Computational mechanisms underlying social evaluation learning and associations with depressive symptoms during adolescence

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Abstract

There is a sharp increase in depression in adolescence, but why this occurs is not well understood. We investigated how adolescents learn about social evaluation and whether learning is associated with depressive symptoms. In a cross-sectional school-based study, 598 adolescents (aged 11-15 years) completed a social evaluation learning task and the short Mood and Feelings Questionnaire. We developed and validated reinforcement learning models, formalising the processes hypothesised to underlie learning about social evaluation. Adolescents started the learning task with a positive expectation that they and others would be liked, and this positive bias was larger for the self than others. Expectations about the self were more resistant to feedback than expectations about others. Only initial expectations were associated with depressive symptoms; adolescents whose expectations were less positive had more severe symptoms. Consistent with cognitive theories, prior beliefs about social evaluation may be a risk factor for depressive symptoms.

Introduction

In order to have successful social relationships, it is useful to understand what others believe about us. Judgements about a person's character, worth, and status are types of social evaluation, and may be particularly important during adolescence. Adolescence is a period of physical, psychological, and social transition between childhood and adulthood spanning 10 to 24 years of age (1). Adolescents spend increasing amounts of time with their peers, whose beliefs strongly influence their evaluations of their own worth (2–4). However, learning about social evaluation may be difficult and, in ambiguous situations, there is potential for bias. When learning about what others think of them, individuals may well be influenced by what they themselves believe. In general, adults exhibit consistent positive biases, making assumptions that they are liked (5–8). According to cognitive models of depression, less positive biases are a risk factor for depression (9,10). Reductions in these positive self-referential biases could lead to more negative interpretations of social interactions, more negative self-esteem, more negative mood, and social withdrawal, all of which are symptoms of depression. Consistent with this, there is evidence from a social evaluation learning task, which simulates social interactions, that adults are better at learning they are liked than disliked (6). This positive self-referential bias decreases with increasing social anxiety and depressive symptoms (6,7,11).

It is unclear whether adolescents demonstrate the same positive biases as healthy adults. In general, self-evaluations become more negative from early adolescence (aged 12-14 years) to mid-adolescence (aged 15-17 years), and mid-adolescents are more negatively influenced by comparing themselves to peers than late adolescents (aged 18-25 years; ,12). Adolescents may also react more negatively to peer rejection and evaluation than adults (13–15). Coupled with the continuing development of the self-concept during adolescence (16), this raises the possibility that adolescents do not demonstrate robust positive biases during social interactions. There is some evidence that late adolescents have positive biases, predicting that peers will like them, whereas early adolescents may make fewer predictions that they will be liked, suggesting that positive biases develop throughout adolescence (17–22). Additionally, late adolescents with more severe depressive symptoms or lower self-esteem report being less certain that peers will like them (18,19,23). However, all these studies have measured adolescents' predictions before interacting with peers, rather than testing how they learn during interactions. Assessing behaviour during learning is arguably more valid and useful than assessing how individuals predict that they will behave. This is particularly important as automatic processing of social evaluation may involve different cognitive mechanisms to explicit expectations (10,24,25).

Computational models can help to provide insight into the cognitive processes underlying learning. The framework of reinforcement learning can be used to model how individuals learn to gain positive feedback and avoid negative feedback, incrementally improving their choices to achieve the best outcome (26,27). These processes might be important for maintaining a positive self-referential bias. Reinforcement learning models of a social evaluation learning task have shown that adults update their expectations differently for learning about the self and others, and place more weight on positive information (28). However, reinforcement learning may differ between adolescence and adulthood, and even between different periods within adolescence (29–35). The capacity to represent the mental states of others and abstract social goals improves during adolescence (36,37). From childhood to adulthood, individuals become better at using feedback, and also become less exploratory in their decision making (38). It is less clear how specific aspects of learning, for example learning from positive and negative information, differ across development (38). It is also possible that social reinforcement learning develops differently to non-social reinforcement learning (34), as positive social feedback may become increasingly rewarding throughout adolescence (37). A recent review concluded that “next to nothing” is known about the development of learning about social evaluation during adolescence (30).

Although there is evidence for impairments in reinforcement learning in depression during adulthood (39), very few studies have tested whether reinforcement learning is associated with depressive symptoms in adolescence (30). In one study using a social evaluation learning task, late adolescents with lower self-esteem had a lower expectancy that they were liked, and also had lower learning rates for social evaluation, indicating a reduced tendency to update their expectations in response to social feedback (40). However, it remains unclear whether these biases are associated with depressive symptoms in early and mid-adolescence (around the ages of 11-15). This is a key developmental period in which to understand these processes. There is a sharp increase in the incidence of depression during adolescence, particularly in girls (41,42). Negative biases in learning about social evaluation may be a risk factor for depression, leading to increased depressive symptoms in adolescence, and this risk factor may be more prevalent in girls (43). However, it is unclear whether this risk factor would be present from early adolescence or emerge during adolescence.

We investigated learning about social evaluation in a large cross-sectional study. Adolescents were recruited from two age groups (young and mid-adolescents aged 11-12 and 13-15 years) to study social evaluation learning before and after the gender difference in depression emerges (42). We had two overarching aims. First, we aimed to investigate how adolescents learn about social evaluation. To do this, we initially analysed participants’ responses on the task to examine behaviour (model-agnostic analyses). We expected adolescents to demonstrate a positive self-referential bias, the magnitude of which would be negatively associated with depressive symptoms. We then developed and validated reinforcement learning models, testing a range of models that formalised the processes that might be involved in learning about social evaluation. We hypothesised that several parameters would be necessary for reinforcement learning models to adequately describe adolescents’ behaviour, including separate learning rates for self-referential and other-referential information and parameters modelling a positive self-referential bias. Second, we aimed to examine whether the processes underlying learning about social evaluation were associated with gender, age, and depressive symptoms in adolescence. We hypothesised that any parameters relating to the positive self-referential bias and self-referential learning would be associated with depressive symptoms. We therefore also expected these parameters to be associated with gender, in line with the higher prevalence of depressive symptoms in girls during adolescence. Given the lack of previous evidence, we explored whether the processes underlying social evaluation learning changed from early to mid-adolescence but did not have any specific age-related hypotheses.

