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Trends in Cognitive Sciences

Opinion

A cognitive-computational account of mood swings in adolescence

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Teenagers have a reputation for being fickle, in both their choices and their moods. This variability may help adolescents as they begin to independently navigate novel environments. Recently, however, adolescent moodiness has also been linked to psychopathology. Here, we consider adolescents' mood swings from a novel computational perspective, grounded in reinforcement learning (RL). This model proposes that mood is determined by surprises about outcomes in the environment, and how much we learn from these surprises. It additionally suggests that mood biases learning and choice in a bidirectional manner. Integrating independent lines of research, we sketch a cognitive-computational account of how adolescents' mood, learning, and choice dynamics influence each other, with implications for normative and psychopathological development.

Highlights

Adolescence is believed to be a period of life where mood swings are pronounced.

While this might reflect adaptive socioaffective flexibility, enhanced mood variability is also a risk factor for mental health problems.

The widespread use of smartphones now enables the capturing of age-related differences in mood dynamics in real life and at a high temporal resolution.

Advances in computational neuroscience have formalized a computational basis of mood variability grounded in reinforcement learning.

Based on this account of mood–learning interactions, and in light of what we know about how adolescents' choices are shaped by learning from the outcomes of their actions and by emotional contexts, we develop a computational framework of how increased mood changes arise in adolescence.

Mood dynamics in adolescence

From falling in love for the first time (whether reciprocated or not), successes and failures at school, the risk of being rejected by peers, to the joys of spending time with friends on the road to independence from one's parents, the period of adolescence is full of emotional ups and downs. Adolescence is also linked to puberty, a time of dramatic biological reconfiguration, with neural and hormonal changes that are associated with changes in mood and affect [1,2]. Accordingly, adolescence is often referred to as a period of 'storm and stress' and the notion of a 'moody adolescent' is paramount in folk wisdom. While mood changes are commonly regarded as a normative aspect of teenage development, pronounced mood swings, which we refer to as enhanced **mood variability** (see Glossary) and **mood instability**, have come into focus as an important risk factor for the development of psychopathology [3–6]. Indeed, adolescence is a markedly vulnerable phase, in which many mental health problems show their onset [7,8].

Here, we consider adolescent mood swings in light of recent advances in computational neuroscience, which have proposed **RL** as a computational basis of mood instability [9,10]. These theories emphasize that emotional states in health and psychopathology are affected by learning and that emotional states, in turn, bias learning processes themselves. Recent studies in adults have revealed insight into the biological basis of such mood–learning dynamics [9–17] (Box 1). Intriguingly, this also revealed implications of computational mood theories for real-world **emotions** outside of the laboratory [18,19].

We first review empirical evidence for the notion that adolescence is characterized by pronounced mood changes. We then outline several computational theories, alongside supporting empirical evidence, which cast mood instability through the lens of RL algorithms. Finally, we summarize the empirical state of the art of how sensitivity to rewards, learning from good and bad outcomes, and choice are altered in adolescents. By amalgamating these three lines of

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Box 1. Neural basis of mood–learning dynamics

Recent computational studies in adults provided insights into the biological basis of mood–learning dynamics by combining learning tasks and computational modeling of behavior with neural measurements and pharmacological manipulations. An earlier fMRI study sought to unravel the neural correlates of the behavioral finding that RPEs drive mood changes [12]. The authors found that blood oxygen-level dependent (BOLD) activity in the ventral striatum reflected both RPEs and subsequent happiness ratings. The ventral striatum receives input from dopamine neurons that encode RPEs [126,127]. This alignment suggests a potential involvement of dopaminergic RPE signals in shaping mood. Indeed, research has demonstrated that augmenting dopamine levels through pharmacological means can enhance the happiness derived from specific types of reward [67]. While RPEs drive changes in participants' mood, mood in turn drives future expectations and behavior. It has been shown that individuals who report more mood instability in everyday life and show a stronger mood bias in their choices are characterized by a pronounced neural bias in responses to rewards in the striatum and other regions of the valuation network of the brain, including the ventromedial prefrontal cortex (vmPFC) [9]. In a recent study, the vmPFC and anterior insula were shown to reflect separate components of mood and to have independent effects on subsequent decision-making [13]: high vmPFC activity was positively correlated with mood and promoted risk-taking by emphasizing potential gains and higher insula activity was negatively correlated with mood and attenuated risk-taking by overweighting potential losses. These fMRI findings were corroborated by a study using intracerebral EEG to show that broadband gamma activity, in the vmPFC and the dorsal anterior insula, was associated with high and low mood, respectively. At the same time, this activity was predictive of increased versus tempered risk-taking by biasing the evaluation of the prospects of gains versus losses [14]. A pharmacological intervention study used selective serotonin reuptake inhibitors along with an experiment to probe mood–learning interactions in healthy adults. This revealed that serotonin enhanced a mood bias by boosting an impact of positive affect on RL [16]. Notably, these insights are derived from studies in adults. Given that the human reward system matures during adolescence [128], an exciting avenue for future research will be to pinpoint the neural correlates of mood–learning interactions in the developing brain.

largely independent research, we propose a computational account of how moods and learning might influence each other in adolescence. Considering the substantial heterogeneity in findings in the field of adolescent emotional development, we propose that adopting a computational perspective enables more precise definitions of adolescents' moods and emotions, as well as variability therein.

Mood fluctuations and emotional reactivity in adolescence

Several age-comparative studies using ecological assessments (Box 2) find more frequent mood changes, operationalized as mood variability and mood instability, particularly in mid-adolescence compared with early [20,21] or late adolescence [21,22]. Of note, there is evidence for more pronounced mood variability in girls than in boys [20–23]. The absence of an age effect in studies including late adolescents in their sample [24,25] might indirectly support findings that mood variability stabilizes toward later adolescence [26] or young adulthood [27]. A decrease in mood variability and mood instability is also observed in longitudinal studies [3,23,28,29]. In sum, despite inconsistencies in measurement and terminology, and perhaps a surprising scarcity of studies, evidence points toward elevated mood variability in adolescents compared with adults.

This variability has been suggested to have an adaptive function, where flexibility toward social-affective stimuli allows adolescents to adequately respond to social demands during adolescence [30–32]. However, there is also evidence that pronounced **mood fluctuations** are linked to psychopathology. This supports the notion that some variability, in the sense of socioaffective flexibility [30], may be adaptive, but too much may be detrimental [32]. Longitudinal evidence shows that measures of mood instability and variability predict negative outcomes, such as the development of delinquency [3], anxiety, and depressive symptoms [28], as well as negative child–parent interactions [33] across adolescence. Emotional instability is also a key transdiagnostic symptom of several mental health problems, including affective disorders [34], attention deficit-hyperactivity disorder (ADHD) [32], and borderline personality disorder [24,35]. In patients, measures of mood instability differentiate between diagnostic entities [35], and were shown to predict not only psychopathology [36,37], but also treatment response [35].

Box 2. Opportunities and pitfalls of measuring adolescents' mood dynamics

There is considerable heterogeneity in both the methods by which mood dynamics are assessed and the terminology used to refer to mood changes [119,120].

One method to assess trait mood fluctuations are questionnaires, asking individuals how often their mood normally changes [129,130]. This relies on not only participants' introspective abilities concerning their present state, but also their retrospective memory of, and ability to infer, changes in emotional state. Problematically for age-comparative studies, introspection [131] and biases in retrospective memory differ between age groups [132].

Time-series data (i.e., repeated within-person measures) can be used to compare the current emotional state across multiple measurements. Here, participants report on their current mood, but do not draw direct conclusions on its dynamics. The latter is instead modeled by the raw within-person mood ratings. Commonly used methods include e-diaries (sampling once daily) and ecological momentary assessment (EMA, higher-frequency sampling in daily life).

E-diaries do not require a portable device to assess mood dynamics. However, participants need to remember a larger time frame (e.g., the previous 24 h). Many findings we summarize in the main text are based on e-diaries [3,28,29,33,133–135]. Reassuringly, recent studies have shown satisfying correspondence between e-diary and EMA [136].

