Freedom from habits: the capacity for autonomous behaviour

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Abstract

The capacity for autonomous behaviour is key to human intelligence, and fundamental to modern social life. However, experimental investigations of the cognitive bases of human autonomy are challenging, because experimental paradigms typically *constrain* behaviour using controlled contexts, and elicit behaviour by external triggers. In contrast, autonomy and freedom imply unconstrained behaviour initiated by endogenous triggers. Here we propose a new theoretical construct of adaptive autonomy, meaning the capacity to make behavioural choices that are free from constraints of both immediate triggers and habitual responding, but nevertheless show appropriate coordination with the environment. Participants (N = 152) played a competitive game in which they had to choose the right time to act, in the face of an opponent who punished (in separate blocks) either choice biases (such as always responding early), habitual sequences of action timing across trials (such as early, middle, late), or habitual responses to the effects of reinforcement (such as win-stay, lose-shift). Adaptive autonomy with respect to each habit was measured by the ability to maintain performance against the opponent even when the corresponding habit was punished, by adapting action selection strategies. We found that participants could become free from habitual choices regarding when to act and could also become free from habits of sequential action. However, they were not able to free themselves from influences of reinforcement, even when these resulted in poor performance. These results point to a new concept of autonomous behaviour as flexible adaptation of habitual behaviour under different classes of external constraint.

Introduction

Animal behaviour depends upon both exogenous, environmental factors and multiple endogenous factors. An important aspect of endogenous action can be conceptualized as a dimension extending from stereotypical behavioural patterns like habits, up to flexible, intelligent, novel actions. Adaptation to environmental challenges, and the ability to find novel solutions, are thought to play a special role in human autonomy and volition. The capacity of human autonomy has often been examined in experimental tasks which encourage participants to act freely (Brass & Haggard, 2007; Fleming, Mars, Gladwin, & Haggard, 2009; Jahanshahi et al., 1995; Libet, Gleason, Wright, & Pearl, 1983) or to act randomly (A. Baddeley, Emslie, Kolodny, & Duncan, 1998; A. D. Baddeley, 1966; Jahanshahi, Dirnberger, Fuller, & Frith, 2000) by explicitly telling them to do so. Such instructions in voluntary-action studies

invite participants to behave in a way that reflects their own understanding of volition and freedom (Haggard, 2008). Outside the laboratory, in contrast, people readily switch between more stereotyped and more autonomous behaviours without explicit instruction, as a function of multiple situational and internal factors.

As such, it remains unclear whether and how people can express behavioural autonomy through volitional actions. We choose competitive games as a good testing ground for this question, for two reasons. First, many competitive games require people to initiate actions endogenously, rather than in response to external stimuli. For example, in the 'rock, paper, scissors' game, each participant selects an action without first seeing the action of their opponent. This stimulus-independence is considered a necessary condition for volition (Jenkins, Jahanshahi, Jueptner, Passingham, & Brooks, 2000). Second, volitional actions are often contrasted with habitual or routine actions (Haggard, 2019). Competitive games offer a convenient way to manipulate the extent to which any particular action is or is not habitual. For example, if a player behaves habitually in a competitive game, their opponent will be able to predict their upcoming choice, and adjust their strategy accordingly. Therefore, an agent playing a competitive game should avoid habitual or exploitative behaviours, and should instead innovate in order to avoid their opponent deriving advantage by predicting their behaviour. Humans and non-human primates indeed respond to competitive pressure by initiating exploratory behaviour (Barraclough, Conroy, & Lee, 2004; Lee, Conroy, McGreevy, & Barraclough, 2004; Lee, McGreevy, & Barraclough, 2005).

The present study therefore investigates human volition and autonomy in a competitive game in which participants could not react to their competitor's current move (stimulus independence), and additionally received more reward when they avoided the competitor's prediction (habit independence). Further, we used several virtual competitor algorithms, each designed to punish a particular kind of habit. Whereas psychologists have often thought of habits as personality traits, we reasoned that habits are under strategic control. A person might stop behaving habitually when a competitor begins to predict, exploit and punish their habitual behaviour. Thus, *change* in habitual behaviour under competitive pressure offers a quantitative measure of individual autonomy with respect to habits.

We conceptualised three distinct "habit families" [†]. The first was simple repetition of the same option (Dolan & Dayan, 2013; Du, Krakauer, & Haith, 2022; Robbins & Costa, 2017). We refer to this as *standard choice habits*. Consider the simple task of repeatedly generating one of three digits (see Figure 1A). Agent X may prefer to choose "1", for whatever reason.

Suppose now that a competitor punishes X for repeating one choice within a game scenario. If X can break her habit, she should now choose the two other digits more often and should approach an agent who has no preference on any options. This adaptive capacity may reflect the autonomy each agent has over their choice habits. We call this quantity *adaptive autonomy*.

The second habit family we considered is *transition habits*. This refers to action chains or routines (Lashley, 1951; Robbins & Costa, 2017; Rosenbaum, Cohen, Jax, Weiss, & van der Wel, 2007). In our example, integer counting ("1, 2, 3") is such a habit (agent X in Figure 1B). The only way to completely avoid such habits is to generate each choice independently from the previous trial. Yet studies of random number generation show people find this difficult (A. Baddeley et al., 1998; A. D. Baddeley, 1966; Bar-Hillel & Wagenaar, 1991). Figure 1B illustrate potential behavioural adaptation to punishing transition habits.

Lastly, we consider how people respond to previous action successes and failures, by considering *reinforcement habits*. In Figure 1C, agent X repeats the digit that has been rewarded. In contrast, we can imagine an agent who generates each choice independently from whether the previous outcome was rewarded or not. Most reinforcement learning approaches assume that a 'win-stay lose-shift' strategy is natural, or even unavoidable (Worthy, Hawthorne, & Otto, 2013). Reinforcement is generally considered a factor that causes a habit. Here we consider that following reinforcement is itself a habit, and test whether people can unlearn this familiar reinforcement habit when it is punished by a competitor. Adaptive autonomy would mean that an agent would be able to break the association between their next action and the previous outcome (Fig. 1C).

In this experiment, we designed a structured series of competitors in a game scenario, in order to selectively punish these specific habits. We thus measured individuals' capacity for adaptive autonomy, defined as the change in behaviour when a specific type of habit was punished. We could thus test the limits of human autonomy for three habit families of choice, transition and reinforcement habits. Habit is generally considered an action under control of model-free reinforcement learning(Dolan & Dayan, 2013), with the distinctive feature that the habitual behaviour continues even when it is no longer rewarding. In this sense, our different experimental conditions should motivate participants to break the corresponding habit, and move from model-free towards model-based behaviour. Adaptive autonomy might reflect a general capacity to suppress any type of habits by developing appropriate new model-based, strategic cognitive control(T. S. Braver, 2012; T. S. Braver, Gray, & Burgess, 2007; Tang, Bugg, Snijder, Conway, & Braver, 2022), or it might alternatively be specific to a particular habit

family. To investigate this question, we explored correlations across individuals in our adaptive autonomy measures for each habit. Finally, we modelled the learning process by which people generated a new action in order to avoid the competitor.

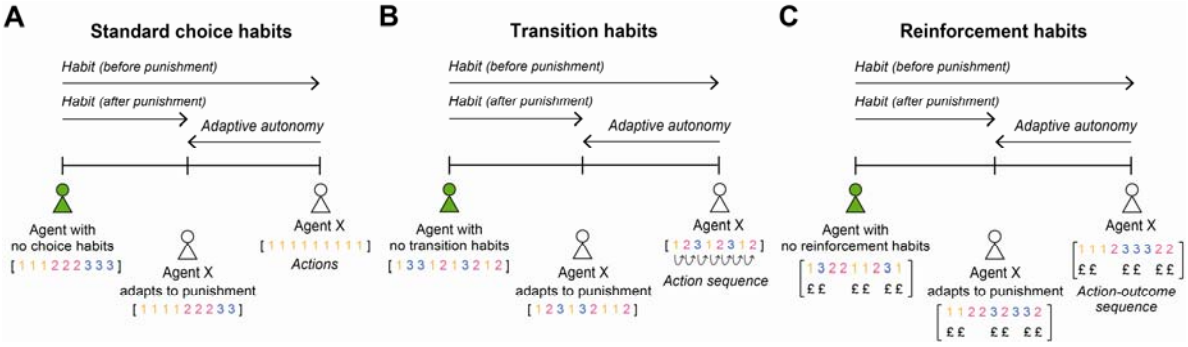

Figure 1. Three habit families in a hypothetical experiment. An agent is required to generate digits 1, 2, 3, as shown in the square brackets. **A**. Agent X exclusively selects the digit 1. They have a *choice habit*. In contrast, an agent with no choice habits selects each digit equally often. **B.** Agent X generates successive digits by counting. In contrast, an agent with no transition habits does not use any obvious transition strategy between moves. **C.** Agent X tends to repeat any action that has just been rewarded. In contrast, an agent with no reinforcement habits does not use information about the outcome of the present action to decide their next action. In each case, the leftward arrow indicates the reduction in a given habit when the opponent punishes that habit by using it to predict the agent's next move, i.e., adaptive autonomy.

Footnote † The concept of a habit has been discussed over centuries by philosophers (Barandiaran & Di Paolo, 2014). Its theoretical framework has been formalised by psychologists and neuroscientists' works, but it is still controversial (Dolan & Dayan, 2013; Du et al., 2022; Robbins & Costa, 2017). A psychologist's view of a habit is that it reflects the formation of stimulus-response associations (Wood & Runger, 2016). A traditional testing ground for habits is a reward devaluation paradigm. Here a reward previously assigned to a stimulus-response association is devalued (Robbins & Costa, 2017). If the response is still automatically evoked by the stimulus, its behaviour is said to be a habit rather than goal-directed. In the present study, we do not aim to examine whether or how habits are formed. Rather, we investigate how people become liberated from their endogenous habitual patterns. The three habit families we conceptualised are considered different expressions of habits. From the perspective of a stimulus-response association, standard choice habits are any obvious responses in any task. Rule habits are those responses evoked by the last response. While reinforcement habits are the responses elicited by the last outcome/feedback. The

precise mechanism by which each habit forms is unimportant. Rather, the concept of three habit families refers to statistical patterns that are not random nor independent and that may be continually shaped by ongoing experience. Thus, volition in our paradigm requires the regulation of salient/habitual patterns and the exploration of new behavioural patterns.

Results

Experimental task

Participants were asked to decide when to press a key that caused some food to be delivered to a storage location. They were competing with a virtual competitor, represented as a flock of birds (Fig. 2A). The birds tried to catch the food during the delivery process, by deciding when to fly out of a tree and across the field. The participant's task was to deliver the food without it being caught by the birds. We programmed the birds to predict the time of the participant's next action based on the history of their reaction times. Based on this prediction, the birds made a choice of when to fly on each trial. They flew at a time that was designed to intercept the food thrown by a participant within one of three intervals: 1) early throw (0–1.5 sec), 2) middle throw (1.5–3.0 sec) or 3) late throw (3.0–4.5 sec). Participants were not told whether the birds chose a continuous or a 3-option distribution. The participants could win a trial by pressing the key during one of two intervals that the birds did not select. The intervals were not explicitly demarcated for the participant, who experienced a continuum of potential action times in each trial. Participants could not perform the task reactively because the birds could travel much faster than the food. If the participants simply waited for a moment when no birds were present and then threw in reaction to that moment, the birds could suddenly appear and intercept the food. Therefore, the participants were instructed to predict when the birds would appear and to try avoid them. This feature means that our participant's actions were stimulus-independent.

There were 4 blocks in total. In each block, the participants competed with a class of competitor that pressurised a specific habit (Fig. 2B). In the baseline block, Competitor 0 was programmed to punish the participants for being impatient: the birds consistently punished a participant who threw in the early interval, so the participant was incentivized to wait to avoid being intercepted. In block 1, Competitor 1 punished standard choice habits: if a participant selected one interval more often than the other two, then the birds became more likely to intercept the food during the same interval. In block 2, Competitor 2 predicted transition habits, and punished any predictable association between the time of the participant's current throw

and the time of the preceding throw. Finally, in block 3, Competitor 3 punished reinforcement habits by seeking out whether the time of the current throw was associated with both the time of the preceding throw and the preceding outcome. Thus, the participants required progressive degrees of autonomy across blocks: they needed in each block to act in a way that was even more unconstrained than required by the competitors they had played previously.