Results

Participants were recruited from eight diverse mixed-gender secondary schools across London. We sampled from two separate age groups, Year 7 (11-12 years old) and Years 9-10 (13-15 years old), maximising power to test gender differences before and after the age at which rates of depression start increasing (42). We recorded participants’ age, gender, and school to include as confounders. Given that participants completed the study in classes of 2-31 adolescents, we also measured the size of the group in which they were tested. Additionally, participants completed an abbreviated nine-item version of the Raven Standard Progressive Matrices Test to measure non-verbal IQ score (range 0-9, not standardised; ,44).

In total, 1829 adolescents were eligible, 687 (38%) of whom had parental consent to participate. Of these, 606 (88%) provided informed assent, 8 (1%) of whom were excluded due to not completing study measures. The final sample consisted of 598 adolescents. Overall, 141 (24%) adolescents were recruited from five schools with low parental consent rates (under 30%) and 457 (76%) adolescents were recruited from three schools with high parental consent rates (over 60%). Participants recruited from schools with low versus high consent did not differ in age, gender, or depressive symptoms, but those from schools with low consent had higher non-verbal IQ score (mean difference (MD)=1.29, 95%CI=0.92-1.66, p<0.001).

Of the 598 participants, 330 (55%) were young adolescents recruited from Year 7 (aged 11-12 years except one aged 13; mean (M)=11.56, standard deviation (SD)=0.50) and 268 (45%) were mid-adolescents from Years 9-10 (aged 13-15 years; M=14.18, SD=0.51). On average, non-verbal IQ score was higher in mid-adolescents (M=4.88, SD=0.12) than young adolescents (M=4.04, SD=0.11; coef=0.84, 95% CI=0.52-1.17, p<0.001). Table 1 shows sample characteristics and social evaluation learning task performance.

Depressive symptoms were measured with the short Mood and Feelings Questionnaire (SMFQ; 45). SMFQ score ranged from 0 to 23 (M=7.05, SD=5.48) in young adolescents and 0 to 26 (M=8.25, SD=5.88) in mid-adolescents. Depressive symptoms were higher in mid- than young adolescents (coef=1.19, 95% CI=0.28-2.11, p=0.01), and higher in girls than boys (coef=2.19, 95% CI=1.28-3.10, p<0.001). There were more depressive symptoms in girls than boys in both age groups (interaction p=0.07).

Table 1. *Demographic characteristics and task performance of adolescents who completed all blocks of the social evaluation learning task.*

	Young adolescents		**Mid-adolescents**	
	Boys (n=168)	**Girls** (n=152)	**Boys** (n=129)	**Girls** (n=138)
	Mean (SD)			
Age (years; range 11-15)	11.57 (0.50)	11.55 (0.51)	14.19 (0.47)	14.16 (0.56)
Raw non-verbal IQ score (range 0-9)	3.82 (2.05)	4.41 (1.87)	4.81 (2.02)	4.97 (2.03)
Depressive symptoms (range 0-26)	6.42 (5.10)	7.80 (5.85)	6.65 (4.94)	9.70 (6.30)
Positive responses (range 0-20)				
Self like	14.73 (4.23)	15.95 (3.29)	15.74 (3.52)	15.47 (3.38)
Self dislike	7.05 (4.32)	6.58 (4.22)	6.23 (3.64)	5.98 (4.50)
Other like	14.93 (3.95)	14.82 (3.83)	15.54 (3.40)	15.57 (3.72)
Other dislike	5.72 (3.69)	5.63 (3.70)	5.20 (3.80)	5.22 (3.77)
Global ratings (range 0-100)				
Self like	64.19 (23.57)	64.70 (21.79)	68.50 (20.35)	66.41 (20.83)
Self dislike	28.92 (24.72)	25.76 (21.97)	26.84 (19.28)	24.72 (18.46)
Other like	65.75 (24.25)	66.46 (20.61)	67.57 (19.38)	68.12 (19.75)
Other dislike	27.66 (23.00)	27.12 (18.01)	27.02 (19.69)	26.01 (17.68)

Note. For positive responses, 20 represented perfect performance in like blocks and 0 indicated perfect performance in dislike blocks. For global ratings 0=dislike, 100=like. Gender was missing for 10 young adolescents and 1 mid-adolescent. Age (years) was missing for 1 young adolescent boy. Depressive symptoms (SMFQ score) was missing for 4 young adolescents (3 boys, 1 girl).

Task performance

The social evaluation learning task was a two-alternative forced choice task based on probabilistic reinforcement learning (7). Participants learnt whether a person was liked or disliked by a computer character (Figure 1). Learning occurred in two conditions: about the participant themselves (self-referential) or about another person (Taylor; other-referential). There were thus four blocks in this task: *self like, self dislike, other like,* and *other dislike*. Participants met a new character every block, and each character was represented by a name on the screen. The name Taylor, and the names of the characters participants met, were chosen to be gender neutral. Participants used trial and error to learn whether the character liked or disliked them (or Taylor) over 20 trials in each block. On each trial, a positive and negative personality characteristic were presented. Participants were asked to choose the word that best corresponded to what the character thought about them or Taylor. They received probabilistic feedback, with 80% contingency, about whether their choice was correct. To initially examine behaviour, we performed model-agonistic analyses of participants' responses on this task. In these model-agnostic analyses, all models were adjusted for confounders (gender, age, non-verbal IQ score, school, and testing group size). Unadjusted results are included in Tables S2-S4. We then modelled how participants learnt about social evaluation using adaptions of Rescorla-Wagner reinforcement learning models (26).

