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How much do you want to learn? High-school students' willingness to invest effort in valenced feedback-learning tasks

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ABSTRACT

High-school students decide in which tasks to invest their cognitive effort on a daily basis. At school, such decisions often relate to feedback-learning situations (e.g., whether or not to do homework exercises). To investigate how willing high-school students are to invest their cognitive effort in such situations, we administered in this preregistered study a feedback-learning task in combination with a cognitive effort-discounting task – a paradigm to quantify willingness to invest effort. We did so to a large sample ($N = 195$) from average educational backgrounds in an ecologically valid setting (a school class). We specifically tested whether high-school students discounted their effort in feedback-learning tasks, which proved to be the case, and whether this discounting was differentially affected by positive and negative feedback, which proved not to be the case. We also found that learning was unaffected by feedback valence, except that students learned better from positive than from negative feedback when high effort was required. These results imply that in a school setting, where feedback learning is common, high-school students are less willing to invest cognitive effort in more effortful tasks irrespective of feedback valence, and that positive feedback can aid learning when high effort is required. We provide several recommendations as to how our proposed combination of feedback learning and effort discounting could be used to understand and improve students' academic motivation.

Educational relevance statement: High school students sometimes struggle with motivation for learning, at least partly because of low willingness to invest their effort. By investigating high-school students' willingness to invest effort for learning within an educational context, we aim to enhance understanding of this decision-making process in high-school students. Our results indicate that in a school setting, where feedback learning is common, high-school students are less willing to invest cognitive effort in more effortful tasks irrespective of whether they receive positive or negative feedback, but that positive feedback can aid learning when learning tasks require high effort. These results imply that positive feedback may reduce the costs of learning or increase its benefits for difficult tasks.

1. Introduction

High-school students' daily-life decisions are often about their willingness to invest cognitive effort. Especially in school-settings, these decisions (e.g., whether or not to do homework exercises) relate to feedback-learning situations. That is, situations in which teachers or tools, such as digital homework systems, provide students with feedback on their learning (Stickles, 2017). Yet, experimental studies assessing willingness to invest cognitive effort usually administer tasks such as working-memory tasks that neither involve feedback nor learning (e.g., Chevalier, 2018; Kramer et al., 2021; Westbrook et al., 2013). Therefore, in this preregistered study, we combine a decision-making paradigm to quantify willingness to invest effort with feedback-learning tasks. We investigate 1) whether we can probe effort-discounting within feedback-learning tasks, 2) whether high-school students' willingness to invest effort for feedback learning is higher when they receive positive or

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negative feedback on this learning, and 3) whether feedback learning itself benefits more from positive feedback or from negative feedback. We do this in an ecologically valid setting (i.e., school class) in a large sample (i.e., 195) of high-school students from average educational backgrounds.

Choices about willingness to invest cognitive effort are thought to be driven by a process in which individuals decide whether a cognitive task is worth their effort or not (Shenhav et al., 2013; Shenhav et al., 2017; Westbrook & Braver, 2015). The field of neuroeconomics offers a promising framework called cognitive effort-discounting (Westbrook et al., 2013). Within this framework, willingness to invest cognitive effort depends on a cost-benefit analysis. If the costs of investing cognitive effort (e.g., becoming tired) exceed the benefits (e.g., a higher grade), people are unwilling to invest effort. In contrast, if the benefits exceed the costs the opposite holds (Westbrook et al., 2013). Such willingness to invest cognitive effort can be quantified using a cognitive effort-discounting task (Kool et al., 2010; Shenhav et al., 2017; Westbrook et al., 2013). In this decision-making task, individuals are given a choice between performing two tasks: a low-effort task for a small amount of money (e.g., 1 euro) or a high-effort task for a larger amount of money (e.g., 2 euros). After each choice-trial, the amount of money offered for the low-effort task is adjusted, that is, the amount increases after individuals choose the high-effort task (e.g., from 1 to 1.50 euros) or decreases after individuals choose the low-effort task (e.g., from 1 to 0.50 euros). After multiple of such choices, the money offered for the low-effort task is taken as the indifference point: the point where an individual is indifferent between performing the low-effort task versus the high-effort task. For example, if an individual is indifferent between performing the low-effort task for 1.40 euros and the high-effort task for 2 euros, then they are willing to give up 0.60 euros in order to avoid performing the high-effort task. In this case, the indifference point is 1.40 euros and quantifies an individuals' willingness to invest effort. The higher this so-called indifference point, the more willing someone is to invest effort. In cognitive tasks unrelated to learning, it has been shown that adults' (e.g., Massar et al., 2016; Westbrook et al., 2013) and adolescents' (Kramer et al., 2021) willingness to invest effort decreases as a function of the required effort. We here test whether the same applies for feedback-learning tasks.