Participants were never told when they should act on any given trial. Participants did not receive any explicit instruction or explanation about which type of habit was punished in each block. Instead, they could only monitor the success/failure of avoiding the birds on each trial, and adapt their behaviour accordingly to try to avoid the birds on future trials. Thus, successful performance under different punishment regimes would depend on implicit mechanisms of behavioural adaptation rather than explicit understanding.

We first checked the percentage of successful bird-avoiding trials. The participants achieved near perfect success rates against Competitor 0 who punished impatience (Fig. 2C; Median [Mdn] = 96.6%). The participants avoided an immediate response and initiated the throw a mean 2.15 sec (SD 0.49 sec) after the trial started (Fig. 2D upper panel). In block 1, the success rate dropped to 66.6%, as would be expected from purely stochastic choices (Fig. 2C; Mdn = 64.3%, $p < .001$, $z = 10.69$ for blocks 0 versus 1, Wilcoxon sign rank). The success rate further decreased in block 2 (Fig. 2C; Mdn = 59.0%, $p < .001$, $z = 5.74$ for blocks 1 versus 2, Wilcoxon sign rank) and even further in block 3 (Fig. 2C; Mdn = 56.9%, $p = .015$, $z = 2.44$ for blocks 2 versus 3, Wilcoxon sign rank). Therefore, our progressive series of punishments increased the predictive power of punishing the participants' responses.

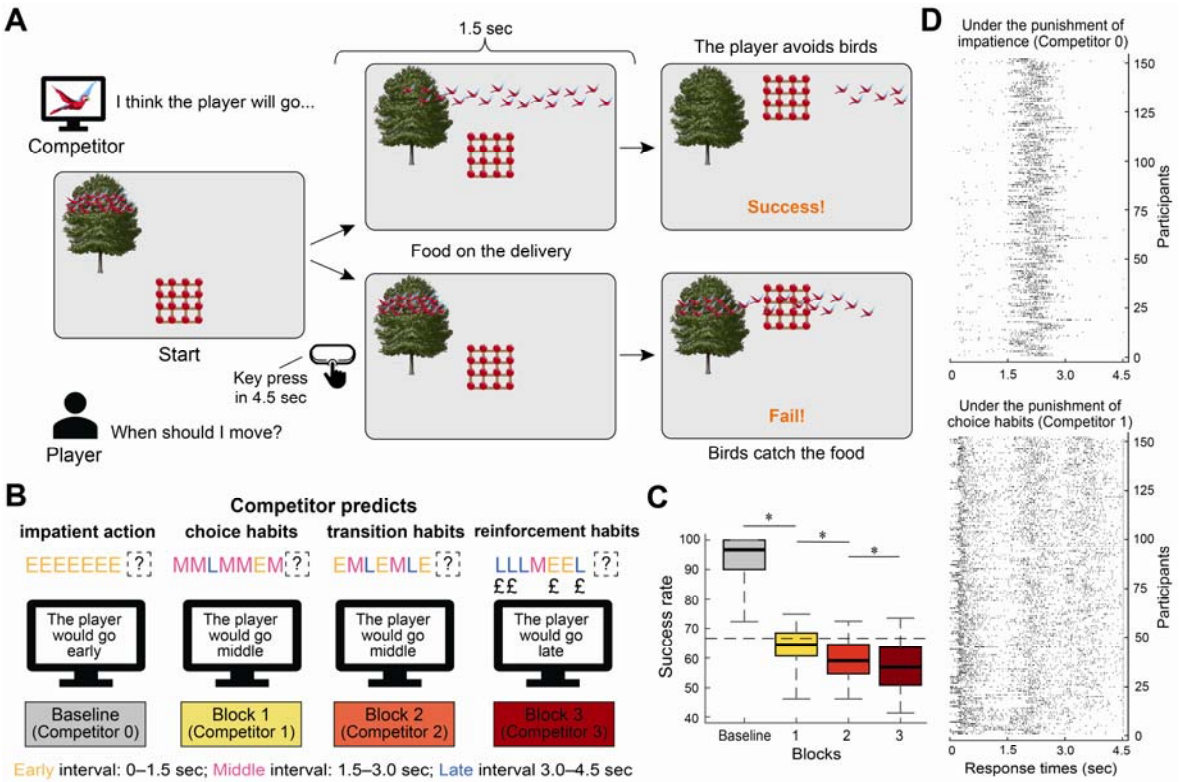

Figure 2. Virtual competitive environments for penalising habitual actions. **A**. A trial sequence. A participant decides when to throw food within a 4.5 second time window. The food is delivered at the top-centre of the screen 1.5 sec after their key press. A virtual competitor (i.e., a flock of birds) attempts to intercept the food by adjusting the time at which it flies out of a tree. Participants win a trial if they throw at a time which avoids the food being caught by the birds. **B**. Experimental design. On each trial, the virtual competitor intercepted the food during one of three action intervals, 1) early throw (0–1.5 sec), middle throw (1.5–3.0 sec) or late throw (3.0–4.5 sec). In the baseline block, the early interval, associated with impatience, was punished. In block 1, *standard choice habits* that favoured any one interval over all others were predicted and punished. In block 2, *transition habits* (i.e., any sequential pattern) were punished. In block 3, *reinforcement habits* (i.e., any outcome dependence) were punished. **C**. Success rate of avoiding the birds against each type of competitor. A dashed line denotes the chance level. For each box, the central mark represents the median, the edges of the box are the 25th and 75th percentiles and the whiskers are the 2.5th and 97.5th percentiles. * p < significant level after Bonferroni correction, Wilcoxon signed rank. N = 152. **D**. Response times before the punishment of choice habits in the baseline block (upper panel) and during the punishment in

block 1 (lower panel). The response time data for each participant are aligned in each row. Each small dot represents a reaction time in each trial.

Do people adapt to punishments of habitual actions?

We next examined the extent to which people could adapt to punishment of different habits. We therefore developed a measure that reflects an individual's tendency towards the habit family selected for punishment on each block. We measured the statistical distance (Kullback-Leibler [K-L] divergence) between the observed probabilities of selecting the early, middle and late intervals, and the probabilities that an agent, who does not have a particular type of habit among three habit families, would exhibit (Figure 3A-C). A lower statistical distance means that the individual is similar to this habit-free agent. We call this quantity a decision bias. The decision bias score *before* the punishment of a specific habit reflects an individual's trait habit regarding when to act. We then looked at the *change* in decision bias scores relative to the previous block, when a given habitual behaviour was punished. We quantified the decision bias score for standard choice habits, transition habits and reinforcement habits, respectively (Figure 3A-C). A greater change in bias score would indicate stronger *adaptive autonomy*, or ability to modulate the trait habit. See *Data analysis* for detailsData analysis.

Participants began to distribute action times appropriately when Competitor 1 started punishing choice habits (Fig. 2D). Accordingly, their choice bias—a statistical distance of the observed choice probabilities from probabilities 0.33 (Fig. 3A)—reduced after punishment (Fig. 3D; Mdn = 1.37 for the punishment of impatience versus Mdn = 0.06 for the punishment of choice habits, $p < .001$, $z = 10.69$, Wilcoxon sign rank). Competitor 1 did not seek transition patterns from one action to the next and allowed participants to still use *transition habits*. We quantified the sequential bias by considering the extent to which probabilities given the previous action are explained by one's own choice probabilities (Fig. 3B). We found that the sequential bias decreased after the competitor pressurised transition habits (Fig. 3E; Mdn = 0.13 for the punishment of choice habits versus Mdn = 0.09 for the punishment of transition habits, $p < .001$, $z = 3.82$, Wilcoxon sign rank). Against Competitor 3, the participants were asked to act even more freely to avoid *reinforcement habits*. We evaluated the reinforcement bias by considering the extent to which probabilities given the combination of previous action and the previous outcome are explained by probabilities given the previous action alone (Fig. 3C). The reinforcement bias did not show any significant improvement under competitor

punishment (Fig. 3F; Mdn = 0.11 for the punishment of transition habits versus Mdn = 0.11 for the punishment of reinforcement habits, p = .79, z = 0.27, Wilcoxon sign rank).

We further tested the possibility that the participants adapted differently to the influence of positive and negative reinforcement. The processes that follow a positive outcome may be different from those that follow a negative outcome (Gehring & Willoughby, 2002; Hajcak, Moser, Holroyd, & Simons, 2006; Vickery, Chun, & Lee, 2011), leading to a stereotypical win-stay lose-shift strategy (Wang, Xu, & Zhou, 2014). We quantified the positive reinforcement bias and the negative reinforcement bias separately (Suppl. Fig. 1A). Nevertheless, we did not find significant improvements in the positive reinforcement bias (Suppl. Fig. 1B; Mdn = 0.29 for the punishment of transition habits versus Mdn = 0.34 for the punishment of reinforcement habits, p = .21, z = -1.26, Wilcoxon sign rank) nor in the negative reinforcement bias (Suppl. Fig. 1B; Mdn = 0.43 for the punishment of transition habits versus Mdn = 0.41 for the punishment of reinforcement habits, p = .19, z = 1.30, Wilcoxon sign rank). These results suggest that people are able to become more autonomous from standard habitual choices and habitual action transitions but cannot break away from outcome dependencies. That is, people display habits of being guided by reinforcement, such as win-stay lose-shift, even when they are discouraged from expressing this habit.

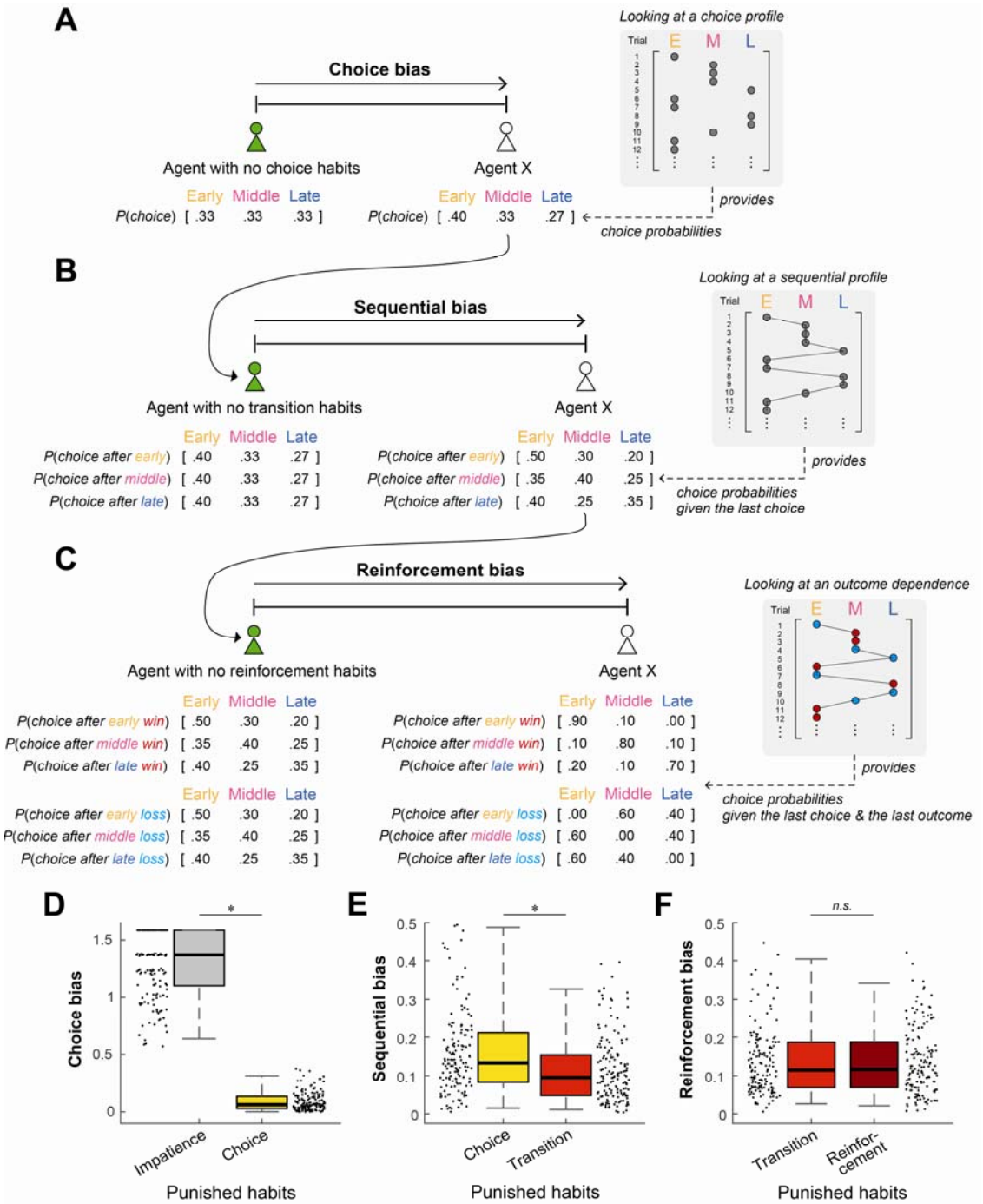

Figure 3. Measuring decision bias scores with respect to different habits. In the raster plot, potential actions for the early, middle and late intervals are shown. A vector of the numerical values illustrates the probabilities for choosing these three actions. **A.** Agent X selects the early interval more frequently than the other two intervals. In contrast, an agent without choice habits selects each interval equally often. We measured the statistical distance between individual