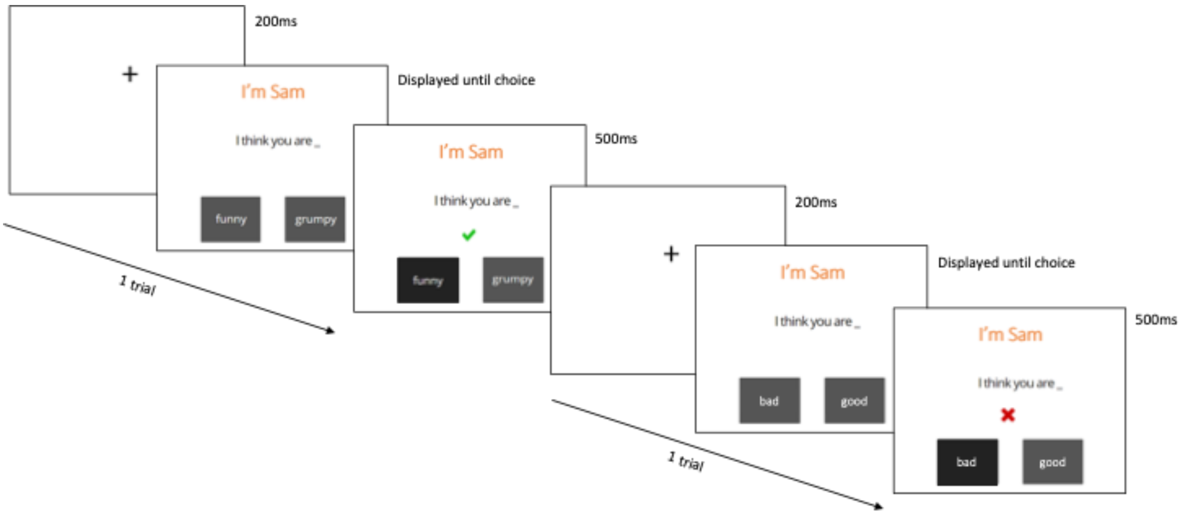

Figure 1. Social Evaluation Learning task. An example of two trials from a self-referential block, in which the computer character is called Sam (character names differed on each block and were chosen to be gender neutral). The participant is learning what Sam thinks of them (self-referential). After viewing a fixation cross, the participant was presented with a positive and negative word pair and instructed to choose the word which best corresponded with what Sam thought about them. They then received feedback about whether their choice was correct (green tick) or incorrect (red cross). Participants used trial and error to learn whether the character liked or disliked them over 20 trials. In the first trial shown here, the participant selected the positive word, which was correct. In the second trial, the participant chose the negative word, which was incorrect. Both trials show true (as opposed to misleading) feedback. Feedback contingency was set at 80%, so that 'correct' responses received an 8:2 ratio of positive to negative feedback and 'incorrect' responses received an 8:2 ratio of negative to positive feedback.

Positive responses

Positive responses were the total number of times participants chose the positive personality characteristic in each block (range 0-20). We first tested how task conditions (exposures) influenced responses (outcome) using multilevel linear regression models. There were 9.36 (95% CI=9.05-9.67, $p<0.001$) more positive responses in *like* than *dislike* rule blocks, demonstrating that participants acquired the task contingencies (Table S2). There was also evidence of a positive self-referential bias. Participants made 0.64 (95% CI=0.33-0.95, $p<0.001$) more positive responses in self-referential than other-referential blocks, and there was a rule-by-condition interaction ($p=0.02$, Table S3). Testing the conditions separately, there was a smaller difference in positive responses in *like* versus *dislike* blocks in the self-referential (coef=8.97, 95% CI=8.52-9.42) than in the other-referential condition (coef=9.74, 95% CI=9.32-10.17).

Next, we used linear regression to test whether responses in each block (exposures) were associated with depressive symptoms (outcome). Positive responses in self-referential blocks were negatively associated with depressive symptoms (Table S4: *like* coef=-0.24, 95% CI=-0.37 to -0.12, p<0.001; *dislike* coef=-0.14, 95% CI=-0.25 to -0.03, p=0.02). There was also evidence for a negative association between positive responses in the other-referential *like* block and depressive symptoms (coef=-0.20, 95% CI=-0.33 to -0.07, p=0.003). There was no evidence for an association between positive responses and depressive symptoms in the other-referential *dislike* block (Figure 3).

Global ratings

Each task block ended with a global rating as participants rated how much the character liked them (or Taylor) on a sliding scale (0=dislike, 100=like). In multilevel linear regression models, we found that participants rated the character's opinion of themselves or Taylor 39.50 points higher in *like* than *dislike* blocks (95% CI=37.88-41.12, p<0.001), demonstrating successful acquisition of the contingencies. Global ratings did not differ across self- or other-referential conditions (Tables S2-S3).

As with positive responses, we then used linear regression to test whether global ratings after each block were associated with depressive symptoms. Global ratings in other-referential and self-referential *dislike* blocks were not associated with depressive symptoms (Table S4). However, global ratings in the self-referential *like* block were negatively associated with depressive symptoms (coef=-0.05, 95% CI=-0.07 to -0.02, p<0.001; Figure 3).

In multilevel linear models, we found no evidence that task performance (positive responses or global ratings) differed according to age group or gender (Tables S2-S3).

Reinforcement learning model

Winning model

We modelled how participants learnt about social evaluation using adaptions of Rescorla-Wagner reinforcement learning models (26). The winning model had five parameters: separate learning rates that decreased over trials for (i) self-referential and (ii) other-referential blocks; (iii) a single inverse temperature parameter; and separate start bias parameters for (iv) self-referential and (v) other-referential blocks. We used inverse temperature parameters instead of temperature parameters to avoid numerical underflow or overflow after taking exponents.

In the model, values for different words (e.g., choosing the 'positive' word in the 'self' condition, $value\_self\_positive_t$) are updated on each trial in that block (*t*), based on the feedback received after that word was chosen ($outcome_t$). The size of this update is governed by separate learning rates for self (α_{self}) and other (α_{other}) conditions. These learning rates were bounded between 0 and 1 and decreased on each trial due to the use of trial number as an exponent (which fitted the data better than constant learning rates: see supplementary methods and results). The value corresponding to the unchosen word (e.g., the negative word when the positive word was chosen) is not updated. The value of choosing the positive word is initialised at the value of the start bias, $start\_bias_{self}$, and the value of choosing the negative word is initialised as the negative of this value. These updates are displayed in the following equations:

$$value\_self\_positive_{t+1} = value\_self\_positive_t + \alpha_{self}^t(outcome_t - value\_self\_positive_t)$$
$$value\_self\_negative_{t+1} = value\ self\_negative_t + \alpha_{self}^t(outcome_t - value\_self\_negative_t)$$

On the first trial of each block (i.e., when *t*=1):

$$value\_self\_positive_t = start\_bias_{self}$$
$$value\_self\_negative_t = -start\_bias_{self}$$

Learning in the other-referential block can be written equivalently, such that, $value\_self\_positive_t$ becomes $value\_other\_positive_t$ for example. These values are then passed through a softmax function, with inverse temperature β, such that the probability that on a particular trial t the participant will choose the positive word is as follows:

$$Probability\_self\_positive_t = \frac{\exp(value\_self\_positive_t \cdot \beta)}{\exp(value\_self\_positive_t \cdot \beta) + \exp(value\_self\_negative_t \cdot \beta)}$$

Again, this can be written equivalently for the other-referential condition.

