Contextual overtraining accelerates habit formation in new stimuli

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Data and code availability

Raw (anonymized) data from all reported tasks, as well as scripts to reproduce the statistical analysis and figures can be found are available at the project's Open Science Framework repository: https://osf.io/cny8z/.

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Abstract

Context plays an important role in the formation and expression of habits but is overlooked in the classical view on habit formation. An important obstacle to empirically studying contextual effects has been the scarcity of reliable habit formation protocols. Here, we introduce a habit formation protocol (N=142) and demonstrate devaluation-insensitivity – the gold standard for assessing habit – in extensively overtrained, but not minimally trained (criterion-trained) subjects. Crucially, in a third group we show habit formation for new, minimally trained stimuli following overtraining in the task context (contextual overtraining). We further show that following overtraining, devaluation-insensitive habits predict performance on a two-stage task, a widely used indirect measure of habitual versus goal-directed processing. Finally, we find that a working memory load slows response times in conditions that require the suppression of trained responses. Our findings shed new light on the role of context in habit formation, showing that extensive training in a stable task context not only causes devaluation-insensitivity of the overtrained stimuli, but accelerates new habit formation in that context.

Introduction

Imagine that you take the same route to your workplace every day. On your first day of work, this requires conscious deliberation, as you weigh the value (travel time and convenience) of each available option. After several months, this daily choice has become habitual; it no longer depends on such deliberation. Habits free up time and cognitive resources. Behaviourally, they are difficult to distinguish from goal-directed behaviour. Only when the habitual response is no longer optimal (e.g. road works make the previously best route less valuable), the habit is exposed through its characteristic inflexibility, operationalised as an insensitivity to devaluation. In the canonical view of habit formation, extensive repetition (overtraining) of a stimulus-response association is required to shift response control from a goal-directed stimulus-response-outcome (S-R-O) representation, which is sensitive to the outcome, to a habitual stimulus-response (S-R) association, which is devaluation-insensitive (Dolan & Dayan, 2013; Robbins & Costa, 2017).

A limitation of this canonical view is that it does not account for other relevant determinants of habit formation such as the task context and its higher-order properties. Computational and behavioural work on cognitive flexibility shows that humans may also learn about such contextual properties, and use this knowledge to optimize performance (Behrens et al., 2007; Gershman et al., 2017; Silvetti et al., 2018; Siqi-Liu & Egner, 2020; Wen et al., 2021). For example, environments where S-R-O contingencies frequently change encourage higher learning rates than more stable contexts (Behrens et al., 2007). From this perspective, a habit overtraining protocol represents an extremely stable task context: contingencies do not change, and one need not represent or attend to the outcome in order to perform the task optimally. Extensive training in such a stable context then predicts the development of devaluation-insensitive habits. A stronger prediction derived from this viewpoint is that new associations may become habitual more quickly in contexts where participants have previously developed a devaluation-insensitive habit. That is, learned higher-order characteristics of the task context (e.g. an extremely stable environment) could be applied to the learning of *new* associations in the same context. This prediction stands in stark contrast to the canonical view on habit formation, which requires overtraining on any new S-R-O association(Adams, 1982; Dolan & Dayan, 2013).

To test this prediction, we developed a novel extensive overtraining protocol that induces devaluation-insensitive habits. While habit formation through overtraining has been demonstrated successfully in rodent paradigms(Adams, 1982; Dickinson et al., 1983), experimentally inducing devaluation-insensitivity through overtraining in *human* subjects is notoriously difficult (de Wit et al., 2018). Instead, current habit paradigms in human subjects typically use no overtraining, instead study error rate or response time effects following devaluation after shorter training (Luque et al., 2019; Robbins & Costa, 2017; Watson et al., 2018; Zwosta et al., 2018). Another approach has been estimating model-based versus model-free learning as a proxy for goal-directed and habitual behaviour (Daw et al., 2011a; Doll et al., 2015; Gillan et al., 2015; Morris et al., 2016; Otto, Gershman, et al., 2013a). Data from recent work using more extensive overtraining (up to 1000 trials per mapping over several days) suggest that habit formation through overtraining might be within reach. Luque at al (Luque et al., 2019) showed that response time switch cost is greater following extensive overtraining, offering potential as an index of habit. Hardwick et al (2019) demonstrated that such extensive repetition of stimulus-response mappings can elicit habitual errors following a rule change if a response deadline is imposed. Prior to this, Wunderlich et al (2012) found neural activity for extensively trained choices in the putamen, an area associated with habitual responses (Yin et al., 2004). In this study, we aim to show habit formation without response time restriction (as in (Hardwick et al., 2019)) by comparing devaluation-insensitivity in participants who undergo extensive overtraining (over 1200 trials per mapping over three days) with participants who only train to criterion (60-120 trials). In addition, we test the hypothesis that extensive experience in the overtrained task context (contextual overtraining) can promote habit formation for *newly introduced*, criterion-trained stimuli in a third group. In addition, we test whether devaluation-insensitive habits following overtraining relate to model-based versus model-free learning as measured in a two-stage task (Daw et al., 2011a; Kool et al., 2016; Otto, Gershman, et al., 2013b) and investigate the effects of a working memory load on devaluation-insensitivity.

Methods

Participants

Data from 142 participants (mean age = 20.4 years, SD 3.9 years, 24 male) were analyzed. Participants were partially paid in course credit and partially depending on their compliance and performance on the task. This variable monetary reward based on performance was 0-20 euros for the 4 day groups, and 0-10 euros for the 1 day group. All participants provided written informed consent. The study was carried out in accordance with the Declaration of Helsinki and approved by the Ethics Committee of the Faculty of Psychology and Educational Sciences at Ghent University.

Design

Participants were divided into three groups (Figure 1A). The first was the criterion training group (N=54), which came to the lab in one day (assessment day), trained on the habit training task for one block, and then devaluation was implemented. The extensive overtraining group (EOT; N=44), overtrained on the habit training task over three days at home, then came to the lab on the fourth day (assessment day). Following a first block, which ended after the participants had reached criterion, the devaluation was implemented. The third group was the contextual overtraining group (COT; N=44). The overtraining part for this group was identical to that in the EOT group: participants were overtrained on the habit training task at home for three days. However, on the assessment day (in the lab), COT participants acquired new mappings between stimuli and new outcomes different from those they had seen before. Devaluation was then carried out on these new mappings.