In the effort literature, two studies assessed valence effects on adults' willingness to invest cognitive effort. We refer to positive conditions as conditions in which participants can earn money and to negative conditions as conditions in which participants can lose money. One study (Nishiyama, 2016) asked participants to imagine cognitively-effortful tasks. In the positive condition, participants were informed that they would receive a small amount of money irrespective of whether or not they would exert effort in the imagined task. Importantly, this amount was chosen such that most people would find it too small to actually exert effort in the task. Participants were then asked to specify the additional amount of money that would lead them to exert effort in the task. In the negative condition, participants were informed that they would pay a small amount of money to somebody else to exert effort in the imagined task. Again, this amount was too small for most people to actually exert effort (i.e., they would always be willing to pay this amount to the other to exert the effort). Participants were then asked to specify the maximum amount of money that they would pay to the other to avoid exerting effort in the task themselves. Results showed the same degree of cognitive-effort discounting in the positive and the negative condition. In addition, another study (Massar et al., 2020) investigated valence effects on effort discounting in sustained-attention and working-memory tasks. In the positive condition, participants could earn money for playing a certain amount of time (e.g., earn 3 dollars for 1 minute or earn 10 dollars for 20 minutes), while in the negative condition, participants could avoid losing money for playing a certain amount of time (e.g., lose 7 dollars for 1 minute or lose 0 dollars for 20 minutes). Results showed that adults were more willing to invest cognitive effort when they could avoid losing money (i.e., negative condition) compared to when they could earn money (i.e., positive condition). Based on this result, the authors concluded that people display loss aversion, that is, that people place more value on resources (e.g., time, energy, money) they can lose compared to resources they can earn (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981).

On the other hand, it also has been hypothesized that positive valence may decrease the perceived costs of investing effort and may increase its benefits (Yee & Braver, 2018), subsequently increasing willingness to invest effort in a positive condition; although no empirical evidence for this hypothesis has yet been found. Up until now, valence effects on willingness to invest cognitive effort have only been investigated in adults, not in adolescents. In addition, these effort studies administered cognitive tasks unrelated to learning, that is, tasks in which people had to imagine effortful scenarios (Nishiyama, 2016), sustained-attention tasks (Massar et al., 2020 Experiments 1–2), and working-memory tasks (Massar et al., 2020 Experiment 3). The question thus remains how valence affects willingness to invest cognitive effort in adolescents and how it does so in feedback-learning tasks. It is especially valuable to understand valence effects in this age group and task because adolescents spend a substantial proportion of time at school, where they invest their cognitive effort in valenced feedback-learning tasks.

In the feedback-learning literature, most adult studies investigating valence effects on learning showed that adults performed equally well in positive and negative conditions (Eppinger et al., 2010; Fontanesi et al., 2019; Kim et al., 2006; Lebreton et al., 2019; Palminteri et al., 2015, 2016; Pessiglione et al., 2006; Ting et al., 2020, 2021; van de Vijver et al., 2015 Experiment 1, but see van de Vijver et al., 2015 Experiment 2; Verburg et al., 2019). That is, when adults have to learn which stimulus in a pair yields the best feedback by choosing between the stimuli, they learn equally well in a condition in which they receive positive feedback after choosing the correct stimulus and blank feedback after choosing the incorrect stimulus (positive condition) as in a condition in which they receive blank feedback after choosing the correct stimulus and negative feedback after choosing the incorrect stimulus (negative condition). In adolescents, only one study (Palminteri et al., 2016) directly compared learning between such positive and negative conditions. Specifically, Palminteri and colleagues presented adolescents with pairs that yielded positive-blank and negative-blank feedback intermixed within the same learning block. Results showed that adolescents chose the stimulus that yielded the best feedback more often when receiving positive-blank feedback than when receiving negative-blank feedback (Palminteri et al., 2016), that is, adolescents learned better in a positive than in a negative condition. Although in the current study we were mainly interested in valence effects on willingness to invest cognitive effort in feedback-learning tasks, we try to replicate the valence effect on feedback learning reported by Palminteri et al. (2016). We did so in a conceptual way (using a different experimental design, i.e., presenting positive-blank and negative-blank feedback in separate learning blocks) enabling us to test whether the conclusions about valence effects on learning hold in different contexts (Crandall & Sherman, 2016).

To test whether adolescents discount their cognitive effort in feedback-learning tasks, whether their willingness to invest effort in such tasks differs when they receive positive or negative feedback on their learning, and whether their learning itself benefits more from positive or negative feedback, we studied a sample of 195 high-school students from average educational backgrounds in an ecologically valid setting. First, we administered a feedback-learning task employing a 3 (effort-level: low, medium, high) × 2 (feedback valence: positive, negative) within-subjects design. After each valence condition, we administered a cognitive effort-discounting task in which high-school students chose between redoing a low-effort learning task for a small reward and a higher-effort learning task for a larger reward.

Regarding willingness to invest cognitive effort, we formulated the following two hypotheses. First, based on an adolescent study using a working-memory task (Kramer et al., 2021), we preregistered that we expected adolescents to discount their effort, that is, we expected smaller indifference points as the level of required effort increases. Second, we preregistered that we expected larger indifference points in the positive than in the negative condition. We argued so because positive valence can decrease the perceived costs of investing effort and increase its benefits (Yee & Braver, 2018), subsequently increasing willingness to invest effort in the positive condition. However, it could also be that we observe loss aversion, that is, smaller indifference points in the positive than in the negative condition, as supported by recent empirical evidence from sustained-attention and working-memory tasks in adults (Massar et al., 2020). Third, we preregistered that we had no expectations regarding valence effects on learning because results on these effects are mixed when looking at the complete adolescent feedback-learning literature (Nussenbaum & Hartley, 2019). However, based on the only adolescent study that directly compared learning in positive and negative conditions (Palminteri et al., 2016), one would expect adolescents to learn better in the positive than in the negative condition.