The initial learning rate for self-referential information (M=0.77, SD=0.17) was smaller than for other-referential information (M=0.82, SD=0.11). This indicates that participants updated their value estimates less for self-referential than other-referential feedback. Additionally, the start bias on self-referential blocks (M=0.12, SD=0.07) was larger than the start bias for other-referential blocks (M=0.06, SD=0.07), signifying that participants had a larger initial positive bias when learning social evaluation about themselves than others. The inverse temperature parameter value (M=2.43, SD=0.75) suggested that participants' choices were quite deterministic.

Associations between model parameters and age group, gender, and depressive symptoms
Using linear regression models, we tested whether any of the parameters derived from the above model differed between age groups or genders (Table 2). Each exposure was tested in a separate univariable linear regression with the model parameter as the outcome. In unadjusted models, there was evidence that the inverse temperature parameter increased with age, indicating that older participants' choices were more deterministic. However, this evidence was attenuated after adjustment for confounders. There was no evidence for associations between age group and other parameters, or any associations with gender.

We then tested whether any of the parameters derived from the above model differed according to depressive symptoms. Depressive symptoms were the exposures and model parameters were the outcomes in separate univariable linear regressions. The learning rate and inverse temperature parameters were not associated with depressive symptoms (Table 2; Figure 2). In contrast, both start bias parameters were negatively associated with depressive symptoms. Adolescents with more severe depressive symptoms were less likely to choose the positive word at the start of both self- and other-referential blocks (Figures 2-3).

Table 2. *Linear regression models testing associations between age group, gender, and depressive symptoms (exposures) and estimated model parameters (outcomes, tested in separate models).*

	Unadjusted models		**Adjusted models**	
	Coef (95% CI)	p value	Coef (95% CI)	p value
Self-referential learning rate				
Age group	0.02 (-0.01 to 0.04)	0.25	-0.01 (-0.04 to 0.02)	0.70
Gender	0.02 (-0.01 to 0.05)	0.17	0.01 (-0.01 to 0.04)	0.30
Depressive symptoms	0.0005 (-0.002 to 0.003)	0.71	0.0002 (-0.002 to 0.003)	0.84
Other-referential learning rate				
Age group	0.01 (-0.003 to 0.03)	0.11	0.01 (-0.01 to 0.03)	0.26
Gender	0.02 (-0.002 to 0.04)	0.07	0.02 (-0.001 to 0.04)	0.06
Depressive symptoms	-0.001 (-0.003 to 0.0002)	0.09	-0.001 (-0.003 to 0.0002)	0.08
Inverse temperature				
Age group	0.19 (0.07 to 0.31)	0.002	0.09 (-0.04 to 0.22)	0.18
Gender	0.07 (-0.05 to 0.19)	0.26	0.03 (-0.09 to 0.14)	0.66
Depressive symptoms	-0.01 (-0.02 to 0.003)	0.19	-0.01 (-0.02 to 0.002)	0.10
Self-referential start bias				
Age group	-0.005 (-0.02 to 0.01)	0.42	-0.01 (-0.03 to 0.001)	0.07
Gender	0.01 (-0.01 to 0.02)	0.39	0.005 (-0.01 to 0.02)	0.42
Depressive symptoms	-0.002 (-0.003 to -0.001)	<0.001	-0.002 (-0.003 to -0.001)	<0.001
Other-referential start bias				
Age group	0.001 (-0.003 to 0.004)	0.69	0.0001 (-0.004 to 0.004)	0.98
Gender	0.001 (-0.002 to 0.005)	0.52	0.001 (-0.003 to 0.005)	0.60
Depressive symptoms	-0.001 (-0.001 to -0.0002)	0.001	-0.001 (-0.001 to -0.0002)	0.001

Note. N=598. In unadjusted models, each exposure was tested in a separate univariable linear regression with the model parameter as the outcome. Each model was then adjusted for potential confounders (continuous age within each age group, school, testing group size, and non-verbal IQ score). Gender was missing for 10 participants and depressive symptoms (SMFQ score) were missing for 4 participants.