Today, 95% of US teenagers have access to a smartphone[i]. Hence, smartphone-based EMA has become a viable option for assessing teenagers' mood dynamics in real life [23,29,36,53,119,133]. EMA is typically conducted through a smartphone application where participants are asked several times a day to rate their current mood [137]. Although EMA is relatively burdensome, it provides insight into within-person dynamics and immediate, or close to, real-time, emotional reactions to events. It enables integration with psychophysiological data [137] or parallel assessment of two dynamic constructs (e.g., mood and self-esteem interactions). EMA also helps to quantify different aspects of mood changes (e.g., mood variability vs. instability).

A higher degree of standardization is needed to improve the comparability between studies [119]: little agreement exists to date on timing intervals and/or frequency of questions, the handling of missing values, and participant instructions. Additionally, EMA scales are often not validated with regard to their psychometric properties [119,137]. Recently, concerns have been raised with respect to the internal validity of EMA ratings due to possible population and moment-selection biases, as well as because being asked to rate one's subjective experience for a research study might alter participants' responses (see [138] for more detail). A plethora of different measures for mood dynamics have been suggested [35,119,136], and recent validation studies caution against using these methods as universally interchangeable [136].

Neuroimaging studies point toward higher emotional responsivity during adolescence

In the developmental literature, **emotional reactivity** has often been operationalized as amygdala activity in response to emotional faces. The latter has repeatedly been shown to peak in adolescence [38–40] or to decrease from childhood to adulthood [41,42], even though results are partly mixed [41,43]. A limitation is that these studies mostly focus on socioaffective context and social stimuli [38,41,44–46]. Additionally, the practice of equating amygdala responsivity with emotional reactivity, often without assessing explicit emotional experiences, may be considered problematic [47].

Determinants and consequences of emotional reactivity and mood fluctuations in adolescence

Overall, the results presented above indicate a decrease in mood variability, instability, and emotional reactivity from adolescence to adulthood, with a potential peak during mid-adolescence. Although these findings are preliminary, they fit well with a general picture of biological and psychosocial development during adolescence. For example, the development of adaptive emotion regulation strategies has been shown to mature during adolescence in some studies [46,48–51]. However, there is heterogeneity in findings [52–54].

On a neural level, enhanced emotional reactivity in adolescence is classically interpreted within dual-system [55,56] or maturation-imbalance [57] models. A common feature of these models is that they assume an asynchronous maturation of a socioemotional (subcortical limbic-striatal) system and a cognitive-control (prefrontal executive) system, with the former maturing earlier

Glossary

Choice stochasticity: refers to randomness in choices. If stochasticity is high, decisions are taken irrespective of learned expected values. If stochasticity is low, choices favor the option with the highest expectation to gain a reward. High stochasticity can be due to poorly learned/memorized values or to a high rate of change in the environment. In such volatile environments, it is advantageous for learners to re-evaluate options that were initially less favorable, allowing them to assess whether the option has gained value over time [112].
Emotional reactivity: corresponds to reaction toward affective stimuli and is equal to the difference between mood baseline and mood after an emotional event:

$$\Delta_{emotion} = rating_{afterevent} - rating_{baseline} \qquad [I]$$

Emotions (vs. moods): emotions are commonly described as transient, lasting mere moments to minutes, while moods are characterized by a longer duration. Using an RL framework, mood and emotions can be regarded as similar phenomena occurring on different timescales. Based on this framework, moods are constructed via a temporal integration of recent outcomes. The time constant of integration is determined by the mood update rate parameter, which is between 0 and 1. If it equals 1, then only the most recent event factors into the resulting emotional state, in which case the term 'emotion' would be more appropriate, whereas a lower update rate would be more appropriate to describe mood (see [10] for more detail).
Mood fluctuation: serves as a superordinate term for various measures of mood swings, such as variability and instability.
Mood instability: captures not only the range of mood ratings, but also the frequency and extent of the single changes between subsequent ratings. For example, the change between ratings that are 2 h apart can be drastic in some cases and minimal in others, which we would not necessarily detect by examining the standard deviation. Thus, quantifying mood instability requires a separate calculation, which can be

than the latter. Indeed, connectivity between frontal regions and the amygdala has been shown to mature over adolescence, which is linked to the development of emotional stability [58,59].

Finally, a substantial physical and hormonal reconfiguration during puberty might account for variance in mood development [60,61]. At the same time, there is evidence that emotional instability is modulated by environmental and social influences, such as parental acceptance [62,63]. Larger mood variability could also be a consequence of the individuation process an adolescent undergoes by becoming independent from parents and spending more time with peers [30–32]. Thus, developmental trajectories are likely highly individual and still very flexible in response to environmental changes.

Mood instability in adolescence through the lens of RL algorithms

RL models formalize a process of evaluating actions based on whether they result in good or bad outcomes [64]. Here, we outline how these models can be utilized to gain mechanistic insight into mood fluctuations among adolescents.

Mood reflects surprise toward unexpected outcomes

At the heart of RL models is the reward prediction error (RPE), the difference between a received outcome and an expected outcome. For example, when receiving a 'like' from someone you thought would not like you [65], an RPE elicits activity in dedicated dopaminoceptive brain areas suggested to comprise the 'reward system of the brain' (Box 1). In RL, RPEs drive the learning process through which expectations are updated.

Only recently have studies begun to expand the scope of RL to include the dynamics of moods and emotions [66] (see [10] for a detailed treatment of how mood and emotions can be defined in RL terms). These studies revealed that mood fluctuations are contingent not only on the valence of outcomes ('good vs. bad'), but also on how surprised individuals are by the outcome of their actions (i.e., by RPEs) [12,15,17,67,68]. RPEs can indeed elicit rapid mood changes, for example, when one's soccer club loses unexpectedly [12,18,19]. A recent study amended this work by showing that it might not be the RPE *per se*, but the magnitude of the change in expectations (i.e., the learning rate multiplied by the RPE; Box 3) that alters mood [10,11]. In this framework, mood changes would be mostly driven by surprising outcomes that change our expectations about the environment (e.g., a surprising 'like' on social media that I attribute to my new haircut), rather than by outcomes that are interpreted to be chance events (e.g., a surprising 'like' on social media I attribute to a mis-click) [10,11]. Note that, under an RL account, internal states or thoughts (in the sense of simulated experience [69]) can affect mood in the same way as external events.

Novelty and volatility in adolescents' environments provoke prediction errors and mood instability

RL models have become immensely popular for characterizing behavior and brain activity in health and disease, but have only recently begun to be applied across development [70,71]. Using quantitative theory-driven RL models enables researchers to make specific predictions about the age-dependent development of constituents of distinct learning and choice processes [72] that are otherwise not directly measurable [73]. They also allow researchers to test whether different cognitive processes underlie behavior in different phases of development by group-specific model selection and model comparison approaches [74,75].

Earlier computational studies suggested that adolescents show heightened RPE or punishment prediction error responsivity, measured by enhanced neural reactivity to events that are better or worse than expected [76–78]. Under an RL account of mood, these stronger RPEs in adolescents lead to stronger mood changes, a mechanism that might explain the pronounced mood

implemented as the mean of the squared successive differences:

$$MSSD = \frac{\sum_{i=1}^{n-1}(x_{i+1} - x_i)^2}{n-1} \quad \text{[II]}$$

Mood variability: describes the range in which mood changes occur. In repeated measurements, it captures the extent to which the single ratings deviate from the overall average, irrespective of the temporal order. Mathematically, it corresponds to the standard deviation:

$$SD = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n}} \quad \text{[III]}$$

Reinforcement learning (RL): computational theory to describe the process of how expectations and actions are shaped based on outcomes from the environment. Future expectations are updated based on the deviation between previous expectations and the actual (perceived) outcome, called prediction errors. Several parameters can modulate an individual's learning predispositions, such as learning rate, stochasticity, reward sensitivity, or choice biases.
Volatility: the rate of change of values in the environment. When volatility is higher, the organism is more uncertain about the value of a choice option (because the 'true' value has fluctuated more in their learning history); thus, the learning rate increases.