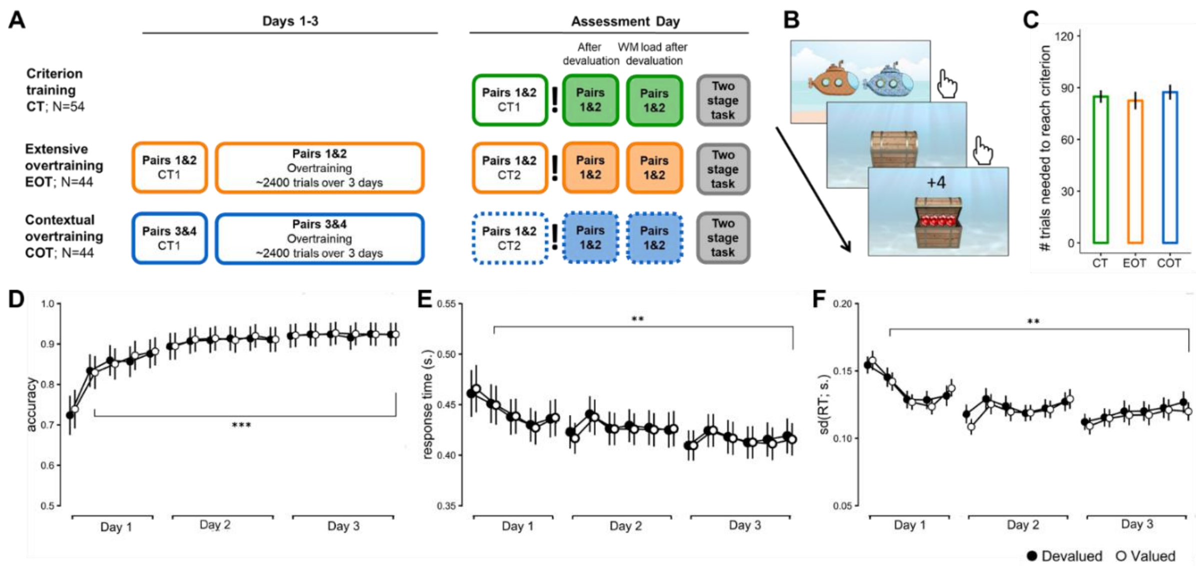

Figure 1. A. Overtraining protocol. Three groups trained on a decision-making task (habit training task) with stable reward contingencies (80% variable ratio) before a devaluation of one of the trained stimulus-response contingencies. One group trained to criterion before devaluation (Criterion training; CT), a second group overtrained extensively before devaluation of one of the overtrained stimuli (Extensive overtraining; EOT), and a third group (Contextual overtraining, COT) initially overtrained on one set of stimuli (full lines) for three days. Then, on day four, the COT group criterion-train on a new set of stimuli (dotted lines) of which one is devalued. Thus, COT participants have experience of overtraining in the stable decision-making environment but are merely criterion-trained on the to-be-devalued stimuli. Participants also completed a dual task version of the post-devaluation, and all completed a two-stage decision-making task at the end of the last session. "!" indicates devaluation. See Supplementary Figure S1 for detailed protocol. B. Sample trial of the habit training task. Participants had 2.5 seconds to choose one of two submarine stimuli. Following the choice, they clicked the space bar to "open" the treasure chest. C. Participants performed an initial criterion-training blocks until they correctly responded for 5 consecutive trials in each condition. There were no group differences in the number of trials needed. D-F. In the two groups that overtrained for three days (EOT and COT groups pooled, N=88), accuracy, RT, and the standard deviation of the RT all improve significantly throughout overtraining. Error bars denote standard error of the mean. ** p<0.01; *** p<0.001.

Tasks

Habit training task

We tested for habit formation and expression in 142 volunteers with a gamified habit training task offering two choice options (submarines) in which participants learn which option yields the biggest reward (treasure) through trial and error. Following training, we implement an offline devaluation message that signaled that one of the outcomes had lost its value. Participants' habit strength was assessed through their inability to flexibly adjust to this devaluation.

The task was embedded in a narrative, whereby participants chose one of two submarines, which each led to a treasure chest at the bottom of the sea (Figure 1B). The position of the two submarine options was counterbalanced between trials and therefore did not predict the outcome. Treasure chests had an 80% probability (variable ratio reward schedule) of yielding either 2 or 4 colored gems, with each gem worth 1 point. The participants were instructed to earn as many points as possible. There were three phases in the task: a training phase, a post-devaluation test phase, and a post-devaluation dual-task phase. A total of 6 pairs of submarines were created, with 2 pairs randomly selected for the habit training task. Gemstone outcomes could have 4 colors, with the stimulus-outcome color and value randomly assigned per participant.

In the *training phase* (Figure 1A), mappings for two stimulus pairs were trained, and reward contingencies did not vary. The training differed between the three groups (Figure 1A). The extensive overtraining group (EOT; N=44), and contextual overtraining group (COT; N=44) group were overtrained on the habit training task over three days, then came into the laboratory on the fourth day (assessment day). These groups initially performed the task until a criterion of five consecutive correct responses per stimulus pair was reached (or for 120 trials, whichever came first). Then, they further trained for 1280 trials per stimulus pair over three days. The criterion-trained group (CT; N=54) only received training on the assessment day.

On the assessment day, all groups performed the same tasks in the lab (Figure 1A). All groups first performed a criterion-training block. For the CT group, this criterion-training block was the only training. For the EOT group, this was simply a block with the already overtrained stimuli that ended when the criterion was reached. The COT participants acquired new mappings between submarines and new colors. Like the overtrained stimuli, the new stimuli had an 80% chance of leading to 2 or 4 gems. Both the stimuli and the gem colors were different from those that were overtrained.

Following the training phase, a *devaluation* was implemented (Figure 2A): the stimulus leading to one of the gem colors was devalued (e.g. "Pay attention, all red gems have disappeared. The corresponding treasure chests will now always be empty and no longer yield any points. Please adjust your responses"). Following devaluation, the optimal choice for one of the stimulus pairs changed (the "devalued pair") while the optimal choice for the other remained the same (the "valued pair"; Figure 2A). In the *post-devaluation test phase* (40 trials per stimulus pair), participants need to change their response to one of the stimulus pairs but not the other in order to maximize reward.

Dual task manipulation

After the post-devaluation test phase, *a post-devaluation dual-task* phase was carried out (40 trials per stimulus pair; Figure 1A, Figure 5A). Here, participants were required to keep into working memory a string of letters (e.g. "HXGKL"; length between 4 and 7 letters, depending on the digit span) at the beginning of the trial, make the choice between the two presented stimuli, and indicate whether a previously presented letter was in the correct location (e.g. "**G**") before receiving the reward. Participants' digit span was assessed via an online tool prior to the experiment. The length of the presented string varied between 4 and 7; if spans were lower than 4 or higher than 7, the used string length was corrected to 4 or 7, respectively.

Two-stage task (model-based versus model-free processing)

The two-stage task is a widely used paradigm to estimate model-free versus model-based reinforcement learning, which are frequently used as proxies for habitual and goal-directed processing respectively (Dolan & Dayan, 2013; Feher da Silva & Hare, 2020; Gillan et al., 2015;

Sebold et al., 2014). We tested the hypothesis that the balance between model-based and model-free processing task predicts habit strength in our sample.

As in the habit training task, the task was embedded in a narrative. Participants chose to "follow" one of two animals to a treasure chest in a forest, that contains between 1 and 10 coins, with each coin worth 1 point. Participants were instructed to learn to follow the animals that guide them to the most profitable treasure chests. Unlike in the habit training task, the values in the treasure chests varied throughout the task (Figure 4B), and the participants had to therefore adjust their preferences to maximize their earnings. There were two pairs of animals, for which the resulting values are yoked (e.g. the rabbit (A) and the raccoon (A') always lead to the same outcome, see Figure 4A). If participants took this task structure into account (model-based reasoning), they could adjust their choices faster than if they did not take this equivalence into account and adjusted their choices solely based on direct experience with a stimulus itself.

This task was adapted from the Kool et al (Kool et al., 2016) two-stage task, which itself is a variant on the widely used two-stage task paradigms first introduced by Daw and colleagues (2011b). We incorporated the modifications proposed by Kool et al, as well as two further modifications. As suggested by Kool et al (2016), the outcome was not probabilistic but ranged between 0 and 10, transitions between the two steps were deterministic, and there was only one choice at the second stage. The authors also suggested making the reward values fluctuate more and accomplished this by increasing the drift rate of the Gaussian drift used to determine reward fluctuations. Instead, we incorporated discrete jumps in the values as opposed to the Gaussian drift but accomplishing the same goal. The task was specifically designed to maximize the advantage of a model-based strategy over a model-free strategy. Kool et al (2016) demonstrated that this increase in the benefit of a model-based over a model-free strategy resulted in higher values of the balance parameter *w* (e.g. a more model-based strategy).