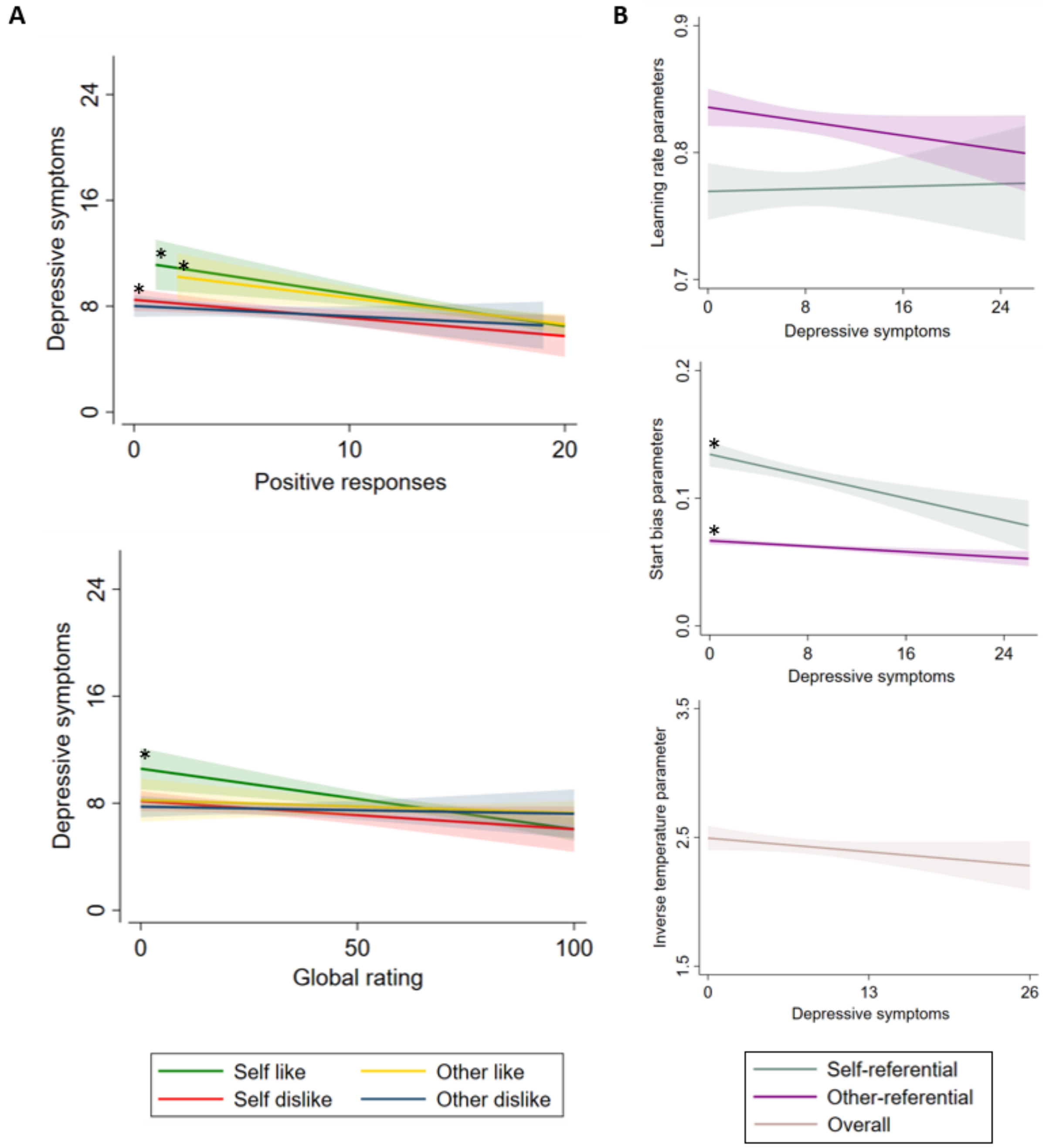

*Figure 2***.** A) Expected depressive symptoms from the fully adjusted linear regression models using observed task performance (positive responses and global ratings). B) Expected parameter values from the fully adjusted linear regression models using parameter estimates (learning rates, start biases, and inverse temperature). All graphs adjusted for age group, gender, continuous age within each age group, school, testing group size, and non-verbal IQ score. Shaded area shows 95% confidence intervals and asterisks indicate significant associations ($p<0.05$). See Figure S6 for plots of the raw data (in comparison to model estimates plotted here).

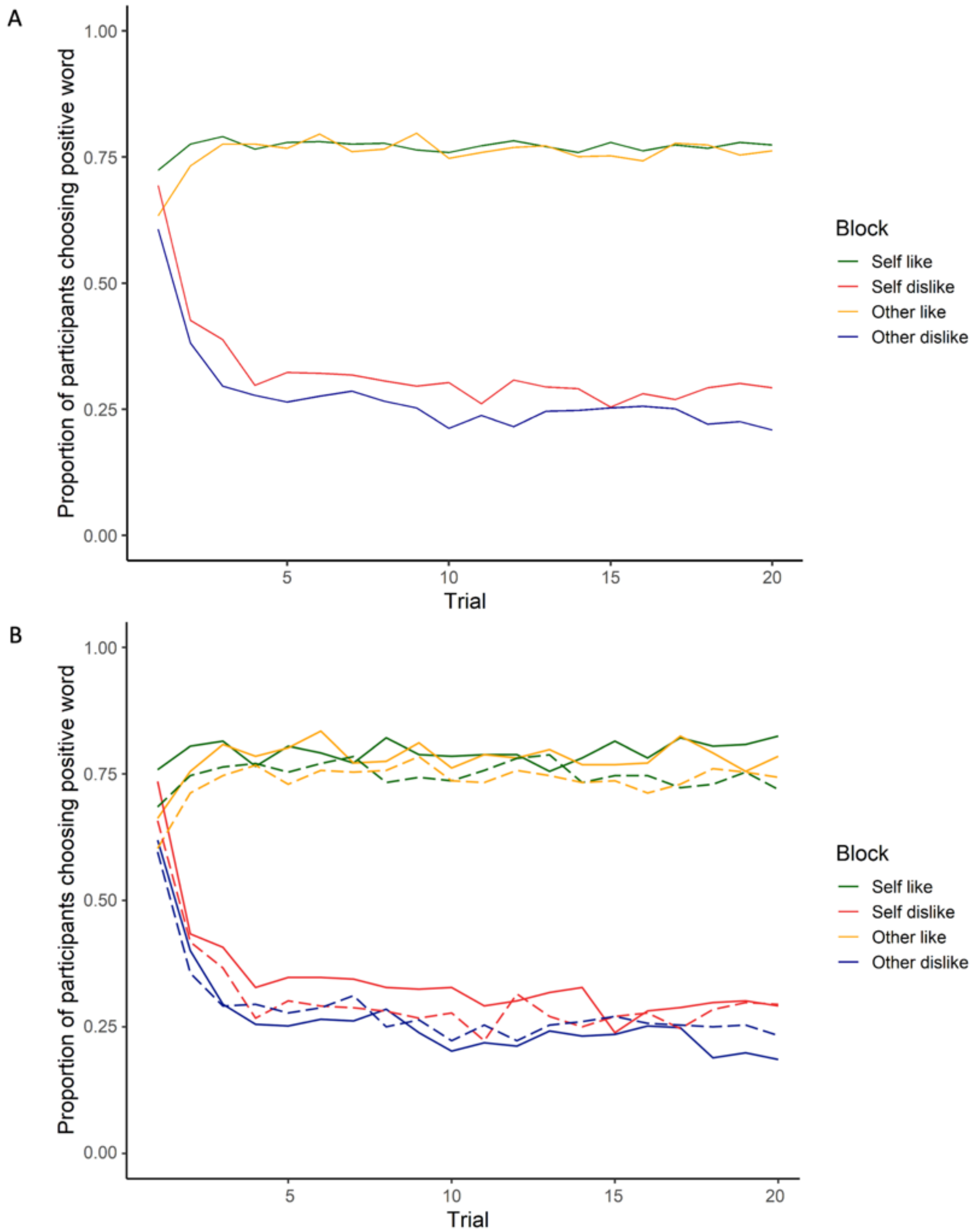

Figure 3. Proportion of participants who chose the positive word on each trial of each block (observed performance). A) Proportion of the whole sample. B) Proportion of participants choosing the positive word according to low versus high depressive symptoms. In order to illustrate this, a median split of depressive symptoms was performed. The solid line indicates participants with low depressive symptoms (SMFQ score ≤ 6; n=302). The dashed line indicates participants with high depressive symptoms (SMFQ score > 6; n=292).