and a habit-free agent with respect to a pattern similarity between their choice probabilities. **B.** The dashed line from the choice bias vector in A to the transition vector in B shows the logical relation between choice and transition: any change in choice bias inevitably changes the transition vector. Sequential bias is considered as the additional change over and above such basic effects of the choice bias. An agent without any transition habits should determine their next action independently from the previous action. **C.** The dashed line from the sequential bias vector in B to the reinforcement vector in C shows the logical relation between transitions and reinforcements. Reinforcement bias is considered as the additional change over and above such basic effects of sequential bias. An agent without any reinforcement habits should determine their next action independently from the previous success or failure. **D-E.** Planned comparisons showing the degree of adaptive autonomy (bias reduction) when choice habits are punished (D), when transition habits are punished (E) and when reinforcement habits are punished (F). * p < significant level after Bonferroni correction, Wilcoxon signed rank. On each box, the central mark represents the median, the edges of the box are the 25th and 75th percentiles and the whiskers are the 2.5th and 97.5th percentiles. Dots adjacent to each box shows individual scores.

Is there a common factor underlying adaptive autonomy for different habits?

The bias reduction between the pre-punishment and the post-punishment phase provides a measure of adaptive autonomy for each habit family (Fig. 3D-F). Theories of domain-general cognitive control propose that proactive, strategic cognitive control acts similarly across cognitive tasks (T. S. Braver, 2012; T. S. Braver et al., 2007; Tang et al., 2022). The adaptive ability to become free of one kind of habit would be expected to correlate with the ability to become free of another habit, to the extent that both depend on a common, domain-general mechanism. In fact, the correlation structure of the changes in our decision bias scores showed poor correlations across our 152 participants (Figure 4; r = -0.07~-0.01). This suggests that the ability to voluntarily regulate one habit is not strongly associated with the ability to regulate other habits. This also suggests that our measurements are separable and evaluate three distinct forms of autonomy conceptualised above, rather than a single common form of autonomy. Since this correlation approach would be undermined by a floor effect of participants who showed no adaptive autonomy at all, we repeated the correlations including only participants who showed a numerical change in decision bias. We did not find significant correlations among adaptive autonomy to the three habit classes even in this restricted group

(r = -0.06~0.04). These results suggest that people recruit distinct cognitive capacities to exert autonomous behaviour when unlearning standard choice habits, transition habits and reinforcement habits, contrary to concepts of a general cognitive control capacity.

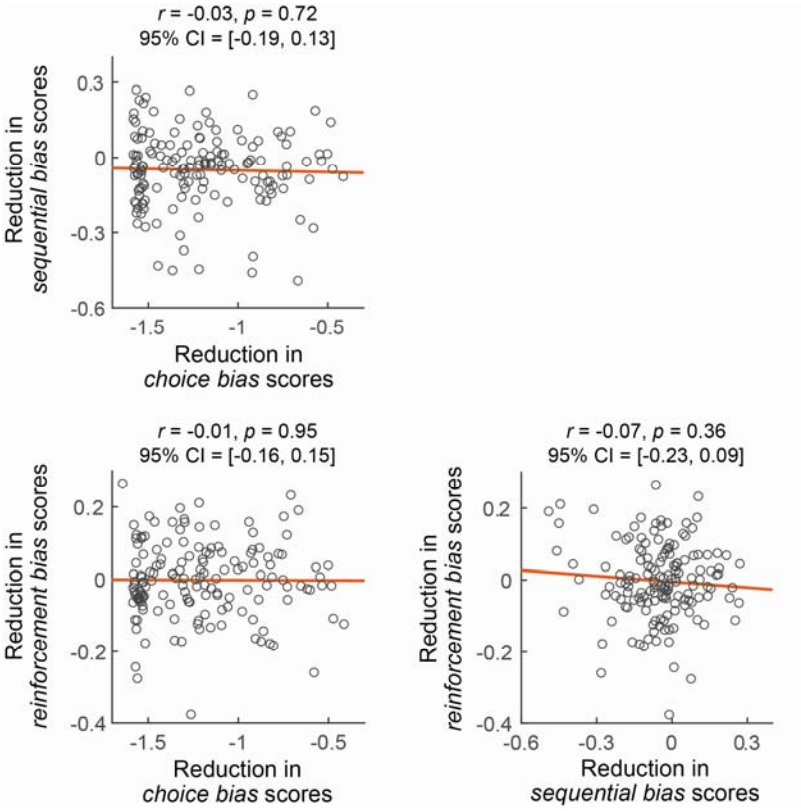

Figure 4. Correlation structure underlying measures of adaptive autonomy. A planned comparison between the pre-punishment and the post-punishment phase in Figure 3D-F provides bias reduction (i.e., adaptive autonomy) for each habit family. Across 152 participants, there is no strong correlation among three measure of adaptive autonomy.

A learning process that accounts for behavioural autonomy

What mechanisms could explain how participants adapted to these pressures? How did they learn actions that successfully avoided their competitor? In competitive games, two strategies can be taken to sustain performance. One strategy is stochastic selection in which actions are chosen randomly. This makes behaviour unpredictable, but involves no interaction with the competitor. An alternative strategy attempts to predict the opponent's next action based on a history of their prior actions (Hampton, Bossaerts, & O'Doherty, 2008; Zhu,

Mathewson, & Hsu, 2012). This strategy is called belief learning (C. F. Camerer, 2003) – broadly speaking, the strategy adopted by the virtual competitor in this task is considered belief learning (BL). Here we consider whether our participants also employed BL by predicting when the birds would fly and avoiding them.

BL goes beyond reinforcement learning (RL) (Sutton & Barto, 2018). If participants used only RL, they would update the value of the action interval they just made, based on whether the throw was successful or fail. In contrast, if participants used BL, they would form a view about which interval the birds were likely to fly in the next trial, and could therefore update the value of all action intervals. This difference in the internal processes allows a BL agent to update the values of the action intervals, thereby prompting a frequent update of the best action. We simulated agents using either RL or BL in our competitive game (see *Simulated play*), and found that belief learning indeed induces a smaller choice bias than simple reinforcement learning (Suppl. Fig. 2), leading to better performance (Fig. 5A). Both RL and BL strategies achieved sufficient success rates under the punishment of impatience (Fig. 5A; Mdn = 96.7% for RL versus Mdn = 98.3% for BL). However, the BL strategy sustained a higher chance of winning than the RL strategy under the punishment of choice habits (Fig. 5A; Mdn = 60% for RL versus Mdn = 66.6% for BL) and under the punishment of transition habits (Fig. 5A; Mdn = 51.6% for RL versus Mdn = 63.3% for BL). BL is therefore potentially useful for acquiring adaptive autonomy under competitor pressure.

To address which of the above strategies (stochastic selection, RL and BL) captured our participants' behaviour, we fitted each model to their choice data (see *Computational models*). Across blocks, we found a clear transition in the best-fitting model (Fig. 5B). According to the summed AICc across participants, the RL model outperformed the stochastic model and BL model under the punishment of impatience (baseline). However, the BL provided a better fit to our participants' action when the competitor started punishing choice habits. The BL model still outperformed when the competitor punished transition habits and reinforcement habits (Fig. 5B). For each model we calculated the number of participants best fit by the model (Fig. 5C) and the protected exceedance probability from the group-level Bayesian model selection (Rigoux, Stephan, Friston, & Daunizeau, 2014; Stephan, Penny, Daunizeau, Moran, & Friston, 2009), which is an omnibus measure of the probability that the model is the best model among tested models. The protected exceedance probability for the RL model to outperform the stochastic model and BL model was close to 100% under the punishment of impatience. The protected exceedance probability for the BL model was close to 100% under

the punishment of choice habits and transition habits, and this was 97% under reinforcement habits (Fig. 5C).

We also fitted a hybrid learning rule which combines reinforcement learning and belief learning (C. Camerer & Ho, 1999; Hampton et al., 2008; Zhu et al., 2012). The hybrid learning rule fitted the data relatively well in all blocks (Fig. 5B). The hybrid learning rule has an additional parameter that describes the weight given to belief learning relative to reinforcement learning. The weight placed on BL in the hybrid model was strongly correlated with the model fit index under the BL only model relative to the RL only model (Fig. 5D). Across blocks, the weight parameter on BL increased from punishment of impatience to punishment of choice habits (Fig. 5E; Mdn = 0.00 for the punishment of impatience versus Mdn = 0.63 for the punishment of choice habits, $p < .001$, $z = 8.32$, Wilcoxon sign rank). That is, belief learning made an important contribution to participants' choices when they were punished for choice habits (Fig. 5E; Mdn = 0.63), transition habits (Mdn = 0.81; versus choice habits, $p = .10$, $z = 1.65$) and reinforcement habits (Mdn = 0.74; versus transition habits, $p = .96$, $z = 0.04$). These findings suggest a shift in learning strategies that followed the demands of the competition: participants first used reward-guided behaviour when it sustained the success rate. Then, once the competitor started predicting habit patterns, participants switched to learning successful actions from the opponent's prior actions. This learning process is considered model-based cognitive control in the sense that the likelihood of the opponent's action is updated and developed. A model comparison thus indicates that adaptive autonomy is related to a shift from model-free control towards model-based control, rather than simply behaving randomly. In the next structural equation modelling, we examine this statistical relationship between adaptive autonomy and belief learning.