Box 3. Simulating hypotheses about adolescent mood dynamics using a computational model of mood–learning interactions

The computational model of mood–learning interactions is described and validated in [11]. It represents a modification of a standard RL model to account for the effects of mood on valuation. Standard RL models build expectations; that is, learn the expected value (Q), by updating it according to a RPE [the difference between an expected (Q) and an obtained reward (R; RPE = R – Q)). Here, we replace R (the actual outcome) with a perceived reward term:

$$\text{reward}_{\text{perceived}} = \text{reward}_{\text{actual}} \times f^{\text{mood}} \quad \text{[I]}$$

When $f = 1$, the actual reward is equal to the perceived reward.

When $f > 1$, the reward is amplified congruent to mood: rewards are perceived as better than they are in good mood and as worse in bad moods.

When subtracting the expected value from the perceived reward, we get the RPE.

$$\text{RPE} = \text{reward}_{\text{perceived}} - \text{value}_{\text{expected}} \quad \text{[II]}$$

Mood reflects the RPE history. The step-size parameter η_h modulates the extent to which mood is updated based on recent RPEs. Note that if $\eta_h = 1$, only the most recent event contributes to the emotional state. According to common psychological concepts, the term 'emotion' would be more adequate for this scenario, whereas a lower mood update rate would correspond to the concept of mood:

$$\text{history}_{\text{RPE}} = \text{history}_{\text{RPE}} + \eta_h \times (\text{RPE} - \text{history}_{\text{RPE}}) \quad \text{[III]}$$

where

$$\text{mood} = \tanh(\text{history}_{\text{RPE}}) \quad \text{[IV]}$$

restricts mood to the range of [–1;1].

The expected value of the stimulus is updated every trial by the RPE and the parameter η_v (value learning rate).

$$\text{value}_{\text{expected}}(v) = \text{value}_{\text{expected}}(v) + \eta_v \times \text{RPE} \quad \text{[V]}$$

Given that some environments are less determinant, a noise parameter reflects a degree of stochasticity of the reward. This parameter determines the range of a stochastic, uniformly distributed reward, centered around $\text{reward}_{\text{magnitude}}$:

$$\text{reward}_{\text{actual}} = \text{uniform}[1 - p; 1 + p] \times \text{reward}_{\text{magnitude}} \quad \text{[VI]}$$

We simulate trial-by-trial expectations, RPEs, and mood by determining the reward in each single trial t. In total, this model includes three free agent parameters (η_h, η_v, and f) and one free environment parameter (p) governing the individual mood–learning dynamics of participants.

variability observed in adolescents. However, the empirical evidence for whether adolescents experience RPEs stronger than other age groups is mixed [79–81].

Why would increased variability be expected? An important point to consider is that RL accounts are built on the basic assumption that an agent takes actions to interact with the environment and is rewarded or punished in turn (Figure 1D), and that the specific environments adolescents navigate differ from those faced by adults. Adolescence is a period of life where many things are explored for the first time (e.g., parties, first job, or sexual experiences [82]). For individuals of all age groups, these are uncertain situations. However, uncertainty might be particularly high in adolescents because they can only draw on a limited repertoire of past experiences. Thus, a typical adolescent environment is likely to trigger frequent positive and negative RPEs. According to the RL perspective sketched above, mood dynamics are shaped by such RPEs. Thus, adolescent environments might provoke frequent peaks in both positive and negative emotional states, which might manifest in enhanced mood variability or instability. Pronounced mood fluctuations in

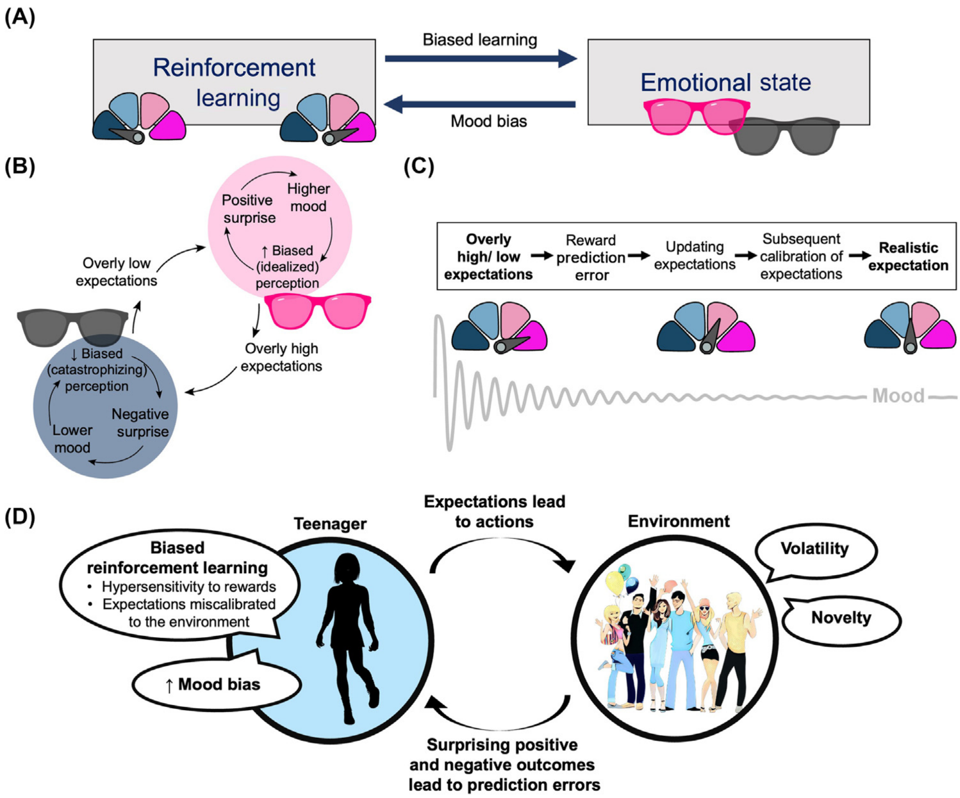

Figure 1. Computational model of mood–learning interactions. (A) Bidirectional relationship between reinforcement learning (RL) and emotional states. Biased RL affects mood. Vice versa, mood can bias perception of reward and consequently learnt expectations about the environment. (B) Mood bias contributes to mood instability: positive surprises increase mood, which biases perception positively. An overly positive perception can lead to high expectations and subsequent disappointment. In turn, negative reward prediction errors (RPEs) decrease mood and bias perception negatively. To move out of the loop, two conditions need to be met: expectations need to be realistic, and mood needs to be approximately neutral. (C) Biased RL: calibration of expectation to the environment. During learning about the environment, mood stabilizes as expectations catch up with actual outcomes encountered in the environment (fewer RPEs). (D) Interaction between the RL processes and typical environment of adolescents. An interaction of adolescents' biased RL and mood bias with their typical environments might underlie enhanced mood instability. Hypothesized mood and learning parameters, as well as environmental conditions that, under an RL model of mood-learning interactions, might explain enhanced mood instability in adolescents, are shown in speech bubbles.

this age group might reflect an enhanced ability to respond appropriately to a volatile context by cycling in and out of various affective states and intensities of affect [30].

Mood biases how outcomes are perceived

Importantly, the RL model of mood–learning interactions [66] is bidirectional (Figure 1A). Not only do RPEs alter mood, but mood also biases how outcomes are perceived: when mood is high, a subsequent reward will be perceived as higher (akin to 'rose-tinted glasses'), whereas low mood makes rewards appear worse (mood bias; Box 3 and Figure 1A,B). In turn, mood-biased RPEs influence further learning, giving rise to expectations that may either be too optimistic (in the case of a positive mood) or too pessimistic (in the case of a negative mood).

