The resource elasticity of control

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Abstract

Action is only warranted when it affords control over the environment. The controllability of an environment, however, may depend on the effort, time, and money that we are willing and able to invest. In such environments, controllability is not fixed. Rather, it is *elastic* to invested resources. Here, we investigate whether and how people infer this elasticity of control, hypothesizing that individual differences in elasticity inference are responsible for misallocation of resources that may lead to psychopathology. To test these hypotheses, we developed a novel treasure hunt game where participants encountered environments with varying degrees of controllability and elasticity. Across two pre-registered studies (N=514), we demonstrate that people infer elasticity and adapt their resource allocation accordingly. We present a computational model that explains how people make this inference, and identify individual elasticity biases which lead to suboptimal resource management. Importantly, we show that overestimation of elasticity is associated with elevated psychopathology involving an impaired sense of control. These findings establish the elasticity of control as a distinct cognitive construct guiding adaptive behavior, and a computational marker for control-related psychopathology.

Introduction

Taking action requires us to invest resources, such as time, money, and effort, and is thus only sensible if our actions have the potential to change the environment to our advantage. Accurate estimation of this potential – that is, of the environment's controllability[1-4] – enables us to make informed decisions as to whether to engage in action[5-7]. Misestimations of controllability thus result in maladaptive behavior, and contribute to mental health disorders such as depression, anxiety, and obsessive-compulsive disorder[8-12].

The degree of control we possess over our environment, however, may itself depend on the resources we are willing and able to invest. For example, the control a biker has over their commute time depends on the effort they are willing and able to invest in pedaling. Likewise, the control a diner in a restaurant has over their meal may depend on how much money they have to spend. In such situations, controllability is not fixed but rather *elastic* to invested resources (i.e., in the same sense that supply and demand may be elastic to changing prices[13]). Importantly, high controllability need not imply high or low elasticity. Controllability can be high, yet inelastic to invested resources – for example, when choosing among equally priced bus routes to work (Figure 1).

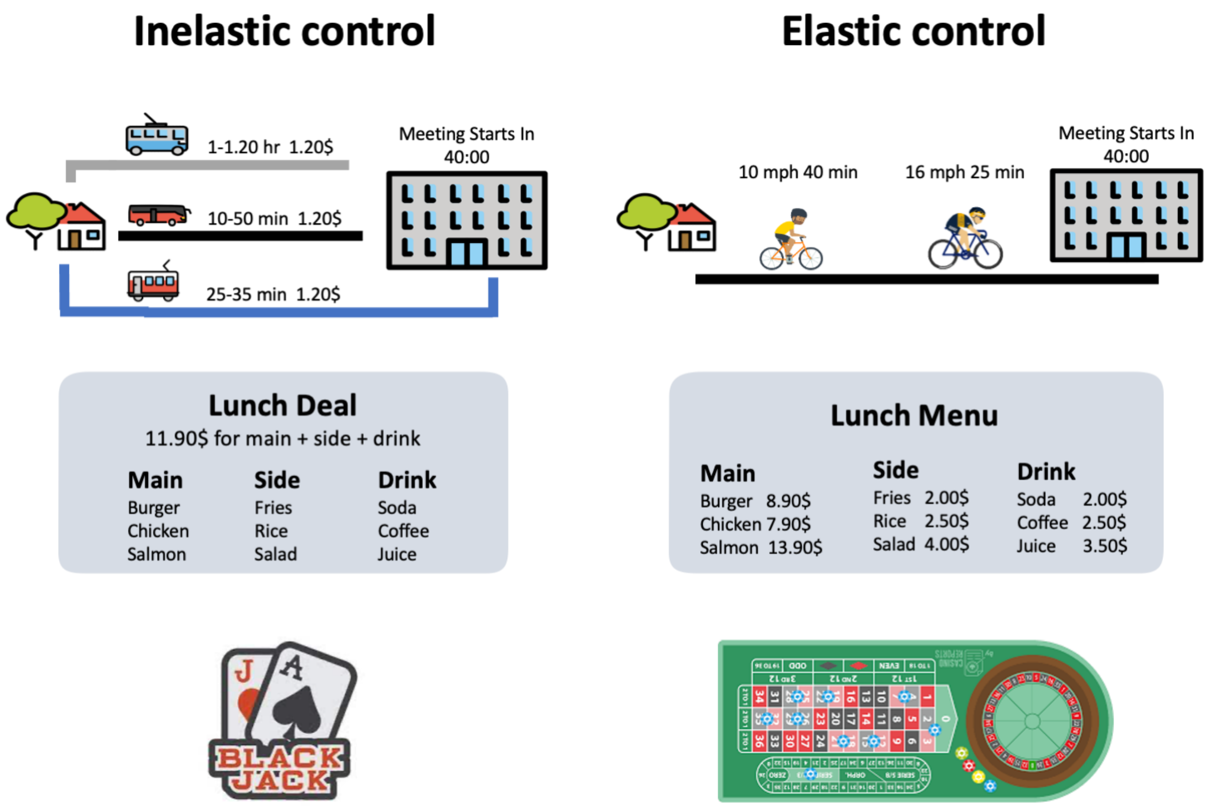


Figure 1. Examples of inelastic vs elastic control: Top – Choosing one of three equally priced public transport routes provides inelastic control over commute time, whereas the control of biker over commute time is elastic to the effort they invest in pedaling. **Middle –** A diner has either inelastic or elastic control over their lunch depending on whether the restaurant offers a fixed-price lunch deal, or a standard menu where dishes vary in price. **Bottom –** the probability of winning in blackjack is inelastic to money, as it only depends on whether one hits or stands, whereas when playing roulette, one can increase the probability of winning by investing more coins to cover more possible outcomes. Importantly, most real-world scenarios lie on a spectrum between these illustrative extremes, such that controllability is partly elastic and partly inelastic.

Knowing the elasticity of control is necessary for deciding whether and how to act. Failing to achieve one's goal, for example, should only lead one to invest more resources in an elastic environment. Critically, in many real-life domains (e.g., studying for an exam), we must use our experiences to infer the degree to which we can improve our outcomes by investing more resources[16-20]. Failure to do so is bound to result in maladaptive behavior, and may thus contribute to mental health disorders. Depressed patients, for instance, are less willing to expend their resources to obtain control[21,26-27], which could result from an underestimation of elasticity. Conversely, the repetitive actions that characterize obsessive compulsive disorder patients[24] could indicate that such patients overestimate elasticity, believing that the additional efforts they invest will yield progressively better outcomes. Ultimately, not having a good grasp of how one's additional efforts influence outcomes is bound to undermine one's sense of agency [14-15].

Thus, here we ask whether and how people infer the elasticity of control over their environment. We hypothesize that individual differences in elasticity inference lead to a mismanagement of one's resources when attempting to control the environment, and are thus associated with psychopathologies involving a distorted sense of control[21-23].

Experimental paradigms to date have tested elasticity and controllability as coupled, such that controllability was either low or elastic[16-20]. Elasticity, however, must be dissociated from controllability to accurately diagnose mismanagement of resources. A given individual, for instance, may tend to overinvest resources because they overestimate controllability – for example, exercising due to a misguided belief that this can make one taller. Alternatively, they may do so because they overestimate the elasticity of control – for example, a chess expert practicing unnecessarily hard to win against a novice. In this latter example, the amount of effort the expert chooses to invest would not change their level of control over the match's outcome. Diagnosing the former source of mismanagement of resources requires a manipulation of controllability, whereas diagnosing the latter requires manipulating the elasticity of control.

Therefore, here we dissociate elastic and inelastic controllability using a novel treasure-hunt game where participants encountered three distinct environments: The first offered *high elastic controllability*, where a high level of control can only be attained by investing extra resources. The second offered *high inelastic controllability*, where control is attainable with any level of resource investment. And the third offered *low controllability*, where control was not attainable despite any level of resource investment. In each environment, participants were allowed to invest various amounts of resources to pursue reward or to altogether forgo pursuing reward. Examining how participants adapted their resource investment to observed outcomes enabled us to determine whether and how participants inferred each environment's controllability and its elasticity.

Across two pre-registered studies (N = 514), we establish that people do indeed infer the elasticity of control. We present a computational model that explains how people make this inference, and identify individual biases in its implementation. We thus show that elasticity overestimation leads to an overinvestment of resources and is associated with elevated psychopathology involving an impaired sense of control. These findings establish the elasticity of control as a distinct inference guiding adaptive behavior, and a computational marker of control-related psychopathology.

Results

We had online participants (first study $= 264$, replication study $= 250$, ages =18-45, Mean 33 ± .6) play a novel treasure-hunt game set across multiple planets. On each trip (trial), participants attempted to travel from an initial location ('desert' or 'fountain') to a treasure (worth 150 coins), located at either the house or the mountain (Figure 2A). Participants could exercise control by boarding the train to reach the house, or the plane to reach the mountain (right-side Figure 2B). The present planet's controllability determined the probability that participants would succeed in boarding the vehicle they selected. In high-controllability planets, participants consistently boarded their preferred vehicle, enabling them to reliably reach their destination. Conversely, in low-controllability planets, participants frequently failed to board and were thus forced to walk to the nearest location, where the treasure was located in only 20% of trials.

To investigate elasticity learning, we allowed participants to invest different amounts of resources in attempting to board their preferred vehicle. Specifically, participants could purchase one (40 coins), two (60 coins), or three tickets (80 coins) or otherwise walk for free to the nearest location. We defined inelastic controllability as the probability that even one ticket would lead to successfully boarding the vehicle, and elastic controllability as the degree to which two extra tickets would increase that probability. Participants were informed that a single ticket allowed them to board the vehicle only if it stopped for them at the station, but that they may be able to increase their chances of boarding by purchasing extra tickets. Each additional ticket awarded participants an attempt to jump onto the moving vehicle after it had already left the main platform (Figure 2C). At the end of each trip, participants were shown where they arrived at, enabling them to infer whether they successfully boarded their vehicle.

To dissociate elasticity from inelastic controllability, each participant visited three randomly sampled planets. In the first planet, controllability was high and inelastic, meaning that no matter how many tickets you purchased, you had a good chance of making your ride (sampled from green area in Figure 2D). In the second planet, controllability was high and elastic, meaning that you needed to purchase two extra tickets to have a good chance of making your ride (Figure 2D, blue). And in the third planet, controllability was low, meaning that no matter how many tickets you purchased, you did not have a good chance of making your ride (Figure 2D, red).

