in task performance and the effect of better-than-expected outcomes on stay probabilities. Contrary to previous studies (e.g., Bolenz et al., 2019; Kool et al., 2017) however, we find no evidence for a relatively greater shift to more model-based decision making as compared to model-free decision making, as reliance on both strategies similarly increased in high-stakes trials. This indicates that participants generally showed greater reliance on goal-directed decision-making strategies in high-stakes trials. In line with this, we found an effect of stakes condition on the inverse softmax temperature (often interpreted as reflecting choice consistency) but not on the relative model-based weight in an alternative parameterization of our computational model (see Supporting Information).

The developmental analyses revealed metacontrol of model-based decision making early on, showing that metacontrol is in principle available at the age of 12 years. There was moderate evidence that stakes-based metacontrol became more pronounced with age across adolescence: Older participants tended to show stronger increases in model-based decision making when outcomes were amplified. This finding extends the results from a recent study reporting that stakes-based metacontrol increased with age in 5- to 11-year-old children (Smid et al., 2020), an age range which is adjacent to our study. Furthermore, the increased metacontrol of model-based decision making parallels findings that the strategic adaptation of physical and cognitive effort toward different reward magnitudes improves from adolescence into adulthood (Insel et al., 2017; Rodman et al., 2020).

We observed comparable age-related increases in the stakes effect for model-free decision making: Older participants showed stronger increases in model-free decision making when outcomes were amplified than younger participants. In line with this, an alternative parameterization of our computational model did not show an age-related increase in the stakes effect on relative model-based weights but an age-related increase in the stakes effect of the inverse softmax temperature (see Supporting Information). Thus, the increasing effect of stakes seems to reflect a more efficient use of goal-directed decision-making strategies.

Together with studies in other age groups (Bolenz et al., 2019; Smid et al., 2020), our findings suggest that metacontrol of decision-making strategies is a cognitive process which is subject to dynamic developmental changes across the lifespan. However, one could also think of potential alternative interpretations for these developmental differences. First, less metacontrol of model-based decision making toward the different stakes conditions might be explained by an attenuated sensitivity to differences in outcomes; that is, the difference in subjective values for low-stakes and high-stakes outcomes might be reduced for adolescents. However, findings from neuroimaging studies speak against this interpretation by showing an increased sensitivity for differences in rewards in adolescents (Insel & Somerville, 2018). Second, the reduced capacity for model-based decision making in younger participants might have constrained the degree to which metacontrol is possible. This would mirror suggestions that higher incentives only boost performance when the task demands match an individual's cognitive capacities (Davidow et al., 2018; Ruel, Devine, et al., 2021). However, we did not find that participants who showed more model-based decision making also showed more stakes-based metacontrol. Thus, our findings seem to suggest that the development of model-based decision making may be independent from the development of stakes-based metacontrol. This is in line with findings that varying the difficulty of cognitive-control tasks does not necessarily affect the adaptation of cognitive effort (Devine et al., 2021) suggesting that the adaptation of effort is to some degree independent from one's capacity for the task.

Valence bias in metacontrol

When avoiding losses, participants showed a greater reliance on model-based decision making than when seeking gains. This was observed in the model-based weights derived from the computational modeling analysis, in the effect of better-than-expected outcomes on stay probabilities and—with lesser certainty—in task performance. It is commonly assumed that losses carry a higher subjective weight than gains (Tversky & Kahneman, 1981). This higher subjective weight of losses might increase the expected benefit of investing in an effortful decision-making strategy and thus affect cost-benefit evaluations that have been hypothesized to underlie metacontrol of decision making (Kool et al., 2017, 2019). In short, the motivation to avoid losses makes people allocate more cognitive resources to a more accurate but also more demanding decision-making strategy.

The effect of outcome valence was reversed for model-free decision making: When outcomes were framed as gains, participants showed more model-free decision making than when outcomes were framed as losses. This suggests that participants may have partly compensated for reduced model-based decision making in gain blocks by switching to a less effortful strategy instead of simply becoming more stochastic in their choices.

Previous studies have reported valence effects on model-based decision making in psychiatric patients or under pharmacological interventions but not in healthy or placebo controls (Voon et al., 2015; Worbe et al., 2016). Importantly, these findings were based on a different decision-making task (Daw et al., 2011) that has been questioned to elicit metacontrol (Kool et al., 2016, 2017). Therefore, the valence effects reported in these studies might not be reflective of an actual modulation of metacontrol but might represent more general effects associated with altered psychiatric or physiological conditions. In contrast, by using a task that previously has been shown to elicit metacontrol (Kool et al., 2017) and by testing a sample of healthy participants, our study provides evidence that outcome valence typically modulates model-based decision making and its metacontrol.