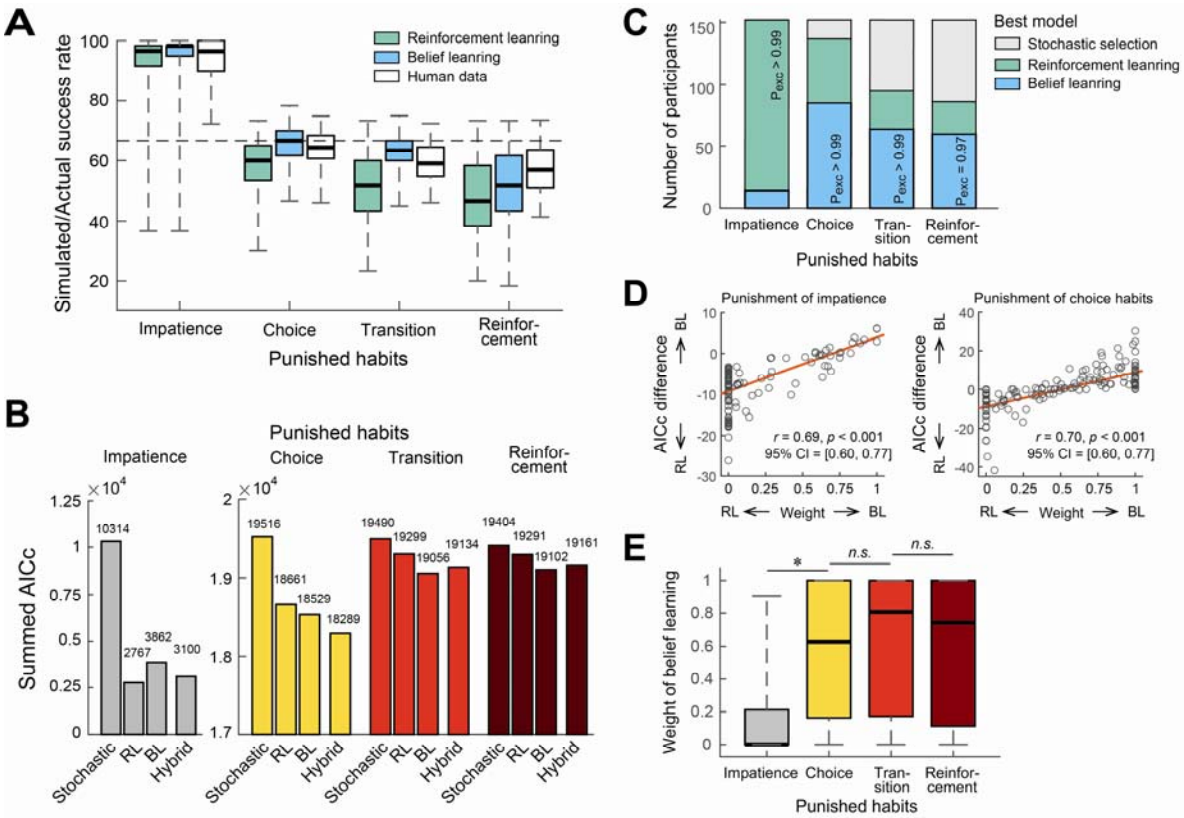

Figure 5. A shift in the strategy to belief learning as competitive demand increases. **A**. Real success rate (white bars) in the actual experiment and fictive success rate (green or blue bars). In simulation, agents who use the reinforcement learning strategy and agent who use the belief learning strategy competed against each class of competitor. **B.** Summed AICc across participants. Lower values of AICc are better. Stochastic: stochastic selection model. RL: reinforcement learning model. BL: belief learning model. Hybrid: hybrid learning rule. **C.** The number of participants best fit by the model. The P_{exc} inserted in the bar denotes the protected exceedance probability that supports the corresponding model. **D.** A weight placed on belief learning relative to reinforcement learning under the hybrid leaning rule. As the weight increases, the BL only model provides a better fit than the RL only model. **E.** A transition in the belief learning weight across blocks. * p < significant level after Bonferroni correction, Wilcoxon signed rank. **A&E.** On each box, the central mark represents the median, the edges of the box are the 25th and 75th percentiles and the whiskers are the 2.5th and 97.5th percentiles.

A shift in learning strategies enhances behavioural autonomy

To this end, we used a latent change score (LCS) model (Carpenter et al., 2019; Kievit et al., 2018; Kievit et al., 2017; McArdle, 2009). LCS models conceptualize the change in score between one time point (before punishment) and the next time point (under punishment) as a latent change factor (see *Latent change score model*). By using a bivariate LCS model, two latent change factors can be modelled. This model allows us to estimate correlated changes between latent factors: the degree to which the bias reduction co-occurs with the change in weight placed on belief learning (i.e., a shift in learning strategies). If participants behaved simply stochastically and reduced a decision bias score, the bias reduction would not co-occur with the change in weight. If, on the other hand, participants adopted belief learning and avoided choice habits, the bias reduction would co-occur with an increase in BL weight.

To address this question, we fitted the bivariate LCS model to our data set. Our observed variables were the choice bias score and BL weight under the hybrid learning rule. To estimate the latent change factors, we used these two scores on the punishment of impatience in the baseline and on the punishment of standard choice habits in block 1, because our planned comparison focused on adaptive autonomy of *choice habits* between these two conditions. Figure 6A illustrates fitted paths (significant paths are shown as thicker lines) from the pre-punishment phase (T0: punishment of impatience) to the post-punishment phase (T1: punishment of standard choice habits). This model, with fixed intercepts, shows a fit close to the saturated (i.e., perfect) model ($\chi^2(4) = 0.00$; RMSEA < 0.001, 90% confidence interval = [0.000, 0.000]; CFI = 1.00; SRMR = 0.00; AIC = -325.1). In bivariate LCS models, three kinds of paths can be estimated. The first is the extent to which the bias reduction is explained by the initial bias before punishment, which is termed auto-regression in LCS models. We found negative auto-regressive effects. This means that individuals who started off with a smaller bias in the baseline gained a smaller bias reduction in block 1, possibly because of a scale attenuation effect by reaching to the lower limit of the bias score. The second is the extent to which the bias reduction is explained by the initial BL weight, which is termed cross-coupling. There were no significant cross-coupling effects: a greater bias reduction in block 1 was not associated with individuals who started off with a greater weight in the baseline.

Notably, we found a medium negative correlated change. This suggests that individuals who gained a greater weight (i.e., a grater shift from RL to BL) between blocks also gained a greater bias reduction when choice habits were punished (Fig. 6B; standardised coefficient = -0.347, 95% confidence interval = [-0.480, -0.199]). When we removed the cross-coupling paths from the model in Figure 6A, the model still fitted the data well ($\chi^2(6) = 2.37$; RMSEA < 0.001,

90% CI = [0.000, 0.053]; CFI = 1.00; SRMR = 0.03; AIC = -326.8). However, removing the cross-coupling paths as well as the path for the correlated change produced a bad model fit ($\chi^2(7)$ = 23.80; RMSEA = 0.126, 90% CI = [0.071, 0.185]; CFI = 0.68; SRMR = 0.10; AIC = -309.0). To validate this finding, we estimated the BL weight under simulation where the competitor's action was randomised. We found no correlated change between bias reduction and the change in the BL weigh (Suppl. Fig. 3), suggesting that our participants likely used the information about the competitor's action. To summarise, these analyses demonstrate that adaptive autonomy is enhanced by developing the intention of the opponent's action through active interaction with a circumstance that is designed to evoke autonomous behaviour: a greater shift toward model-based control is related to a boosted autonomy. See *LCS models* in the supplement for further details.

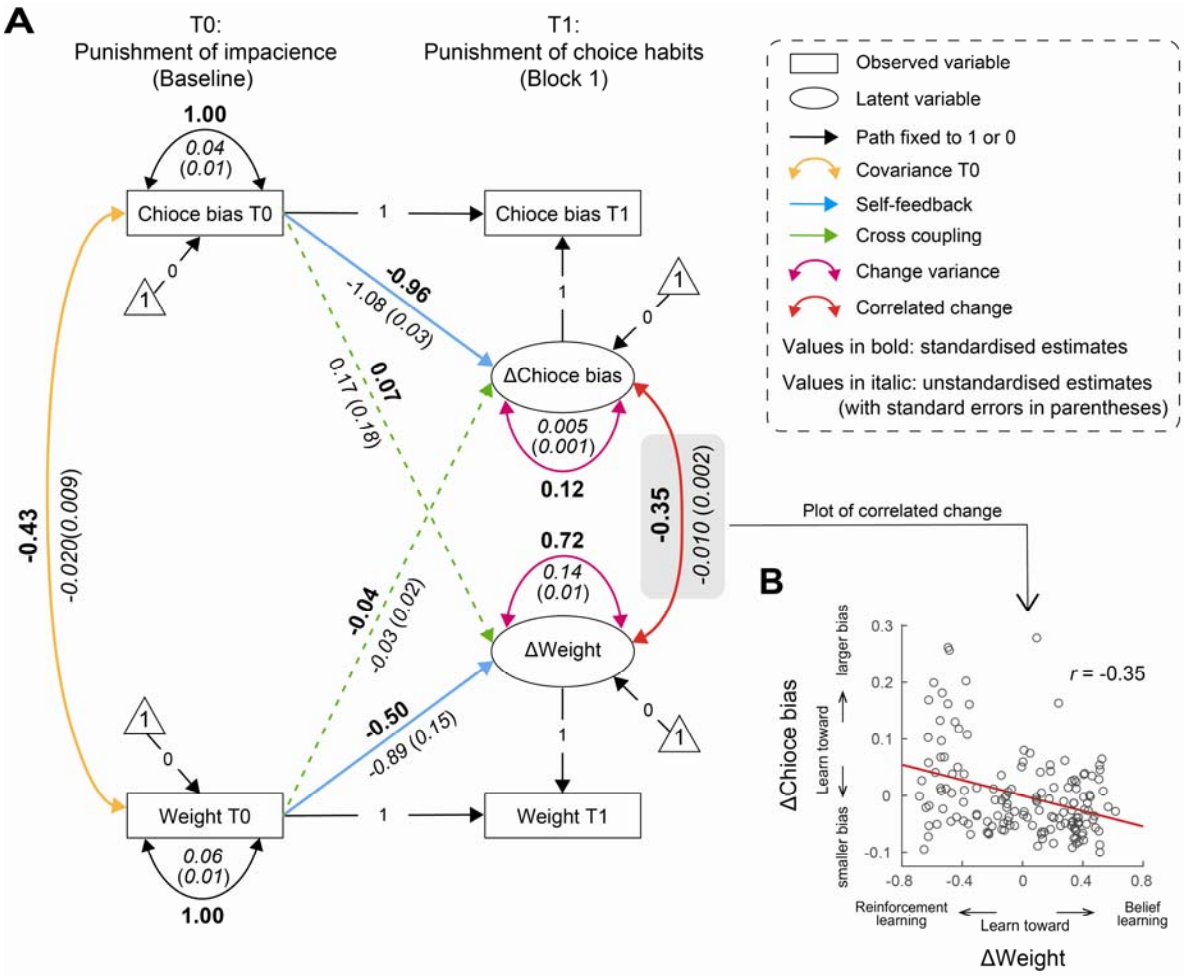

Figure 6. The bivariate latent change score model of adaptive autonomy and strategic learning. **A**. Estimated parameters. The change score in the choice bias was modelled as a latent factor between the score before the punishment of choice habits (baseline) and that under the punishment (block 1). A latent change in the belief learning weight was modelled similarly. Values in bold are standardised parameter estimates, and values in italic are un-standardised parameter estimates (with standard errors in parentheses). Solid lines indicate that the parameter is significant at $p < .05$. **B**. Scatter plot of correlated change. The bias reduction in choice habits is correlated with a greater shift from reinforcement learning to belief learning.

Discussion

It is widely assumed that humans have a capacity for autonomous behaviour. However, its cognitive basis is not well understood. We developed an experimental paradigm that implicitly elicits autonomous behaviour, in the form of a decision when to act so as to escape a competitor. We measured the extent to which people could express autonomy by adapting their behaviour to free themselves from different types of habits. We found that people can become autonomous regarding standard choice habits and transition habits, but are limited in their ability to become free of reinforcement habits. We further showed, in a large sample, that adaptive autonomy with respect to choice habits is uncorrelated with adaptive autonomy with respect to transition habits and that to reinforcement habits. This suggests distinct cognitive modules for these three forms of autonomy, rather than a common module or a single form.

Measures of autonomy

Traditional experimental psychology struggles to investigate autonomy. Experimental approaches to the study of volition often involved giving people a paradoxical instruction regarding what they should do (A. D. Baddeley, 1966; Brass & Haggard, 2007; Fleming et al., 2009; Jahanshahi et al., 1995; Libet et al., 1983). The few studies that have examined human autonomous behaviour typically used competitive game contexts (Forder & Dyson, 2016; Wang et al., 2014; Wong, Merholz, & Maoz, 2021), and have rarely considered subtypes of autonomy. We conceptualized three forms of autonomy, as freedom from three cognitively distinguishable types of habit: *standard choice habits*, *transition habits* and *reinforcement habits*. We attempted to evoke autonomous behaviour by programming a competitor to punish any lack of each type of autonomy. Using a statistical distance measure derived from information geometry, we developed measures that approximate a person's trait for each habit, and we further quantified the extent to which people could break a specific habit when punished. We found no strong correlations between these three types of adaptive autonomy, making a single common underpinning cognitive control function unlikely, and supporting the idea that behavioural autonomy involves dissociable components. In tasks where participants react to external stimuli quickly, it has been suggested that a domain-general top-down control is used to solve different cognitive tasks (T. S. Braver, 2012; T. S. Braver et al., 2007; Tang et al., 2022). However, in free, stimulus-independent action, our results suggest that a domain-specific top-down control independently regulates each particular form of autonomy: there are multiple ways to act freely, and it is important to consider *from what* an agent may be free. We

studied choice biases, sequential biases and reinforcement biases, but other biases of free action doubtless also exist. We showed that, for example, an agent who becomes increasingly free from choice bias may yet be unable to free themselves from the biasing effects of reinforcement.