Importantly, the order of these planets was randomized, and participants did not know in advance which planet they were visiting. Thus, they could only infer a planet's controllability and elasticity from the outcomes of their actions. Moreover, to increase sensitivity to individual biases, we had all participants visit a fourth planet where purchasing any number of tickets (0, 1, 2, 3) was equally optimal (Figure 2D, black circle). We also homogenized participants' initial learning experiences by giving them three free tickets for the first five visits to every planet. As we shall see below, this latter measure also helped dissociate between different models of how participants solved the task.

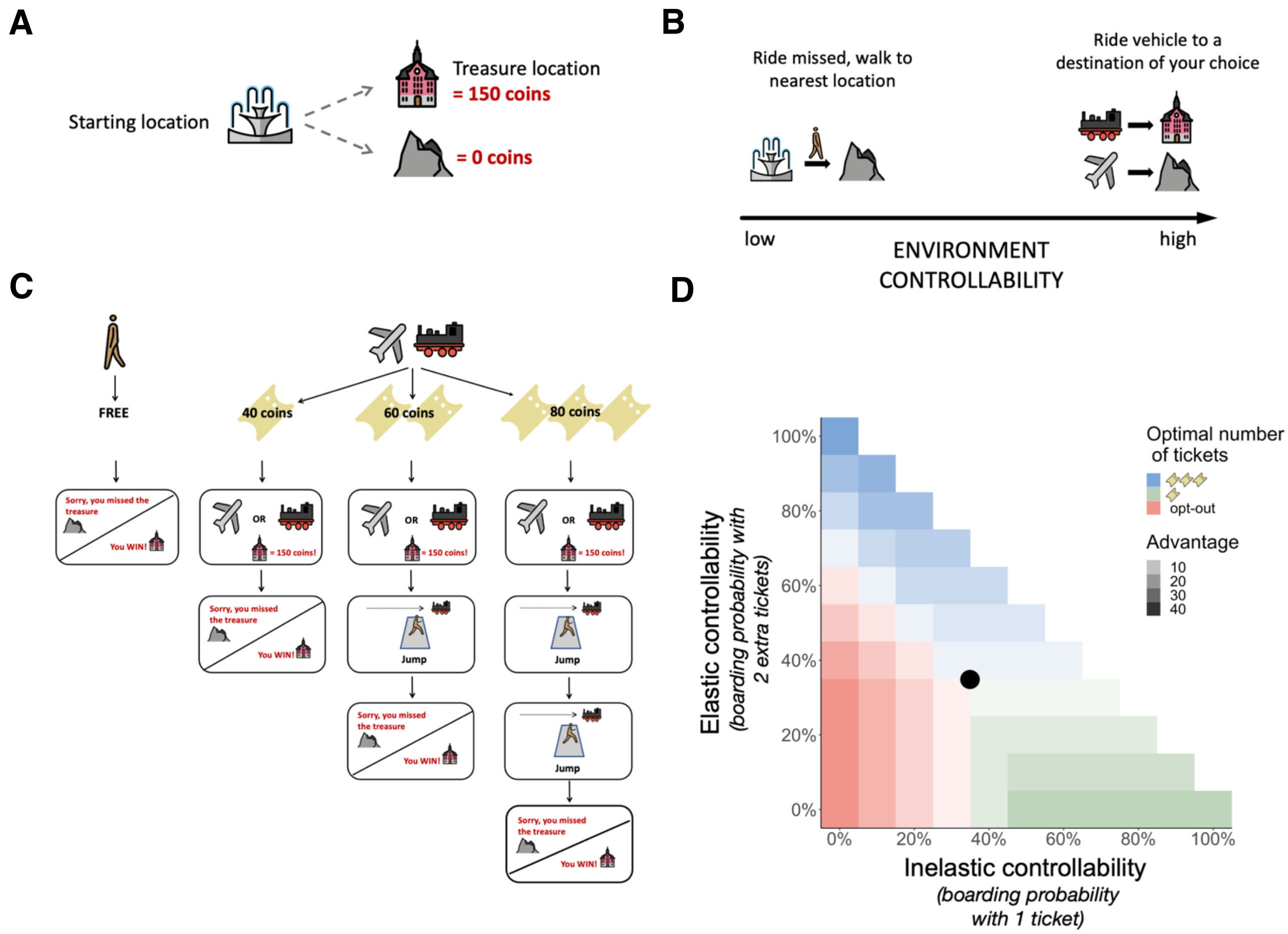


Figure 2. Experimental design: (A) **Goal.** On each trip to a planet, participants' goal was to reach a treasure located either at the house or the mountain (B) **Transition rules.** Participants could exercise control by boarding either the plane or the train to a destination of their choice, whereas missing the ride sent the participant walking to the nearest location (which happened to be the treasure location in only 20% of trials). (C) **Trip structure.** At the beginning of each trip, participants selected whether to purchase 1, 2, or 3 tickets to attempt to board their vehicle of choice, or walk for free to the nearest location. If the participant purchased at least one ticket, they were allowed to choose between the plane and the train. Then, for each additional ticket purchased, the participant was given an opportunity to increase their chances of boarding the vehicle. Specifically, the chosen vehicle appeared moving from left to right across the screen, and the participant attempted to board it by pressing the spacebar when it reached the center of the screen. At the end of the trip, participants were shown where they arrived at, allowing them to infer whether they successfully boarded the vehicle. (D) **The space of possible planets.** Planets varied in inelastic controllability – the probability that even one ticket would lead to successfully boarding the vehicle – and in elastic controllability – the degree to which two extra tickets would improve the probability of successfully boarding the vehicle (one extra ticket provided half the benefit). The color corresponds to the optimal number of tickets (0, 1 or 3) in each planet. The darker the color the higher the advantage in expected value gained by purchasing the optimal number of tickets relative to the second-best option. Each participant made 30 consecutive trips in one planet from the green area, one planet from the blue area, one planet from the red area, and one planet with identical characteristic across all participants (black circle).

People adapt to the elasticity of control

To determine whether participants inferred elasticity, we first examined how they adapted their resource investment across planets. We found that participants were more likely to purchase tickets ('opt in') in more controllable planets, whether controllability was elastic (Initial and

Replication studies, p<.001; mixed logistic regression) or inelastic (Initial and Replication studies, p <.001; Figure 3A&C). Conversely, participants purchased more extra tickets only in planets with high elastic controllability (Initial p =.01, Replication p=.004; mixed probit regression; Figure 3B&C). Although substantial individual differences were observed in this regard (Figure 3D), these results show that most participants successfully adapted to the controllability and elasticity of the environments they visited.

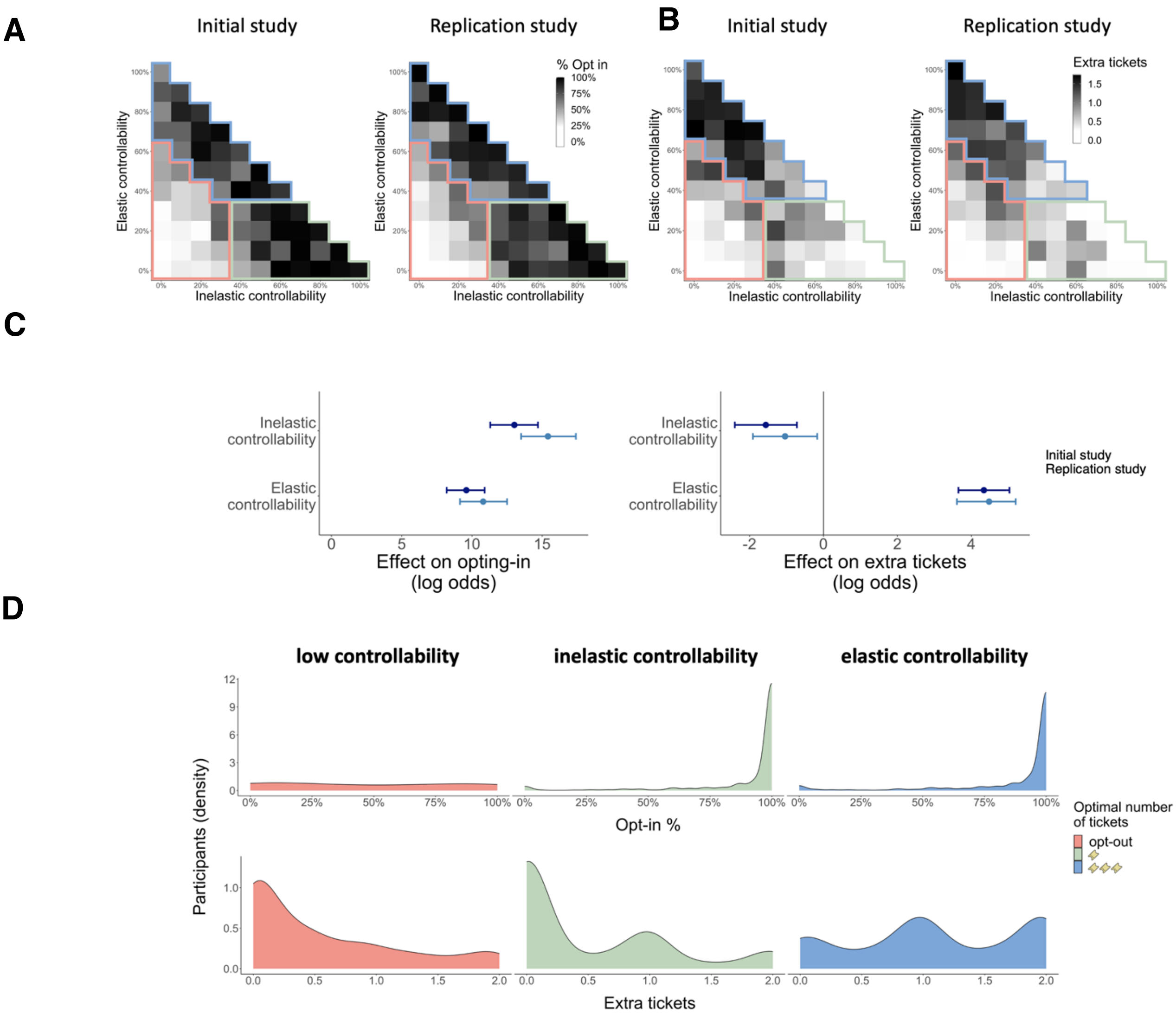


Figure 3. Participants adapted to the elasticity of control: Results from initial (N = 264) and replication (N = 250) studies. (A) **Opt-in percentage across all planets.** Participants opted-in more frequently on controllable planets (outlined in blue and green) than on uncontrollable planets (outlined in red) (B) **Extra tickets purchased across all planets.** Participants purchased more extra tickets in planets with high elastic controllability (outlined in blue). An average of 11 to 12 participants visited each planet in each of the studies. (C) **Effect of elastic and inelastic controllability on opting in and the purchasing of extra-tickets.** Bars show estimated fixed effects and 95% CIs from mixed logistic (opt-in) and probit (extra tickets) regressions. (D) **Individual differences.** Distribution of participants by opt-in rate (top) and average number of extra tickets purchased (bottom) across both studies, shown separately for planets with low controllability (red), high inelastic controllability (green), and high elastic controllability (blue).

