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Empowerment contributes to exploration behaviour in a creative video game

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Studies of human exploration frequently cast people as serendipitously stumbling upon good options. Yet these studies may not capture the richness of exploration strategies that people exhibit in more complex environments. Here we study behaviour in a large dataset of 29,493 players of the richly structured online game 'Little Alchemy 2'. In this game, players start with four elements, which they can combine to create up to 720 complex objects. We find that players are driven not only by external reward signals, such as an attempt to produce successful outcomes, but also by an intrinsic motivation to create objects that empower them to create even more objects. We find that this drive for empowerment is eliminated when playing a game variant that lacks recognizable semantics, indicating that people use their knowledge about the world and its possibilities to guide their exploration. Our results suggest that the drive for empowerment may be a potent source of intrinsic motivation in richly structured domains, particularly those that lack explicit reward signals.

Exploration—seeking out potentially useful information—is prevalent in our everyday lives. From choosing a restaurant to finding a suitable workplace, we need to explore our options to be able to make good decisions. A fundamental tension in all these scenarios exists between exploring unknown options and exploiting known options. An algorithmic account of human exploration must explain both what to explore and when to explore.

Psychologists and neuroscientists have extensively studied human exploration in simple and highly controlled multi-armed bandit tasks[1,2]. In these tasks, participants choose between a set of options ('arms'), each associated with an unknown reward distribution. It is the participants' goal to maximize rewards by repeatedly sampling arms and collecting the resulting rewards. Ideal agents should explore by combining the immediate reward and the value of information for each action; they can do so by thinking through all possible future actions and calculating how much rewards would increase if more knowledge about the reward distributions was collected. However, such optimal exploration strategies are computationally intractable. Researchers have therefore focused on the heuristic strategies of exploration that humans might employ[3,4]. Some evidence suggests that people use sophisticated uncertainty-based heuristics[5–7].

In this Article, we propose that human exploration strategies are richer than what has previously been described. In particular, we believe that current models of human exploration do not capture the intrinsically motivated exploration strategies observed in the real world[8–10]. As an example, consider how children play with their environment, curiously trying out new things to understand and learn about the world, or how scientists explore and arbitrate between different hypotheses to advance our collective knowledge. In many of these settings, direct rewards are very sparse and it is often not even clear what the reward is. Yet people can spend time on activities without such rewards; these preferences reflect intrinsic exploratory drives. Current laboratory tasks are not rich enough to study these types of behaviour quantitatively. We, therefore, propose to study human exploration in more complex and richly structured environments. One such environment is the online game 'Little Alchemy 2', in which players start out with four basic elements: water, fire, earth and air. They can then use their intuitive semantic understanding and always

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combine two elements, which sometimes leads to new elements. Each created element is added to an inventory for use in future combinations (Fig. 1a). The combination results are semantically meaningful (for example, combining water with fire produces steam, and can lead to increasingly complex elements, such as humans; Fig. 1b). Gameplay is not random: people selectively choose which elements to combine, and thereby follow particular paths through the vast state space of element inventories. Importantly, players do not receive any extrinsic rewards during the game, yet may play for several hours. Thus, we believe that 'Little Alchemy 2' offers a better and more realistic testbed to investigate intrinsic exploration strategies than many current laboratory tasks. In the current paper, we analysed a large dataset of 29,493 players who collectively produced more than 4 million trials.

We show that players' exploration behaviour is best described not only by a model grounded in external reward signals, as well as uncertainty-guided and recency-guided exploration, but also by an exploration as empowerment model that we propose in this paper. Uncertainty-guided exploration is a well-known strategy that can be formalized as the tendency to combine elements that have not frequently been used before. Exploration as empowerment is a novel description of human exploration that can be formalized as the attempt to create elements that can be used to create even more elements. This is similar to how scientists explore when they are trying to gain insights that enable them to gain even further insights and therefore explore even more. Using two simpler versions of the 'Little Alchemy 2' testbed, we show that our previous results can be replicated in an experimental setting and that the effect of empowerment on participants' exploration strategies vanishes if we remove the semantics of the game. These results push our understanding of human exploration strategies away from simple strategies of exploration in simple tasks and towards the rich repertoire of intrinsic exploration strategies found in rich environments.