In this framework, mood, and a moderate mood bias, are adaptive: positive versus negative mood signals a general increase or decrease in reward availability in the environment, respectively. Imagine a group of peers that a teenager has previously found congenial, but in which they suddenly face hostility from certain group members. Reacting with particularly low mood in response to these unexpected negative social experiences would bias the perception of subsequent social interactions, also with other members of the group, in a negative direction. Such mood-driven generalization enables the teenager to efficiently learn to avoid the whole group. As adolescents often influence each other [83], the entire group may have turned hostile, such that avoiding it protects the teenager from further experiences of exclusion and enables the exploration of friendly social environments. Rewarding social interactions with a new peer group then elicit particularly strong positive RPEs (due to negative expectations formed by the hostile peer group), which in turn elevate mood and favor spending time with the more benevolent group. Under this model, mood is in homeostasis once expectations catch up with perceived outcomes: our teenager's mood should normalize after having integrated into the new peer group (Figure 1C). This example is deliberatively reductive and misses other factors (e.g., self-esteem, socialization, or self-control) that will influence the adolescent's reactions. However, it illustrates that mood instability is adaptive by signaling the varying availability of rewards in the (social) environment and by helping to adapt quickly to changing environmental demands. Indeed, in simulations, agents with a mood bias show more adaptive behavior compared with agents with stable neutral mood [84], and mood biases decisions across many different scenarios [85].

Mood instability arises when expectations do not catch up with outcomes

The RL model discussed above also implicates scenarios where these mood–learning interactions might go awry. This is the case when, as learning progresses, expectations do not catch up with perceived outcomes, or deviate even further (Figure 1B). This might happen in at least two different ways. One possibility is that the influence of mood on valuation (mood bias) is pronounced (see Figure 2A for simulation). The other possibility is that biased RL gives rise to mood fluctuations (see Figure 2C for simulation). To derive a framework of how pronounced mood changes arise in adolescence, we consider both these routes here in light of what we know about how adolescents' choices are biased by emotional context, and how adolescents learn from the outcomes of their actions.

Mood instability due to pronounced mood biases

One mode for enhanced mood instability corresponds to an overly strong mood bias in some individuals. Whenever an individual experiences an unexpected outcome in their learning environment, an increased mood bias leads to not only hypersensitivity to rewards when mood is high, but also hyposensitivity to rewards when mood is low. That is, good mood first leads to the learning of an overly optimistic reward value, which will lead to disappointment (i.e., negative RPEs) once mood returns to normal. The disappointment will then lead to bad mood, followed by overly pessimistic learning of reward value, followed by positive surprises (Figure 1B). Computational simulations of elevated mood biases demonstrate that this oscillatory loop indeed leads to pronounced mood instability (Figure 2A [9]). In the case of our exemplary adolescent who experienced hostility in their peer group, an overly strong mood bias may direct the individual away from actually friendly groups because even very positive social feedback can still be perceived as negative when in a low mood. This computational theory was empirically backed up by observations that adults who self-reported stronger trait levels of mood variability showed stronger mood biases when choosing between options of which the value was learned in different moods [9]. Potentially related to the computational concept of a mood bias, classical accounts of adolescent decision-making emphasize that an emotional context exerts a particularly strong effect on choices in adolescence [38,86–88]. This effect has been primarily studied using emotional cognitive control tasks [89]. In these studies, teenagers are less efficient at overriding affective interference when

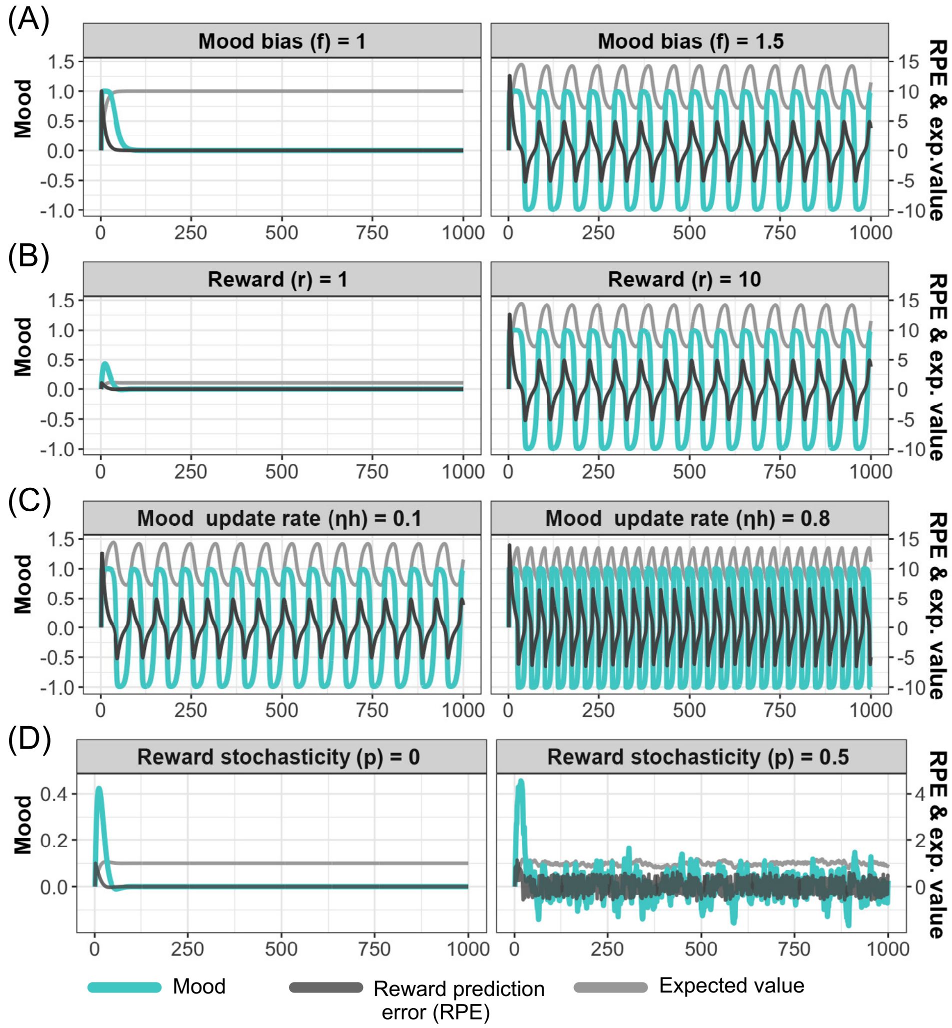

Figure 2. Simulation of a mood–learning interaction based on a reinforcement learning (RL) model. Simulation of the manipulation of key RL parameters that determine a mood–learning interaction. Fluctuations in mood are visualized in color (y-axis left: mood), whereas the corresponding dynamics of reward prediction errors (RPEs) and expected values are plotted in gray tones (y-axis right: RPE and expectations). We simulate 1000 trials (x-axis) of learning about one stimulus, resulting in 1000 simulated data points for mood, RPEs and expected values. In (A–D), we show the effect of varying the following parameters while keeping the others constant: mood bias, reward magnitude, mood update rate, and stochasticity of rewards. The simulation relies on a computational model introduced in [11], summarized in Box 3. (A) Manipulation of mood bias (1vs. 1.5), while keeping constant reward of 10, mood update rate of 0.1, and reward stochasticity of 0. A mood bias of 1.5 causes mood fluctuations. The larger the bias is, the longer the intervals are in extreme high or extreme low emotional states. (B) Manipulation of reward magnitude (set 1 vs. 10), while keeping constant mood bias of 1.5, mood update rate of 0.1, and reward stochasticity of 0. An increase in the reward magnitude (while keeping the mood bias >1) leads to larger fluctuations because larger RPEs produce larger mood responses. (C) Manipulation of mood update rate (0.1vs. 0.8), while keeping constant mood bias of 1.5, reward of 10, and reward stochasticity of 0. The mood update rate influences the frequency of mood changes. The frequency of mood changes increases with increasing mood update rate. (D) Manipulation of the stochasticity of reward, by setting p = 0 (no stochasticity) versus p = 0.5 (high stochasticity), while keeping constant mood bias of 1.5, reward of 1, and mood update rate of 0.1. In an unpredictable environment (right), mood dynamics are highly noisy. A completely deterministic environment (left) leads to a stabilization of mood.

making a choice, in the context of both negative and positive emotions [38,58,86,87,90,91]. These findings have been influential in the development of leading theories on adolescent behavior. However, critically, age differences in how mood affects valuation in an RL context have yet to be investigated.