People infer the elasticity of control

That participants adapted to elasticity does not necessarily mean they inferred elasticity. Successful adaptation may also be achieved merely by treating each possible level of resource investment as a separate course of action. One could thus learn the degree of control afforded by each course of action (i.e., purchasing 1, 2, or 3 tickets), and then choose the one that affords the highest expected value considering its cost. This simple strategy could achieve optimal performance given unlimited experience. However, it would not be as efficient as a strategy that employs elasticity inference, because it does not make use of the dependencies that exist between different levels of resource investment in the degrees of control they afford. Thus, upon failing to board a vehicle despite purchasing 3 tickets, the simpler strategy would need to purchase 1 or 2 tickets to know these options would fail as well, whereas an agent equipped with the concept of elasticity would conclude that controllability is low, and it is thus best to opt out. Conversely, upon succeeding to board with 3 tickets, the simpler strategy would tend to favor purchasing 3 tickets, over 1 or 2 tickets, even if the extra tickets confer no benefit, whereas an agent that infers elasticity would not favor 3 over 1 or 2 tickets because it received no evidence that controllability is elastic (i.e., that the extra tickets help).

To determine which of these models best describes the way participants solved the task, we formalized the simpler strategy as the ‘controllability model’, and an elasticity-inferring strategy as the ‘elastic controllability model’ (pre-registration: https://aspredicted.org/CHW_12H). Both models use beta distributions, characterized by parameters *a* and *b,* to represent the probability of boarding when purchasing different numbers of tickets, but only the elastic controllability model learns latent elasticity estimates. Specifically, in the ‘controllability model’, three beta distributions represent the expected level of control from purchasing 1, 2, or 3 tickets. Thus, the parameters of these distributions ($a_{\mathrm{n}}, b_{\mathrm{n}}, \mathrm{n} \in \{1, 2, 3\}$) accumulate the number of times each number of tickets led (a_{n}) or did not lead (b_{n}) to successful boarding. Conversely, in the ‘elastic controllability model’, the beta distributions represent a belief about the maximum achievable level of control (a_{control}, b_{control}) coupled with two elasticity estimates, specify the degree to which successful boarding requires purchasing at least one ($a_{\mathrm{elastic}\geq 1}, b_{\mathrm{elastic}\geq 1}$) or specifically two ($a_{\mathrm{elastic2}}, b_{\mathrm{elastic2}}$) extra ticket. Figure 4 shows schematically how the two models differ in updating their estimates in response to different types of outcomes. Both models similarly use these estimates to compute an expected value for purchasing 0, 1, 2, or 3 tickets, and accordingly choose between these options (see Methods, pg. 20-23, for model equations).

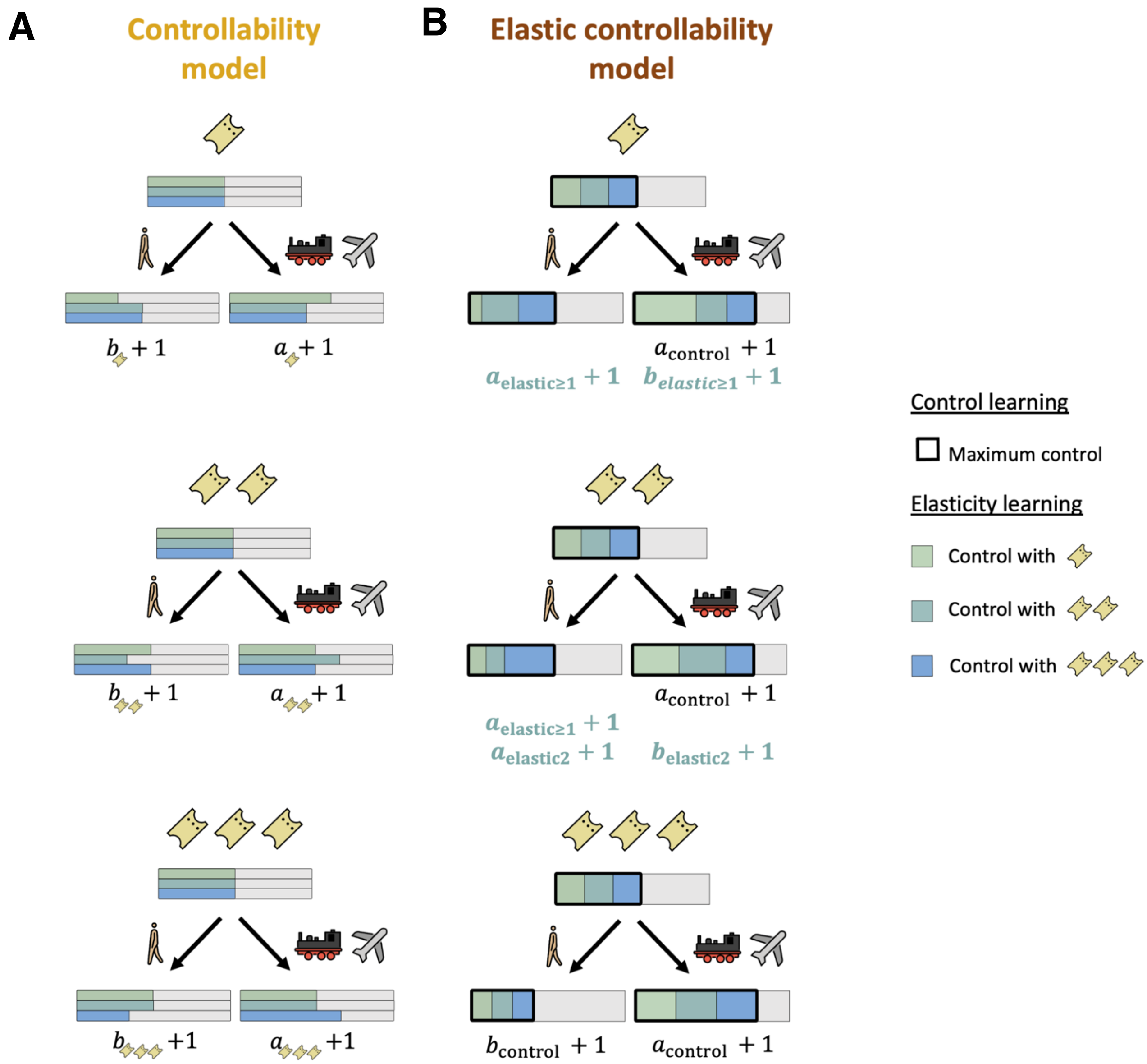


Figure 4. Computational models: Illustration of the learning rules of the *controllability* and *elastic controllability* models. The width of the colored region represents the estimated control, shown as a percentage of absolute control (gray area) along with the update rules based on each outcome.

(A) **Controllability model:** This model treats the purchase of 1, 2, and 3 tickets as distinct actions. It accumulates evidence for the effectiveness (a) or lack of effectiveness (b) of each action based solely on whether or not the action led to successful boarding, illustrated by changes in the width of the shaded region corresponding to each ticket amount.

(B) **Elastic Controllability model:** Represents beliefs about maximum control (black outline) and the degree to which at least one or specifically two extra tickets are necessary to obtain control. These are combined in calculating the expected control with 1, 2, and 3 tickets, demonstrated by the bars. The arrangement of the bars illustrates that, only in the elastic controllability model, controllability offered by extra tickets is added up on top of what is offered by a single ticket. The model updates its beliefs as follows: **Top –** Successfully boarding with one ticket provides evidence of high maximum controllability ($a_{\text{control}} + 1$; expanded shaded region) and reduces the perceived need to purchase extra tickets ($b_{\text{elastic}\geq 1} + 1$), increasing expectations of purchasing 1, relative to 2 or 3, tickets (light green expanded). A failure to board does not change estimated maximum controllability, but rather suggests that 1 ticket might not suffice to obtain control ($a_{\text{elastic}\geq 1} + 1$; light green diminished). **Middle** – Successfully boarding with 2 tickets provides evidence of high maximum controllability ($a_{\text{control}} + 1$; expanded shaded region), and reduces the perceived need to purchase two extra tickets ($b_{\text{elastic2}} + 1$), increasing expectations of purchasing 1 or 2, relative to 3, tickets (light & dark green expanded). Here too, a failure to board does not change estimated maximum controllability, but rather suggests that 2 tickets might not be sufficient ($a_{\text{elastic2}} + 1$; light & dark green diminished). **Bottom** – Successfully boarding with 3 tickets provides evidence of high maximum controllability ($a_{\text{control}} + 1$; expanded shaded region), but offers no insight about whether fewer tickets would suffice to obtain it. Failure to board with 3 tickets provides evidence of low controllability ($b_{\text{control}} + 1$; diminished shaded region).

Examining the predictions of both models, each simulated using the parameter setting that best fit participants' choices, showed that the elastic-controllability model was better than the controllability model at opting-out in low controllability planets (elastic-controllability model % opt in $= 49\% \ \pm .01$, controllability model % opt in $= 63\% \ \pm .01$; Figure 5C, top panel). Most importantly, this higher level of performance closely matched participants' behavior (% opt in $=$ $47\%, \pm .02$). Furthermore, the elastic controllability model was also better at not purchasing extra tickets in low-controllability (elastic controllability extra tickets = .49$\pm .01$ controllability extra tickets = .65$\pm .01$) and inelastic-controllability (elastic controllability extra tickets = .58$\pm .01$ controllability extra tickets = .66$\pm .01$) planets, and this too was more closely aligned with participant behavior (low-controllability extra tickets = 51$\pm .02$, inelastic-controllability extra tickets = 53$\pm .02$; Figure 5C, bottom panel).

Beyond these general aspects of task behavior, having participants start on every planet with free 3-ticket trips also enabled us to examine their response to succeeding or failing with 3 tickets, prior to any other experiences on the planet (Figure 5D). As noted above, failure with 3 tickets makes the controllability model favor 1 and 2 tickets over 3 tickets, whereas success with 3 tickets makes it favor 3 tickets over 1 and 2 tickets. Critically, neither the participants nor the simulation of the elastic controllability model showed these effects. Upon failing with 3 tickets, both participants and the elastic model primarily favored to opt out. Conversely, if they succeeded with 3 tickets, they did not become less likely to purchase 1 or 2 tickets.