A Rescorla-Wagner update rule (Rescorla & Wagner, 1972) was used to model learning by the model-based and the model-free system. Each system separately updates the values for all four stimuli. Consider trial t, where stimulus pair A-B was presented, and stimulus A was selected. The model-free learner updates the model-free value of stimulus A ($V(\mathrm{A})_{t,\mathrm{MF}}$) based on the previous model-free value of A ($V(\mathrm{A})_{t-1,\mathrm{MF}}$) and the outcome at trial t:

$$V(A)_{t,MF} = V(A)_{t-1,MF} + \alpha * (Outcome_t - V(A)_{t-1,MF})$$

The model-based learner similarly updates the model-based value of A based on the previous model-based value of A and the outcome:

$$V(A)_{t,MB} = V(A)_{t-1,MB} + \alpha * (Outcome_t - V(A)_{t-1,MB})$$

In addition, as the model-based learner is able to exploit the task structure (the equivalence between A and A'), the model-based value of stimulus A' is also updated to be the same as the model-based value of stimulus A.

$$V(A')_{t,MB} = V(A)_{t,MB}$$

Values are weighted by balance parameter *w* to arrive at the combined value for each stimulus (Kool et al., 2016). The parameter *w* ranges from 0 to 1; *w* = 0 corresponds to fully model-free behaviour, whereas *w* = 1 indicates fully model-based behaviour.

$$V(A)_t = w * V(A)_{t,MB} + (1 - w) * V(A)_{t,MF}$$

Finally, a softmax action selection rule (Sutton & Barto, 2018) was used to compute the probability of the participant selecting stimulus A (out of a choice between A and B). Equations omit trial index *t* for simplicity. The inverse temperature β expresses participants' tendencies to either strongly adhere to value differences (exploit; higher inverse temperature) or choose more randomly (explore, lower inverse temperature). Two additional parameters were added to the softmax equation to capture perseveration that could underlie response tendencies related to the previous responses irrespective of the stimulus value (Kool et al., 2016; Lau & Glimcher, 2005). First, there may be a tendency to select the same stimulus as the previous trial (choice perseveration). Second, there may be a tendency to make the same motor response (press the same button) as in the previous trial (motor perseveration). These tendencies are captured by the choice perseverance parameter π and the motor perseverance (response stickiness) parameter ρ, respectively:

$$P(A) = \frac{e^{(\beta * V(A) + \rho * MotorA + \pi * ChoiceA)}}{e^{(\beta * V(A) + \rho * MotorA + \pi * ChoiceA)} + e^{(\beta * V(B) + \rho * MotorB + \pi * ChoiceB)}}$$

Several models were fitted to participants' choice behaviour, whereby up to five free parameters were included; the learning rate α, the inverse temperature β, the balance parameter *w* the motor perseverance (response stickiness) parameter ρ and the choice perseverance (choice stickiness) parameter π. Models were selected based on the Bayesian Information Criterion (BIC).

Analysis

All statistical analyses were carried out in R (https://www.r-project.org/), using the packages afex, phia, boot, and lmer4. Computational modeling was carried out in Matlab (The MathWorks, Inc., MA, USA), and parameter values further processed in RFor both accuracy and RT, missed trials are omitted from the analysis. All our measures of response time (RT) indicate the RT on correct trials only. Data and analysis availability. Raw (anonymized) data from the reported tasks, as well as analysis scripts to reproduce the statistical analysis and figures can be found are available at the project's Open Science Framework repository: https://osf.io/cny8z/.

Signatures of automaticity

Across the two overtrained groups, we assessed how accuracy, RT and variability of the RT (standard deviation of the RT) changed throughout the three days of overtraining using repeated measures ANOVAs, with Block and Stimulus pair as independent variables. As the dependent variables were not normally distributed, Wilcoxon signed rank tests were carried out to test for differences between the first block of overtraining (the block following criterion-training) and the last block of overtraining.

Habit assessment and outcome insensitivity

To test whether habits were indeed created with our overtraining protocol, we analyzed performance in the post-devaluation test phase. Here, the difference between the devalued and the still-valued stimulus pair indicated devaluation-insensitivity. We chose this metric of devaluation-insensitivity because it controls for the generally disruptive event of the devaluation message on accuracy and RT. This salient event would make it inappropriate to compare the (to-be) Devalued condition before and after the rule change/devaluation. If devaluation-insensitivity is larger in the extensively overtrained (EOT) than in the criterion-trained (CT) group, it indicates that the overtraining protocol was successful in inducing a habit. A third group, the Contextual Overtraining (COT) group underwent extensive overtraining on a first stimulus set but was tested for sensitivity to devaluation on a second, criterion-trained stimulus set (Figure 1A, Figure 2B). If habit formation requires extensively repeated stimulus-response associations, we expect this group to show about as much devaluation-insensitivity as the criterion-trained (CT) group. By contrast, if participants have learned the higher-order properties of the overtrained task context, this context may signal that flexibility is unnecessary. In this case, we expect faster reliance on habitual representations, and therefore *more* devaluation-insensitivity than the criterion-trained group.

To test these hypotheses, we carried out mixed model analyses on accuracy (generalized linear mixed effects) and RT (general linear mixed effects) during the post-devaluation test phase with Group (levels: EOT, COT and CT) and Devaluation (levels: Devalued and Valued) as fixed factors and Subject as a random intercept). To avoid that differences between groups be caused by overall poorer performance even on the trained contingency that is not devalued, we excluded very poor performing outliers in the Valued condition. Specifically, we excluded participants who performed lower than Q1 - 1.5*IQR (in this case an average accuracy of 0.66) on the Valued condition following devaluation. This method identified 7 participants: five from the CT group, one from the EOT group and one from the COT group (see Supplementary Figure S2). Importantly, we did not carry out *any* selection at the level of the performance on the Devalued condition, which is where differences in flexibility would apply. Thus, this exclusion is orthogonal to the contrast of interest, Group*Devaluation. We also report results from the analysis without any excluded participants. Significant Group*Devaluation interactions indicate differential habit formation according to the training protocol and were followed up with Holm-adjusted post-hoc tests.

Learning during criterion training on second stimulus set

If participants have learned the higher-order properties of the context (e.g., the context is extremely stable) during overtraining, they may be able to apply this knowledge to the formation of a new S-R-O mapping in the same context, resulting in faster learning. We investigated this possibility by looking at the acquisition of the second stimulus-response-outcome mapping on day 4 (assessment day; Figure 1A) participants in the contextual overtraining (COT) The speed with which RTs decreased and accuracies increased during the acquisition of the second mapping (COT 2nd S-R-O) was estimated and compared with that during the initial training for EOT and COT groups, and performance on the already overtrained mapping on day 4 in the EOT group. All four blocks considered are criterion-training blocks which are terminated when the participant produces the correct response 5 times consecutively. Therefore, there is a systematic pattern whereby worse performers contribute more of the data towards the end of the block. To avoid distortions because of this, we restricted the analyses to the portion of the data where >50% of the subjects were represented, namely trials 3-57 (Supplementary Figure S5). Response times were analyzed by fitting a power function with two free parameters to the average RTs for each trial.

$$RT = \frac{a}{1 + Trial^b}$$

where parameter *a* expresses the intercept, and *b* the exponent; the latter expresses the speed of RT decrease. A 95% confidence interval was bootstrapped around this estimate using 10,000 samples and a leave-one-out procedure). A statistical comparison was carried out between the exponent (*b*) estimate for the second S-R-O mapping and the three other exponent estimates (COT 1st S-R-O, EOT 1st S-R-O, and EOT overtrained mapping) by using the bootstrapping samples as a null distribution against which the likelihood of the point estimate for the second S-R-O was assessed (Supplementary Figure S6). Accuracy data were analyzed using logistic regression. To estimate intercept and slope separately for each of the four learning events (COT 1st S-R-O, EOT 1st S-R-O, COT 2nd S-R-O, and EOT overtrained mapping), accuracy was used as a dependent variable and Trial as the independent variable. To assess the difference between these metrics, a logistic regression with Trial and Learning event as independent variables was run. Significant Trial*Learning Event interactions indicate that learning rates were different for the different learning events; such significant interactions were followed up with Holm-adjusted post-hoc tests. The subject-specific estimates for Trial (slope parameter) were extracted for each learning event to visualize differences between learning events.