Mood instability due to biased RL

The model of mood–learning interactions also entails that the adaptive function of mood depends on the integrity of the underlying learning and choice process, which updates expectations about the environment (Figure 1C). Model simulations show that mood fluctuations can be provoked by an individual's sensitivity to rewards and by how well-learnt expectations are calibrated to the environment (i.e., if a learner's expectation of what is good and bad in the environment reflects the actual value of options well). Here, we review how these different ingredients of RL might be altered in adolescents and consider that, together, they might form biased adolescent RL that contributes to mood fluctuations (Figure 1D).

Higher sensitivity to rewards and punishments leads to mood instability

Higher rewards provoke stronger mood fluctuations under an RL model of mood–learning interactions (Figure 2B). Computationally, this effect is equally predicted if rewards are in fact higher or if the learner is simply more responsive to the reward. Indeed, there is a rich developmental literature characterizing hypersensitivity and higher responsivity to reward in adolescents compared with adults [92–94]. Much of the evidence for this view comes from studies measuring neural correlates of reward processing; a meta-analysis found that adolescents generally showed an increased likelihood of reward-related neural activation compared with adults [95]. Further evidence for a peak in reward-associated behaviors during adolescence comes from self-report questionnaires [96–98]. Such an emphasis on potential rewards (e.g., money, fun activities, or peer acceptance) may also lead to risky decision-making by biasing adolescents to choose high-reward, high-risk options [94,99,100]. Epidemiological observations suggest that, across the globe, adolescence is the age period when individuals begin to engage in many risk-taking behaviors [94,96]. Additionally, adolescents exhibit greater sensitivity to negative social feedback than do adults [101]. In sum, there is some evidence that adolescents might be subjectively more sensitive toward both rewards and punishments, potentially rendering them more prone toward mood fluctuations. However, the learning and choice mechanisms underlying this particular adolescent sensitivity remain to be elucidated.

Higher mood- and value-learning rates lead to mood instability

An important parameter in RL models is the value-learning rate, which controls the extent to which RPEs are used to update expectations (Box 3). If value learning rates are higher, sensitivity to the RPEs and, thus, to recent outcomes, is enhanced. In our computational model of mood–learning interactions, in addition to a value-learning rate, a specific mood-learning rate governs the updating of mood as a function of RPEs (Box 3). Simulations show that higher mood-learning rates lead to more pronounced mood fluctuations (Figure 2C). Asymmetries in learning from positive versus negative feedback are important in this context. In an exemplary scenario, if an individual updates negative surprises less than positive surprises, this would lead to overly positive expectations. In turn, the individual would encounter more negative surprises that are also of higher magnitude and, thus, suffer from lower mood on average.

What do we know about how learning rates develop across adolescence? The development of mood learning rates has not been directly researched and we suggest this is an important direction for future research. However, over the past decade, multiple studies using computational modeling have tried to characterize how adolescents' value-learning rates differ from other age groups. The results of these studies appear mixed: some researchers found learning rates declined with age [102]. Other work reported no change in learning rates from adolescence to young adulthood [74], while others reported an increase in learning rates from adolescence, or from childhood, to adulthood [103,104]. Similar variability in findings is observed when considering developmental differences in learning rates for positive and negative outcomes [77,78,103,105–107]. This heterogeneity may be interpreted best in light of the heterogeneity of task structures used in different studies [108]: a given task structure exposes the individual to particular environmental demands and this determines whether higher or lower learning rates [109], or asymmetries in learning from positive versus negative outcomes [110], are adaptive. Thus, interindividual differences in how people learn from outcomes in an experimental task, as reflected in individual RL parameter estimates, may stem from different degrees of adaptation to the (task) environment. Consequently, the heterogeneity in empirical findings might reflect age differences in this degree of adaptation [71]. Under this assumption, adolescents' expectations would not be optimally aligned with the environment. Consider an adolescent who does not use their teacher's feedback optimally to prepare for an exam and, thus, might, to their own surprise, underperform in the test. Such a mis-estimation of demands in the environment leads to more RPEs (the pupil is particularly disappointed at the outcome of the exam as they had expected it to go ok) and, therefore, will prompt more frequent mood changes.

Stochasticity leads to mood instability

Another computational component of RL is **choice stochasticity**, namely the degree to which choices are determined by learned expectations. The less stochastic a person is, the more likely they are to choose the options that they have learned are more rewarding. Higher estimates in stochasticity model parameters might simply reflect poor learning [111] and, indeed, in many studies using learning tasks, adolescents do worse compared with adults [71]. Poor learning again entails expectations that are not calibrated well with the environment, which, under an RL account, will lead to stronger RPEs and, thus, stronger mood changes (Figure 2D).

Computationally, however, choice stochasticity can also reflect a (mis-)estimation of the **volatility** in the environment. High stochasticity can be adaptive in an environment where values tend to change ('high volatility' [112]) because it leads to the exploration of low-value options that may have increased in value since they were last visited [113]. For this reason, higher estimated volatility also motivates stronger value updates [11,109], which may themselves lead to stronger mood changes [11]. Consider a teenager who had always performed well in maths. With higher volatility estimates, they would, despite their consistently good performance in the past, be more likely to expect a change in their grades in the next maths test (i.e., that they might do badly this time). They would then be more surprised (and happy) about yet another good grade than someone who is absolutely sure that they are a maths ace.

Cross-sectional and longitudinal studies have indeed found age-related decreases of stochasticity (i.e., choices become more consistent with learned expectations) [74,81,83,114–116] and adolescents' RL bias appears to be particularly suited to volatile environments [117]. It is an exciting open question whether elevated choice stochasticity in adolescence reflects poor learning, or whether it is adaptive in environments typical for adolescents, in which exploration is beneficial [71,117,118].

Concluding remarks

The adolescent literature points to several specifics in adolescent reward processing and RL as candidates for mechanisms linked to alterations in adolescent mood. We have seen that, computationally, pronounced mood instability can stem from an amplified responsivity to outcomes in the learner. Such amplification can be provoked by factors that enhance the sensitizing effect

Outstanding questions

What is the specific shape of adolescent mood dynamics: enhanced mood variability, instability, periodic fluctuations, or noisier mood?

Do teenagers experience pronounced mood swings across the entire spectrum of emotions (e.g., positive and negative or the whole spectrum of discrete emotional states)?

What is the adaptive function of higher mood variability in adolescence?

Which aspect of biased learning accounts for pronounced mood changes in adolescence?

What are the neurodevelopmental correlates of mood–learning interactions in adolescence?

of mood (i.e., mood bias), by a subjective hypersensitivity to outcomes, or by factors that mitigate the habituating effects of learning (e.g., stochasticity) (Figure 1D). Whether any (and, if so, which) of these factors accounts for higher real-life mood changes in adolescence remains an open empirical question (see Outstanding questions). Novel experimental and computational tools [9,12–15], combined with ecological momentary assessment (EMA), or ambulatory physiological assessment are available to elucidate these mechanisms further. Given the heterogeneity in findings, there is a need to develop robust and reliable tests of affective phenomena in adolescents [41,119,120].

Emotions and mood serve important functions in evaluating past outcomes, and the availability of rewards in the environment, in the service of future actions aimed at fulfilling one's needs [10]. Thus, adolescents' higher emotional reactivity and mood fluctuations are likely to correspond to high socioaffective flexibility allowing them to efficiently react to the novel demands they are facing when starting to navigate (social) environments independently. Importantly, a higher degree of mood changes might also simply be the reflection of a typical adolescent environment that is packed with (positive and negative) surprises. However, we have reviewed evidence that pronounced mood instability is also a risk factor for mental health problems. It is exciting that innovative computational approaches now enable us to not only assess mood dynamics in real life (Box 2), but also probe neurocomputational mechanisms of learning and choice dynamics experimentally in daily life, even in concert with their neural correlates [15,121]. Given the popularity of smartphone use among adolescents, designs close to daily life (EMA) may further help to differentiate normative mood fluctuations in adolescence from those that signal risk for the development of mental health problems. This echoes with recent calls in computational psychiatry to characterize time-varying alterations of cognition and emotion in context [122,123]. Such an approach has the potential to revalidate the effectiveness of treatment strategies and to dissect heterogeneity in treatment response [35,124]. Prospectively, such designs also allow for immediate interventions in real life (via the smartphone) when risk signs occur [125].

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Declaration of interests

No interests are declared.