In fact, failure with 3 tickets even made participants favor 3, over 1 and 2, tickets. Presumably, failure resulted in increased uncertainty about whether it is at all possible to control one's destination, and thus, participants who nevertheless opted in invested as much resources as they could to resolve this uncertainty. This directly contradicts the controllability model, but also goes beyond the behavior exhibited by the elastic controllability model. To capture this aspect of participants' behavior, we modified the elastic controllability model (elastic controllability*) such that it would increase its elasticity estimates when controllability is reduced. Model comparison consistently supported this modification (Initial study: log Bayes Factor = 143 Replication study: log Bayes factor = 155). More importantly, both the original and modified elastic controllability models explained participants' behavior better than the controllability model (Initial: log Bayes Factor ≥ 270, Replication: log Bayes Factor ≥ 148; Figure 5E). These results establish that people infer the elasticity of control, and thereby adapt their resource allocation to the environment's controllability and its elasticity.

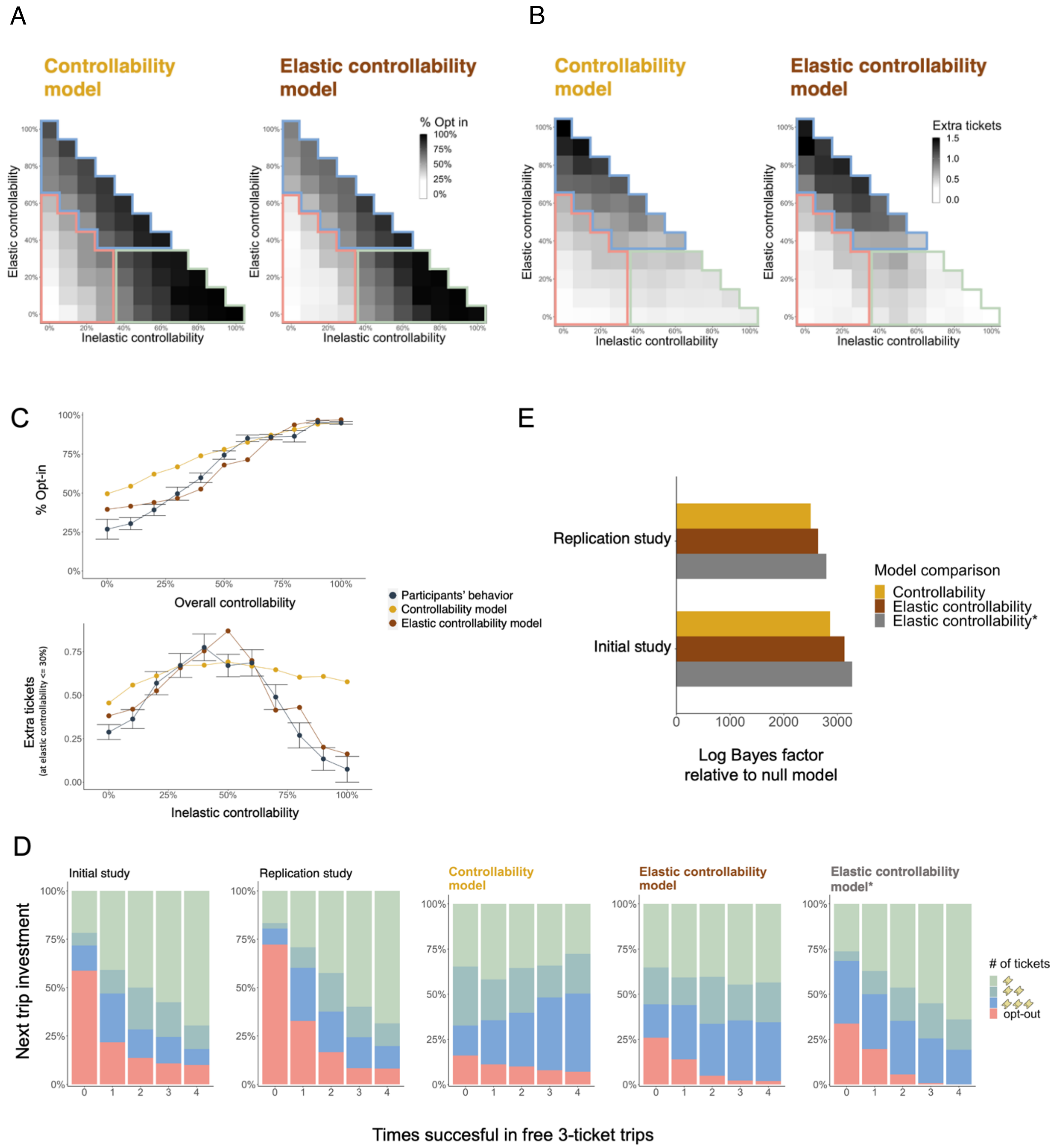


Figure 5. Model simulations: (A) **Opt-in.** Proportion of opt-in by the controllability and elastic controllability models across all planets. Each region is outlined by the color corresponding to the optimal ticket strategy (Blue: 3 tickets, Green: 1 ticket, Red: opt-out). (B) **Extra ticket purchases.** Extra tickets purchased by the controllability and elastic controllability models across all planets. Here too, each region is outlined by the color corresponding to the optimal ticket strategy. (C) **Comparison of opt-in rates and extra ticket purchases made by models and participants. Top -** Proportion of opting-in as a function of overall controllability. **Bottom -** The number of extra tickets purchased for each level of inelastic controllability when elasticity did not warrant purchasing extra tickets (i.e. below 30%). (D) **Resource investment following free 3-ticket trips.** The distribution of resource investment choices made immediately following the free 3-ticket trips, as a function of the outcomes of those trips. Results are shown for the two studies (Initial, Replication), the controllability model, and the original and modified variant of the elastic controllability models. (E) **Model comparison.** Consistency of each model with participant behavior is shown as log Bayes factor compared to a null model wherein participants have distinct preferences among different number of tickets to purchase but no latent controllability estimates.

Individual elasticity biases explain misallocation of resources

To determine whether the elastic controllability* model could identify individual biases in elasticity inference, we fitted the model to participants' choices and thus derived each participant's beliefs about controllability ($\gamma_{\text{controllability}}$) and elasticity ($\gamma_{\text{elasticity}}$) prior to visiting a given planet. $\gamma_{\text{controllability}}$ is used to initialize the model's belief about the maximum available control (a_{control}, b_{control}), with higher values reflecting stronger prior beliefs that planets are controllable. $\gamma_{\text{elasticity}}$ is used to initialize the model's elasticity estimates (a_{elastic}, b_{elastic}), with higher values reflecting stronger prior beliefs that control is elastic (see Methods, pg. 22). The stronger the belief, the greater its influence on choices to opt in ($\gamma_{\text{controllability}}$) and purchase extra tickets ($\gamma_{\text{elasticity}}$) regardless of observed outcomes. In addition to these two model parameters, we examined four additional parameters that directly influence opting-in and the purchase of extra tickets. These include an inverse temperature parameter (β), which specifies the stochasticity with which expected values affect resource investment choices, and baseline-preference parameters for purchasing 1, 2, or 3 tickets (α1, α2, α3). Across both samples, shared variance among parameters never exceeded 14% (Supplementary Figure S1), and was particularly low for the controllability and elasticity priors (Initial study: 5%, Replication study: 3%). Thus, a tendency to assume the environment is controllable did not imply a tendency to assume that control is elastic, establishing elasticity and controllability inferences as distinct facets of individual differences.

To examine the variance in resource investment explained by each of the parameters, we regressed participants' opt-in rates and extra ticket purchases on their fitted model parameters (Figure 6A). We found that a higher controllability bias (higher $\gamma_{\text{controllability}}$) was associated with more opting in (Initial study *p*<.001, Replication study *p*<.02; logistic regression) and more extra tickets purchased (Initial *p*<.001, Replication *p*<.001; probit regression) on low-controllability, as compared to high-controllability, planets. Thus, a prior assumption that control is likely available was reflected in a futile investment of resources in uncontrollable environments.

In contrast, a higher elasticity bias was associated with the purchasing of more extra tickets on planets with inelastic, as compared to elastic, controllability (Initial study: $\beta = .18, 95\%\ \text{CI} = [0.03,\ 0.34], \text{p} = .02$; Replication study: $\beta = .15, 95\%\text{CI} = [0.02\ \ 0.28], \text{p} = .02$; linear regression). Thus, a prior assumption that control is likely elastic was primarily reflected in a needless investment of extra resources in environments where control could be obtained more cheaply.

Other parameters were also associated with individual differences that are consistent with the parameters' roles in the model. Specifically, the inverse temperature parameter (β) was associated with a more optimal allocation of resources, all three baseline preference parameters (α1, α2, α3) were associated with opting in, and α2 and α3, in particular, were also associated with the purchasing of more extra tickets (Figure 6A).