Relevance to classical neuropsychological tasks

Our study evokes behavioural phenomena that neuropsychologists have traditionally studied using arbitrary, open-choice tasks. For instance, our measure of choice bias is related to the capacity to inhibit a prepotent, impulsive action (Mischel, Ebbesen, & Zeiss, 1972). People usually place costs on waiting, preferring earlier rewards; a form of temporal discounting (Story, Vlaev, Seymour, Darzi, & Dolan, 2014). The sequential bias we measured reflects executive control and working memory which are often assessed using random number generation tasks (A. Baddeley et al., 1998; Jahanshahi et al., 2000). In these tasks, people cannot sufficiently randomise numbers and tend to seek simple rules such as repetition, counting or alternation (A. D. Baddeley, 1966; Bar-Hillel & Wagenaar, 1991). In contrast, the capacity to avoid the reinforcement bias is related to voluntary regulation of reward-seeking behaviour (Bechara, Damasio, Damasio, & Anderson, 1994; Lejuez et al., 2002) and to the balance between exploitation and exploration (Cohen, McClure, & Yu, 2007). These classical preferences are often seen as robust individual traits affecting any relevant task (Neiman & Loewenstein, 2011; Ota, Shinya, & Kudo, 2016; Ota, Shinya, Maloney, & Kudo, 2019). Here we instead see these biases as a state function of cognitive control processes. We developed a competitive game in which participants would need to avoid some specific preference or bias in order to obtain rewards. Our results demonstrate that people can balance choice frequencies and break transitions between actions. Our results suggest that, when circumstances require, people can appropriately increase their behavioural autonomy.

In contrast, we found people could not avoid reinforcement habits. Neither positive reinforcement bias nor negative reinforcement bias changed when penalised. A stereotypical win-stay lose-shift behaviour has been shown in competitive games (Ota, Tanae, Ishii, & Takiyama, 2020; Wang et al., 2014). In particular, people are less flexible regarding changing lose-shift behaviour than win-stay behaviour when adopting to new game rules (Forder & Dyson, 2016; Sundvall & Dyson, 2022). The experience of a negative outcome generates a quicker decision and an impulsive response on the next trial (Dyson, Sundvall, Forder, & Douglas, 2018). Indeed, event-related brain potentials show a greater negative amplitude after

negative outcome feedback than after positive outcome feedback (Gehring & Willoughby, 2002; Hajcak et al., 2006). We note that individuals vary in their ability to avoid habitual behaviour after negative reinforcement. These individual differences are associated with post-error reaction times. Individuals who make quicker decisions after a loss than after a win show a poorer performance than individuals who make slower responses after a loss (Dyson, 2021). Therefore, overcoming impulsivity after failure may be a key aspect of volitional control for humans.

Sustaining autonomy during interactions with the world

Our model comparisons showed that participants did not achieve adaptive autonomy simply by behaving randomly. Rather, their choice strategy depended on feedback process in a way that they interacted with the environment. Reinforcement learning updates the best action by a reward prediction error while belief learning updates the best action by an action prediction error, defined as a difference between the expected action competitor would take and the actual action taken. Unlike classical reinforcement tasks, there was no explicit rewarding option that participants can exploit, because our task was designed to produce stimulus-independence and participants experienced the continuum of the time. Nevertheless, both reinforcement learning and belief learning provided better fits to participants' performance than random selection. Both reinforcement learning and belief learning can contribute to volitional, self-generated actions, because both are determined by internal representations of expected values, rather by an immediate stimulus (Frith, 2013). Furthermore, belief learning is considered to recruit a mentalizing or an implicit understanding of what the other agent would intend and do (Amodio & Frith, 2006; Hampton et al., 2008). These neural substrates are often found in separate neural networks: the reward prediction errors are encoded in the ventral striatum (McClure, Berns, & Montague, 2003; O'Doherty et al., 2004; Zhu et al., 2012) while the prediction errors about the state of the environment are encoded in several areas including the rostral anterior cingulate, the medial prefrontal cortex and the posterior superior temporal sulcus (Hampton et al., 2008; Zhu et al., 2012).

Mentalising is a key cognitive component recruited in competitive games (Hampton et al., 2008; Zhu et al., 2012). We found that, when the competitor started predicting people's upcoming action, people also switched started predicting the competitor's action, switching the strategy from reinforcement learning to belief learning. This result suggests that people implicitly learned a model of the competitor's strategy (or the likelihoods of the competitor's

actions) based on a sampling of previous trials. We further demonstrated that a greater adaptive autonomy was associated with a greater shift to belief learning. Habit is considered an action under control of model-free reinforcement learning, and therefore breaking habit recruits control of model-based behaviour (Dolan & Dayan, 2013). By a combination of the experimental paradigm and structural equation modelling, our study indeed reveals a statistical relation between breaking habit and move from model-free towards model-based behaviour. In our task, this process must have been implicit, because participants were not told anything about the algorithm the competitor used. We cannot tell whether participants discovered and explicitly represented the punishment rules used by the competitor, but we speculate that explicitly understanding the constraints on behaviour might be associated with increased autonomy.

To conclude, we have developed a new experimental paradigm and analysis pipeline to study when and how human actions can become autonomous. We propose a new theoretical construct of *adaptive autonomy*, meaning the capacity to free one's behavioural choices from constraints of habitual responding, when a particular habit becomes dysfunctional, for example due to environmental changes like the competitive pressure in our game scenarios. We have shown that people can indeed express adaptive autonomy, and that they do so by reducing the habitual elements of their behaviour, including habits of choice, habits of rule-based sequential action and habits of being guided by reinforcement. These appear to be three distinct forms of adaptive autonomy, rather than a single common cognitive mechanism for avoiding all habits, for example by strategic randomness. We show that becoming free from the effects of reinforcement is particularly difficult. Finally, by showing that belief learning plays an important part in boosting autonomy, we show a strong connection between autonomous action and mentalising abilities.

Limitations

The three habit forms we tested were hierarchical. The standard choice habit – favouring one action over all others – is more general, while the reinforcement habit is more specialised. Therefore, we ordered experimental blocks so that the competitive game algorithms could penalise habits progressively and serially. Each block implicitly required participants to act more freely and unpredictably than the preceding block. This fixed order may limit the generalisability of our results, but the order we used is the most reasonable. The differences we observed between the different forms of adaptive autonomy could be confirmed

in further between-participant studies. We also note that the AICc difference between the hybrid learning rule and the stochastic selection model became relatively small at the punishment of transition habits (block 2), relative to the punishment of choice habits (block 1; Figure 5B). Some proportion of the participants (37.5% in Figure 5C) was not fully explained by the hybrid learning rule in block 2. These participants might have behaved more stochastically due to a practice effect or might have found a way to become more free from habits of transition. That is being said, our model captured the participant's performance at least at some extent. Models that better capture a transition between actions could be addressed in future.

Empiricist view versus nativist views of human autonomy

Our work is broadly compatible with an empiricist view of human autonomy as opposed to a nativist view. In our view, some of the key attributes historically associated with "free will", such as the ability to act endogenously and purposefully, can be acquired, or at least adapted, through experience. Such adaptation requires people to make novel, non-habitual, 'smart' actions in certain situations. We found that people were more or less successful in adapting their trait habits both at the individual level and at the level of different punishments. An individual's degree of autonomy is unique and contingent on environmental constraints. A strongly nativist view would suggest that autonomy is a state that occurs inside an individual's mind and is independent of the external environment. However, our results imply that being sensitive to the contingencies of the external environment is key to autonomy, and that autonomous agents are characterised by appropriate reaction to the restrictions that the environment places on their own actions. In this sense, autonomy can be seen a reasoned, goal-oriented response that occurs through interaction with an environmental context.

Methods

Participants

One hundred and fifty-nine participants (age range = 18–45, M = 29.5 yo, SD = 7.2) were recruited online via the Prolific website (https://www.prolific.co/). Participants received a basic payment of £3.75 for their participation in a 30 minute experiment. They earned a bonus of up to £4 based on their performance on the task. There were 95 female participants and 64 male participants. Recruitment was restricted to the United Kingdom. Seven participants were

excluded from the analysis (Suppl. Info.) and the remaining 152 participants were analysed. All procedures were approved by the Research Ethics Committee of University College London. Participants gave informed consent by checking and validating the consent form.

Experimental design

Apparatus. We used the JavaScript library jsPsych (de Leeuw, 2015) and the plugin jsPsych-psychophysics (Kuroki, 2021) to program the task and hosted the experiment on the online research platform Gorilla (https://gorilla.sc/) (Anwyl-Irvine, Massonnie, Flitton, Kirkham, & Evershed, 2020), which participants could access through their browser on their own computer. We assumed that monitor sampling rates were typically around 60 Hz, with little variation across computers (Anwyl-Irvine et al., 2020). The size and position of stimuli were scaled based on each participant's screen size which was automatically detected. The size of stimuli reported below are for a monitor size of 15.6" (view point size, width x height: 1536 x 746 pixels). A short version of our task is available to play online: https://research.sc/participant/login/dynamic/5D39406C-8AB9-4F6D-8FD7-9F995D9DCB83

Stimuli and task. Each trial started with a fixation cross, which appeared for 0.6–0.8 seconds. The images of a tree, a flock of birds and a basket containing apples then appeared (Fig. 2A). A tree (width x height: 307 x 375 pixels) was shown on the left of the screen and a flock of birds (width x height: 30 x 22 pixels each) were located on the tree. A rectangular basket of apples (width x height: 153 x 167 pixels) was presented in the bottom centre. After the fixation cross disappeared and all images appeared, the participants were given 4.5 sec to throw the food. Pressing a key initiated delivery of the food to a storage location which was located at 447 pixels forward from the start point. This delivery took 1.5 sec. We programmed the birds to attempt to intercept and catch the food. The birds on each trial were designed to intercept the food thrown within one of three intervals: 1) early throw (0–1.5 sec), 2) middle throw (1.5–3.0 sec) or 3) late throw (3.0–4.5 sec). After their departure, it took approximately 0.25 sec for each bird to reach the storage location; the birds passed through that point. The participants competed with the virtual competitor, aiming to deliver food before or after the birds reached the storage location. We counted whether one of the birds overlapped with the food when the delivery was completed (at the offset of moving). If this was the case, the food was caught, and the participant lost a trial. If not, the food was delivered without it being caught, and the participant won a trial. If no response was submitted before 4.5 sec, the food was launched

automatically, and a trial was terminated as a timeout. Finally, we provided a feedback message: “Success!”, “Fail!” or “Timeout!”, which lasted for 1.0 sec. The next trial then started with a fixation cross.

In the instructions, we emphasised the following points. First, merely reacting to the moment when a stimulus is absent – the birds resting in the tree – will not win the game because the birds can travel much faster than the food. Second, merely waiting for the birds to pass is not a solution because of the time constraint. Third, the birds’ flying interval is not the same on every trial, nor is it random. Instead, the birds can learn when the participant tends to act. Therefore, predicting when the birds will likely fly out of the tree and randomising the time to throw are important. The participants were not told an explicit strategy the competitor exploited.

Procedure. Participants first received the instructions and viewed a set of demonstrations about the task. Following some practice trials, the participants completed four blocks of the game with a 1-minute break between blocks. The baseline block lasted 2.5 minutes while the remaining blocks 1, 2 and 3 lasted 5 minutes each. The participants got as many throws of the food as they could in the 2.5 or 5 minutes. The participants could check remaining time in each block. We used time, and not trial number, to terminate each block so that participants did not respond immediately on every trial, finishing the game early. The bonus payment was determined by the percentage of throws that successfully avoid birds and was paid up to £1 for each block: if 40 out of 60 throws are successful, we paid £1 x 66.6% = £0.66 (average bonus, baseline: £0.94; block 1: £0.63; block 2: £0.59; block 3: £0.57). The success rate and the timeout rate were included in the feedback. Nevertheless, we assumed that some participants might consume time by not focusing on the game. To prevent this, we encouraged participants to sustain the proportion of timeout trials under 5%.