Extending models of human exploration

Previous studies on human exploration have coalesced around two strategies: random and directed exploration. Both use uncertainty about the available options to guide exploration behaviour but differ in how uncertainty is assumed to guide behaviour[1]. Whereas directed exploration applies an information bonus to seek out options with higher uncertainty, random exploration predicts that choice stochasticity increases with higher uncertainty across all available options. While earlier studies did not produce consistent empirical evidence for uncertainty-guided exploration in human decision making (for example, refs. 3,11), recent studies have provided converging evidence in favour of such strategies[4,6,12,13].

What many of the previous studies on human exploration have in common, is that they used the fairly simple paradigm of multi-armed bandits and only collected data from a small number of participants. Although these tasks have contributed to a deeper understanding of human exploration behaviour, their simplicity might have masked more sophisticated strategies that people could apply in richer settings. Indeed, the strategies humans can employ in exploration tasks—and which can be found empirically—are clearly limited by the complexity of the used experimental paradigms[8]. The study of empowerment, for example, requires a change of influence on future options, which is not possible to assess in multi-armed bandits without changing rewards or dynamic states, as well as an intuitive understanding of which actions can be empowering, for example by using an intuitive understanding of which objects in a game can be combined.

To set the stage for our analyses of people's playing behaviour, we first describe the 'Little Alchemy 2' game in more detail before then explaining the algorithmic ideas behind uncertainty-guided exploration and exploration as empowerment.

A quintessential game of exploration

In the present work, we look at the game 'Little Alchemy 2', created and released by Jakub Koziol in 2017. By August 2021, the game had been downloaded over ten million times[14]. The idea of the game is simple: players start with an inventory of only four elements: earth, fire, water and air. Players can create new elements by always combining two already existing elements. The resulting elements are added permanently to the inventory and can be used from then onward (Fig. 1a). The successful combinations and their results are semantically meaningful. For example, the combination of fire and earth leads to lava, which can be combined with sea to create primordial soup. These can be the first steps to create life and—eventually—human in the further course of the game (Fig. 1b). 'Little Alchemy 2' offers a total of 720 elements, ranging from basic items like energy or glass to extremely specific elements like cookie dough or Frankenstein's Monster. Between these elements, there are 3,452 combinations (out of 259,560; Supplementary Information) that successfully create other elements. The game has a few additional rules, but they are not relevant for our analysis (for more details, see Supplementary Information). We believe that 'Little Alchemy 2' is a quintessential game of exploration because players do not play for rewards but instead are intrinsically motivated to explore the game tree and create new elements. It offers a rich and semantically meaningful structure, which probes humans' intuitions about the combinability of its elements. Similar games have been used as a paradigm to study artificial agents' commonsense knowledge when trained on natural language corpora[15].

Uncertainty-guided exploration

How can and should people explore element combinations in 'Little Alchemy 2'? We compare two different strategies in terms of how well they describe players' behaviour in the game: uncertainty-guided exploration and exploration as empowerment.

One class of heuristics is to use one's uncertainty about different options to guide one's exploration behaviour. For example, one way to implement simple uncertainty-guided exploration is to assume an uncertainty bonus that encourages the sampling of options that have not been sampled frequently in the past. Models of human exploration using this type of uncertainty-guidance have been very prolific, describing behaviour in simple multi-armed bandits[5], bandits with correlational structures[16], as well as real-world decision-making problems[17]. Uncertainty-guided exploration, therefore, constitutes a good candidate model to describe human exploration in more complex paradigms as well. In 'Little Alchemy 2', an uncertainty-guided strategy would correspond to tracking how often one has used particular elements before and then using the elements more that have not been used frequently. It can be formalized as

$$U_e = \sqrt{\frac{\log(T)}{t_e + 1}}, \tag{1}$$

where the uncertainty value U of each element e depends on the total number of trials T so far and the number of times t_e the element has been chosen in the past. The higher the uncertainty value of a combination (the sum of the individual values of the two respective elements), the higher the probability of choosing that combination.