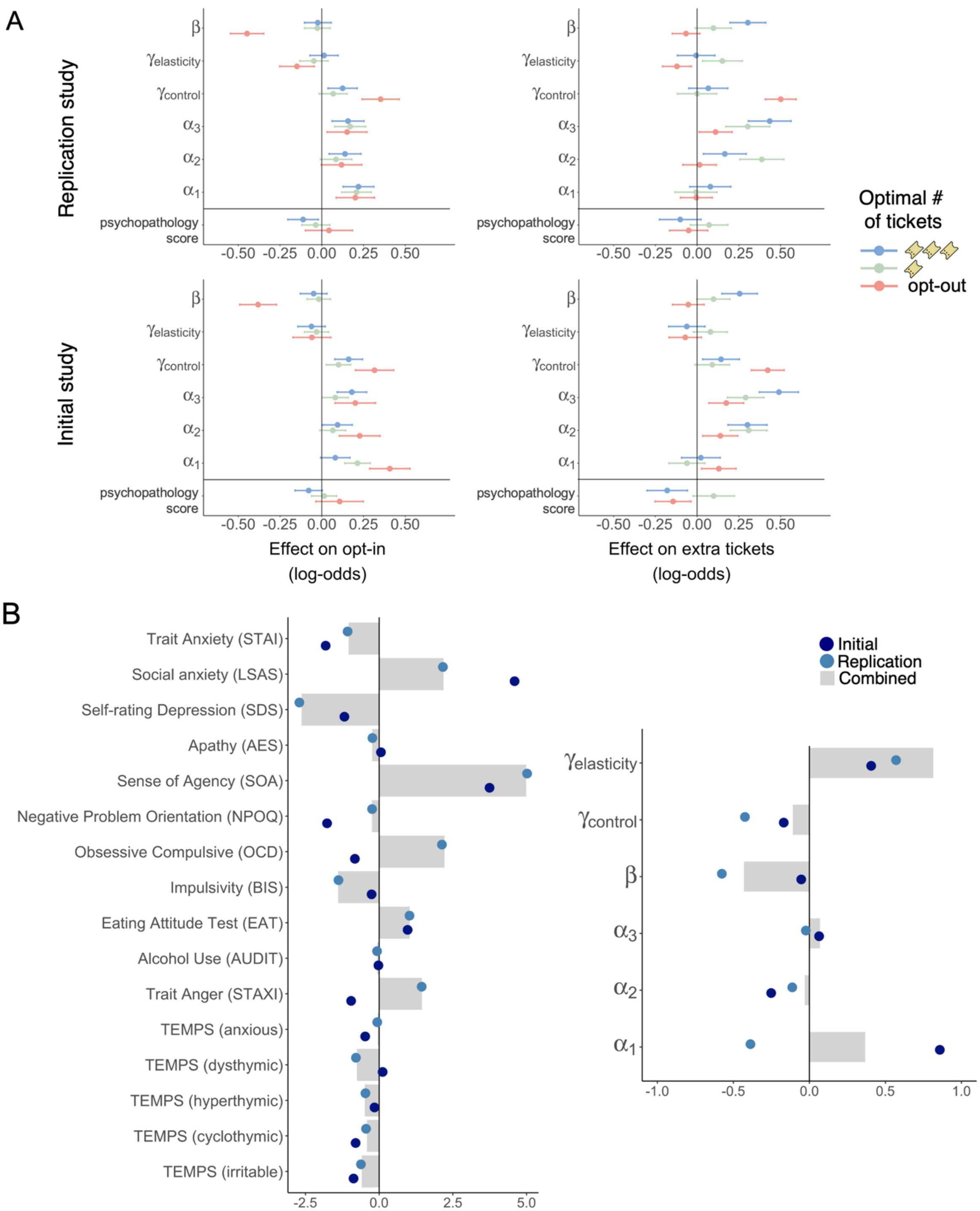
In sum, participants differed in how they allocated their resources across environments, with prior beliefs about controllability explaining misallocation of resources in uncontrollable environments, and prior beliefs about elasticity explaining misallocation of resources in environments where control was inelastic.

Individual elasticity biases are associated with psychopathology

To examine whether the individual biases in controllability and elasticity inference have psychopathological ramifications, we assayed participants on a range of self-report measures of psychopathologies previously linked to a distorted sense of control (see Methods, pg. 24). We then ran a canonical correlation analysis (CCA) to examine the relationship between the self-report measures and the model parameters underlying individual biases in task behavior. CCA is a useful method of characterizing relationships between two sets of variables, by assigning a canonical loading to each variable that maximizes the correlation between the linear combinations of each set of variables. The canonical loading of each measure thus indicates the contribution of that variable to the overall correlation. We assessed statistical significance against a null distribution obtained by permuting the model parameter relative to the psychopathology scores. This showed that the canonical correlation was significant in both the Initial (p=.01) and the Replication (p=.02) studies.

To obtain more robust estimates of the CCA loadings, we next ran a canonical correlation analysis on both datasets combined (Figure 6C, ρ=.33, p=.004). On the side of model parameters, the elasticity prior parameter ($\gamma_{\text{elasticity}}$) received the highest loading. By comparison, the controllability prior parameter received a lower loading with the opposite sign. A further permutation test showed that the contribution of the elasticity prior parameter to the parameter-psychopathology correlation was itself significant (*p*=.04; Figure 6D).

Loadings on the side of psychopathology were dominated by an impaired sense of agency (SOA), obsessive compulsive symptoms (OCD), and social anxiety (LSAS) – all symptoms that have been linked to an impaired sense of control[22-25]. Conversely, depression scores (SDS) received a negative loading, consistent with evidence of a lower willingness to expend one's resources in depression[21,26-27]. This psychopathological profile also manifested in raw task measures, since, like the elasticity prior parameter, it too was associated with the purchasing of more tickets on planets where controllability was less elastic (Initial: $\beta = .19, 95\%\ \mathrm{CI} = [.06,.32]$, p=.004; Replication: $\beta = .13,\ 95\%\ \mathrm{CI} = [.01,.25], \mathrm{p} = .03;$ linear regression; Figure 6A). Thus, we found a distinct psychopathological profile involving a distorted sense of agency associated with a bias in elasticity inference.


A
Replication study
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β
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α3
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psychopathology score
-0.50 -0.25 0.00 0.25 0.50
Effect on opt-in (log-odds)
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B
Trait Anxiety (STAI)
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Self-rating Depression (SDS)
Apathy (AES)
Sense of Agency (SOA)
Negative Problem Orientation (NPOQ)
Obsessive Compulsive (OCD)
Impulsivity (BIS)
Eating Attitude Test (EAT)
Alcohol Use (AUDIT)
Trait Anger (STAXI)
TEMPS (anxious)
TEMPS (dysthymic)
TEMPS (hyperthymic)
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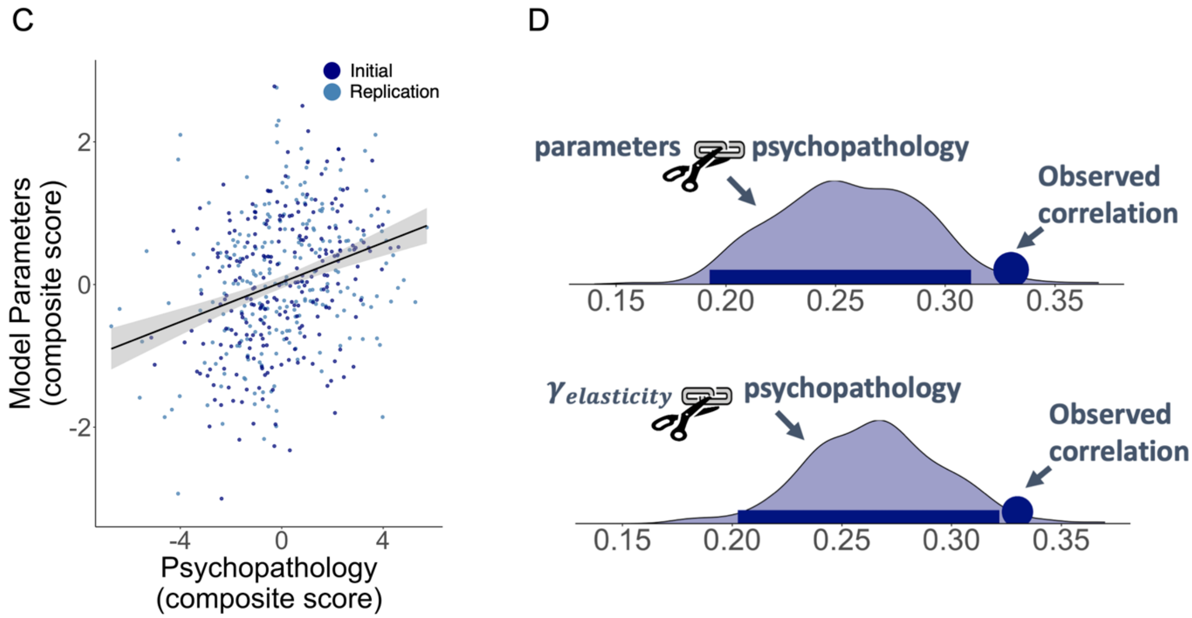


Figure 6. Individual biases in controllability and elasticity inference: (A) **Model parameters and task behavior.** Model parameters fitted to each participant's task behavior were used as predictors of opt-in (left; multiple logistic regressions) and extra ticket purchases (right; multiple probit regressions) separately for low controllability (red), high elastic controllability (blue) and high inelastic controllability (green) planets. In a separate analysis, participants' composite psychopathology scores (see panel C) were similarly used to predict opt-in (left; logistic regression) and extra ticket purchases (right; probit regression). Bars represent regression coefficients and 95% CIs. (B) **Model parameters and psychopathology.** Loadings from a Canonical Correlation Analysis (CCA) between model parameters and self-report psychopathology measures. Self-report measures were scored such that higher values reflect higher levels of psychopathology. Loadings are shown for the Initial (dark blue), Replication (light blue), and combined (gray bars) datasets. The magnitude of the loading reflects the degree to which each measure contributes to the correlation between parameters and self-reports. (C) **Model parameters and psychopathology composite scores.** For each participant, a composite psychopathology score was calculated by multiplying their self-report scores with their CCA-derived loadings, and a composite model parameter score was calculated by multiplying their parameter fits and corresponding loadings. Each dot represents an individual participant. Black line: group-level posterior slope. Gray shading: standard error. (D) **Significance testing.** p-values for the observed CCA correlation (circle) were computed against empirical null distributions (shaded area and bar showing 95% high-density interval). The top null distribution was obtained by shuffling the model parameter fits (top) relative to the psychopathology scores (top), and the bottom null distribution was obtained by shuffling only the elasticity prior parameter ($\gamma_{\text{elasticity}}$) while keeping all other parameters and self-report scores matched (bottom).

Discussion

Across two pre-registered studies, we demonstrate that humans infer the elasticity of control over their present environment, and this informs their decisions of whether and how to act. Accordingly, we found that a bias to overestimate elasticity leads to a mismanagement of resources, and is associated with elevated psychopathology involving an impaired sense of agency.

Unlike prior work that treated controllability and elasticity as coupled, our studies dissociated elastic and inelastic controllability, revealing that individuals who typically assume that taking action is worthwhile (overall controllability) do not necessarily assume that investing more resources in taking action is worthwhile (the elasticity of control). In fact, elasticity and controllability biases were oppositely related to psychopathology, revealing a psychopathological profile that combines underestimation of control with overestimation of the degree to which investing more resources is necessary to obtain control.

The observed elasticity biases across individuals are particularly striking given the simplicity of the experimental task in comparison to real-life scenarios. Unlike the task, where successful boarding directly determined a trip's outcome, in many real situations many actions may contribute to a single outcome. In this regard, the present work introduces a new kind of credit-assignment problem[28], which involves identifying not only which actions influenced the outcome but also which of these actions was made more effective by investing more resources in its execution. Moreover, whereas in the task elasticity increased linearly with the number of tickets, resource investment in real life often exhibits non-linear effects. Specifically, further increases in resource investment often result in diminishing returns, and beyond a certain point, even worse outcomes (e.g. hiring too many employees, making the work less efficient). Additionally, real life typically doesn't offer the streamlined recurrence of homogenized experiences that makes learning easier in experimental tasks. These complexities introduce substantial additional uncertainty into inferences of elasticity in naturalistic settings, thus allowing more room for prior biases to exert their influences. The elasticity biases observed in the present studies are therefore likely to be amplified in real-life behavior.