We observed a valence bias for model-based weights when stakes were low but not when stakes were high. Similarly, task performance did not further increase as a consequence of the loss framing in high-stakes trials. One possible explanation for this differentiation could be that participants show ceiling performance already for high-stakes trials during gain blocks and thus might not be able to further increase model-based decision making when outcomes are framed as losses. One way to test this would be by making the task more demanding. This should lead to a more selective use of model-based decision making and could uncover potential valence effects even in the high-stakes condition.

Contrary to our expectations, we did not find developmental differences in this valence bias. While previous studies have reported independent developmental trajectories for processing gains and losses (Insel & Somerville, 2018) and stronger valence-related asymmetries for learning in adolescents (Palminteri et al., 2016), our results might suggest that these developmental effects are not necessarily reflected in higher-order decision-making processes such as metacontrol. However, our task design also differed in some aspects from previous studies (Insel & Somerville, 2018; Palminteri et al., 2016): For instance, we employed a block-wise manipulation of outcome valence while in these other studies, the framing of outcomes as gains or losses changed across trials. Trialwise manipulations of outcome valence have been suggested to result in higher ambiguity about the current valence condition (cf. literature review in Verburg et al., 2019), so age differences in these trialwise approaches could potentially also reflect differences in resolving this ambiguity. It remains a question for future research how these differences in task design might affect behavior in adolescents and adults. Despite our comparably large sample size, there was still a considerable degree of uncertainty in our analysis of developmental differences in framing effects. Thus, it is not warranted to completely rule out any potential for developmental effects on these cognitive processes.

There was moderate evidence for age-related changes in valence effects on model-free decision making with the interaction effect of stakes condition and valence condition becoming more pronounced with age. Keeping in mind the exploratory character of this analysis, this points to the possibility that developmental differences in valence effects are more likely to be observed for simpler rather than complex and effortful decision-making strategies. Clearly more research is needed in this area to uncover the developmental changes in the effects of valence biases on decision strategies of different complexity.

Limitations

Recently, concerns have been raised as to whether the often reported mixture of model-based and model-free decision-making strategies reflects an artifact due to participants misconceiving the experimental tasks and people instead actually fully rely on a model-based strategy (Feher da Silva & Hare, 2020). While these concerns have been brought up with reference to a decision-making task different from the one used in our study, we also think that it is unlikely that participants in our study only relied on a model-based strategy. First, we observe a worse model fit when the model-free strategy is omitted from the reinforcement-learning model (see Supporting Information), indicating that model-free decision making is a necessary component of participant behavior. Second, if participants were actually relying only on a model-based strategy throughout the task, our within-subject experimental manipulations would need to affect how participants (mis-)conceived the task in order to generate the observed differences in model-based weights. That would imply different conceptions of the task from trial to trial within individual participants. We think that it is unlikely and rather think that the observed differences in model-based weights indicate that behavior actually resembled more closely a model-based strategy in some conditions than in others. Therefore, we think that our experimental paradigm is suitable to assess metacontrol of decision-making strategies.

We interpret metacontrol of decision making as being indicative of the adaptation of cognitive effort in decision making. However, we do not have a direct marker of effort to support this interpretation. The results of an analysis that takes response time as an indicator of cognitive effort do not consistently mirror the patterns observed for model-based weights (see Supporting Information). One potential reason for this is that model-based computations can occur at multiple points in time during a trial (e.g., during the presentation of the stakes cue or during the presentation of the first-stage state) and thus do not necessarily affect response times at a specific stage in the task. Future studies could use physiological variables such as pupil dilation or neural activity to assess developmental differences in effort allocation (though see Shenhav et al., 2017, for potential caveats in measuring cognitive effort).

Our computational model makes several simplifying assumptions. For example, while we use the same stimuli for the spaceships across blocks, we do not assume that reward expectations carry over from one block to the next. However, given the high reward learning rate (cf. Table S1), we think that the effect of this simplification is minimal because potentially transferred reward expectations will be overwritten quickly within one or two trials. Note that high reward learning rates are adaptive in this task because participants directly observe the true value of the states and do not need to integrate observed outcomes over multiple trials as in other paradigms (such as Daw et al., 2011).

CONCLUSIONS

In this study, we found that both adolescents and adults show metacontrol of model-based decision making. Furthermore, metacontrol seems to continue to develop from adolescence into young adulthood. We also found that metacontrol is sensitive to outcome valence: When outcomes are framed as losses, participants show a greater willingness to engage in the cognitively more demanding, model-based decision-making strategy. This valence bias in metacontrol is present in both adolescents and young adults. However, contrary to our predictions, we did not find evidence for developmental differences in this gain–loss asymmetry on metacontrol.

ETHICS STATEMENT

The ethics committee of the Technische Universität Dresden approved the study (ethics certificate EK 519122015).

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CONFLICT OF INTEREST

The authors declare no competing interests.

DATA AVAILABILITY STATEMENT

All data and analysis scripts can be found at osf.io/a7ek9.

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