Competitor design

The virtual competitor design was primarily inspired by primate work (Barraclough et al., 2004; Lee et al., 2004) and by rat work (Tervo et al., 2014). We programmed the learning algorithm (i.e., birds) to seek out behavioural patterns in the participant’s choice history and to pressure participants into novel behaviour. The participants could decide the time to act between 0 sec (as soon as birds and food appeared) and 4.5 sec (until timeout). To make the competitor’s

prediction simple, we discretised the time window into three intervals, 1) early interval (0–1.5 sec), middle interval (1.5–3.0 sec) and late interval (3.0–4.5 sec). Given past behaviour, the competitor predicted which response interval a participant was likely to select. Accordingly, the two other intervals were primed for winning: if the participant threw the food during the interval predicted by the competitor, the participant lost. If the participant threw the food during one of two other intervals, the participant won. We adjusted the birds' departure times by taking their travel time (0.25 sec) and the food delivery/travel time (1.5 sec) into account: if a prediction was made on the late interval, the birds departed from the tree at the period of 4.25–5.75 sec, and they reached the delivery point during 4.5–6.0 sec to catch the food when it was delivered.

We designed four distinct competitors (Fig. 2B). First, in the baseline block, Competitor 0 punished participants for being impatient. In this block, the birds blocked the early throw on every trial. Thus, the stimulus-absence behaviour corresponded with waiting until the middle interval. Competitor 0 measured the volitional control to resist immediacy or external triggers (Haggard, 2019). Second, in block 1, Competitor 1 predicted *standard choice habits* (choice preferences) – which interval the participant is going to select –. On each trial, a history of the participant's past ten choices was used to estimate the probabilities of selecting the early, middle and late interval. The choice probabilities were then used to generate the competitor's prediction on the upcoming choice. For instance, if the participant chose the early interval seven times, the middle interval twice, and the late interval once, the competitor penalised the early interval 70% of the time, the middle 20% of the time and the late 10% of the time. Thus, Competitor 1 required participants to balance their general choice frequencies.

In block 2, Competitor 2 sought out *transition habits* (sequential patterns) – which interval the participant is going to select after the participant made a particular response –. A history of the past 60 trials was used to estimate the conditional probabilities of selecting three intervals given the previous reaction time. The estimated probabilities were conditioned on the last reaction time ± 0.5 sec. Suppose a participant took 2.5 sec to act in the previous trial. Competitor 2 might discover that, in the past, the participant chose the early interval twice, the middle interval twice, and the late interval six times after the participant had acted in 2.0-3.0 sec. In this case, Competitor 2 penalised the late interval 60% of the time. We assumed that using the previous response time (i.e., continuous variable) is more powerful to predict the next response than using the previous response interval (i.e., categorical variable). Competitor 2 pressured participants in avoiding habitual transition patterns. Finally, in block 3, Competitor 3 punished *reinforcement habits* (outcome dependence) – which interval the participant is going

to select after the participant made a particular response and won a trial or lost a trial –. Competitor 3 used the same search algorithm as Competitor 2 with the exception that they added the last outcome to look for conditional response intervals. Competitor 3 required participants to act independently from the previous outcome.

Data analysis

Because the birds intercepted one of the three response intervals, we mainly analysed the data that was discretised into 1) the early response: responding in 0–1.5 sec, 2) the middle response: responding in 1.5–3.0 sec, 3) the late response: responding in 3.0–4.5 sec (including timeout).

Quantifying decision bias scores. Statistical distance is a standardised way of measuring the extent to which the observed probability distribution is different from the target probability distribution. We calculated the Kullback-Leibler divergence to quantify the extent to which the participant's choice probability distribution is different from the choice probability distribution that a habit-free agent would exhibit, a proxy of three habit families. See Figure 3.

1) Choice bias. Competitor 1 punished standard choice habits in selecting one interval more often than the other two. The probabilities of choosing the early, middle and late interval for a habit-free agent would be 0.33, respectively. We computed the choice probabilities $P(c)$ given a history of intervals each participant chose in each block. The K-L divergence is then

$$D_{KL\ choice\ bias} = \sum_{c\ \in\ E,M,L} P(c)\log_2\left(\frac{P(c)}{0.33}\right) \tag{1}$$

2) Sequential bias. Competitor 2 punished transition habits on the top of choice habits. Similar to computing the choice probabilities, we computed the conditional probabilities of choosing the early, middle and late interval given the interval chosen on the previous trial $P(c|c_{-1})$. We measured the K-L divergence of these participant's conditional probabilities from the participant's choice probabilities. The K-L divergence for each previous interval c_{-1} is computed as

$$D_{KL\ c_{-1}} = \sum_{c\ \in\ E,M,L} P(c|c_{-1})\log_2\left(\frac{P(c|c_{-1})}{P(c)}\right) \tag{2}$$

The total K-L divergence as a weighted sum is then

$$D_{KL\ sequential\ bias} = \sum_{c_{-1} \in E,M,L} P(c_{-1}) \cdot D_{KL\ c_{-1}} \tag{3}$$

Since we conditioned the K-L divergence on the previous interval chosen, we took the proportion of observing that situation into account, and we weighed each divergence by this prior probability. The target probabilities (i.e., habit-free agent) were set to be the participant's own choice probabilities, rather than purely stochastic choices 0.33. Therefore, $P(c|c_{-1})$ becomes equivalent to $P(c)$ and the K-L divergence becomes zero, as long as the participant selects three intervals independently from the previous choice (even if the participant favours one interval). This way, we quantified the deviation of patterns associated with the previous choice from sequential patterns logically expected from the participant's own choice probabilities. Competitor 2 specifically detected and punished this conditional dependence.

3) Reinforcement bias. Competitor 3 punished reinforcement habits on the top of choice habits and transition habits. Similar to computing the choice probabilities, we computed the conditional probabilities of choosing the early, middle and late interval given the interval chosen and the outcome obtained on the previous trial $P(c|c_{-1}, o_{-1})$. We measured the K-L divergence of these participant's conditional probabilities from the participant's conditional probabilities given the previous interval solely. The K-L divergence for each previous interval c_{-1} and each previous outcome o_{-1} is computed as

$$D_{KL\ c_{-1},o_{-1}} = \sum_{c \in E,M,L} P(c|c_{-1}, o_{-1}) \log_2 \left(\frac{P(c|c_{-1}, o_{-1})}{P(c|c_{-1})} \right) \tag{4}$$

The total K-L divergence as a weighted sum is then

$$D_{KL\ reinforcement} = \sum_{c_{-1} \in E,M,L} \sum_{o_{-1} \in \substack{success \\ fail}} P(c_{-1}, o_{-1}) \cdot D_{KL\ c_{-1},o_{-1}} \tag{5}$$

Since we conditioned the K-L divergence on the previous interval chosen and the previous outcome obtained, we took the proportion of observing that situation into account, and we weighed each divergence by this joint prior probability. The target probabilities (i.e., habit-free agent) were set to be the participant's own conditional probabilities given the previous interval solely. Therefore, $P(c|c_{-1}, o_{-1})$ becomes equivalent to $P(c|c_{-1})$ and the K-L divergence

becomes zero, as long as the participant selects three intervals independently from the previous outcome (even if the participant's choice depends on the previous interval). This way, we quantified the deviation of patterns associated with both the previous choice and the previous outcome from patterns logically expected from the conditional dependence on the previous choice solely. Competitor 3 specifically detected and punished this outcome dependence. We also quantified the positive reinforcement bias and the negative reinforcement bias, separately (Suppl. Fig. 1). We computed the K-L divergence of the conditional probabilities given the previous interval and the previous win only or the previous loss only from purely stochastic choices 0.33. Here the statistical distance can be argued as the distance between the participant's post-win behaviour or post-loss behaviour and the habit-free agent who is purely random. These measures were used to generate Figure 3.

Statistical analysis. We tested the performance difference by Wilcoxon signed rank test. The alpha level of 0.05 was corrected by the number of tests we performed in each class of test (Bonferroni correction).

Computational models

Reinforcement learning. We tested a reinforcement learning (RL) model in which an action value is updated via a Rescorla-Wagner rule (Sutton & Barto, 2018). On each trial, an RL agent selects an action from the early, middle or late interval $a \in E, M, L$. For an action a selected on a trial t, the value of action a is updated by a prediction error δ:

$$\delta_t = r_t - V_t(a) \tag{6}$$

where r_t is the actual reward received (1 for successfully avoiding birds and 0 for failure) and $V_t(a)$ is the current expected reward for that action. The reward prediction error δ_t is then used to update the value of the selected action, weighted by the learning rate α

$$V_{t+1}(a) = V_t(a) + \alpha\delta_t \tag{7}$$

Belief learning. In a belief learning (BL) model, a BL agent infers the opponent's state of mind – what option the opponent is going to select – and decides on the action that maximises the expected reward (C. F. Camerer, 2003; Hampton et al., 2008; Zhu et al., 2012). Actions $a' \in E, M, L$ are available for the competitor to choose. For each action $a \in E, M, L$ on trial t, the value of that action is updated by a prediction error

$$\delta_t = r_t - V_t(a) \tag{8}$$

where $r_t = -1$ if a' is same as a (i.e., the competitor selects the same response interval as the participant) while $r_t = 0$ if a' is different from a (i.e., the competitor selects a different response interval). This prediction error is the difference between the current expected value and the negative reward derived from the competitor's current choice. Therefore, the updated expected value of action reflects the likelihood of the competitor's choice: the larger the value, the less likely the competitor choose. The same rule with the RL model was used to update the value of action a, with the exception that the values of all three intervals were updated on every trial. Suppose that the birds repeatedly selected the early interval to intercept the food. A direct observation of the birds' flight at the early interval decreases the value of the early interval. At the same time, this observation implies that the birds did not fly at the middle nor the late interval. This increases the values of these intervals.

Hybrid learning. We modelled the hybrid learning rule (aka. experience weighed attraction) as a combination of reinforcement learning and belief learning (C. Camerer & Ho, 1999; Hampton et al., 2008; Zhu et al., 2012). After updating the value of the action in each learning process, the hybrid rule combines the values of the action such that

$$V_{t+1}(a) = (1 - w) \cdot V_{t+1}^{RL}(a) + w \cdot V_{t+1}^{BL}(a) \tag{9}$$

where one additional free parameter w is used to weigh the relative contribution placed on belief learning over reinforcement learning.

For all models, the action values were converted into the choice probabilities using the soft-max function to simulate action selection,

$$P_t(a) = \frac{e^{\beta \cdot (V_t(a) + b(a))}}{\sum_{a \in E,M,L} e^{\beta \cdot (V_t(a) + b(a))}} \tag{10}$$

where $P_t(a)$ is the probability of choosing the interval a. The inverse temperature parameter β scales the relative difference between the choice probabilities, which scales decision uncertainty. We added the decision preference term b with an exponential temporal discounting (Story et al., 2014):

$$b(a) = e^{-\rho \cdot T(a)} \tag{11}$$

where T is the time corresponding to the chosen interval (T = 0, 1.5 or 3.0 sec for the early, middle or late interval, respectively). The parameter ρ scales the relative preference to earlier intervals, which captures an individual's temporal discounting or impatience to wait.

For each model, we fitted the model decision probabilities to the participant's choice interval data by minimizing the negative log-likelihood of the observed choices using Bayesian adaptive direct search (BADS) (Acerbi & Ma, 2017). Free parameters were optimised individually for each participant and separately for each block with the following boundaries: $\alpha \in [0,1]$, $\beta \in [0,20]$, $\rho \in [0,0.2]$, $w \in [0,1]$. The parameter w was fixed to 0 for the reinforcement learning model and fixed to 1 for the belief learning model. For the stochastic selection model, we fixed the parameters α and w to 0 so that this model could only capture the participants' decision uncertainty and their choice preference. This model produced constant model decision probabilities across all trials. In this nested structure, a better model index relative to the stochastic model would indicate the presence of a feedback process.

To verify that we had found the global minimum, we repeated the search process with different starting points. For model comparison, we applied AICc—Akaike information criterion with a correction for finite sample size—to each participant and model as the information criterion for goodness-of-fit (Burnham & Anderson, 1998; Hurvich & Tsai, 1989). The summed AICc across participants was reported in Figure 5B. The parameters best fitted by the hybrid learning rule are illustrated in Supplementary Figure 5 and the correlation matrix among the parameters is shown in Supplementary Figure 6.

Simulated play

During simulated play, an RL agent and a BL agent played against the prediction algorithm used by each class of competitor. The competitor's prediction was made using a history of choices a simulated agent made rather than using real data. For each simulated play of 60 trials (which is approximately equal to the number of trials in the real game), the success rate was computed. We simulated each agent's behaviour given a set of model parameters. Each set of parameters was determined by an extensive grid search in the parameters' space. The simulation play was repeated 3,000 times for each parameter set.