Our finding that elasticity biases are associated with agency-related psychopathologies raises interesting questions for future research on the causal nature of this association. One possibility is that biased elasticity inferences distort one's sense of agency by leading to maladaptive resource allocation that results in consistently suboptimal outcomes. Another possibility is that people who already have a reduced sense of agency, attempt to compensate for this feeling by investing more resources despite minimal benefit, thus demonstrating an elasticity bias. Importantly, these possibilities are not mutually exclusive. That is, elasticity biases and a distorted sense of agency could reinforce each other in a cyclical manner. Longitudinal studies tracking or manipulating elasticity beliefs while monitoring changes in real-life resource investment and subjective sense of agency, could resolve how elasticity biases and psychopathology influence each other.

Our operationalization of controllability aligns with previous work that defined controllability as the degree to which actions influence the probability of obtaining a reward[3-4,6]. Other notable studies defined controllability as the degree to which actions predict subsequent states, independent of reward[1a]. Here we adhered to the former definition due to our present focus on resource elasticity, since individuals are unlikely to invest resources to gain control if control does not yield more reward. That said, we followed the latter work in ensuring that controllability is not confounded with predictability[1b], in the sense that in planets with high controllability, outcomes were not necessarily more predictable than in planets with low controllability (See Methods). This enabled us to specifically assess individual inferences concerning controllability and its resource elasticity.

In interpreting the present findings, it needs to be noted that we designed our task to be especially sensitive to overestimation of elasticity. We did so by giving participants free 3 tickets at their initial visits to each planet, which meant that upon success with 3 tickets, people who overestimate elasticity were more likely to continue purchasing extra tickets unnecessarily. Following the same logic, had we first had participants experience 1 ticket trips, this could have increased the sensitivity of our task to underestimation of elasticity in elastic environments. Such underestimation could potentially relate to a distinct psychopathological profile that more heavily loads on depressive symptoms. Thus, by altering the initial exposure, future studies could disambiguate the dissociable contributions of overestimating versus underestimating elasticity to different forms of psychopathology.

Another interesting possibility is that individual elasticity biases vary across different resource types. For instance, a given individual may assume that controllability tends to be highly elastic to money but inelastic to effort. Future studies could explore this possibility by developing tasks that compare individuals' elasticity beliefs across different resource types (e.g., money, time, effort). This would clarify whether elasticity biases are domain-specific or domain-general, and thus elucidate their impact on everyday decision-making.

Methods

Pre-registration

Both the Initial and Replication studies were pre-registered prior to data collection. The pre-registrations included hypotheses, sample sizes, exclusion criteria, task design, analysis plans (regressions, CCA), and computational models. Detailed pre-registration documents are available at https://aspredicted.org/Q7M_BHR and https://aspredicted.org/CHW_12H.

Participants

We used the Prolific online platform (prolific.com) to recruit participants (Initial study N = 264, Replication study N = 250). Participants were selected based on their demonstrated high engagement levels in prior studies, fluency in English, and absence of psychiatric diagnoses. Due to cultural differences in the perception of controllability[29] participants were recruited from English speaking western countries. The average age of participants across both datasets was 33 years old (SE =.6), and 38% were female.

The sample size was determined using a power analysis as described below. Exclusion criteria were applied to ensure data quality and participant engagement. Specifically, participants were excluded if they demonstrated inattentiveness (defined as more than 8 mistakes on comprehension quizzes during the instruction phase), displayed less than 90% accuracy in selecting the correct vehicle corresponding to its pre-learned destination (indicating a lack of task comprehension), or chose not to purchase any tickets in 90% or more of trials across all experimental conditions (suggesting a lack of engagement with the task). These criteria led to the exclusion of 22 participants (8.3% exclusion rate) from the initial study and 23 participants

(8.9% exclusion rate) from the replication study. Participants gave written informed consent before taking part of the study, which was approved by the university's ethics review board (approval number: 2022-06213). Participants were paid at a rate of 9 euros per hour.

Experimental Task

Participants were informed about the location of a treasure (150 coins, worth 15¢ of bonus monetary compensation) and could exercise control by boarding the train to reach the house, or the plane to reach the mountain. (see main text and Figure 2). Forgoing or failing to board resulted in walking to the nearest location which happened to be where the treasure was located 20% of the time.

The first ticket (cost = 40 coins) allowed participants to select their desired vehicle, but it only stopped for them at the platform some percentage of the time, corresponding to the inelastic controllability of the planet. Participants could purchase up to 2 additional tickets (cost = 20 coins each) to attempt boarding the moving vehicle after it had left the platform. This improved the probability of boarding in correspondence with the elastic controllability of the planet.

When participants purchased a second or third ticket, the chosen vehicle appeared moving from left to right across the screen, and participants attempted to board it by pressing the spacebar when it reached the center of the screen. The precision of each boarding attempt was quantified as the absolute distance of the vehicle from the screen's center at the time of the press. Unless elastic control was below 15%, boarding attempts with precision in the top 15 percentile relative to the participant's prior performance automatically succeeded, and unless elastic control was above 85%, those in the bottom 15 percentile automatically failed. For the remaining attempts, the outcome was probabilistically determined such that the overall probability of successfully boarding matched the elasticity of control on that planet. To verify that participants' pressing ability did not bias their preference for purchasing extra tickets, we ran a mixed probit regression of the number of extra tickets purchased on participants' average press precision. We found no significant effect ($p = .45$).

At the end of each trip, participants were shown where they arrived, allowing them to infer whether they successfully boarded their vehicle. Since this feedback is only interpretable if participants knew each vehicle's destination, we only included participants in subsequent analyses if they chose the vehicle corresponding to the destination of the treasure with at least 90% accuracy (Mean 97% $\pm 2\%$, see first exclusion criteria).

To allow sufficient learning of each planet's elasticity and controllability, participants took 30 consecutive trips on each planet. This trip count was determined based on pilot data (N=19) analyzing when participants' strategies stabilized. We examined the standard deviation in ticket choices over the final 5 trips and found stabilization after around 15 trips (STD = 0.51). Based on this, we provided an initial 15 trips for learning, then analyzed ticket choices starting from trip 16 onward per planet. This approach followed our pre-registered plan.

To homogenize learning experience across participants, we gave participants three free tickets for the first five visits to every planet. However, only four of those trips were informative, since on one of every five trips (randomly placed), the treasure was located in the nearby location, making boarding inconsequential for reaching it.

Planet types

To study elasticity learning across all possible degrees of controllability and elasticity, 66 unique planet conditions were generated by systematically varying inelastic controllability (the probability of the chosen vehicle stopping at the platform if purchasing a single ticket) and elasticity (the added probability of boarding from purchasing 2 extra tickets) from 0 to 100% in 10% increments. The treasure value (150 coins) and ticket costs (40 coins for the first ticket, 20 coins for extras) were chosen so that the optimal strategy, as determined by expected value calculations (*equation 11*), was to purchase 0 tickets on 22 planets (low controllability condition), 1 ticket on a different set of 22 planets (high inelastic controllability condition), and 3 tickets on the remaining 22 planets (high elastic controllability condition). Participants were randomly assigned one planet from each condition, while ensuring they could earn roughly the same total number of coins if they made optimal choices (Initial study= $45\pm.3$, Replication study $46 \pm .3$). To address potential confounds between controllability and predictability[1b], we designed the experiment such that high-controllability planets (where purchasing 1 or 3 tickets was optimal) were not inherently more predictable than low-controllability planets. We quantified predictability as the entropy of the probability distribution determining whether the participant will or will not arrive at the rewarded location. For 60% of participants, purchasing tickets on high-controllability planets decreased entropy (i.e., increased predictability) compared to low-controllability planets, whereas for the other 40% it increased entropy (i.e., decreased predictability). To increase sensitivity to individual differences, all participants first encountered a planet where purchasing any number of tickets (0, 1, 2, or 3) yielded the same expected value (EV = 30 coins).

Initial training

Prior to engaging in the task, participants completed 90 practice trials. These practice trials were divided equally across planets with high inelastic controllability, high elastic controllability, and low controllability. To reinforce participants' understanding of how elasticity and controllability were manifested in each planet, they were informed of the planet type they had visited after every 15 trips.

Power analysis

The sample sizes for both the initial and the replication studies were pre-registered before data collection commenced. For the initial study, we derived the sample size of 264 participants using a power analysis aiming to estimate with high accuracy (credible interval width < 0.1) the likelihood that participants will opt-in for any combination of elastic and inelastic control (66 total combinations). For this purpose, we used Kruschke's (2014) procedure for Bayesian Power Analysis[30]. Based on pilot data (N=19), we fitted a Bayesian Beta Binomial model to the proportion of opt-ins in the planet with no optimal strategy (and therefore the highest variability in behavior would be expected), and found that 12 participants were required for the credible interval of the binomial proportion parameter to be lower than 0.1. Since each participant completes 3 combinations of elastic and inelastic control, we multiplied the required sample size by the total number of planets in each condition (22) which results in an estimate of n=264.

To examine whether this sample size is sufficient to detect significant effects of elastic and inelastic controllability on opting in (analysis 1), and the purchasing of extra tickets (analysis 2; see pg. 4-5), we used a bootstrap procedure whereby we sampled 264 participants from the pilot data and ran the regression analyses on them. We repeated this procedure for 50 iterations, each time recording $\beta_{elastic}, \beta_{inelastic}$, and their p-values. For analysis 1, we found that both $\beta_{elastic}$ and $\beta_{inelastic}$ were significantly above 0 in all iterations, and for analysis 2, $\beta_{elastic}$ was significantly above 0 in all iterations, thereby giving us >98% power to detect all of our effects of interest. Confidence intervals were derived from a binomial test in which a positive significant coefficient counted as a success.