Two-stage task

Participants performed a two-stage task (Daw et al., 2005), modified according to the recommendations by Kool et al (2016) (see Figure 1A, Figure 4A). For more detail on the computational model analyses, see Supplementary Information. Seven models were fitted, with the winning model containing 4 free parameters: β, w, π, and ρ. The parameter w expresses the balance between model-free (w =0) and model-based processing (w =1).

First, to test for the possible presence of baseline differences in w between the three groups, we carried out a non-parametric Kruskal-Wallis test, with w as the dependent variable and Group as the independent variable.

To assess the predictive value of w for devaluation-insensitivity, a linear regression was carried out with devaluation-insensitivity (the difference in accuracy between Devalued and Valued stimulus pairs after devaluation) as a dependent variable, and w and Group as independent variables. Significant interactions were followed up with Holm-adjusted post-hoc tests. We also ran non-parametric Spearman correlations between w and devaluation-insensitivity separately for each group.

Dual task manipulation

We tested whether devaluation-insensitivity is more pronounced under a working memory load. Habitual errors are more likely when a person is distracted or tackling other tasks (Wood & Rünger, 2016). We assessed the impact of reduced working memory capacity after the first post-devaluation block in the reward-based decision-making task (Figure 1A). We implemented a dual-task version of the habit task whereby participants were required to keep a string of letters in short-term memory whilst performing the habit training task (Figure 4A). We hypothesized that a working memory load following devaluation might increase devaluation-insensitivity in extensively overtrained subjects, by decreasing subjects' ability to override habitual responses. To test for habit expression under dual-task conditions, we carried out the same mixed models as described above, in the post-devaluation dual-task blocks. To explicitly compare for differences in devaluation-insensitivity between single and dual-task conditions, we also carried out a further mixed model ANOVA on all post-devaluation trials, where we were interested in a three-way interaction between Group (levels: EOT, COT and CT), Devaluation (levels: Devalued and Valued), and Load (levels: No Load and Load). Given the fixed order of the blocks (the post-devaluation dual-task block always followed the post-devaluation block), main effects of dual-task block cannot be interpreted. Rather, Group*Devaluation*Load interactions indicate an effect of the working-memory load on devaluation-insensitivity. Significant interactions were followed up with Holm-adjusted post-hoc tests.

Results

Criterion training

To assess whether extensive overtraining induces habit formation, participants performed the habit training task either until they chose the optimal stimulus 5 times consecutively (Criterion-Trained group; CT; N=49) or for an additional 1280 trials per mapping over three days after this criterion was reached (extensive overtraining group; EOT; N=43). It took participants on average 84.9 trials

(SD=29.49) to reach criterion and this number did not differ significantly between the groups (rmANOVA: $F(2, 139) = 0.30$, $p=0.740$; Figure 1C).

Signatures of automaticity

Participants who overtrained became more accurate (first vs last block of overtraining: 83% vs. 92% correct; Wilcoxon signed rank test: V= 6575, $p<0.001$) and faster (first vs last block of overtraining: 441ms vs 414ms; Wilcoxon signed rank test: V= 2606, $p=0.002$) throughout overtraining (Figure 1D). Response times also became less variable (first vs last block of overtraining: 197ms vs 160ms; Wilcoxon signed rank test: V= 2494, $p=0.007$; Figure 1D) indicating stereotypy, a signature of automaticity (Robertson et al., 2004).

Extensive overtraining successfully induces habit

Following devaluation, participants had to adjust by changing their response to the devalued stimulus pair, while they could keep responding habitually to the (still-)valued stimulus pair (Figure 2A). The difference in accuracy on devalued versus valued stimulus pairs was taken as the measure of devaluation-insensitivity, and therefore habit strength. Results showed that habit induction through overtraining was successful. While all groups performed worse on the Devalued stimulus pair (mean accuracy Devalued = 0.73, SD=0.44) than on the Valued stimulus pair after devaluation (mean accuracy Valued = 0.91, SD=0.29; mixed model ANOVA: $\chi^2(1) = 544.55$, $p<0.001$; Figures 2 B-C, Supplementary Figure S3), there was a significant Group * Devaluation interaction (mixed-model ANOVA: $\chi^2(2) = 27.50$, $p<0.001$). The criterion-trained group showed significantly less devaluation-insensitivity than the extensively overtrained group (Post-hoc test: EOT vs CT: χ^2 (1) = 24.34, $p<0.001$). Thus, our overtraining protocol was able to reliably induce habitual errors in human participants in naturalistic behavior (i.e. without response deadlines). When these analyses include the poorest performers, results show the same significant Group * Devaluation interaction (mixed-model ANOVA: $\chi^2(2) = 56.15$, $p<0.001$), with the CT group exhibiting less devaluation-insensitivity than the EOT group (Post-hoc test: EOT vs CT: χ^2 (1) = 48.11, $p<0.001$).

Contextual overtraining is sufficient to induce habits in new stimulus-response pairs

To investigate how new habit formation is affected by prior overtraining in the same context, we further introduced a contextual overtraining group (COT; N=43). Results showed that the contextual overtraining (COT) group was significantly more affected by devaluation than the CT group was, and similarly affected to the extensively overtrained group (COT vs EOT: $\chi^2(1) = 2.09$, p=0.148; COT vs CT: $\chi^2(1) = 28.64$, p<0.001; Figure 2C-D). Thus, it appears that following overtraining in the stable task context, mere criterion-training on a new stimulus-response-outcome mapping was sufficient to induce habit.

Unlike in other overtraining paradigms with restricted response times (Hardwick et al., 2019), our participants were able to choose freely when to respond. Responses were slower on devalued trials (mean RT devalued: 571ms, SD=216ms) than on valued trials (mean RT valued: 517ms, SD=188ms; difference: $\chi^2(1) = 188.33$, p<0.001; Figures 2E-F, Supplementary Figure S4). While we might expect non-specific RT reductions following extensive training, it is interesting that RTs are significantly faster in the overtrained groups despite lower accuracy (main effect of Group (χ^2 (2) = 40.05, p<0.001; comparison EOT vs CT: $\chi^2(1) = 24.89$, p<0.001; comparison COT vs CT: $\chi^2(1) = 35.23$, p<0.001). That is, overtrained groups appear to speed up when responding habitually, even when their performance (accuracy) suffers. We also found a significant Group * Devaluation interaction ($\chi^2(2) = 22.06$, p<0.001), whereby the RT difference between Valued and Devalued trials was larger in the criterion-trained condition than in either the extensively overtrained (EOT vs CT: $\chi^2(1) = 10.81$, p=0.002) or the contextual overtrained conditions (COT vs CT: $\chi^2(1) = 19.84$, p<0.001), which did not differ significantly from one another (COT vs EOT: $\chi^2(1) = 1.23$, p=0.267). Results were very similar when including all participants (Group * Devaluation interaction: $\chi^2(2) = 16.36$, p<0.001) driven by differences between CT and EOT ($\chi^2(1) = 8.16$, p=0.009) and CT and COT ($\chi^2(1) = 14.55$, p<0.001), with no significant difference between COT vs EOT ($\chi^2(1) = 0.81$, p=0.367).