2. Method

This study was preregistered at the Open Science Framework (https://osf.io/83hkd). All materials and methods matched the preregistration, unless indicated otherwise. Data and analysis code are publicly available at https://osf.io/xeqs5/.

2.1. Participants

A total of 195 secondary-school students participated in this study ($M_{age} = 14.20$ years, $SD_{age} = 0.80$ years, $N_{male} = 100$). The Dutch school system comprises three educational tracks that range in their orientation from applied to theoretical and in what percentage of students attend those tracks: pre-vocational (50%), pre-applied university (30%) and pre-university (20%) (Maslowski, 2020). The pre-vocational track is viewed as the average track, as half of the students attend this track. All participating students followed a pre-vocational, and thus average, track. This study was conducted in accordance with the declaration of Helsinki, and approved by the Ethics Review Board of the Psychology Department from the University of Amsterdam (file number: 2020-DP-11667). Students provided active informed consent and parents of all students provided passive informed consent (i.e. parents were provided with comprehensive information about the study and were given two weeks to indicate whether their child was not allowed to participate).

2.2. Experimental design

The experiment consisted of a feedback-learning task, an effort-discounting task, and several questionnaires. In the feedback-learning task, participants learned the correct spelling of pseudo words based on feedback, resembling how high-school students learn vocabulary in new languages. We adopted a 2 (feedback valence) × 3 (effort) within-subjects design, totaling to six learning blocks. In the positive feedback-valence condition, participants could earn points (or not), while in the negative condition they could lose points (or not). We operationalized effort as the number of spellings that needed to be learned in parallel. After participants completed (three learning blocks within) a valence condition, they performed an effort-discounting task where they chose which learning task from that valence condition they wanted to redo. As we had two valence conditions, participants performed this sequence of learning blocks and effort discounting twice. To check whether our effort manipulation worked, participants answered questions on subjective effort after each learning block. At the end of the experiment, participants also answered questions on whether they preferred redoing the learning tasks in either valence condition and questions on how sensitive they were to rewards.

2.3. Materials

2.3.1. Feedback-learning task

2.3.1.1. Task design. Participants performed a two-choice probabilistic feedback-learning task in which they learned the correct spelling of pseudo words. Each participant started with a positive or a negative feedback-valence condition (counterbalanced across participants). In the positive condition, participants usually (i.e., in 75% of the cases) earned 10 points (i.e., positive feedback) and sometimes (i.e., in 25% of the cases) earned 0 points (i.e., blank feedback) when they chose the correct spelling; they usually earned 0 points and sometimes 10 points when they chose the incorrect spelling. In the negative condition, participants usually lost 0 points (i.e., blank feedback) and sometimes lost 10 points (i.e., negative feedback) when they chose the correct spelling; they usually lost 10 points and sometimes lost 0 points when they chose the incorrect spelling. In each valence condition, participants performed three blocks varying in effort level: a low-effort block in which they learned two spellings in parallel, a medium-effort block in which they learned three spellings, and a high-effort block in which they learned four spellings. We randomized the order of the effort levels per participant, but the order remained the same across valence conditions within participants.

In each valence condition, participants first completed a practice block in which two pseudo-word pairs were presented eight times each (i.e., 16 trials), in a random order per two trials (i.e., same pair max. twice in a row). Hereafter they completed three learning blocks (one per effort level) each consisting of 48 trials. Note that we kept the number of trials in each block equal to standardize time-on-task across blocks, resulting in different repetitions per pair per effort level (i.e., 24 in the low-effort, 16 in the medium-effort, and 12 in the high-effort task). After each block, the percentage of choices for the correct spelling was displayed on the screen to enhance motivation and promote learning. Which spelling was correct was determined randomly for each participant with one restriction: not all correct spellings could contain the same letter combination. This correct spelling remained the same across trials within a block.

2.3.1.2. Feedback. We used 75% congruent feedback such that, per word pair, congruent feedback was provided in three out of four trials. Within these four trials, the order of congruent and incongruent feedback was randomized. Probabilistic feedback, that is, feedback that is sometimes incongruent, is commonly-used in the feedback-learning literature (e.g., Hämmerer et al., 2011; van den Bos et al., 2009) as it resembles the real world (e.g., your favorite pizza tastes good in most pizzerias, but not in all of them). Besides, probabilistic feedback prevents ceiling effects in learning performance, obscuring potential valence effects. We specifically chose 75% congruent feedback to match Palminteri et al. (2016), because this study also investigated valence effects on adolescent learning using positive-blank and negative-blank feedback.

2.3.1.3. Timing. As illustrated in Fig. 1, each trial started with a fixation cross (1000 mS) followed by presentation of two spellings of pseudo words accompanied by an image (RT to max. 2500 mS). The participant chose between the spellings and received feedback (1000 mS).