For the replication study, we derived the sample size of 250 participants using a power analysis aiming for 95% power to detect a significant ($p <.05$) canonical correlation between the model-derived parameters and questionnaire scores (see analysis on pg. 12). For this purpose, we sampled with replacement from the initial dataset (n=264) which had showed a significant canonical correlation (p=.01; see results pg. 13), and calculated the p-value of a CCA in the subsample. We repeated this procedure for 100 iterations, each time recording the calculated p-value. To ensure our sample size was sufficient to detect significant effects in the regression models predicting opt-in and extra ticket purchases from the composite psychopathology score with over 95% power (described on pg. 13) we conducted another bootstrap analysis. We sampled 250 participants with replacement each time calculating the composite score and ran the regression analyses on that score, repeating this procedure 100 times. We found that $\beta_{composite}$ was significant ($p<.05$) in 95% of iterations (95% power).

Regression analyses

Mixed model regression analyses were performed using the "ordinal" package which fits cumulative mixed models via Laplace approximations[31]. The model predicts the likelihood of purchasing tickets (logistic model) and how many extra tickets are purchased (probit model) on the last 15 trips on each planet. Predictors included fixed and random effects for elastic and inelastic controllability and fixed and random intercepts per participant and planet number, with the latter included to account for potential learning or fatigue effects. Statistical significance was assessed using the Wald Z Test[32] with normality assessed using the Shapiro-Wilk Test[33].

Computational Modeling

To assess whether participants inferred elasticity or merely learned the control afforded by each course of action separately, we fit two competing reinforcement-learning models ('*controllability*' and '*elastic controllability'*). Both models use beta distributions defined by parameters (a , b), to form controllability beliefs for each ticket quantity n ($n \in \{1, 2, 3\}$), but only the elastic controllability model leverages the dependencies that exist between different levels of resource investment. Below, we expand on the computations underlying both models.

Controllability model

The controllability model accumulates the number of times that each ticket quantity *n* led to successful or unsuccessful boarding:

$$\mathrm{a}_{\mathrm{n}} \leftarrow \mathrm{a}_{\mathrm{n}} + \mathrm{O}$$
$$\mathrm{b}_{\mathrm{n}} \leftarrow \mathrm{b}_{\mathrm{n}} + (1 - \mathrm{O}) \qquad \textit{(equation 1)}$$

Where O=1 if boarding was successful and O=0 if not. The probability of boarding with 1,2 or 3 tickets on planet s is thus simply the expected value of that particular beta distribution:

$$\mathrm{p(boarding|n, s)} = \frac{\mathrm{a_n}}{\mathrm{a_n + b_n}}. \qquad \textit{(equation 2)}$$

Here and in all subsequent models, learning only takes place when the treasure is not located on the nearby planet, which makes it possible to identify boarding success.

Elastic controllability model

The *elastic controllability model* explains ticket choices based on latent beliefs about the controllability and elasticity of each planet (see Figure 4). These beliefs are represented by three beta distributions, each defined by two parameters (a, b). The expected value of one beta distribution (defined by $a_{\text{control}}, b_{\text{control}}$) represents the belief that boarding is possible (controllability) whereas the expected value of the other two beta distributions represent the belief that successful boarding is added by purchasing at least one ($a_{\text{elastic}\geq 1}, b_{\text{elastic2}}$) or specifically two ($a_{\text{elastic2}}, b_{\text{elastic2}}$), extra tickets (elasticity).

Thus, the parameter a_{control} accumulates the number of successful boarding attempts with any number of tickets, whereas b_{control} accumulates the number of failed boarding attempts despite purchasing the maximum number of tickets (3 tickets):

$$\mathrm{a}_{\text{control}} \leftarrow \mathrm{a}_{\text{control}} + 1 \text{ if win with 1,2, or 3 tickets}$$
$$\mathrm{b}_{\text{control}} \leftarrow \mathrm{b}_{\text{control}} + 1 \text{ if lose with 3 tickets} \qquad \textit{(equation 3)}$$

A failure to board with fewer tickets doesn't reduce the maximum controllability estimate but instead suggests that more tickets or the maximum number of tickets may be needed to obtain control:

$$\mathrm{a}_{\text{elastic}\geq 1} \leftarrow \mathrm{a}_{\text{elastic}\geq 1} + 1 \text{ if lose with 1 or 2 tickets}$$
$$\mathrm{a}_{\text{elastic2}} \leftarrow \mathrm{a}_{\text{elastic2}} + 1 \text{ if lose with 2 tickets} \qquad \textit{(equation 4)}$$

Conversely, successfully boarding with fewer tickets is evidence that obtaining controllability does not require maximal or any extra tickets:

$$\mathrm{b}_{\text{elastic}\geq 1} \leftarrow \mathrm{b}_{\text{elastic}\geq 1} + \text{ if win with 1 ticket}$$
$$\mathrm{b}_{\text{elastic2}} \leftarrow \mathrm{b}_{\text{elastic2}} + 1 \text{ if win with 2 tickets} \qquad \textit{(equation 5)}$$

To account for our finding that failure with 3 tickets made participants favor 3, over 1 and 2, tickets, we introduced a modified elastic controllability* model, wherein purchasing extra tickets is also favored upon receiving evidence of low controllability (loss with 3 tickets). This effect was modulated by a free parameter κ:

$$a_{\text{more}} \leftarrow a_{\text{elastic1}} + \kappa \text{ if lose with 3 tickets}$$
$$a_{\text{elastic2}} \leftarrow a_{\text{elastic2}} + \kappa \text{ if lose with 3 tickets} \qquad \textit{(equation 6)}$$

The estimated controllability and elasticity, as characterized by the expected value of the three beta distributions ($C_{\text{total control}}, C_{\text{more}}, C_{\text{full}}$), is used to derive the probability of boarding the selected vehicle with 1, 2, or 3 tickets. Thus, the estimated probability of boarding with 1 ticket is an estimate of inelastic control, that is, the percentage of the total control $C_{\text{total control}}$ that does not require investing more resources:

$$\mathrm{P}(\text{boarding}|n = 1) = \mathrm{C}_{\text{total control}} \times (1 - \mathrm{C}_{\text{more}}) \qquad \textit{(equation 7)}$$

For 2 tickets, the added probability of boarding is an estimate of what percentage of total control is elastic (C_{more}) but does not require investing maximal resources $(1 - \mathrm{C}_{\text{full}})$:

$$\mathrm{P}(\text{boarding}|n = 2) = \mathrm{P}_s(\text{boarding}|n = 1) + \mathrm{C}_{\text{total control}} \times \mathrm{C}_{\text{more}} \times (1 - \mathrm{C}_{\text{full}}) \qquad \textit{(equation 8)}$$

Finally, since 3 tickets is the maximum resource investment, the estimated probability of boarding with 3 tickets is equivalent to an estimate of total attainable control.

$$\mathrm{P}(\text{boarding}|n = 3, s) = \mathrm{C}_{\text{total control}} \qquad \textit{(equation 9)}$$

Models' resource investment

Because participants win 20% of the time even when they fail to board their selected ride, we calculate the probability of arriving at the treasure with *n* tickets as:

$$\mathrm{P}(\text{win}|n) = \mathrm{P}(\text{boarding}|n) + .2 \times (1 - \mathrm{P}(\text{boarding}|n)) \qquad \textit{(equation 10)}$$

Then, taking the possible reward ($\mathrm{R} = 150$) and ticket costs ($\mathrm{C} = \{40,20,20\}$) into account, the expected value for purchasing n tickets ($n = \{1,2,3\}$) tickets is:

$$\mathrm{V}(n) = (\mathrm{R} - \textstyle\sum_{i=1}^{n} \mathrm{C}_i) \times \mathrm{P}(\text{win}|n) - \sum_{i=1}^{n} \mathrm{C}_i \times (1 - \mathrm{P}(\text{win}|n)) \qquad \textit{(equation 11)}$$

One exception to this rule is the expected value of opting out, $\mathrm{V}(0)$, which is similar across all planets, and equals the potential reward (150) times the probability that walking will lead to the reward (0.2).

The probability that a participant will purchase 0, 1, 2, or 3 tickets is calculated using the SoftMax function such that:

$$p(n) \propto \beta \times \mathrm{V}(n) + \alpha_n + \rho \times \mathrm{I}(n_{t-1} == n) \qquad \textit{(equation 12)}$$

where β is an inverse temperature parameter, α_{1-3} are parameters that represent participants' fixed tendencies to purchase 1, 2, or 3 tickets respectively, and ρ is a perseveration parameter that represents participant tendency to purchase the same number of tickets as in the last trial (n_{t-1}). A_0 is set to 0 to maintain parameter identifiability.

We compared the aforementioned models to a null model wherein participants have distinct preferences among different number of tickets (α_{1-3}) and perseveration (ρ) but no latent controllability estimates ($\beta = 0$ in equation 12). We also evaluated variants of both models that replaced the SoftMax-based exploration (governed by inverse temperature β) with a decaying epsilon-greedy approach. This epsilon-greedy variant, which begins with a fixed exploration rate that decreases with the number of trials[57], performed significantly worse at explaining participants' choices compared to the SoftMax-based models.

Prior controllability and elasticity beliefs

To capture prior biases that planets are controllable and elastic, we introduced parameters $\gamma_{\text{controllability}}$ and $\gamma_{\text{elasticity}}$, each computed by multiplying the direction (λ – 0.5) and strength (ϵ) of individuals' prior belief. $\Lambda_{\text{controllability}}$ and $\lambda_{\text{elasticity}}$ range between 0 and 1, where values above 0.5 indicate a bias towards high controllability and elasticity, and values below 0.5 indicate a bias towards low controllability and elasticity, whereas $\epsilon_{\text{controllability}}$, $\epsilon_{\text{elasticity}}$ ($\epsilon > 0$) capture the confidence in the bias. These parameters were thus used to initialize the beta distributions representing participants' beliefs:

$$
\begin{aligned}
a_{\text{controllability}} &= 2 \times \epsilon_{\text{controllability}} \times \lambda_{\text{controllability}} \\
b_{\text{controllability}} &= \epsilon_{\text{controllability}} \times (1 - \lambda_{\text{controllability}}) \\
a_{\text{more,full}} &= \epsilon_{\text{elasticity}} \times \lambda_{\text{elasticity}} \\
b_{\text{more,full,}} &= \epsilon_{\text{elasticity}} \times (1 - \lambda_{\text{elasticity}}) \qquad \textit{(equation 13)}
\end{aligned}
$$

$a_{\text{controllability}}$ is multiplied by 2 so that in the absence of a bias, it would have equal preference for purchasing 0 to 3 tickets (this requires that $C_{\text{controllability}} = \frac{2}{3}$, $C_{\text{more,full}} = \frac{1}{2}$).