Latent change score model

Latent change score (LCS) models are the statistical framework that captures the process underlying the change in the variables of interest at two measurement occasions (Carpenter et

al., 2019; Kievit et al., 2018; Kievit et al., 2017; McArdle, 2009). LCS models conceptualise the score of variable X at time point $T2$ as

$$X_{T2} = \beta X_{T1} + \Delta X \tag{12}$$

where the score X_{T2} is a function of the score X_{T1} weighted by an auto-regressive (i.e., self-feedback) parameter β and some residual ΔX. By fixing the regression weight of X_{T2} on X_{T1} to 1, the change score ΔX can be simply rewritten as

$$\Delta X = X_{T2} - X_{T1} \tag{13}$$

In structural equation modelling, the change score can be defined as a latent factor by fixing a factor loading on the score X_{T2} to 1. By this mathematical manipulation, the change between $T1$ and $T2$ is modelled as a latent factor. Bivariate LCS models predict the change score by an auto-regressive parameter β and a cross-coupling parameter α:

$$\Delta X = \beta X_{T1} + \alpha Y_{T1} \tag{14}$$

$$\Delta Y = \beta Y_{T1} + \alpha X_{T1} \tag{15}$$

In this equation, the auto-regressive parameter β captures the degree to which the initial score X_{T1} predicts (or is proportional to) the change score ΔX. The cross-coupling parameter α captures the degree to which the initial score in another domain Y_{T1} predicts (or is proportional to) the change score ΔX. Above these effects, the bivariate LCS models quantifies the variance-covariance structure in the change factor, which estimates the correlated change: the degree to which the change score in one domain ΔX covaries with the change score in another domain ΔY after taking auto-regressive and cross-coupling effects into account. See Kievit et al., 2018 & McArdle, 2009 for reviews and Kievit et al., 2017 & Carpenter et al., 2019 for its applications.

We examined the inter-relationships between adaptive autonomy and a shift in learning strategies. There were three decision bias scores (choice bias, sequential bias and reinforcement bias) and four hybrid model parameters (learning rate, decision uncertainty, decision preference and relative weight of belief learning). Considering potential correlations among seven variables, we controlled for the influences of the other five variables on bivariate changes. In Figure 6, we used the choice bias score and the belief learning weight. We first regressed all other five variables against these two scores and retaining only the residuals from the regression. We then used the residual scores in the choice bias and the residual scores in

the belief learning weight at two measurement points (baseline and block 1) to fit the bivariate LCS model. Therefore, any parameter estimates in the path model were considered a mere relationship between two variables included in the model. Because we fitted the bivariate LCS model to residuals, parameter estimates for the initial intercepts (i.e., mean initial scores) and change intercepts (i.e., mean change scores) were fixed to zero.

Models were estimated in the lavaan package for R (version 0.6-11) (Rosseel, 2012). We used maximum likelihood estimation with robust (Huber-White) standard errors and a scaled test statistic. We evaluated overall model fit using the root-mean-square error of approximation (RMSEA; acceptable fit: < 0.08; good fit < 0.05), the comparative fit index (CFI; acceptable fit: 0.95 to 0.97; good fit > 0.97) and the standardized root-mean-square residual (SRMR; acceptable fit: 0.05 to 0.10, good fit: < 0.05) (Schermelleh-Engel, Moosbrugger, & Müller, 2003).

Competing interests

The authors declare no competing interests.

Author's contributions

Conceptualization, KO and PH; data collection, KO; investigation, KO, LC, and PH; formal analysis, KO; writing – original draft, KO; writing – review & editing, KO, LC and PH; supervision, LC and PH; funding acquisition, PH.

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Data and code availability

The data frame for a representative participant is available in the supplementary data . The data frames for all the participants and the codes used to generate the figures will be posted.

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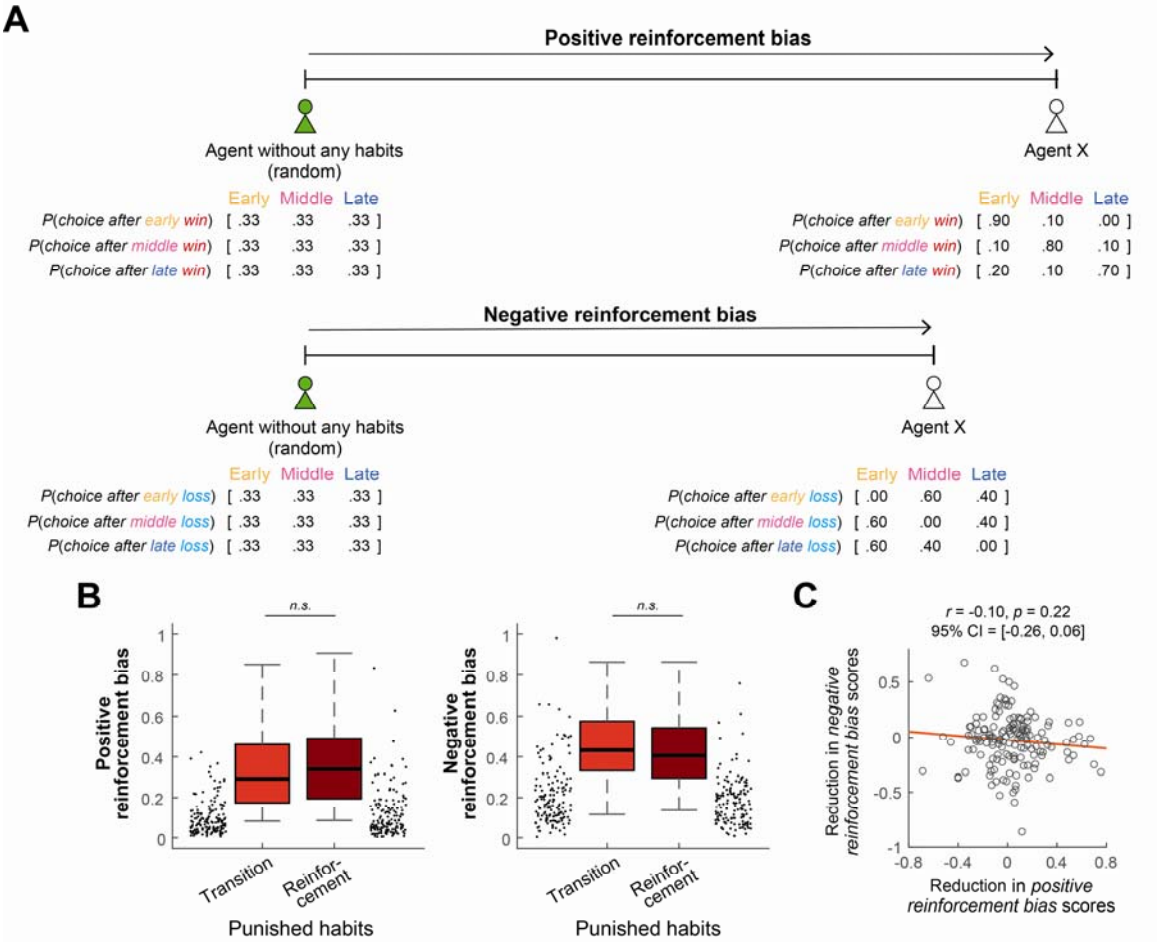
Supplementary Information

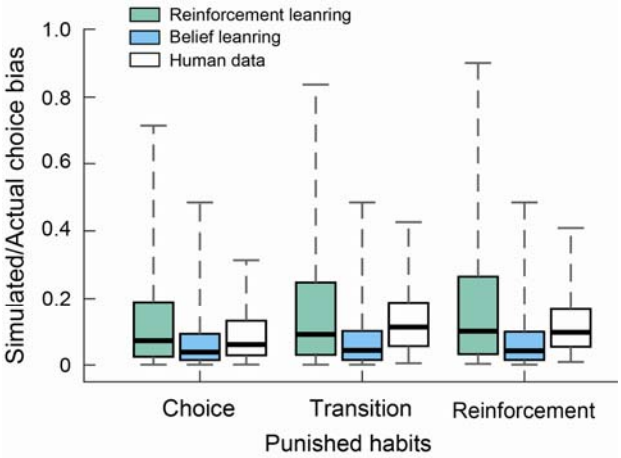
Exclusion criterion

We encouraged participants to sustain timeout trials under 5%. We checked the histogram of the timeout rates. Seven participants displayed a timeout above 13 %. This was considerably high compared with the other participants (0–5%: 119 participants; 5–8%: 27 participants; 8–11%: 6 participants; 13–20%: 5 participants; >20%: 2 participants). These participants might not be able to follow the instructions or might not be able to keep their attention on the task, thereby removed from the analysis.



Supplementary Figure 1. Positive and negative reinforcement bias

A. The reinforcement bias vector in Figure 3C is broken down for positive reinforcement bias and negative reinforcement bias. The statistical distance between an agent without any habits (purely random agent) and participants is computed. **B.** Planned comparisons shows the degree adaptive autonomy (bias reduction) when reinforcement habits are punished. **C.** There is no correlation between the bias reduction in the positive reinforcement bias and the bias reduction in the negative reinforcement bias. The ability to adapt away from a win-stay type behaviour is not associated with the ability to adapt away from a lose-shift type behaviour across participants.



Supplementary Figure 2. Simulated play

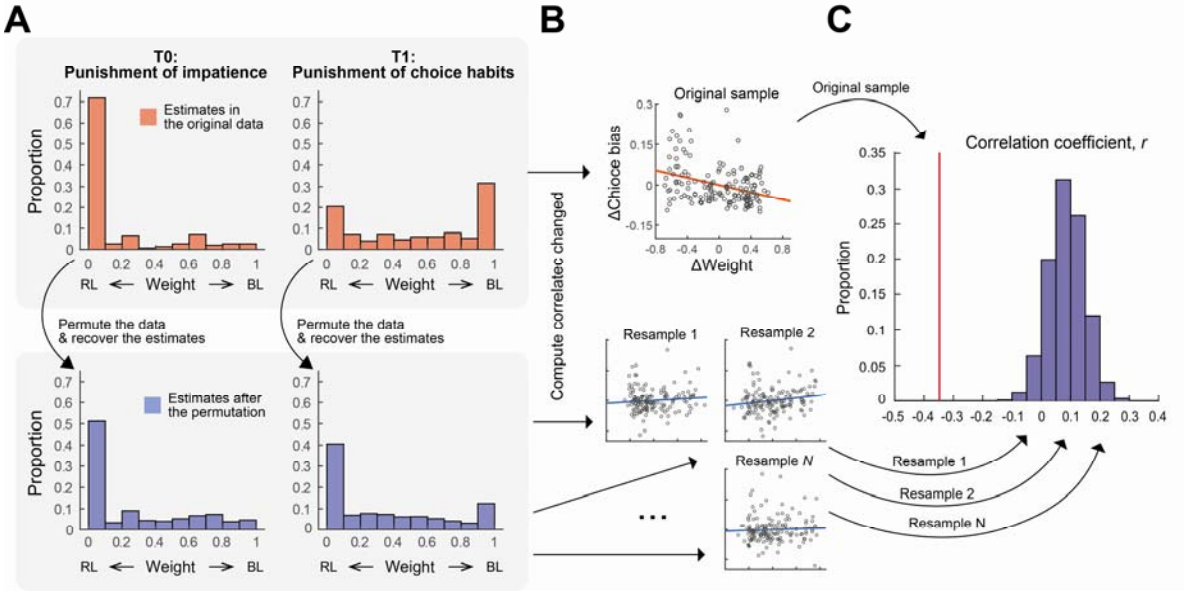
Real choice bias (white bars) in the actual experiment and fictive choice bias (green or blue bars) in simulated play. We simulated the choice bias from agents using the reinforcement learning (green) and agents using the belief learning (blue) (see *Simulated play*). Belief learning produced a smaller choice bias in all punishment schemes.

LCS models

We performed a follow up analysis. First, we randomised the competitor's action in the data we fitted the hybrid rule, in order to validate whether the competitor's past action affected the participant's next action. This permutation operation indeed disrupted the estimates of the BL weight (Suppl. Fig. 3A). In the permutation sample, the bias reduction in the choice habit was not negatively correlated with a shift towards belief learning (Suppl. Fig. 3B&C). Therefore, a correlated change shown in Figure 6 cannot be simply explained by a mere artefact in fitting the data.