2.3.1.4. Stimuli. The spellings of the pseudo words were partly obtained from and partly constructed for the current study following the same rules as used in previous research (de Jong et al., 2009; Kramer et al., n.d.; Verburg et al., 2019): all spellings were one-syllable words, included the letter combination ei/ij or au/ou, consisted of five letters, followed Dutch language rules, and differed at least one letter from existing Dutch words. The two spellings in a pseudo-word pair were homophones (i.e., sounded the same). We constructed four sets of four pseudo-word pairs

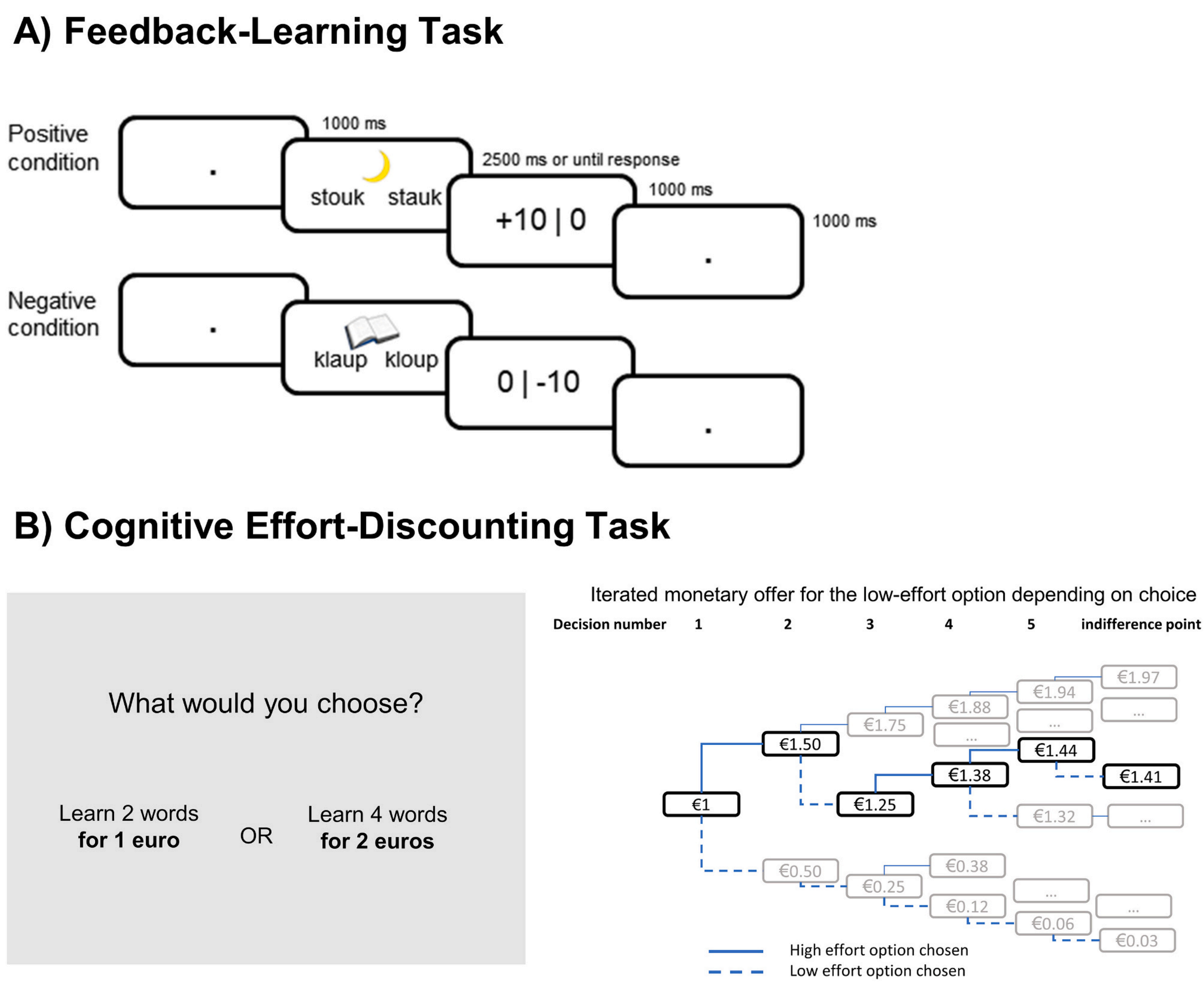

Fig. 1. A) Example trial sequence for a learning block in the feedback-learning task in the positive (top sequence) and negative condition (bottom sequence). B) Example trial in the cognitive effort-discounting task (left panel), and a possible decision tree arriving at an indifference point of €1.41 after five decisions (right panel).

per letter combination, from which pairs were randomly selected per block. The pseudo-word pairs in a set had the same letter combination, and all started and ended with different consonants. Each pair was accompanied by an image to promote learning (see e.g., Ouellette & Fraser, 2009); these pair-image combinations were fixed across participants.