Exploration as empowerment

Other exploration strategies could also be at play in more complex scenarios such as 'Little Alchemy 2'. One such strategy is empowerment[18]. Exploration as empowerment centres around the idea of exploring options that enable the generation of as many more options as possible. This idea is also at the centre of many examples of real-world exploration. For example, in the pharmaceutical sciences, researchers attempt to find new methods to produce vaccines even faster in the future. Children at play might also exhibit this kind of intrinsic drive to explore actions that train them to explore even more actions[9,19]. Empowerment differs from uncertainty-guided strategies, in that it focuses

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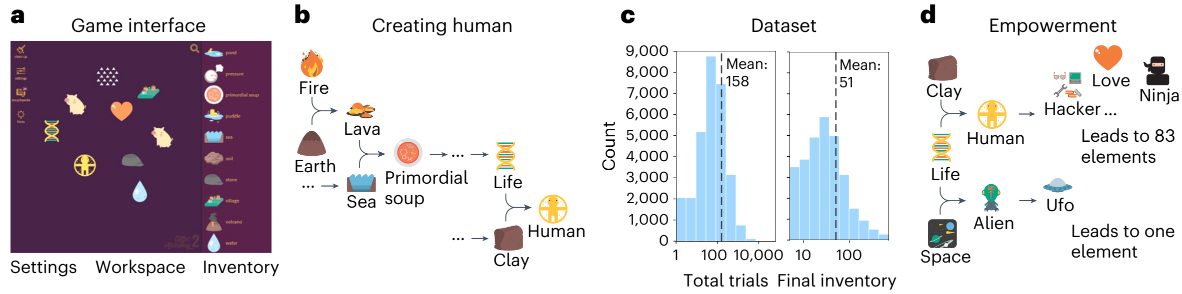

Fig. 1 | 'Little Alchemy 2'. a, Game interface. Players can use the workspace to combine two elements in an attempt to create new elements, which get added to the inventory and can be used for future combinations. **b**, Creating human. 'Little Alchemy 2' is a richly structured game in which semantically meaningful combinations can create up to 720 unique elements. **c**, Dataset of 29,493 players attempting a total of 4,691,033 combinations. Participants played for 158 trials and found 51 elements on average. **d**, Example of empowerment algorithm. Combining life with clay creates human, which can lead to 83 other elements in total, such as hacker, love and ninja. Combining life with space creates alien, which can only lead to one other element, UFO. Thus, combining life with clay is the more empowering action.

less on reducing uncertainty about the environment and more on the intrinsic drive towards a state of maximum influence[20]. It would not be easily possible to study exploration as empowerment in multi-armed bandits as the influence on future options cannot be changed during the experiment. Nonetheless, we believe that empowerment captures a quintessential component of intrinsic exploration such as in children's play and scientific investigations: the attempt to do things that enable one to do even more things in the future.

In the context of 'Little Alchemy 2', empowerment translates into the players' intrinsic desire to create elements that offer many new successful combinations. We therefore call an element empowering the more distinct elements it can lead to by combination with all other possible elements in the game, provided that the true game tree is known. For example, the element human in combination with other elements leads to 83 new elements, while alien leads to only 1 new element (Fig. 1d). Thus, the element human is more empowering than the element alien. The empowerment value of a combination is the empowerment value of the resulting element—so the number of elements it can create. In our example, the combination of space and life has a lower empowerment value (1) than clay and life (83). Without knowledge of the true game tree, empowerment requires both a semantic understanding of what elements could come out of a particular combination as well as an intuitive understanding of how potent, that is combinable, the resulting elements could be. Thus, studying empowerment requires a richly structured and semantically meaningful game tree such as the one afforded by 'Little Alchemy 2'.