Sensitivity analyses: effect of age group

In the preceding analyses, we assumed that all adolescents represented a single population, with inter-individual variability such that young and mid-adolescents all lie on a continuum in parameter space. This model correctly accounted for 68.11% (SD=11.47%) of young adolescents' choices versus 69.89% (SD=10.14%) of mid-adolescents' choices (mean difference (MD)=1.79, 95% CI=0.03-3.55, p=0.05), a significant, albeit small, difference.

To check that this difference had not biased the results, we re-estimated the final model with separate priors, allowing for different means and distributions of parameters in each age group. This marginally improved model evidence (total BIC=57,928, AIC=50,805) compared to estimation with priors for the whole sample (total BIC=57,976, AIC=50,854). This implementation of the model also accounted for the observed choices of mid-adolescents (M=70.56%, SD=9.87%) better than young adolescents (M=68.33%, SD=11.65%; MD=2.23, 95%CI=0.50-3.96, p=0.01).

In this implementation, there was no evidence that the self-referential learning rate (MD=0.02, 95% CI=-0.01-0.05, p=0.21) or other-referential start bias (MD=0.002, 95% CI=-0.004-0.01, p=0.44) differed between young versus mid-adolescents. However, the other-referential learning rate was higher in mid-adolescents (M=0.83, SD=0.11) than young adolescents (M=0.81, SD=0.13; MD=0.02, 95% CI=0.004-0.04, p=0.02), and the inverse temperate parameter was higher in mid-adolescents (M=2.58, SD=0.57) than young adolescents (M=2.33, SD=0.84; MD=0.25, 95% CI=0.13-0.37, p<0.001). Additionally, the self-referential start bias parameter was more positive in young adolescents (M=0.13, SD=0.08) than mid-adolescents (M=0.10, SD=0.06; MD=0.03, 95%CI=0.02-0.04, p<0.001). Adjusting for depressive symptoms did not alter the evidence for any of these age differences. In summary, in comparison to young adolescents, mid-adolescents updated their value estimates more for other-referential feedback, made more deterministic choices, and had a less positive initial self-referential bias.

Using parameter estimates from this implementation of the model, there was still evidence that both start bias parameters were negatively associated with depressive symptoms (self-referential adjusted coef=-0.002, 95% CI=-0.003 to -0.001, p<0.001; other-referential adjusted coef=-0.001, 95% CI=-0.001 to -0.0001, p=0.03).

Discussion

In this study, we examined the processes underlying learning about social evaluation in adolescence. Consistent with our hypotheses, in model-agnostic analyses of behaviour, we found that adolescents demonstrated a positive self-referential bias during learning, as has been shown in adults (6,7). Also as in adults (11), the magnitude of this positive bias was negatively associated with depressive symptoms. We also found evidence that other-referential learning was negatively associated with depressive symptoms, which was not expected. Although participants demonstrated that they had learnt the task rules after each block, they did not rate the character's opinion of themselves differently to the character's opinion of another person. This has also been found in adults (7) and may reflect a distinction between biases in learning and more reflective global appraisals after the event (25). Adolescents who rated themselves as less liked also had more severe depressive symptoms, as in adults (11).

Our reinforcement learning model showed that adolescents started with a positive expectation that they and others would be liked, and this positive bias was larger for the self than others. During learning, adolescents used feedback to update their expectations about social evaluation less for themselves than others. This suggests that adolescents have an initial positive self-referential bias when learning about social evaluation, which is more resistant to feedback than learning about others. Using parameters derived from our reinforcement learning model, we found that adolescents' initial expectations about whether both they and others were liked were associated with depressive symptoms; adolescents with more severe depressive symptoms were less likely to act as if they and others were liked when meeting a new character. Contrary to previous studies (40), we did not find evidence that other learning processes were associated with depressive symptoms.

Our winning model was similar to the model of this task in adults, as it had separate initial learning rates for self-referential and other-referential evaluation and an initial positive bias parameter (28). However, in contrast to research in adults (28), our winning model did not include separate parameters for learning from trials in which the positive or negative word was correct. This suggests that adolescents may learn about social evaluation more optimally than adults, learning equally well when outcomes are positive and negative. We also found no evidence for separate parameters according to whether feedback was positive or negative, suggesting that adolescents did not learn differently based on whether they made the correct choice. This differs to previous evidence that adolescents learn preferentially from positive, relative to negative, feedback (35,46,47). However, these studies did not use social reinforcement learning paradigms. One study of social reinforcement learning found lower learning rates for positive social feedback in adolescents than children and adults but did not report whether learning from positive versus negative social feedback differed during adolescence (48). One possibility is that the highly salient nature of peer interactions during adolescence may increase the impact of all aspects of interactions, leading to equal learning from positive and negative feedback. This requires testing in future studies.

Our results indicate that it is prior beliefs that underlie the association between social evaluation learning and depressive symptoms in adolescence, and not other aspects of learning. Importantly, this finding was robust to the modelling approach chosen and adjustment for confounders. This is consistent with evidence that adolescents with higher self-esteem expect to be liked in another social reinforcement learning task (40) and corresponds to predictions about whether peers will like you in previous behavioural studies (18,19,21–23). These beliefs may be learnt during development and then applied to new situations, providing a mechanism through which adverse experiences could lead to depressive symptoms. For example, if an individual is repeatedly exposed to negative social experiences, such as being bullied, they could develop the belief that they are not liked by others. When performing the social evaluation task, these individuals might then have a less positive prior, making them less likely to learn that they are liked by others. In this study, we cannot demonstrate a causal effect of these processes on depressive symptoms. Our findings are consistent with this hypothesis, as proposed by cognitive models of depression (9,10). However, it is equally possible that changes in depressive symptoms cause changes in the processes underlying learning, or that the association is bidirectional or caused by a third factor. Although the causal direction of these associations remains unclear, this study adds to our understanding of the psychopathology of depression by showing the importance of prior beliefs in social evaluation learning. Longitudinal data is needed to test the hypothesis that adverse experiences lead to less positive beliefs about social evaluation, which are then associated with increases in depressive symptoms during adolescence.

Contrary to our hypotheses, we found no evidence for gender differences in learning about social evaluation. This was surprising given the association between prior beliefs and depressive symptoms and the higher prevalence of depressive symptoms in girls than boys during adolescence. We have previously proposed that gender inequality may cause girls to have more negative self-schema, which could lead to more negative prior beliefs (43). It is possible that girls have more negative self-schema in adolescence, but this was not captured by performance on our social evaluation learning task. However, previous studies have also found no evidence that expectations of, or reactions to, social evaluation differed between boys and girls in adolescence (49–51). This suggests that other mechanisms may contribute to the emergence of the gender difference in depression during adolescence.