2.3.1.5. Incentives. We did not incentivize learning performance in the feedback-learning task to prevent these incentives to interfere with valence effects. Specifically, we did not want participants to only do their best in the positive condition because they would feel like they could only earn money in this condition. This procedure is common in the feedback-learning literature, with previous studies observing valence effects without incentivizing learning performance (e.g., Bischoff-Grethe et al., 2009; Ferdinand & Opitz, 2014; Kreussel et al., 2012). Instead, we incentivized participants based on their choices in the effort-discounting task (see below), as is common in that literature (e.g., Westbrook & Braver, 2015; Kramer et al., 2021; Chong et al., 2016).

2.3.2. Cognitive effort-discounting task

After completing three learning blocks in one valence condition, participants completed a series of trials in which they chose which learning task they wanted to redo. Choices were always between redoing the low-effort task for a small reward (i.e., learning two spellings for 1 euro) or one of the higher-effort tasks (i.e., the medium- or high-effort task) for a larger reward (i.e., learning three or four spellings for 2 euros). After a participant chose one of the effort-reward combinations, a black border was displayed around this chosen combination until the participant confirmed the choice; as such, choices were self-paced and participants could switch between combinations before confirming. When participants chose the higher-effort task, the amount offered for the low-effort task on the next trial increased. In contrast, when participants chose the low-effort task, the amount offered for the low-effort task on the next trial decreased according to the following adjustment procedure (Green & Myerson, 2004): the offer in- or decreased half as much as on the previous trial, starting from 0.5 × the initial offer (see also Fig. 1). The resulting amount offered for the low-effort task after a run of five trials signified the indifference point, that is, the amount at which a participant was indifferent between the two effort-reward combinations. The indifference point thus quantifies how willing a participant was to invest effort in the higher-effort compared to the low-effort task. The higher the indifference point, the more willing someone is to invest effort. In total, participants performed four effort-discounting runs (i.e., a low versus medium run and a low versus high run after learning in each valence condition) each consisting of five trials, resulting in four indifference points. Hereafter the computer randomly selected one of the participants' choices from the discounting trials. Participants were informed that the computer would select which task they would redo and that they would receive the amount offered for redoing that task. To make sure participants would really consider the effort-reward combinations, we explained that they would only receive the reimbursement when they did their best while redoing the task. Because of time restrictions, participants only redid the chosen task for 12 trials, even though they thought it would be for 48 trials (i.e., the length of a learning block).

2.3.3. Subjective effort

To assess subjective effort, and thus whether our effort manipulation worked, we administered the NASA-Task-Load-Index (NTLX; Hart & Staveland, 1988) after every learning block. The NTLX contained five items that participants answered on a 7-point scale, ranging from 1 = "not at all" to 7 = "very much". An example item of the NTLX is: "how hard did you have to work to accomplish your level of performance?". The items were presented in the same order every time and to every participant. We used the sum of the five items as a measure of subjective effort. The internal consistency of the NTLX was poor to moderate (with α ranging from .52 to .67) for the six learning blocks (see Supplemental Table III).

2.3.4. Valence preference

To explore whether participants preferred to learn in one of the valence conditions, and whether this depended on effort level, we asked them whether they preferred learning in the positive or negative condition. We did so for the three effort levels separately in a random order and after they performed all feedback-learning and effort-discounting tasks.

2.3.5. Reward sensitivity

As the effort-discounting task uses rewards to quantify willingness to invest effort, individual differences in sensitivity to these rewards may affect the indifference points. Therefore, we also administered the reward responsiveness scale from the Behavioral Activation System Scales (BAS; Carver & White, 1994). The scale consists of five statements for which participants indicate how true that statement is for them, on a 5-point scale ranging from 1 = "very true for me" to 5 = "very false for me". An example item is: "When I'm doing well at something, I love to keep at it". The items were presented in the same order to all participants. This scale shows acceptable internal consistency, α = .65–.73 (Carver & White, 1994; Jorm et al., 1999). We used the sum of these five statements as a measure of reward sensitivity.

2.3.6. Cognitive ability

After completing all other measures, participants performed a shortened version of Raven's progressive matrices as a measure of cognitive ability. This 15-item version substantially shortens administration time while highly correlating with the original 60-item version (Kramer & Huizenga, 2023; Langener et al., 2022). We included this task in our test battery to test whether potential effects found in the main analyses could be ascribed to differences in cognitive ability (which proved not to be the case). Details and results from these exploratory analyses are reported in Supplemental Text II.

2.4. Procedure

The experiment took place in one of the school's classrooms and lasted between 30 and 45 minutes. After a short introduction, students signed an informed consent form and started the experiment. They first performed three feedback-learning tasks in one of the valence conditions alternated with answering subjective effort questions (i.e., after each learning task). Then they performed the first cognitive effort-discounting task. This sequence of three learning tasks, subjective effort questions, and cognitive effort-discounting task was then repeated in the other valence condition. Hereafter, in this specific order, participants filled out the valence preference questions and reward sensitivity scale, and performed the short Raven on a laptop. They did so by themselves, but with 19 to 27 students present in the classroom. The experiment was programmed and administered using NeuroTask (NeuroTask Scripting Beta, www.scripting.neurotask.com). After the experiment, students received a reimbursement between €0 and €2 based on a randomly-selected discounting trial. In this way, reimbursement was based on students' effort-based choices (our measure of interest), but not on their learning performance.