Results

We look for signatures of uncertainty-guided exploration and empowerment in a dataset of online players of the game 'Little Alchemy 2' using statistical and cognitive modelling. Additionally, we change the structure of the game to investigate whether a simpler paradigm and a version without rich game semantics could lead to similar results. Further details can be found in Methods, as well as in Supplementary Information. In the first section of Results, we present the online dataset and some descriptive analyses. In the following two sections, we show that humans incorporate the empowerment value in their behaviour and look at the performance of different models playing the game. Afterwards, we address people's intuitive semantic understanding of the game and how an approximation of this understanding can be integrated into the empowerment model. In the following section, we show that humans use a mixture of exploration as empowerment and uncertainty-guided exploration when playing the game. Finally, we extend our results by gathering two similar datasets from online experiments, omitting the semantic structure of the game in one of them.

Online game data

We collected data from anonymous online players of the game over a duration of 3 weeks, resulting in a dataset of 29,493 players who tried over four million combinations. From each player, we know the whole course of their gameplay, that is, the order of tried combinations, starting with the basic inventory of four elements. Players played for an average of 158 trials and discovered an average of 51 elements (Fig. 1c; mean number of trials 158.06, standard deviation (s.d.) 695.38; mean number of elements 50.91, s.d. 76.42). A total of 563 players even played for longer than 1,000 trials, with 16 of them playing over 10,000 trials. A total of 3,206 players managed to have an inventory with more than 100 elements; 9 players managed to find all possible 720 elements.

Drivers of exploration behaviour

What strategies do humans use to explore the space of possible elements? Players immediately used elements that they had just created very frequently (Fig. 2a). We therefore further analysed what drove players to immediately use a new element after it had just been created. The idea of this analysis was that if people have a good intuition about empowerment, then they should immediately use empowering elements as soon as they have been created. This analysis showed that players had a preference to use an element immediately after creating it if the element had a higher empowerment value, that is the actual number of elements it could lead to. We assessed the size of the effect by comparing their choices with a simulated random performance, which revealed that they differed meaningfully ($\beta = 0.43$, $t = 6.59$, $P < 0.001$; human: $\beta = 0.47$, $t = 12.26$, $P < 0.001$; random: $\beta = 0.04$, $t = 0.76$, $P = 0.45$—for details, see Supplementary Information). This suggests that people incorporate the empowerment value of the different elements in their decision to immediately use a newly created element.

Another aspect of people's playing behaviour is the point in time at which they stop playing the game. What motivates players to continue combining elements? We analysed whether continuation of play is more influenced by the recent creation of successful combinations, or by the recent creation of empowering elements. We regressed the decision of continuation of the players in the current trial onto the value of the previous two trials (average number of successful trials in the success model and average empowerment values of all created elements in the empowerment model). We found that the empowerment value of discovered elements had a positive effect on continuation of play ($\beta = 0.41$, $z = 42.62$, $P < 0.001$), while the success value had a negative effect ($\beta = -0.31$, $z = -33.18$, $P < 0.001$, Fig. 2b). These effects remained robust when controlling for the number of trials and the size of the inventory, as well as when using the previous one to five trials for this analysis (for further details, see Supplementary Information).