We initially found evidence that mid-adolescents made more deterministic (less random) choices than young adolescents, although this was attenuated after adjusting for confounders. This is likely to be because higher non-verbal IQ was associated with more deterministic choices. However, non-verbal IQ might be on the causal pathway, as adolescents with higher IQ might be better at completing the task (thus making less random choices), meaning we could be over-adjusting and obscuring the association with age. However, the age difference in the inverse temperature parameter might also be due to differences in the extent to which the model accurately described learning (35). Inverse temperature parameters might capture noise in estimates, leading to lower values when there is a larger mismatch between performance and model algorithms (35). When modelling the age groups using separate priors, we found that mid-adolescents made more deterministic choices, updated their expectations more for others, and had a less positive initial self-referential bias than young adolescents. These age differences were not a result of increases in depressive symptoms. This in line with evidence that individuals become less exploratory in their decision making (38) and better able to represent the mental states of others and abstract social goals during adolescence (36,37). The reduction in positive self-referential bias with age may occur because self-evaluations become more negative during adolescence (12,42).

This study has several strengths. Our sample was included participants scoring across the full range of depressive symptoms, which we analysed continuously. This design boosts statistical sensitivity to detect any associations between learning about social evaluation and depressive symptoms (52). The sample was recruited from eight diverse schools, making it more representative than many previous experimental developmental studies. However, poor parental consent rates in several schools was a limitation. Selection bias may have occurred, as participants had higher non-verbal IQ in schools with low parental consent rates. Nevertheless, most of the sample were from schools with high consent and opt-out consent was used to recruit nearly half of the sample.

In computational analyses, we compared models representing assumptions about different mechanisms underlying behaviour and captured patterns which were not apparent in standard analyses. However, there are some limitations of the winning model. Despite the use of decreasing learning rates over trials, the initial learning exhibited by the model was slower than the observed behaviour. Start biases from the model were smaller than in observed behaviour and, for like blocks, the asymptote of positive choices was a little high. We used a hierarchical approach to parameter fitting that improves estimates, minimising extreme or incorrect parameter assumptions (53,54), but also requires specification of the population structure of the data. We assumed that young and mid-adolescents represent a single population, which may have led to underestimation of age differences. In simulations, modelling groups separately provides a closer recovery of true effect sizes (54). However, simulations were based on diagnostic groups, whose task performance may differ more substantially than adolescents aged 11-12 versus 13-15 years. Additionally, modelling the age groups using separate priors in a sensitivity analysis did not substantially alter our findings.

In summary, we found robust evidence that adolescents have positive biases in learning what others think about both themselves and others. Reductions in these positive biases are associated with depressive symptoms. Consistent with cognitive models of depression (9,10), less positive beliefs about others' opinion of the self could lead to a more negative self-image, lower self-esteem, more negative mood, and more negative information available for later rumination. This could in turn result in lower perceived social success and social withdrawal. Despite the gender difference in the prevalence of depressive symptoms, there was no evidence for gender differences in learning about social evaluation. However, we did find evidence for a decrease in positive self-referential biases with age, which was not explained by depressive symptoms, and may be due to the increase in negative self-evaluations during adolescence. Overall, these findings add to our understanding of the psychopathology of depression in adolescence, indicating that it is adolescents' prior beliefs that are associated with depressive symptoms, and not their learning rates. If our findings are replicated in longitudinal studies, prevention or treatment strategies for depression could target reinforcement learning processes, such as adolescents' beliefs about what people will think of them and others, aiming to instil more positive biases.

Methods

Participants

Participants were recruited from eight diverse mixed-gender secondary schools across London. We sampled from two separate age groups, Year 7 (11-12 years old) and Years 9-10 (13-15 years old), maximising power to test gender differences before and after the age at which rates of depression start increasing (42). There were no restrictions on whether adolescents had any mental or physical health problems or were receiving psychotropic medication or psychological therapy. We aimed to recruit 160 girls and 160 boys in each age group (total n=640) so that we had at least 90% power to detect gender differences in choices on the social evaluation learning task of 0.4 standard deviations or more within each age group (α=0.05). Our final sample (n=598) gave us 90% power to detect differences of this magnitude.

Ethical approval

Ethical approval was obtained from University College London (project 3453/001). Informed consent was provided by all parents/carers of participants and informed assent was provided by all participants. Participants' parents provided informed opt-in or opt-out consent, dependent on the school their child was attending. Only seven (2%) parents chose to opt-out. All procedures complied with the ethical standards of the relevant committees on human experimentation, the Helsinki Declaration (2008 revision), and General Data Protection Regulation. Participants could opt-in to a prize draw to win one of ten £50 Amazon vouchers after completing questionnaires.

Measures

Social evaluation learning task

This was a two-alternative forced choice task based on probabilistic reinforcement learning (7). Participants learnt whether a person was liked or disliked by a computer character (Figure 1). They were not asked to pretend that the characters were real. Learning occurred in two conditions: about the participant themselves (self-referential) or about another person (Taylor; other-referential). There were thus four blocks in this task: *self like, self dislike, other like,* and *other dislike*. The order in which participants saw these blocks was randomised and counterbalanced. Participants met a new character every block, and each character was represented by a name on the screen. The name Taylor, and the names of the characters participants met, were chosen to be gender neutral. On each trial, a positive and negative word pair was presented (e.g. funny/grumpy). Participants were asked to choose the word that best corresponded to what the character thought about them (self-referential) or Taylor (other-referential). Participants received probabilistic feedback, with 80% contingency, about whether their choice was correct. They used trial and error to learn whether the character liked or disliked them (or Taylor) over 20 trials in each block. Blocks ended with a global rating that asked participants to rate how much the character liked them (or Taylor) on a sliding scale (0=dislike, 100=like). We recorded choices (positive versus negative word selected) and feedback on each trial, the number of positive responses during each block, and global rating after each block.

Twenty word pairs were seen for the participant themselves, and 20 for Taylor (see supplementary methods). Words were emotive adjectives describing personality characteristics (e.g. cool/boring, funny/grumpy). Positive and negative words were selected from databases according to their age of acquisition (55–59). The oldest mean age of acquisition of any included word was 8.78 years (SD=1.99). Positive and negative words were paired, matched firstly on age of acquisition. We also aimed to pair semantically linked words, minimise differences in psycholinguistic parameters (number of syllables, usage frequency, meaningfulness, familiarity, arousal), and maximise differences in likeableness, valence, and desirability ratings. The name Taylor, and the names of the characters participants met, were chosen to be gender neutral.