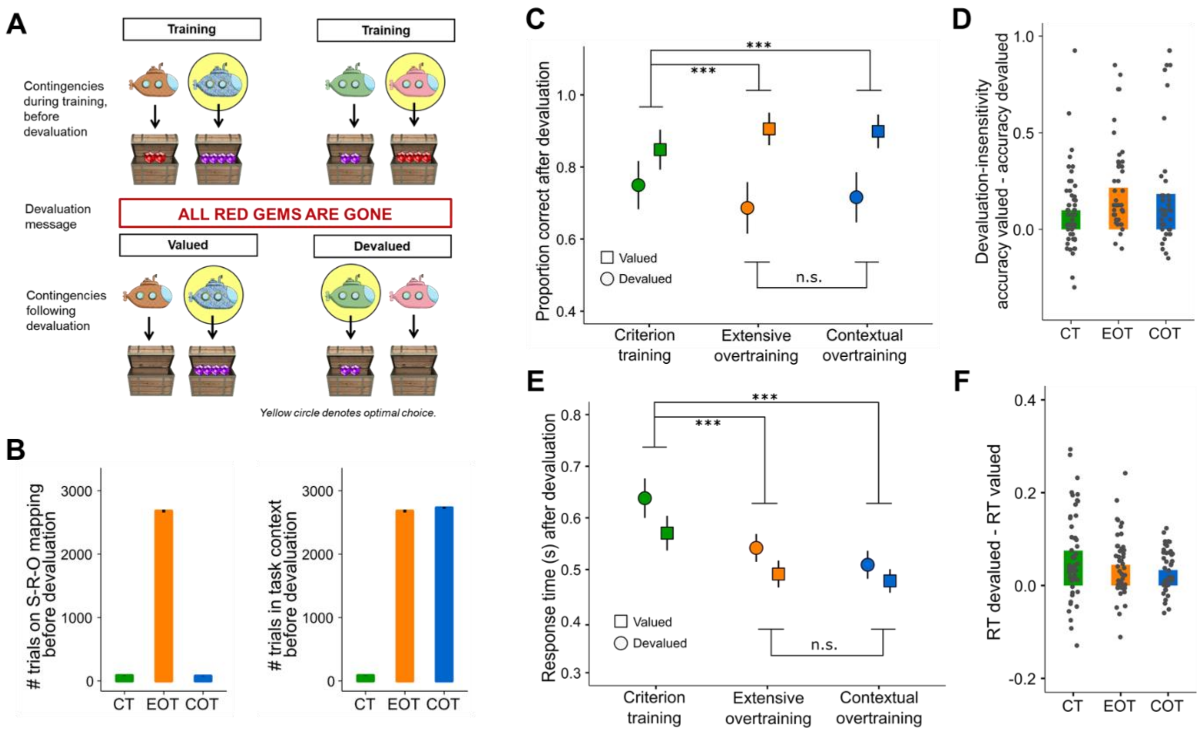

Figure 2. A. Task contingencies and devaluation manipulation. Participants were trained to select the most rewarding of two submarine stimuli (80% reinforced). Following training, a devaluation message was displayed informing the participants that the gems of one color had disappeared (each gem represents 1 point) and the corresponding treasure chests would always be empty (0% reinforced). In the Valued condition, the most rewarding choice remains the same, whereas in the Devalued condition, participants need to override the trained response to select the most rewarding option. B. Training protocol. Number of training trials with the to-be-devalued stimulus-response-outcome contingencies before devaluation (left). Number of training trials in the stable task context before devaluation (right). C. Accuracies for Valued (square) and Devalued (circle) conditions after devaluation. All groups perform worse in the Devalued condition where the trained response should be overridden, but this difference is significantly larger in both the extensively overtrained (EOT) and the contextual overtrained (COT) groups compared to the criterion trained (CT) group. D. Bars indicate the average devaluation-insensitivity (accuracy Valued – accuracy Devalued) per group, with individual outcome insensitivity overlaid. E-F. Response time (RT) is significantly lower in both overtrained groups, and in the Valued condition. The RT difference between Valued and Devalued

stimuli is larger in the criterion-trained group than in the overtrained groups. Individual participant data see Supplementary Figures S3-4. Error bars denote standard error of the mean. ***$p<0.001$ n.s. no significant difference ($p>0.1$).

Signatures of accelerated habit learning when learning a new stimulus-response mapping in the overtrained context

To investigate whether the overtraining experience in the task context impacts habit formation on a new S-R-O mapping, we examined how accuracy and response time evolved during the *second* criterion training (before devaluation; see Figure 1A, white box with dotted blue border), when participants from the contextual overtraining group learned a new S-R-O mapping in the already overtrained task context. If habit formation is accelerated, we expect RTs and accuracies to improve faster during the second criterion training compared to the first. Indeed, RTs at the start of the second criterion training (COT group, assessment day) start off about as slow as those during initial training (Figure 3A) but then show a significantly faster exponential decrease (COT 2^{nd} S-R-O vs. EOT and COT 1^{st} S-R-O, $p<0.001$; COT 2^{nd} S-R-O vs. EOT overtrained, $p<0.001$; Figure 3B, Supplementary Figure S6). Similarly, accuracy increased significantly faster when learning a second S-R-O mapping in the overtrained task context compared to learning the first S-R-O mapping (COT 2^{nd} S-R-O vs. EOT and COT 1^{st} S-R-O, $p<0.001$; COT 2^{nd} S-R-O vs. EOT overtrained, $p<0.001$; Figure 3D).