For consistency, in the 'controllability model', the controllability estimates for each ticket quantity are initialized for each ticket quantity n, where n={1,2,3}, as:

$$
\begin{aligned}
a_n &= \epsilon_n \times \lambda_n \\
b_n &= \epsilon_n \times (1 - \lambda_n) \qquad \textit{(equation 14)}
\end{aligned}
$$

Here, to ensure no preference between different ticket quantities in the absence of a bias, a_1 is multiplied by 2 and a_2 is multiplied by $\frac{3}{2}$.

Model fitting

Reinforcement-learning models were fitted to participants' choices via an expectation maximization approach used in previous work[34-36]. We generated random parameter settings drawn from predefined group-level distributions and calculated the likelihood of observing the participants' choices given each parameter setting. We then approximated the posterior estimates of the group-level prior distributions for each parameter by resampling the parameter values, weighted by their respective likelihoods, and refitted the data based on the updated priors. This iterative process of resampling and refitting continued until no further improvement to model fit. To determine the best-fitting parameters for each individual participant, we computed a weighted average of the final batch of parameter settings, where each setting was weighted by the likelihood it assigned to the individual participant's choices.

Model parameter β was initialized by sampling from a Gamma distribution ($k = 1$, $\theta = 1$), λ was initialized by sampling from a Beta distribution ($\alpha = 1$ *and* $\beta = 1$), ϵ was initialized by sampling from a Lognormal distribution ($\mu = 0$, $\sigma = 1$)., and all other parameters ($\alpha_{1-3}, \rho, \kappa$) were initialized by sampling from a Normal distribution ($\mu = 0$, $\sigma = 1$).

Validation of model fitting procedure

To validate the model fitting procedure, we simulated data using each model and using the model comparison procedure to recover the correct model (S1 table). Furthermore, we validated our parameter fits by simulating data using the best fitting parameters for each parameter and then recovering those parameters. The correlations for the parameters of interest were all equal or greater than $r = .74$ and at least .63 for all other parameters (see Table S2).

Model comparison

To compare between models, in terms of how well each model accounted for participants' choices, we employed the integrated Bayesian Information Criterion (iBIC)[37-38]. First, we estimated the evidence for each model (L) by calculating the mean likelihood of the model given 200,000 random parameter settings sampled from the fitted group-level prior distributions. Subsequently, we computed the iBIC by penalizing the model evidence to account for model complexity, following this formula: iBIC = 2 ln L + k ln n, where k represents the number of fitted parameters, and n is the number of subject choices used to compute the likelihood. Lower iBIC values indicate a more parsimonious and better-fitting model.

Model simulations

To examine the predictions of the 'controllability' and 'elastic controllability' models, we simulated choices using the best-fitting parameter settings obtained from participants' actual choices. For generality, planets were randomized in the simulation as they were in the actual experiment, such that a simulated participant did not visit precisely the same planets as the actual participant. Furthermore, to avoid discrepancies between models, each planet was repeated the same number of times for both models. 2000 simulations were performed with each model.

Individual differences

We examined individual biases in elasticity inference using participants' best-fitting parameters for beliefs about controllability ($\gamma_{\text{controllability}}$) and elasticity ($\gamma_{\text{elasticity}}$). In addition to these focal parameters, we also examined four other parameters that directly influence opt-in decisions and extra ticket purchases: an inverse temperature/noise parameter (β) and three baseline preference parameters (α1, α2, α3).

We then regressed participants' actual opt-in (logistic regression) and extra ticket purchases (probit regression) in each of the 3 controllability conditions on participants' parameters. Regressions were performed in the lme4 package in R using Rstudio[38]. Statistical significance was assessed using the Wald Z Test[32] with normality assessed using the Shapiro-Wilk Test[33].

Self-report measures

To assess trait-level agency beliefs and related psychopathologies, we administered the Sense of Agency Scale (SOA)[40]. Additionally, we measured dysfunctional attitudes toward problem-solving via the Negative Problem Orientation Questionnaire (NPOQ) [41], and temperamental differences (five domains: hyperthymic, dysthymic, cyclothymic, irritable, and anxious) via the Temperament Evaluation Questionnaire (TEMPS-A)[42-43].

Additionally, we incorporated a selection of questionnaires used by Gillan et al. (2016)[44], which assess three factors—Anxious-depression, Compulsive behavior and intrusive thought, and Social withdrawal—linked to goal-directed control deficits. These include the Apathy Evaluation Scale[45] (AES), Eating Attitudes Test[46] (EAT), Alcohol Use Disorders Identification Test[47] (AUDIT), Barratt Impulsiveness Scale[48] (BIS), Liebowitz Social Anxiety Scale[49] (LSAS), Self-Rating Depression Scale[50] (SDS), Trait Subscale of the State-Trait Anxiety Inventory for Adults[51] (STAI; Spielberger, 1983), and the revised Obsessive-Compulsive Inventory[52] (OCI-R). We utilized abbreviated versions of these questionnaires following the methodology of Wise and Dolan (2020)[53], who refined the questionnaires using a classifier to retain the items most contributory to variance in the three factors without significant information loss.

As preregistered, we aggregated the scores of the selected items from each questionnaire independently for inclusion in our CCA. Questionnaires were scored following the corresponding scoring guide, but in such a way that larger scores always indicate greater psychopathology. Based on best practice recommendations[54-55], participants were screened for inattentive responding with infrequency items ('I competed in the 1917 Summer Olympic Games') which resulted in the removal of 11 participants (Initial: 6, Replication: 5).

Directly using the scores from questionnaires of varying lengths in the CCA can give undue influence to short questionnaires, whose scores are likely more noisy. To mitigate this problem, we adjusted the standard deviation of each questionnaire's score proportionally to the square root of its number of items before conducting the CCA (in accordance with the formula for standard error). After performing the CCA on these weighted scores and normalized model parameters, the resulting canonical loadings were transformed back to their original standardized scale, ensuring that the reported loadings accurately reflected the original, unweighted scale of the questionnaire scores.

Canonical Correlation Analysis (CCA)

Canonical correlation analysis was implemented using the robust CCA method based on projection pursuit ('ccAPP' package;)[56]. We searched for the single canonical dimension that maximizes the Spearman correlation between the model parameters and psychopathology scores. Significance testing was conducted using a two-tailed permutation test with 1,000 iterations. In each iteration, the model parameters were shuffled relative to the psychopathology scores, and the canonical correlation was recalculated. The observed canonical correlation was then compared to this null distribution to obtain a p-value. To evaluate the contribution of the elasticity prior parameter ($\gamma_{\text{elasticity}}$) to the parameter-psychopathology correlation, we performed an additional permutation test. In this test, only the elasticity bias estimates ($\gamma_{\text{elasticity}}$) were shuffled, while all other model parameters and self-report scores remained constant.

To assess how the identified psychopathological profile manifests in raw task measures, we calculated a composite psychopathology score for each participant. This score was derived by multiplying individual participant scores by CCA-derived loadings, representing their position on the psychopathology spectrum. We then used this composite score as a predictor ($\beta_{composite}$) in a linear regression model to forecast the difference in average opt-in and extra ticket behavior between conditions where controllability was high and inelastic versus high and elastic.

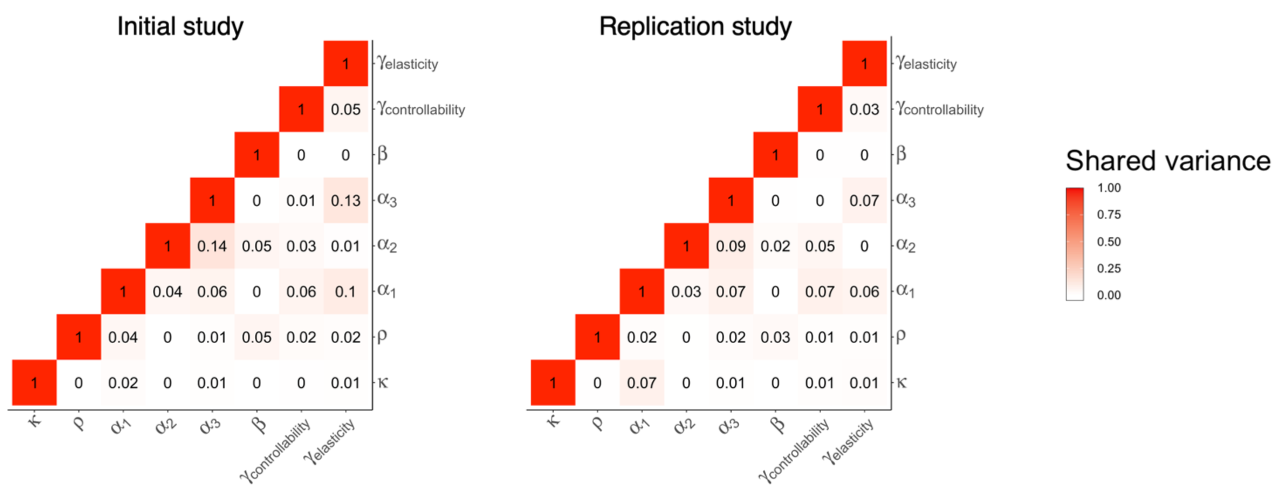
Supplementary Information

S1 Table. Model validation. 10 full experimental datasets were simulated using each model. Rows indicate the model used to simulate data and columns indicate the model recovered from the data using the model comparison procedure.

	Controllability	**Elastic controllability**	**Null**
Controllability	10	0	0
Elastic controllability	0	10	0
Null	0	0	10

S2 Table. Parameter Recovery. We validated our model fitting procedure by simulating data using the best fitting parameters for each subject and then recovering those parameters. Our correlation between simulated and recovered parameters was at least .74 for all parameters of interest that capture the effects of the experimental conditions, and at least .63 for all other parameters.

Parameter	Correlation between Simulated and Recovered Parameters
$\boldsymbol{\beta}$	**.91**
$\boldsymbol{\gamma_{\mathrm{controllability}}}$	**.77**
$\boldsymbol{\gamma_{\mathrm{elasticity}}}$	**.74**
$\boldsymbol{\alpha_1}$	**.82**
$\boldsymbol{\alpha_2}$	**.81**
$\boldsymbol{\alpha_3}$	**.81**
$\boldsymbol{\rho}$	**.89**
$\boldsymbol{\kappa}$	**.63**



S1 Figure. Shared variance between elastic controllability* model parameters. Heatmaps display squared Pearson correlations between parameter pairs for initial (left) and replication (right) studies. Color intensity indicates shared variance magnitude (0-1). Parameters: $\gamma_{\mathrm{controllability}}$, $\gamma_{\mathrm{elasticity}}$, β, a_{1-3}, ρ, κ. Diagonal elements=1; off-diagonal elements reveal parameter interdependencies.

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