Resources

[i] www.pewresearch.org/internet/2022/08/10/teens-social-media-and-technology-2022/

References

1. Ernst, M. *et al.* (2019) Pubertal maturation and sex effects on the default-mode network connectivity implicated in mood dysregulation. *Transl. Psychiatry* 9, 103
2. Buchanan, C.M. *et al.* (1992) Are adolescents the victims of raging hormones? Evidence for activational effects of hormones on moods and behavior at adolescence. *Psychol. Bull.* 111, 62–107
3. Maciejewski, D.F. *et al.* (2019) Most fare well-but some do not: distinct profiles of mood variability development and their association with adjustment during adolescence. *Dev. Psychol.* 55, 434–448
4. Broome, M. *et al.* (2015) Mood instability: significance, definition and measurement. *Br. J. Psychiatry* 207, 283–285
5. Sperry, S.H. *et al.* (2020) Emotion dynamics concurrently and prospectively predict mood psychopathology. *J. Affect. Disord.* 261, 67–75
6. Fristad, M.A. (2022) Editorial: Mood instability: what it is, why it matters, and what to do about it. *J. Am. Acad. Child Adolesc. Psychiatry* 61, 1224–1226
7. Paus, T. *et al.* (2008) Why do many psychiatric disorders emerge during adolescence? *Nat. Rev. Neurosci.* 9, 947–957

8. Solmi, M. *et al.* (2022) Age at onset of mental disorders worldwide: large-scale meta-analysis of 192 epidemiological studies. *Mol. Psychiatry* 27, 281–295
9. Eldar, E. and Niv, Y. (2015) Interaction between emotional state and learning underlies mood instability. *Nat. Commun.* 6, 6149
10. Emanuel, A. and Eldar, E. (2023) Emotions as computations. *Neurosci. Biobehav. Rev.* 144, 104977
11. Blain, B. and Rutledge, R.B. (2020) Momentary subjective well-being depends on learning and not reward. *eLife* 9, e57977
12. Rutledge, R.B. *et al.* (2014) A computational and neural model of momentary subjective well-being. *Proc. Natl. Acad. Sci. U. S. A.* 111, 12252–12257
13. Vinckier, F. *et al.* (2018) Neuro-computational account of how mood fluctuations arise and affect decision making. *Nat. Commun.* 9, 1708
14. Cecchi, R. *et al.* (2022) Intracerebral mechanisms explaining the impact of incidental feedback on mood state and risky choice. *eLife* 11, e72440
15. Eldar, E. *et al.* (2018) Decodability of reward learning signals predicts mood fluctuations. *Curr. Biol.* 28, 1433–1439.e1437
16. Michely, J. *et al.* (2020) A mechanistic account of serotonin's impact on mood. *Nat. Commun.* 11, 2335
17. Keren, H. *et al.* (2021) The temporal representation of experience in subjective mood. *eLife* 10, e62051
18. Villano, W.J. *et al.* (2020) Temporal dynamics of real-world emotion are more strongly linked to prediction error than outcome. *J. Exp. Psychol. Gen.* 149, 1755–1766
19. Otto, A.R. and Eichstaedt, J.C. (2018) Real-world unexpected outcomes predict city-level mood states and risk-taking behavior. *PLoS One* 13, e0206923
20. Larson, R. and Lampman-Petraitis, C. (1989) Daily emotional states as reported by children and adolescents. *Child Dev.* 60, 1250–1260
21. Toenders, Y.J. *et al.* (2022) Mood variability during adolescent development and its relation to sleep and brain development. *bioRxiv*, Published online October 29, 2022. https://doi.org/10.1101/2022.08.23.505008
22. Weinstein, S.M. and Mermelstein, R.J. (2013) Dynamic associations of negative mood and smoking across the development of smoking in adolescence. *J. Clin. Child Adolesc. Psychol.* 42, 629–642
23. van Roekel, E. *et al.* (2016) Depressive symptoms and the experience of pleasure in daily life: an exploration of associations in early and late adolescence. *J. Abnorm. Child Psychol.* 44, 999–1009
24. Santangelo, P.S. *et al.* (2018) Affective instability across the lifespan in borderline personality disorder – a cross-sectional e-diary study. *Acta Psychiatr. Scand.* 138, 409–419
25. Silk, J.S. *et al.* (2003) Adolescents' emotion regulation in daily life: links to depressive symptoms and problem behavior. *Child Dev.* 74, 1869–1880
26. Larson, R.W. *et al.* (2002) Continuity, stability, and change in daily emotional experience across adolescence. *Child Dev.* 73, 1151–1165
27. Dvorak, R.D. *et al.* (2016) Daily associations between emotional functioning and alcohol involvement: moderating effects of response inhibition and gender. *Drug Alcohol Depend.* 163, 46–53
28. Van Lissa, C.J. *et al.* (2017) The cost of empathy: parent–adolescent conflict predicts emotion dysregulation for highly empathic youth. *Dev. Psychol.* 53, 1722–1737
29. Maciejewski, D.F. *et al.* (2015) A 5-year longitudinal study on mood variability across adolescence using daily diaries. *Child Dev.* 86, 1908–1921
30. McKone, K.M. and Silk, J.S. (2022) The emotion dynamics conundrum in developmental psychopathology: similarities, distinctions, and adaptiveness of affective variability and socioaffective flexibility. *Clin. Child. Fam. Psychol. Rev.* 25, 44–74
31. Guyer, A.E. *et al.* (2016) The neurobiology of the emotional adolescent: from the inside out. *Neurosci. Biobehav. Rev.* 70, 74–85
32. Breaux, R. *et al.* (2020) Variability in positive and negative affect among adolescents with and without ADHD: differential associations with functional outcomes. *J. Affect. Disord.* 274, 500–507
33. Maciejewski, D.F. *et al.* (2014) The development of adolescent generalized anxiety and depressive symptoms in the context of adolescent mood variability and parent-adolescent negative interactions. *J. Abnorm. Child Psychol.* 42, 515–526
34. Li, H. *et al.* (2019) Use of ecological momentary assessment to detect variability in mood, sleep and stress in bipolar disorder. *BMC Res. Notes* 12, 791
35. Pulcu, E. *et al.* (2022) Using a generative model of affect to characterize affective variability and its response to treatment in bipolar disorder. *Proc. Natl. Acad. Sci. U. S. A.* 119, e2202983119
36. O'Donnell, L.A. *et al.* (2018) Mood instability as a predictor of clinical and functional outcomes in adolescents with bipolar I and bipolar II disorder. *J. Affect. Disord.* 236, 199–206
37. Rizk, M.M. *et al.* (2019) Variability in suicidal ideation is associated with affective instability in suicide attempters with borderline personality disorder. *Psychiatry* 82, 173–178
38. Hare, T.A. *et al.* (2008) Biological substrates of emotional reactivity and regulation in adolescence during an emotional go-nogo task. *Biol. Psychiatry* 63, 927–934
39. Pfeifer, J.H. *et al.* (2011) Entering adolescence: resistance to peer influence, risky behavior, and neural changes in emotion reactivity. *Neuron* 69, 1029–1036
40. Vijayakumar, N. *et al.* (2019) Affective reactivity during adolescence: associations with age, puberty and testosterone. *Cortex* 117, 336–350
41. Bloom, P.A. *et al.* (2022) Age-related change in task-evoked amygdala—prefrontal circuitry: a multiverse approach with an accelerated longitudinal cohort aged 4–22 years. *Hum. Brain Mapp.* 43, 3221–3244
42. Swartz, J.R. *et al.* (2014) Age-related changes in the structure and function of prefrontal cortex–amygdala circuitry in children and adolescents: a multi-modal imaging approach. *NeuroImage* 86, 212–220
43. Crone, E.A. and Dahl, R.E. (2012) Understanding adolescence as a period of social–affective engagement and goal flexibility. *Nat. Rev. Neurosci.* 13, 636–650
44. Decety, J. *et al.* (2012) The contribution of emotion and cognition to moral sensitivity: a neurodevelopmental study. *Cereb. Cortex* 22, 209–220
45. Silvers, J.A. *et al.* (2017) The transition from childhood to adolescence is marked by a general decrease in amygdala reactivity and an affect-specific ventral-to-dorsal shift in medial prefrontal recruitment. *Dev. Cogn. Neurosci.* 25, 128–137
46. Silvers, J.A. *et al.* (2012) Age-related differences in emotional reactivity, regulation, and rejection sensitivity in adolescence. *Emotion* 12, 1235
47. Poldrack, R.A. (2011) Inferring mental states from neuroimaging data: from reverse inference to large-scale decoding. *Neuron* 72, 692–697
48. Pozzi, E. *et al.* (2021) Neural correlates of emotion regulation in adolescents and emerging adults: a meta-analytic study. *Biol. Psychiatry* 89, 194–204
49. Schweizer, S. *et al.* (2020) Age-related differences in affective control and its association with mental health difficulties. *Dev. Psychopathol.* 32, 329–341
50. Cracco, E. *et al.* (2017) Emotion regulation across childhood and adolescence: evidence for a maladaptive shift in adolescence. *Eur. Child Adolesc. Psychiatry* 26, 909–921
51. Theurel, A. and Gentaz, E. (2018) The regulation of emotions in adolescents: age differences and emotion-specific patterns. *PLoS One* 13, e0195501
52. Ahmed, S. *et al.* (2018) Using temporal distancing to regulate emotion in adolescence: modulation by reactive aggression. *Cognit. Emot.* 32, 812–826
53. Nook, E.C. *et al.* (2021) High emotion differentiation buffers against internalizing symptoms following exposure to stressful life events in adolescence: an intensive longitudinal study. *Clin. Psychol. Sci.* 9, 699–718
54. Van Cauwenberge, V. *et al.* (2017) Developmental changes in neural correlates of cognitive reappraisal: an ERP study using the late positive potential. *Neuropsychologia* 95, 94–100
55. Steinberg, L. (2008) A social neuroscience perspective on adolescent risk-taking. *Dev. Rev.* 28, 78–106