2.5. Data analyses

To assess learning, we fitted a logistic mixed-effects regression model to participants' choices (choices for the correct spelling coded as 1, for the incorrect spelling as 0) using lme4 (Bates et al., 2014) in R version 4.1.3 (R Core Team, 2018). As the number of repetitions per pair differed as a function of effort-level, we only used the first 12 repetitions (i.e., the number of repetitions in the high-effort task) of each pair in this analysis. Our model included fixed effects of effort (3 levels; low, medium, and high; treated as factor), valence (2 levels; positive and negative), linear and quadratic trial (orthogonalized using the poly function in R), and all interactions. We modeled random intercepts and random slopes for valence per participant and fixed their covariance to zero. Note we included neither random slopes for effort nor for trial as a model including these effects failed to converge. We ran two contrasts, one with the low-effort level and one with the medium-effort level as reference, to compare all three effort levels to each other. As preregistered, to correct for these three comparisons, *p*-values below 0.05 were multiplied by three. Note that we also preregistered to perform computational modeling to assess how effort requirements affect feedback learning. As these results mostly resemble the learning results as obtained from the mixed-effects analysis, we only report on them in Supplemental Text I and Supplemental Figs. I–IV.

To assess effort discounting, we fitted a linear mixed-effects regression model to participants' indifference points, again using the lme4 package. Our model included fixed effects of effort (2 levels; low-medium and low-high), valence (2 levels; positive and negative), reward sensitivity (BAS sum score; mean-centered and scaled), learning performance (average proportion of correct choices across all six tasks; mean-centered and scaled), the interaction between effort and valence, and the interaction between valence and performance. We modeled random intercepts and random slopes for effort and valence per participant, and fixed their covariance to zero.

To check whether our effort manipulation was effective, we tested whether subjective effort increased as manipulated effort levels increased. To do so, we fitted a non-preregistered and thus exploratory linear mixed-effects regression model on participants' NTLX scores with fixed effects of effort (3 levels; low, medium, and high; treated as factor), valence (2 levels; positive and negative), their interaction, and random intercepts per participant.

Finally, to assess self-reported valence preferences, we fitted a non-preregistered and thus exploratory logistic mixed-effects regression model on participants' valence preference choices (coded 1 for positive and 0 for negative) with effort level as fixed effect (3 levels; low, medium, and high; treated as factor) and a random intercept per participant.

3. Results

3.1. Descriptives and manipulation check on effort manipulation

Table 1 shows means and standard deviations for NTLX scores, and indifference points for each valence condition and effort level. Exploratory results from a linear mixed-effects analysis on participants' NTLX scores (i.e., subjective effort) showed that participants reported higher

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Table 1
Average subjective effort (NTLX), willingness to invest effort (indifference point) and percentage correct per valence condition and effort level.

Valence	Effort	NTLX	Indifference point	Percentage correct
Negative	Low	19.0 (6.1)		58.4 (0.19)
	Medium	19.4 (6.0)	1.39 (0.57)	55.0 (0.17)
	High	19.7 (5.7)	1.23 (0.61)	55.0 (0.14)
Positive	Low	19.1 (6.0)		60.8 (0.20)
	Medium	19.6 (5.9)	1.37 (0.58)	55.4 (0.17)
	High	19.8 (5.9)	1.22 (0.60)	58.2 (0.17)

Note. Values between brackets indicate standard deviations. NTLX scores could range from 5 to 35. Indifference points could range from 0.01 to 1.99 euros. Percentage correct was computed over the last four trials of each stimulus pair in the feedback-learning task.

subjective effort in the high- compared to the low-effort task ($\beta = 0.73$, $p = .04$), but no differences between the low- and medium-effort task ($p = .20$) and between the medium- and high-effort task ($p = .46$). These effects were similar across valence conditions (all p's $> .55$). Taken together, this indicates that our effort manipulation was partly successful.

3.2. Effort-discounting results

Our main questions were whether high-school students discounted their effort in feedback-learning tasks and whether this effort-discounting was differentially affected by positive and negative feedback on their learning. To investigate these questions, we performed a linear mixed-effects analysis on participants' indifference points (see Supplemental Table II for full results). Results from this analysis showed a main effect of effort ($\beta = -0.08$, $p < .001$), that is, indifference points decreased as effort increased, but no effects including valence (main effect of valence: $p = .76$; valence $\times$ effort interaction: $p = .97$), indicating indifference points and effort-related differences between indifference points were unaffected by feedback valence. Also, we ruled out that students that displayed higher indifference points did so because they performed better (main effect of performance: $p = .68$; valence $\times$ performance interaction: $p = .97$) or because they were more sensitive to rewards ($p = .25$).