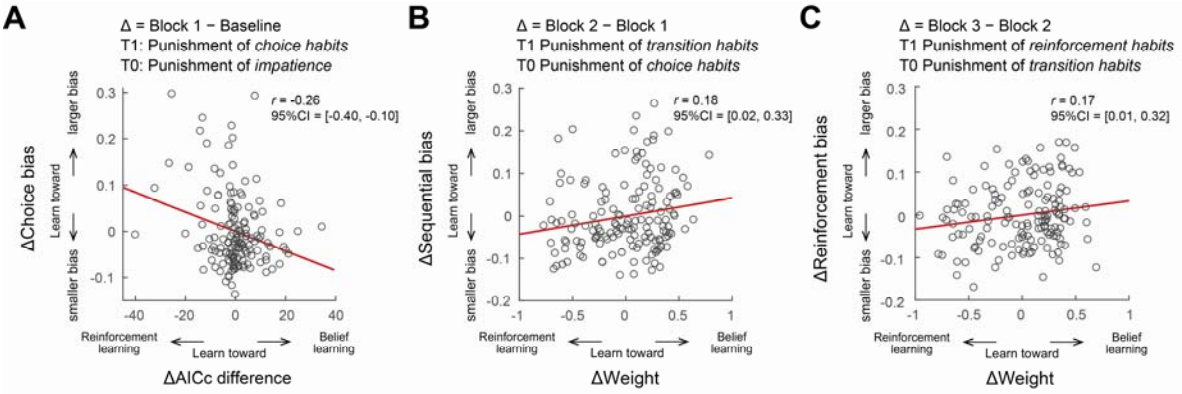
Second, we used the choice bias score and the difference in AICcs between the RL only model and BL only model, instead of the BL weight. We used these observed variables measured at the punishment of impatience in the baseline and the punishment of standard choice habits in block 1. We found that the bias reduction co-occurred with a shift towards belief learning (Suppl. Fig. 4A). This result validates that the correlated change in Figure 6 is unlikely to be due to the boundaries of the parameter estimates under the hybrid learning rule.

Lastly, we checked the possibility that the bias reduction in the sequential bias or the reinforcement bias co-occurs a shift in learning strategies. We did not find that the reduction in the sequential bias co-occurs with a shift towards belief learning, when the transition habits were punished in block 2 (Suppl. Fig. 4B). Nor did we find that the reduction in the reinforcement bias co-occurs with a shift towards belief learning, when the reinforcement habits were punished in block 3 (Suppl. Fig. 4C). These follow-up analyses confirm that our finding is not simply explained by an artefact in estimating a decision bias score and the BL weight in the same choice data set.



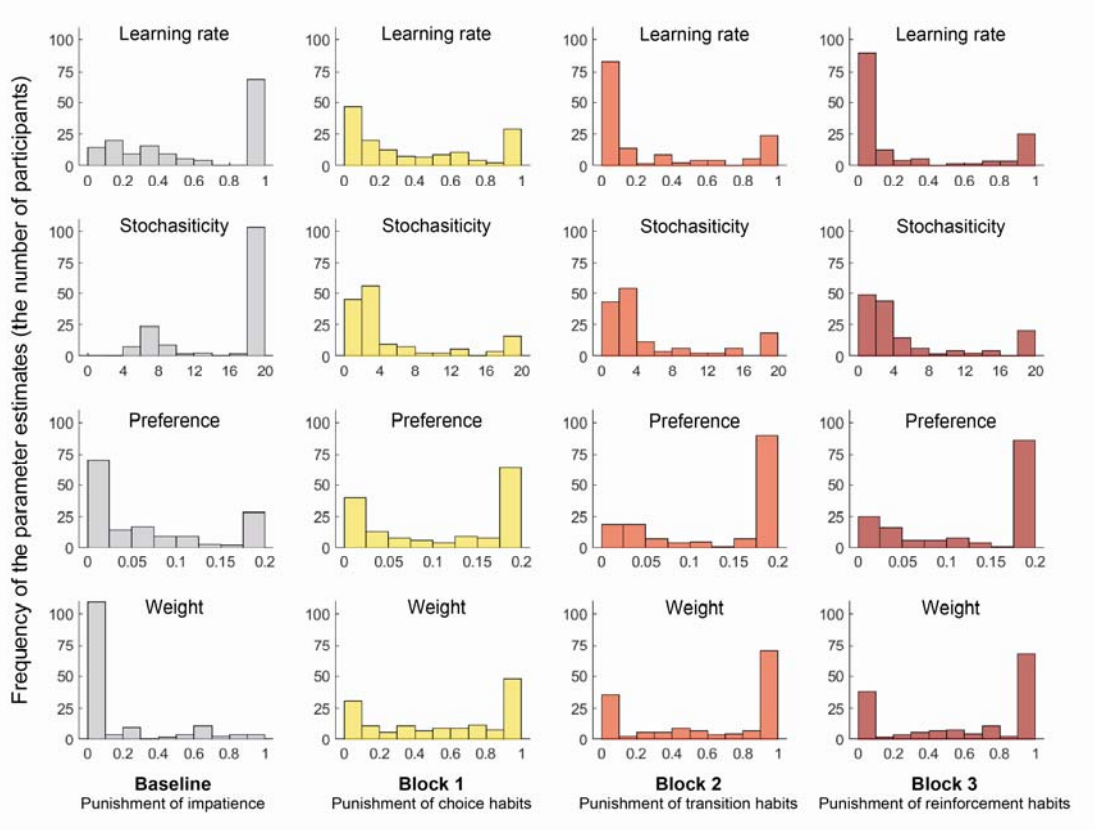
Supplementary Figure 3. Permutation operation

A simulated experiment using permutation operation. **A**. In upper panels (red bars), we show the proportion of the belief learning weight estimated under the hybrid learning rule. A weight increases between blocks. In this model fitting, a trial sequence of rewards (success or failure) and that of birds' flight interval (early, middle or late interval) were used to simulate the participant's choice interval (see *Computational models*). If the competitor's past action was important for participants to decide the next their action, permutating the competitor's action would disrupt the estimates of the BL weight. To validate this, we swapped the birds' flight interval. If the participant's choice interval was late and the competitor's interval was early on a particular trial, we swapped the birds' interval to the middle one. This operation does not change an outcome of the action but does randomise the competitor's action. In each iteration, we permutated the birds' interval 75% of the time and estimated the BL weight under the hybrid rule. We repeated this procedure 100 times for each participant and for each block. The parameter estimates recovered from the permutation sample are shown in lower panels (blue bars). The BL weights are right-skewed and differ from the original estimates. **B**. In the upper panel, we replot Figure 6B. The correlation coefficient in this original sample (r = -0.347) is plotted as a vertical red line in the panel C. In lower panels, we plot the correlated change estimated from the permutation sample. We show three representative plots. The proportion of these correlation coefficients is shown as a blue histogram in the panel **C**. The 95% confidence interval ranged from -0.03 to 0.20. This analysis validates the robustness of estimating the belief learning weight and the robustness of estimating the coefficient in the correlated change.



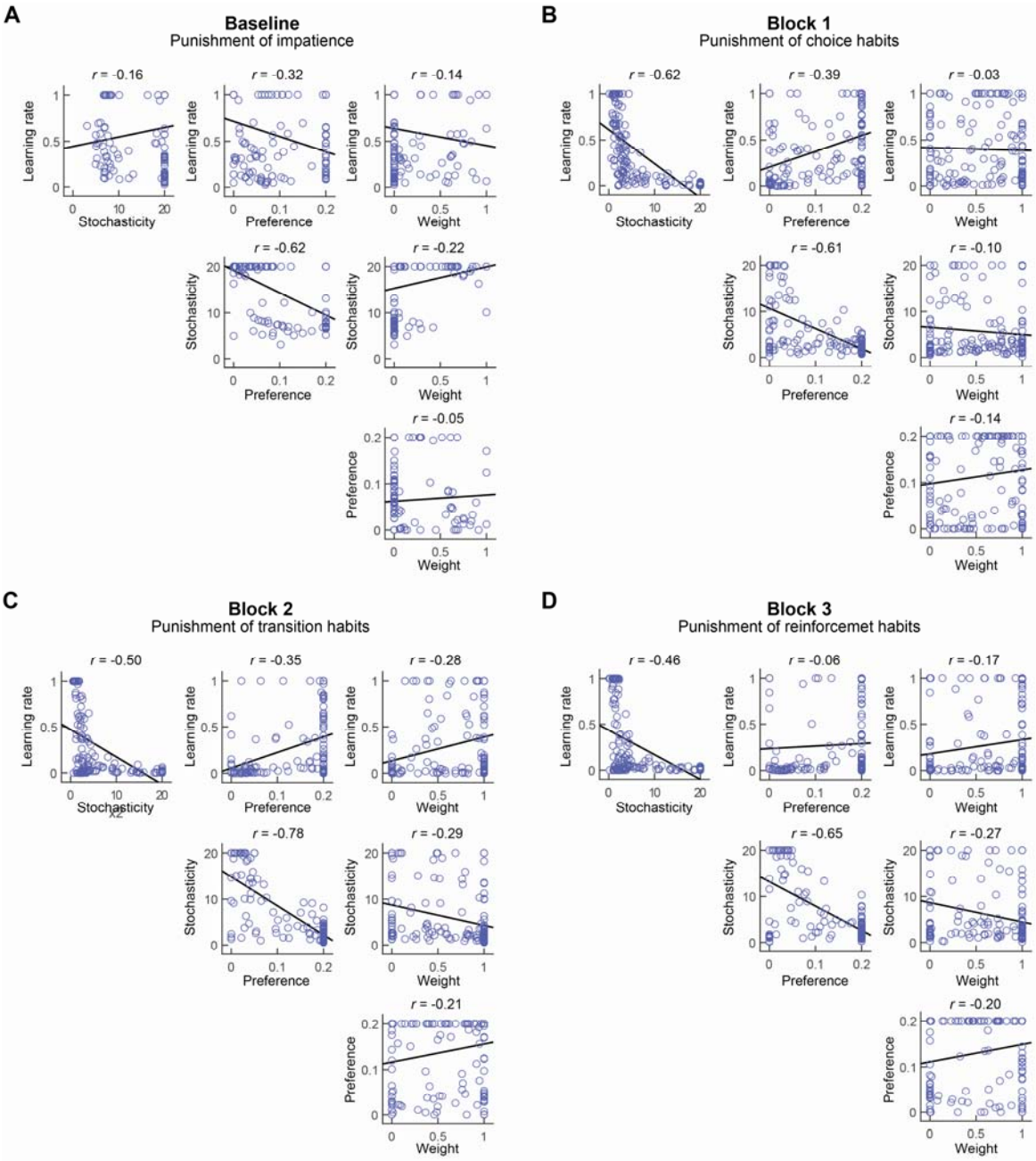
Supplementary Figure 4. A variant of LCS models

We made variants of LCS model by fitting the model to data set in panels A-C. Estimated parameters in the path model were omitted for the sake of space. We only visualised the scatter plot of correlated change as we did in Figure 6B. **A**. A latent change in AICc difference between the RL only model and BL only model, the change from the baseline to block 1 is modelled and plotted against a latent change in choice bias scores. We found a negative correlated change between these two factors (standardised coefficient = -0.256, 95% CI = [-0.398 -0.101]). **B**. A latent change in the weight under the hybrid learning rule, the change from block 1 to block 2 is modelled and plotted against a latent change in sequential bias scores. We did not find a negative correlated change (standardised coefficient = 0.180, 95% CI = [0.021 0.330]). **C**. A latent change in the weight under the hybrid learning rule, the change from block 2 to block 3 is modelled and plotted against a latent change in reinforcement bias scores. We did not find a negative correlated change (standardised coefficient = 0.168, 95% CI = [0.009 0.319]).



Supplementary Figure 5. Model parameters

We show the parameter estimates best-fitted by the hybrid learning rule. The number of participants in each bin of the parameter values is represented by a histogram. The columns indicate blocks from the baseline to block 3. The rows indicate four free parameters in the hybrid model.



Supplementary Figure 6. A correlation matrix among model parameters

We plot a correlation matrix among free parameters across participants. We note that there is no strong correlation between the weight parameter and the other three parameters.