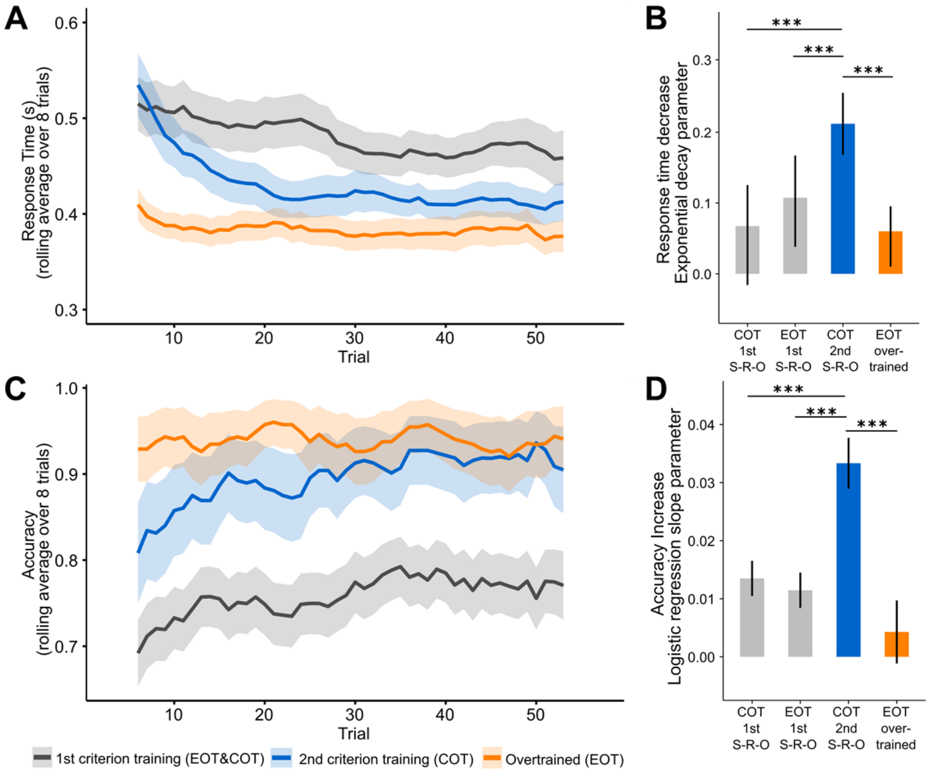

Figure 3. Learning during the criterion training blocks on Days 1 and 4. Rolling average of the response times during the first criterion-training block (CT1 in Figure 1A) combined for extensive overtraining (EOT) and contextual overtraining (COT) groups (grey), during criterion-training of the second S-R-O mapping in the COT group (CT2 in Figure 1A; blue), and the overtrained mapping during the first block on Day 4 in the EOT group (orange). Shaded areas denote +/- 1 standard error. B. Exponential decay parameter estimated from two-parameter exponential fit to RTs. The exponential decay is significantly steeper during the second criterion training compared to initial training in the new task context and compared to already overtrained performance. Error bars denote bootstrapped 95% confidence intervals. C. Rolling average of the accuracy during initial training (grey), training of a new S-R-O mapping in an overtrained context (blue), and already overtrained performance (orange). D. Slope parameter estimate from logistic regression on the accuracy data. Accuracy increases significantly faster when training a new mapping in an overtrained context compared to learning a new mapping in a novel context and compared to overtrained performance. Panels B and D represent parameter estimates and associated variability based on group analyses. Error bars denote standard error of the mean. *** p<0.001.

Habit strength in overtrained groups predicts balance between model-free and model-based processing in two-stage task

We fit 7 computational models to the data to estimate our parameter of interest, the balance parameter w: the balance between model-based and model-free learning.. The winning model had 4 free parameters (Supplementary Table S2). As expected given the task modifications, which incentivize model-based processing (Feher da Silva & Hare, 2020; Kool et al., 2016), we observed a negatively skewed distribution of w, with about half of the participants behaving completely model-based (Supplementary Table S3). As hypothesized, we find that devaluation-insensitivity is significantly predicted by w ($F(1, 126) = 11.95$, $p<0.001$),Group ($F(2, 126) = 3.43$, $p=0.036$), and the interaction between Group and w ($F(2, 126) = 9.04$, $p<0.001$). Comparing the relationship between devaluation-insensitivity and w between groups, we find that both in the EOT and the COT groups, there are significant correlations between w and devaluation-insensitivity (EOT Spearman's rho = -0.37, p=0.016; COT Spearman's rho=-0.55, p<0.001). In contrast, devaluation-insensitivity in the CT group does not correlate with how model-based the subjects behave (CT Spearman's rho=0.044, p=0.768; Figure 4C). In sum, we find that model-free versus model-based learning in a two-step task predicts devaluation-insensitivity in the overtrained groups, but not in the criterion-trained group. Analyses including all participants show the same pattern, with a w * Group interaction ($F(2,133) = 8.51$, $p<0.001$, driven by significant relationships between w and devaluation-insensitivity in the EOT (Spearman's rho = -0.37, p=0.014) and the COT groups (Spearman's rho= -0.57, p<0.001), but not the criterion-trained group (CT Spearman's rho= -0.010, p=0.946).

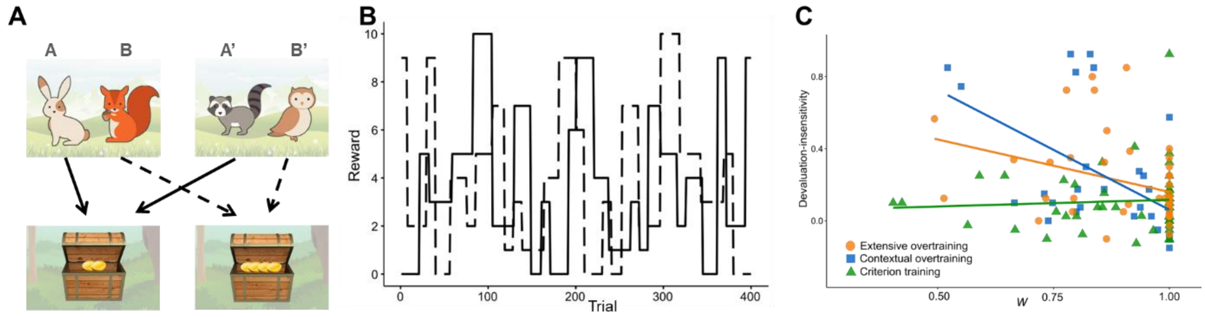

Figure 4. A. Adapted two-stage task. Participants can earn coins by selecting an animal to follow to a treasure chest; animals are yoked so that the choices offered in each pair are equivalent. A model-based learner can exploit this task structure and updates the value of the chosen and yoked stimulus at each trial, while a model-free learner only updates the value of the chosen stimulus. B. Reward contingencies are deterministic and change in large steps at change points (full line: A-A' rewards; dashed line: B-B' rewards). C. Devaluation-insensitivity is predicted by the estimated balance between model-based and model-free processing in the two habitual groups. For the EOT and COT groups (but not the CT group), a larger parameter w (indicating more model-based processing) in the two-stage task predicts more habitual errors (more devaluation-insensitivity) in the devaluation task.

Dual-task following devaluation increases processing time for devalued choices

The distinction between goal-directed and habitual processing has long been embedded in dual-systems frameworks (Dolan & Dayan, 2013; Kahneman, 2011; Wood & Rünger, 2016), whereby the fast, efficient habits are linked to the heuristic system, while the slower, more computationally demanding goal-directed choices are linked to the analytic system. In this framework, the habitual system produces a default response, which is overridden, if necessary, by the goal-directed system, provided the latter has the necessary time and working memory available. In line with this, imposing response deadlines makes them more prone to habitual responses (Hardwick et al., 2019). Similarly, model-based processing has been shown to depend on working memory capacity (Otto, Gershman, et al., 2013a; Otto, Raio, et al., 2013; Smittenaar et al., 2013). We tested whether devaluation-insensitivity is more pronounced under a working memory load. The three groups did not significantly differ from one another in terms of working memory capacity (Mean length of WM load string used= 6.23, SD=0.82; Group effect: $F(2,131)=0.37$, $p=0.695$; see Figure 5B) or in their performance on the dual task (mean accuracy: 0.83, SD= 0.10; Group effect: $F(2,131)=0.65$, $p=0.525$; see Figure 5B). Only trials on which the WM probe was answered correctly were included in the analysis. In this dual-task block, both overtrained groups still showed significantly more devaluation-insensitivity than the criterion-trained group (Group*Devaluation interaction: $\chi^2(2) = 27.50$, $p<0.001$; CT vs EOT: $\chi^2(1) = 24.35$, $p<0.001$; CT vs COT: ($\chi^2(1) = 14.10$, $p<0.001$, see Figure 5C). That is, the effects of overtraining on devaluation-insensitivity remain, even after 40 trials to learn from the altered outcome.