56. Luna, B. and Wright, C. (2016) Adolescent brain development: implications for the juvenile criminal justice system. In *APA Handbook of Psychology and Juvenile Justice* (Heilbrun, K., ed.), pp. 91–116, American Psychological Association
57. Casey, B.J. *et al.* (2008) The adolescent brain. *Dev. Rev.* 28, 62–77
58. Casey, B.J. *et al.* (2019) Development of the emotional brain. *Neurosci. Lett.* 693, 29–34
59. Heller, A.S. *et al.* (2016) Changes in cortico-subcortical and subcortico-subcortical connectivity impact cognitive control to emotional cues across development. *Soc. Cogn. Affect. Neurosci.* 11, 1910–1918
60. Klipker, K. *et al.* (2017) Within-person changes in salivary testosterone and physical characteristics of puberty predict boys' daily affect. *Horm. Behav.* 95, 22–32
61. Andersen, E. *et al.* (2022) Methods for characterizing ovarian and adrenal hormone variability and mood relationships in peripubertal females. *Psychoneuroendocrinology* 141, 105747
62. Brose, A. *et al.* (2013) Life contexts make a difference: emotional stability in younger and older adults. *Psychol. Aging* 28, 148–159
63. Mendo-Lázaro, S. *et al.* (2019) The role of parental acceptance–rejection in emotional instability during adolescence. *Int. J. Environ. Res. Public Health* 16, 1194
64. Sutton, R.S. and Barto, A.G. (1998) *Reinforcement Learning: An Introduction*, MIT Press
65. Will, G.-J. *et al.* (2017) Neural and computational processes underlying dynamic changes in self–esteem. *eLife* 6, e28098
66. Eldar, E. *et al.* (2016) Mood as representation of momentum. *Trends Cogn. Sci.* 20, 15–24
67. Rutledge, R.B. *et al.* (2017) Association of neural and emotional impacts of reward prediction errors with major depression. *JAMA Psychiatry* 74, 790–797
68. Liuzzi, L. *et al.* (2022) Magnetoencephalographic correlates of mood and reward dynamics in human adolescents. *Cereb. Cortex* 32, 3318–3330
69. Sutton, R.S. (1990) Integrated architectures for learning, planning, and reacting based on approximating dynamic programming. In *Machine Learning Proceedings 1990* (Porter, B. and Mooney, R., eds), pp. 216–224, Elsevier
70. Bolenz, F. *et al.* (2017) Developmental changes in learning: computational mechanisms and social influences. *Front. Psychol.* 8, 2048
71. Nussenbaum, K. and Hartley, C.A. (2019) Reinforcement learning across development: what insights can we draw from a decade of research? *Dev. Cogn. Neurosci.* 40, 100733
72. van den Bos, W. and Eppinger, B. (2016) Developing developmental cognitive neuroscience: from agenda setting to hypothesis testing. *Dev. Cogn. Neurosci.* 17, 138–144
73. van den Bos, W. *et al.* (2018) Computational neuroscience across the lifespan: promises and pitfalls. *Dev. Cogn. Neurosci.* 33, 42–53
74. Palminteri, S. *et al.* (2016) The computational development of reinforcement learning during adolescence. *PLoS Comput. Biol.* 12, e1004953
75. Rigoux, L. *et al.* (2014) Bayesian model selection for group studies—revisited. *NeuroImage* 84, 971–985
76. Cohen, J.R. *et al.* (2010) A unique adolescent response to reward prediction errors. *Nat. Neurosci.* 13, 669–671
77. Jones, R.M. *et al.* (2014) Adolescent-specific patterns of behavior and neural activity during social reinforcement learning. *Cogn. Affect. Behav. Neurosci.* 14, 683–697
78. Hauser, T.U. *et al.* (2015) Cognitive flexibility in adolescence: neural and behavioral mechanisms of reward prediction error processing in adaptive decision making during development. *NeuroImage* 104, 347–354
79. Javadi, A.H. *et al.* (2014) Adolescents adapt more slowly than adults to varying reward contingencies. *J. Cogn. Neurosci.* 26, 2670–2681
80. van den Bos, W. *et al.* (2012) Striatum–medial prefrontal cortex connectivity predicts developmental changes in reinforcement learning. *Cereb. Cortex* 22, 1247–1255
81. Waltmann, M. *et al.* (2023) Diminished reinforcement sensitivity in adolescence is associated with enhanced response switching and reduced coding of choice probability in the medial frontal pole. *Dev. Cogn. Neurosci.* 60, 101226
82. Siegel, J. and Shaughnessy, M.F. (1995) There's a first time for everything: understanding adolescence. *Adolescence* 30, 217
83. Reiter, A.M.F. *et al.* (2021) Preference uncertainty accounts for developmental effects on susceptibility to peer influence in adolescence. *Nat. Commun.* 12, 3823
84. Pessiglione, M. *et al.* (2023) Origins and consequences of mood flexibility: a computational perspective. *Neurosci. Biobehav. Rev.*, 105084
85. Heerema, R. *et al.* (2023) Mood fluctuations shift cost–benefit tradeoffs in economic decisions. *Sci. Rep.* 13, 18173
86. Somerville, L.H. *et al.* (2011) Frontostriatal maturation predicts cognitive control failure to appetitive cues in adolescents. *J. Cogn. Neurosci.* 23, 2123–2134
87. Dreyfuss, M. *et al.* (2014) Teens impulsively react rather than retreat from threat. *Dev. Neurosci.* 36, 220–227
88. Cohen, A.O. *et al.* (2016) When is an adolescent an adult? Assessing cognitive control in emotional and nonemotional contexts. *Psychol. Sci.* 27, 549–562
89. Luciana, M. *et al.* (2018) Adolescent neurocognitive development and impacts of substance use: overview of the adolescent brain cognitive development (ABCD) baseline neurocognition battery. *Dev. Cogn. Neurosci.* 32, 67–79
90. Cohen-Gilbert, J.E. and Thomas, K.M. (2013) Inhibitory control during emotional distraction across adolescence and early adulthood. *Child Dev.* 84, 1954–1966
91. Grose-Fifer, J. *et al.* (2013) Attentional capture by emotional faces in adolescence. *Adv. Cogn. Psychol.* 9, 81–91
92. van Duijvenvoorde, A.C. *et al.* (2016) What motivates adolescents? Neural responses to rewards and their influence on adolescents' risk taking, learning, and cognitive control. *Neurosci. Biobehav. Rev.* 70, 135–147
93. Schreuders, E. *et al.* (2018) Contributions of reward sensitivity to ventral striatum activity across adolescence and early adulthood. *Child Dev.* 89, 797–810
94. van Duijvenvoorde, A.C. *et al.* (2022) Risks and rewards in adolescent decision-making. *Curr. Opin. Psychol.* 48, 101457
95. Silverman, M.H. *et al.* (2015) Neural networks involved in adolescent reward processing: an activation likelihood estimation meta-analysis of functional neuroimaging studies. *NeuroImage* 122, 427–439
96. Steinberg, L. *et al.* (2018) Around the world, adolescence is a time of heightened sensation seeking and immature self-regulation. *Dev. Sci.* 21, e12532
97. Altikulaç, S. *et al.* (2019) Age and gender effects in sensitivity to social rewards in adolescents and young adults. *Front. Behav. Neurosci.* 13, 171
98. Braams, B.R. *et al.* (2015) Longitudinal changes in adolescent risk-taking: a comprehensive study of neural responses to rewards, pubertal development, and risk-taking behavior. *J. Neurosci.* 35, 7226–7238
99. Freeman, C. *et al.* (2020) Neural response to rewards predicts risk-taking in late but not early adolescent females. *Dev. Cogn. Neurosci.* 45, 100808
100. Eckstrand, K.L. *et al.* (2017) Heightened activity in social reward networks is associated with adolescents' risky sexual behaviors. *Dev. Cogn. Neurosci.* 27, 1–9
101. Rodman, A.M. *et al.* (2017) Development of self-protective biases in response to social evaluative feedback. *Proc. Natl. Acad. Sci. U. S. A.* 114, 13158–13163
102. Decker, J.H. *et al.* (2015) Experiential reward learning outweighs instruction prior to adulthood. *Cogn. Affect. Behav. Neurosci.* 15, 310–320
103. Master, S.L. *et al.* (2020) Distentangling the systems contributing to changes in learning during adolescence. *Dev. Cogn. Neurosci.* 41, 100732
104. Davidow, J.Y. *et al.* (2016) An upside to reward sensitivity: the hippocampus supports enhanced reinforcement learning in adolescence. *Neuron* 92, 93–99
105. Christakou, A. *et al.* (2013) Neural and psychological maturation of decision-making in adolescence and young adulthood. *J. Cogn. Neurosci.* 25, 1807–1823
106. Moutoussis, M. *et al.* (2018) Change, stability, and instability in the Pavlovian guidance of behaviour from adolescence to young adulthood. *PLoS Comput. Biol.* 14, e1006679