Depressive symptoms

Participants completed the short Mood and Feelings Questionnaire (SMFQ), a 13-item self-report measure of depressive symptoms over the last two weeks (45). Items were rated on a scale of 0-2 (total 0-26), with higher scores indicating greater severity. Missing responses were imputed for participants who responded to 10 or more questions using each individual's mean SMFQ score per item (n=116, 19%).

Confounders

We recorded participants' age, gender, school, and the size of the group in which they were tested. Participants completed an abbreviated nine-item version of the Raven Standard Progressive Matrices Test (non-verbal IQ score; ,44).

Procedure

Groups of 2-31 adolescents used computers, laptops, or tablets to access Gorilla (www.gorilla.sc) in class and complete measures online. After providing informed assent, participants completed a battery of measures, intended for use in several studies. Participants first completed the social evaluation learning task, followed by the Raven Standard Progressive Matrices Test, a recall task, and the SMFQ. We have previously reported performance on the recall task (60).

Statistical analyses

To initially examine behaviour, model-agonistic analyses were performed using Stata 16 (61). We first aimed to test how task conditions, age, and gender influenced responses. We analysed the number of positive responses (range 0-20) and the global rating (range 0-100) in each of the four blocks (*self like, self dislike, other like, other dislike*). If participants learnt the task rules, we would expect positive responses and global ratings to be higher in *like* than *dislike* blocks. Given that the four blocks were clustered within each individual, we used linear multilevel models to analyse responses, with positive responses and global ratings the outcomes in separate models. We included random intercepts for participant, and estimated the task conditions (*self*/*other*, *like*/*dislike*), demographic variables of interest (age group, gender) and confounders as fixed effects. Next, we aimed to test whether task performance was associated with depressive symptoms. We used linear regression to test whether responses in each block were associated with depressive symptoms. We used linear regression and not multilevel models as depressive symptoms (the outcome) did not vary within individuals. We included responses in all four blocks in the same model to adjust for overall task performance, for both positive responses and global ratings. Results from these analyses are described in more detail and all models are presented before and after adjustment for confounders in in the supplementary materials (Tables S2-S4).

Reinforcement learning models

All reinforcement learning analyses were performed using R version 3.6.0 and RStudio version 1.2.5001, with packages bbmle, boot, reshape2, Hmisc, ggplot2, and RStan (62–71). We aimed to model how participants learnt about social evaluation using adaptions of Rescorla-Wagner reinforcement learning models (26). Here we describe the key features of the models, with further details presented in the Supplement. Each reinforcement learning model consists of two parts, which formalise how participants use feedback to choose between the two possible actions in this task - selecting the positive word or selecting the negative word. The learning model defines how participants learn the value of each action, with values updated on each trial as participants receive feedback. The action model then describes how those values are turned into choices. These models, the fitting procedure, and how we selected a parsimonious model which provided a good fit to the data, are described in more detail in the supplementary materials.

To briefly summarise, we fit different models to the data in two stages. First, we focussed on modifying learning rates, testing whether there should be separate learning rates for: a) choices in different *conditions* (self vs. other), b) choosing words of different *valences* (positive vs. negative), c) trials with different *outcome* words (positive vs. negative), and d) trials with different *feedback* presented (positive vs. negative). After identifying the best fitting model class in stage one, we then considered further types of modifications to the winning model type: whether learning rates *decreased* over trials, as participants' learning reached a plateau rapidly (Figure 2), and the addition or omission of '*bias*' parameters, capturing either a tendency at the start of a block to choose the positive/negative word, or a bias throughout the blocks towards positive/negative words (both of which could also be separated by *self*/*other* condition). The best-fitting model was determined using a combination of model evidence (as summarised using information criteria; 72), parameter recovery from synthetic data, and generative performance (i.e., the extent to which fitted model parameters were able to recapitulate participants' choices). This combination of approaches was chosen as distinguishing between models using qualitative patterns in the data has been recommended over quantitative model comparison (72–74). During the process of determining the best-fitting model, parameters were estimated using a hierarchical maximum *a posteriori* estimation approach, with multiple initial points and 20 iterations. Once the winning model had been determined, a Markov-Chain Monte-Carlo (MCMC) approach was taken to parameter estimation, which minimises error in parameter recovery (54).

Associations with age group, gender, and depressive symptoms

Next, we examined whether any of the processes involved in learning differed by age group, gender, or depressive symptom severity. Using estimates from the winning model, we initially tested whether age group, gender, and depressive symptoms (exposures) were associated with each parameter (outcome) in univariable linear regression models. We then adjusted each model for confounders.

Sensitivity analysis: effect of age group

In the preceding analyses, we assumed that all adolescents represented a single population, with inter-individual variability such that young and mid-adolescents all lie on a continuum in parameter space. This was based on the lack of previous evidence for age differences in social reinforcement learning from early to mid-adolescence. However, it is possible that young and mid-adolescents are two separate populations, with separate, overlapping, distributions of task performance. To investigate this, we first tested whether generative performance of the winning model differed according to age group. We used an independent samples t-test of the percentage of trials on which simulated choice matched observed choice. We then repeated parameter fitting, using hierarchical MCMC sampling with young and mid-adolescents as two groups with separate priors. We tested whether this was a better model of task performance by using the BIC and AIC and simulating task choices, which we then compared to observed performance. Finally, we examined whether parameter estimates differed across the two age groups using independent sample t-tests.

Author contributions

JKB was responsible for the original study proposal and securing funding, with input from GeL, JR, SJB, and GlL. JKB had overall responsibility for the study management, data collection, and drafting of the manuscript. JKB and ACP performed the analyses. ACP, GeL, JR, SJB, and GlL assisted with planning and interpreting analyses and writing of this manuscript. All authors contributed to, and approved, the final manuscript.

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Conflict of interest
JKB, GeL, GlL, SJB and JPR report no financial interests or potential conflicts of interest. ACP was the named secondee on an MRC Proximity-to-Discovery award with Roche (who provided in-kind contributions and have sponsored travel).

Data availability
The datasets generated during and analysed during the current study are available from the corresponding author on reasonable request.

Code availability
The code written and used during the current study is available from the corresponding author on reasonable request.

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