Next, apart from inferring valence preferences from the effort-discounting task, we also directly asked students whether they preferred learning in the positive or negative valence condition per effort level. As illustrated in Supplemental Fig. V, students reported a preference for learning with positive feedback valence in each effort level. Results from a mixed-effects regression model on this self-reported valence preference showed that the preference for learning with positive valence reduced from the low-effort to medium-effort block ($\beta = -1.95$, $p < .001$) and from the low-effort to high-effort block ($\beta = -1.70$, $p < .001$), but did not differ between the medium-effort and high-effort blocks ($p = .39$). Thus, participants especially preferred positive feedback valence when the learning task required low effort, less so when it required higher effort.

Together, the results indicate that participants showed lower willingness to invest effort in learning tasks that required higher effort. They also indicate that willingness to invest effort is unaffected by valence when measured experimentally; however, participants reported a preference to perform learning tasks with positive feedback valence, especially when low effort was required.

3.3. Feedback-learning results

We also assessed whether feedback valence affected learning performance using a logistic mixed-effects analysis on participants' choice accuracy (see Supplemental Table I for full results). As illustrated in Fig. 2, results showed a main effect of valence in the high-effort blocks ($\beta = 0.06$, $p = .01$), but not in the low- and the medium-effort blocks (both p's $> .66$). Results also showed a valence $\times$ effort interaction such that valence effects differed between the low- and high-effort blocks ($\beta = 0.07$, $p = .03$), but not between the low- and medium-effort and between the medium- and high-effort blocks (both p's $> .13$). Thus, participants performed better with positive than with negative feedback when high effort was required, but we observed no valence differences at the other effort levels. Moreover, results showed no valence $\times$ trial interactions (all p's $> .06$) and no valence $\times$ effort $\times$ trial interactions (all p's $> .06$). Together, the results suggest that valence did not affect learning, except for that participants performed better in the positive condition when high effort was required.

4. Discussion

In the current study we investigated 1) whether high-school students discount their effort in feedback-learning tasks, 2) whether this discounting is differentially affected by positive or negative feedback on their learning, and 3) whether feedback valence affects learning itself. Results showed that high-school students indeed discounted cognitive effort in feedback-learning tasks. However, the degree of discounting was similar for feedback-learning tasks involving either positive or negative feedback; although students reported to prefer learning tasks with positive as opposed to negative feedback valence. High-school students' learning performance was in general unaffected by feedback

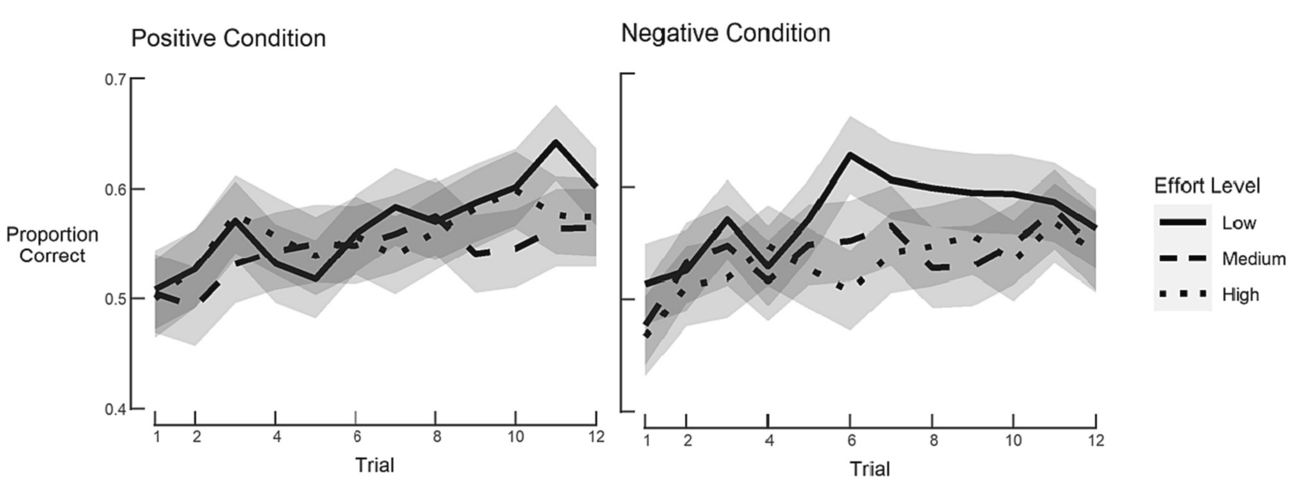

Fig. 2. Proportion of choices for the correct spelling across trials in the six learning blocks.
Note. Shaded areas represent one standard error of the mean.

valence, except for high-effort learning tasks where students seemed to benefit more from positive than negative feedback.

Recently, it was shown that effort discounting occurs in adolescents performing working-memory tasks (Kramer et al., 2021). Our current results extend these findings to feedback-learning tasks. Our finding of effort discounting in feedback-learning tasks indicates that high-school students are aware of the effort costs in such tasks and suggests that they monitor these costs, something deemed important to increase learning outcomes (e.g., de Bruin et al., 2020). For instance, a recent review showed that when students take their invested cognitive effort in a prior learning activity into account when choosing a new learning activity, this improved learning outcomes (Van Gog et al., 2020).