Comparing Load and No Load condition, participants did not make more habitual errors under working memory load (Accuracy: Load*Devalued interaction; $\chi^2(1) = 0.51$, $p=0.474$), nor was there a differential effect according to training group (Accuracy – Load*Group*Devalued interaction: $\chi^2(2) = 0.65$, $p=0.724$). In contrast, response times were more affected by working memory load in the Devalued than the Valued condition (RT: Load*Devalued interaction; $\chi^2(1) = 74.88$, $p<0.001$), indicating longer processing time specifically when an (over)trained choice was successfully overridden. However, this pattern did not differ by Group (RT: Load*Group*Devalued interaction: $\chi^2(2) = 5.69$, $p=0.058$), Thus, while the working memory load increased response times specifically when a trained response must be overridden, this added processing time was not affected by the training experience before devaluation. Results were similar when all participants were included.

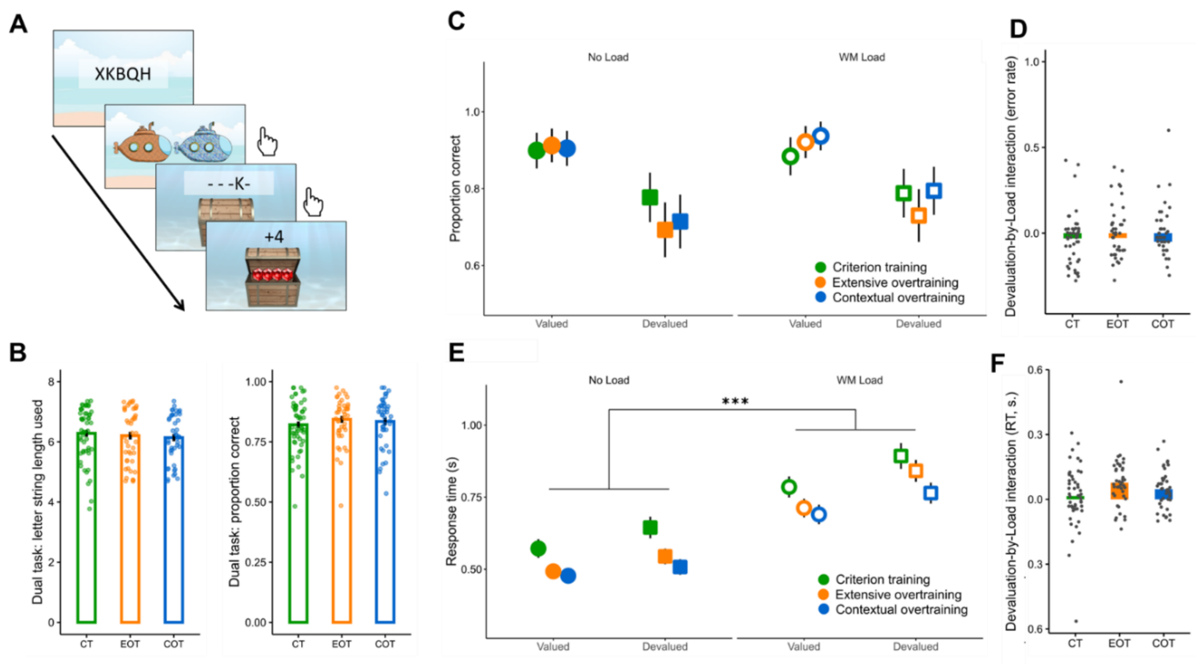

Figure 5. A. Trial structure in the dual-task block. Participants were required to keep a string in working memory while selecting a stimulus. In order to open the treasure chest, they had to correctly indicate whether the presented letter was in the correct place within the string (press right) or not (press left). B. The length of the presented string was tailored to participants' performance on a digit span task. The length of the strings did not significantly differ between groups. (left) Participants' performance on the dual task did not differ between the three groups. (right). C. Accuracies In the single task (No Load) and dual task (WM Load) devaluation blocks. The effects of Group and Devaluation were preserved in the dual-task block, but the working memory load did not affect the Devaluation effects. D. Response times in the single task and dual task devaluation blocks. The effects of Group and Devaluation were preserved in the dual-task block, and the working memory load significantly increased the response time difference between the Devalued and Valued condition across groups. Individual participant data see Supplementary Figures S7-8. Error bars denote standard error of the mean. *** p<0.001.

Discussion

Habit formation is typically conceptualized as a transition from flexible, goal-directed responses sensitive to value change to rigid, devaluation-insensitive habitual responses achieved by extensive behavioral repetition (overtraining) of a stimulus-response mapping (Adams, 1982; Dolan & Dayan, 2013; Wood & Rünger, 2016). This view does not incorporate effects of prior learning history in the same task context, despite insights from learning psychological and computational perspectives that this might be the case(Bouton & Todd, 2014; Silvetti et al., 2018). In this study, we introduce an extensive overtraining protocol that induces habits through overtraining and allows experimental control over habit induction. We found that previous overtraining in the task context accelerated the development of devaluation-insensitive habits for newly introduced stimulus-response contingencies.

Extensive overtraining on our habit training task decreased participants' ability to flexibly adjust their choice behavior following a devaluation compared to criterion-training. This is notable, as previous efforts to form habits in the laboratory have been mixed (de Wit et al., 2018; Hardwick et al., 2019; Luque et al., 2019; Tricomi et al., 2009). The most significant feature of paradigms that manage to create habits, appears to be the number of overtraining trials, with effective paradigms using over 1000 trials (Hardwick et al., 2019; Luque et al., 2019). The number of trials we implemented was much larger than typical (1280 trials per mapping versus a maximum of 160 in previous work) and was spread over multiple days. In fact, our criterion-training condition included a comparable number of trials to the habit training conditions in other paradigms (de Wit et al., 2018; Gillan et al., 2015; Luque et al., 2019; Sjoerds et al., 2016). Further suggesting that more extensive overtraining can lead to habit formation, striatal areas associated with habitual responses are recruited only following extensive overtraining (Wunderlich et al., 2012), and extensively overtrained participants make habitual errors following a rule change if a response deadline is imposed(Hardwick et al., 2019). Here, we show that extensive overtraining can lead to habitual errors even in more naturalistic conditions using free response times.

In line with our findings, earlier habit work shows that even shorter instrumental (criterion) training can increase errors after a rule change (slips of action), and increase the time needed for an accurate response (Gillan et al., 2015; Luque et al., 2019; Watson et al., 2018; Zwosta et al., 2018). However, we show here that extensive training beyond this point increases error rate and RT effects significantly. Apart from these quantitative differences between criterion-trained and extensively overtrained responses following devaluation, we suggest there may be important qualitative differences. Well-developed neuroscientific work in animal models has tied goal-directed and habitual behaviour to separable striatal circuits, with the dorsolateral striatum (analogue to putamen) crucial for devaluation-insensitive habit representations, and the dorsomedial striatum (analogue to caudate) crucial for the reward-sensitive goal-directed representation (Balleine & O'Doherty, 2010; Yin et al., 2004, 2005). Given that the neural substrate of criterion-trained choices is different from that of overtrained, putatively habitual choices (Ceceli & Tricomi, 2018; Foerde, 2018; Lesage & Stein, 2016; Morris et al., 2016; Yin et al., 2004), resulting behavior may relate differently to other functions (e.g. cognitive control) and dysfunctions (e.g. addiction). Such qualitative differences may also explain an interesting pattern in the present two-stage task results. Errors in both overtrained, putatively habitual groups, but not in the criterion-trained, putatively goal-directed group correlate with a tendency for model-free reasoning. With a potential qualitative difference in mind, further research investigating the relationship between habit and psychiatric diagnoses such as obsessive-compulsive disorder and addition should consider the length of training in the habit induction protocols.