107. Rosenbaum, G.M. *et al.* (2022) Valence biases in reinforcement learning shift across adolescence and modulate subsequent memory. *eLife* 11, e64620
108. Eckstein, M.K. *et al.* (2022) The interpretation of computational model parameters depends on the context. *eLife* 11, e75474
109. Behrens, T.E. *et al.* (2007) Learning the value of information in an uncertain world. *Nat. Neurosci.* 10, 1214–1221
110. Cazé, R.D. and van der Meer, M.A. (2013) Adaptive properties of differential learning rates for positive and negative outcomes. *Biol. Cybern.* 107, 711–719
111. Findling, C. *et al.* (2019) Computational noise in reward-guided learning drives behavioral variability in volatile environments. *Nat. Neurosci.* 22, 2066–2077
112. Piray, P. and Daw, N.D. (2021) A model for learning based on the joint estimation of stochasticity and volatility. *Nat. Commun.* 12, 6587
113. Wilson, R.C. *et al.* (2014) Humans use directed and random exploration to solve the explore–exploit dilemma. *J. Exp. Psychol. Gen.* 143, 2074–2081
114. Buritica, J.M.R. *et al.* (2019) The computational basis of following advice in adolescents. *J. Exp. Child Psychol.* 180, 39–54
115. Moutoussis, M. *et al.* (2021) Decision-making ability, psychopathology, and brain connectivity. *Neuron* 109, 2025–2040.e2027
116. Chierchia, G. *et al.* (2022) Confirmatory reinforcement learning changes with age during adolescence. *Dev. Sci.* 26, e13330
117. Eckstein, M.K. *et al.* (2022) Reinforcement learning and Bayesian inference provide complementary models for the unique advantage of adolescents in stochastic reversal. *Dev. Cogn. Neurosci.* 55, 101106
118. Nussenbaum, K. *et al.* (2023) Novelty and uncertainty differentially drive exploration across development. *eLife* 12, e84260
119. Reitsema, A.M. *et al.* (2022) Emotion dynamics in children and adolescents: a meta-analytic and descriptive review. *Emotion* 22, 374–396
120. Bailen, N.H. *et al.* (2019) Understanding emotion in adolescents: a review of emotional frequency, intensity, instability, and clarity. *Emot. Rev.* 11, 63–73
121. Zech, H. *et al.* (2023) Measuring self-regulation in everyday life: reliability and validity of smartphone-based experiments in alcohol use disorder. *Behav. Res. Methods* 55, 4329–4342
122. Scholl, J. and Klein-Flügge, M. (2018) Understanding psychiatric disorder by capturing ecologically relevant features of learning and decision-making. *Behav. Brain Res.* 355, 56–75
123. Hitchcock, P.F. *et al.* (2022) Computational psychiatry needs time and context. *Annu. Rev. Psychol.* 73, 243–270
124. Reiter, A.M. *et al.* (2021) Neuro-cognitive processes as mediators of psychological treatment effects. *Curr. Opin. Behav. Sci.* 38, 103–109
125. Balaskas, A. *et al.* (2021) Ecological momentary interventions for mental health: a scoping review. *PLoS One* 16, e0248152
126. Schultz, W. *et al.* (1997) A neural substrate of prediction and reward. *Science* 275, 1593–1599
127. Knutson, B. and Gibbs, S.E. (2007) Linking nucleus accumbens dopamine and blood oxygenation. *Psychopharmacology* 191, 813–822
128. Eckstrand, K.L. *et al.* (2022) Development of reward circuitry during adolescence: depression, social context, and considerations for future research on disparities in sexual and gender minority youth. *Ann. Rev. Dev. Psychol.* 4, 231–252
129. Claes, L. *et al.* (2014) The Dutch version of the Emotion Reactivity Scale: validation and relation with various behaviors in a sample of high school students. *Eur. J. Psychol. Assess.* 30, 73–79
130. Eckblad, M. and Chapman, L.J. (1986) Development and validation of a scale for hypomanic personality. *J. Abnorm. Psychol.* 95, 214–222
131. Weil, L.G. *et al.* (2013) The development of metacognitive ability in adolescence. *Conscious. Cogn.* 22, 264–271
132. Zurbriggen, C.L.A. (2021) Rosy or blue? Change in recall bias of students' affective experiences during early adolescence. *Emotion* 21, 1637–1649
133. Dietvorst, E. *et al.* (2021) Grumpy or depressed? Disentangling typically developing adolescent mood from prodromal depression using experience sampling methods. *J. Adolesc.* 88, 25–35
134. Neumann, A. *et al.* (2011) Emotional dynamics in the development of early adolescent psychopathology: a one-year longitudinal study. *J. Abnorm. Child Psychol.* 39, 657–669
135. Maciejewski, D. *et al.* (2023) Beyond main effects? Affect level as a moderator in the relation between affect dynamics and depressive symptoms. *J. Emot. Psychopathol.* 1, 356–372
136. Schneider, S. *et al.* (2020) Comparability of emotion dynamics derived from ecological momentary assessments, daily diaries, and the day reconstruction method: observational study. *J. Med. Internet Res.* 22, e19201
137. Ebner-Priemer, U.W. and Trull, T.J. (2009) Ecological momentary assessment of mood disorders and mood dysregulation. *Psychol. Assess.* 21, 463–475
138. Stone, A.A. *et al.* (2023) Evaluation of pressing issues in ecological momentary assessment. *Annu. Rev. Clin. Psychol.* 19, 107–131