Regarding feedback-valence results on willingness to invest cognitive effort, we expected adolescents to be more willing in the positive than in the negative condition because positive feedback may decrease the costs of investing effort and may increase its benefits (Yee & Braver, 2018). However, based on the concept of loss aversion (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981), one would expect adolescents to be more willing to invest effort in the negative than in the positive condition. Our results showed similar effort-discounting in both valence conditions and thus did not provide evidence for either hypothesis. These empirical results are in line with an adult study showing no valence effects on willingness to invest cognitive effort when imagining effortful scenarios (Nishiyama, 2016), but contradict another adult study showing higher willingness to invest cognitive effort in negative than positive sustained-attention and working-memory tasks (Massar et al., 2020). They also contradict a previous study showing that adolescents are more willing to invest non-cognitive, that is physical, effort in tasks in which they could avoid losing money (negative condition) as compared to tasks in which they could earn money (positive condition; Farinha & Maia, 2021).

There are several explanations for the absence of valence effects on effort discounting in our study. First, it could be that adolescents are truly willing to invest cognitive effort irrespective of feedback valence. If this is the case, this then implies that willingness to invest effort is different in feedback-learning tasks than in other cognitive and physical tasks, emphasizing the importance of studying phenomena in tasks that closely resemble real-life situations. Second, it could be that we found a null result because our negative condition did not trigger loss aversion. We chose to reimburse participants based on effort-discounting choices because this was our outcome of interest. As such, participants did not actually win or lose money in the feedback-learning task. To preclude that this lack of consequences explains our null result, future studies are advised to reimburse participants based on both the learning and effort-discounting task, and to work with endowments (as common in the loss-aversion literature; e.g., Barkley-Levenson et al., 2013).

Like these main effort-related results, our learning results showed that high-school students' learning was in general unaffected by feedback valence (although positive feedback seemed to facilitate learning in high-effort learning tasks). We thus did not replicate findings presented by Palminteri et al. (2016), who found that students learned better when receiving positive-blank feedback than when receiving negative-blank feedback, even though our sample size was much larger. As we used a different experimental design (i.e., presenting positive-blank and negative-blank feedback in separate blocks as opposed to within the same block), this suggests that adolescents only learn better from positive than from negative feedback when these types of feedback are presented within the same block, not when they are presented in separate blocks. In another paper (Schaaf et al., under review), we suggest that this is because adolescents experience problems interpreting blank feedback in designs combining positive-blank and negative-blank feedback within the same block. However, the absence of a valence effect on learning could also be explained by the absence of performance-related reimbursements in the current study, that is, that participants were not reimbursed based on learning performance, while this was the case in the study by Palminteri et al. (2016).

One potential shortcoming of this study resides in the low to moderate internal consistency observed in the NTLX scale, used to assess subjective effort. Regardless, it successfully detected variations in subjective effort between effort levels, which was the goal of including this scale. The scale's low reliability may be due to its multidimensional nature, as also noted by others (Tubbs-Cooley et al., 2018). Future studies might investigate the origin of this low reliability and might benefit from separate analysis or exclusion of less relevant items such as performance (as performance may be defined as an outcome rather than characteristic of effort).

The current study suggests several lines for future research. First, it can be tested whether effort discounting in feedback learning is related to academic motivation. Such a relation was not observed for effort discounting in working-memory tasks, but may be more likely for feedback learning, as it relates more closely to academic contexts. If willingness to invest cognitive effort in feedback-learning tasks can be used as a proxy of academic motivation (Paas et al., 2005), it can be used to experimentally assess adolescent's motivation for learning. Second, this combination of tasks can be used to assess effects of task manipulations on effort discounting. For instance, researchers could manipulate the content of the material to be learned (e.g., from word-learning to math exercises) to examine how willingness to invest effort in learning tasks differs between different school subjects. Also, researchers could manipulate the magnitude or nature of rewards that can be earned in the cognitive-effort discounting task (e.g., increase the amount of money that could be earned for high-effort options, or change the nature of the reward from money to points or actual grades) in order to examine how varying magnitudes or types of reward could aid adolescents' willingness to invest cognitive effort.

5. Conclusion

To conclude, our results suggest that high-school students discount their effort in feedback-learning tasks, and that, in general, effort-discounting and feedback learning are both unaffected by valence. Yet, exploratory analyses suggested that especially in low-effort feedback-learning tasks, high-school students prefer positive feedback over negative feedback. In addition, when looking at the feedback-learning results, positive feedback seemed to aid learning in learning tasks that required high effort. These results imply that in a school setting, where feedback learning is common, high-school students are less willing to invest cognitive effort in more effortful tasks. In addition, when high effort is required, positive feedback may help reduce these effort costs of feedback learning, increase its benefits, or both. This emphasizes the importance of identifying which costs and benefits high-school students consider for schoolwork to promote students' school-related effort investments.

CRediT authorship contribution statement

Anne-Wil Kramer: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Jessica V. Schaaf:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Hilde M. Huizenga:** Conceptualization, Methodology, Writing – review & editing, Supervision, Funding acquisition.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.lindif.2023.102375.

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