Using our habit overtraining protocol, we investigated whether habit formation is specific to the overtrained stimulus-response mappings, or whether higher-order properties of the task context can facilitate new habit formation. The traditional model of habit formation does not account for such higher-order learning, but similar contextual higher-order learning has been studied from a computational modeling perspective (Behrens et al., 2007; Mathys et al., 2014; Silvetti et al., 2018).

Our results showed that devaluation-insensitive habits are expressed after merely criterion training when introducing a novel set of stimuli and outcomes in the overtrained task context. In fact, in our sample, habit strength for a new stimulus-response mapping after contextual overtraining was similar to habit strength after extensive overtraining with the same stimulus-response mapping throughout. Habits developed without extensive training on any component of the later devalued stimulus-response-outcome mapping, given that both the submarine stimuli and the gem outcomes were different from the previously overtrained stimulus set.

Our data suggest that participants are able to apply overtrained higher-order properties of the task context to the formation of new habits. When examining the (criterion) training phase of a second S-R-O mapping in the already overtrained task context, performance (i.e., speed and accuracy) improve significantly faster than during initial training. In fact, although initial RTs are similar to those of a novel mapping, RTs at the end of this short second training are similar to those of an already overtrained mapping. One might argue that participants have not become habitual but have simply become better at this type of task after days of practice. However, the resulting insensitivity to devaluation confirms that a habit was in fact formed. The fast and accurate performance on the novel mapping comes at the cost of flexibility.

The importance of context is well-documented in habit expression (Wood & Rünger, 2016) and in transfer of learning generally (Bouton & Todd, 2014, 2014; Gershman et al., 2010; Rivière et al., 2019), with a matching context typically a necessary condition for habit expression or transfer. Specific to overtrained habits, recent evidence shows that rats who have overtrained a response will show devaluation-insensitivity in the training context, but not in a new context (Thrailkill & Bouton, 2015). We now show that overtraining in a given context can accelerate future habit formation in that trained task context. We speculate that during overtraining on the first mapping, participants are able to learn higher-order properties of the task (such as an optimal learning strategy and a required level of cognitive flexibility), tied to the context. In this case, participants might learn that the outcome contingencies will not change, that the exact nature of the outcome (here, the gem colour) is irrelevant to good performance, and therefore that it is safe to rely on speedy stimulus-response representations for optimal performance. When new stimuli and outcomes are introduced in this context, participants can generalize these higher-order properties to the novel stimulus set, accelerating a reliance on less flexible but faster stimulus-response associations. This role of participants' learning histories in the task context indicates a need to factor in higher-order learning into our understanding of habit formation and expression. Our findings dovetail nicely with recent work showing meta-learning of cognitive flexibility (Siqi-Liu & Egner, 2020; Xu et al., 2022).

An interesting feature of the habitual decisions, particularly after devaluation, is their speed. Response times for overtrained responses were much faster than those for criterion-trained responses, despite clear feedback about the lower accuracy. Participants seemed unable to slow down to potentially give better (goal-directed) responses. Previous work has shown that extensive overtraining combined with response deadlines can expose habits(Hardwick et al., 2019). In these studies, participants make habitual errors when forced to respond fast. In the present study, we show habitual errors with faster RTs, but without formally *requiring* this speed. Speculatively, the overtraining experience in a stable context may prompt participants to rely on a fast and frugal habitual representation rather than the slower and cognitively demanding goal-directed representation. It is an open question whether an instructed delay might help to successfully override habitual responses.

Model-free and model-based processes are thought to underpin goal-directed and habitual responses respectively (Daw et al., 2005; Dolan & Dayan, 2013). Consistent with this idea, we find that devaluation-insensitivity (habit strength) after overtraining predicts the balance between model-based and model-free learning strategies. That is, in the extensive overtraining group and the contextual overtraining group, participants who behaved more model-based in the two-stage task made fewer habitual errors following devaluation. This relationship was absent in the criterion-trained group. Previous work had shown a relationship between two-stage task performance and slips-of-action following shorter (criterion) training (Friedel et al., 2014; Gillan et al., 2015; Sjoerds et al., 2016) and with compulsive disorders such as OCD (Gillan et al., 2016; Luijten et al., 2020; Nebe et al., 2018) and addiction, although evidence is mixed for the latter (Nebe et al., 2018; Sebold et al., 2014). The relationship with overtrained habits had remained untested thus far. The present results suggest that the ability to override fast, habitual choices in favor of more accurate goal-directed choices following devaluation is related to participants' tendency to engage in model-based (reinforcement) learning. In the criterion-trained group, which underwent a similar treatment to the instrumental training in other habit paradigms (de Wit et al., 2018; Gillan et al., 2015; Sjoerds et al., 2016; Watson et al., 2018), we do not detect a relationship between model-based versus model-free processing and habitual errors. This differential pattern could indicate that the cognitive processes underlying performance after devaluation are different for overtrained compared to criterion-trained responses, in line with the different neural correlates underlying choice behavior following overtraining (Smith & Graybiel, n.d.; Wunderlich et al., 2012; Yin & Knowlton, 2006).

Finally, we found only a limited impact of a working memory load on habitual errors after devaluation. Habits have long been framed in terms of a dual-systems framework, whereby the goal-directed system is identified with the limited-resource analytic system, and the habitual system with the heuristic system(Dolan & Dayan, 2013; Kahneman, 2003). In this framework, one might expect more habitual errors under dual task conditions, but this had not yet been tested with a devaluation paradigm. We observed no effects of the working memory load on the number of habitual errors, but participants were significantly slower following devaluation on trials where the habitual response needed to be overridden (devalued trials). We found that this effect was only marginally different between the different groups: the extensively overtrained group tended to show a stronger increase in response time than the criterion-trained group. A limitation of the implementation of the dual task approach here was that the dual task block came after a first, single-task devaluation block.

Thus, participants were able to learn from this intervening post-devaluation block. This may have obscured some of the group-specific effects on accuracy and response time. Future work can further elucidate the effects of working memory depletion on the propensity for habitual errors.

In sum, we introduce a habit overtraining protocol that can reliably induce habits in humans. Critically, we find that overtraining in a stable, habit-inducing context can accelerate habit formation for new stimulus-response mappings. Performance improved faster when acquiring a second habit in a previously overtrained task context, and devaluation-insensitive habits formed in the time it takes to train to criterion. We further show that overtrained habits, but not errors following shorter training, correlated with more model-free processing. Finally, imposing a working memory load after devaluation slowed response times when suppression of the trained response was required. The striking effect of contextual overtraining indicates that the canonical view of habit formation in instrumental learning terms is incomplete. Further lines of research can elucidate contextual determinants of habit formation and expression, and their neural underpinnings.

Author contributions

EL and TV conceived of and designed the tasks, computational modeling, and data analysis strategy. EL collected the data and performed the data analyses. EL and TV wrote the manuscript.

Acknowledgments

Elise Lesage was supported by grant 12T2517N from Marie Skłodowska-Curie Actions under COFUND grant agreement 665501, and by grant 12T2521N from the Research Foundation Flanders (FWO). Tom Verguts is supported by Research Foundation-Flanders (FWO)/Fonds National de la Recherche Scientifique EOS Grant G0F3818N. The authors would like to thank Robert Hardwick for the use of and support with the OpenFL/Haxe code base that formed the basis for the experimental task software. The authors would also like to thank Anna Marzecova and Robert Hardwick for insightful discussion and comments on the manuscript.

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