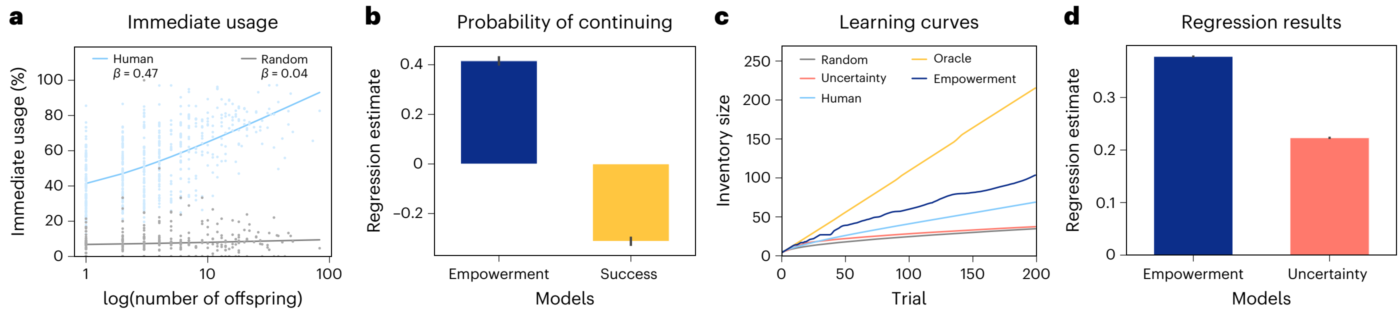

Fig. 2 | Empowerment results. a, Percentage of immediately used newly discovered elements depending on their empowerment value—how many elements they can produce. Players were more likely to immediately use more empowering elements than would be expected under a random performance. **b**, Probability of continuing the game. While the empowerment value of recently discovered elements had a positive influence on participants' probability of continuing the game, the success of combinations did not. **c**, Performance of different models when playing 'Little Alchemy 2'. The uncertainty model performed marginally better than chance, while the empowerment model performed better than humans. The oracle model indicates the performance of an optimal agent. **d**, Regression coefficients of best-performing model. A combination of empowerment and uncertainty described human behaviour in 'Little Alchemy 2' best. Error bars indicate the standard error of the mean.

This means that players' decisions to continue the game were mostly influenced by how empowering recently created elements were. The negative effect of success indicates that players might like to 'end on a high', meaning they would rather quit the game shortly after finding a (non-empowering) element, than after not finding an element for multiple trials.

Model performance in playing the game

We assessed the performance of different models by letting them play the game from the beginning. We tested the performance of the empowerment approach by creating a model based on the empowerment values of the actual underlying game tree of the original game and compared this model to a random choice, an oracle, and an uncertainty-based exploration model.

The random model picks the elements of the next combination randomly from the current inventory. The oracle model knows the actual game tree and chooses combinations that always result in the discovery of a new element, thus simulating the behaviour of a perfect agent. The uncertainty model picks elements based on how often they have been used so far (equation (1)). The more often an element has been chosen, the less likely it is to be chosen again. The empowerment model bases its decisions on the empowerment value of the possible combinations.

The values of the latter two models were converted into probabilities using a softmax function before a combination was selected according to these probabilities. Each model also had a perfect memory, that is, they never tried past combinations again. We ran each model 1,000 times over 200 trials. In Fig. 2c, we plotted the average inventory size over time while also comparing to human players. The oracle model and the empowerment model outperformed human players. This was expected because both of these models knew the true underlying game tree of the actual game, while people did not. The uncertainty-based and the random model performed worse than humans. Since human performance was between these two kinds of models, it is conceivable that players were using a mixed strategy, similar to other theories of human learning and decision making[6,21].

Approximating the intuitive semantics of the game

We believe that players have an intuitive understanding of which elements are combinable and empowering and which are not, which we operationalized in our empowerment model. However, the empowerment model must be based on a game tree to calculate the values of the different combinations. Our focus lies on comparing how the different models describe human behaviour, but the human players do not know the true underlying game tree. Therefore, we had to find another reasonable semantic basis for the empowerment model, which captures people's intuitive understanding of which elements can be combined and which cannot. Clearly, it would not be feasible to ask players about their intuitions about all possible 720 × 720 element combinations (see also Supplementary Information). Thus, we decided to approximate human semantic understanding using neural networks trained on parts of the underlying game tree. To represent the elements in a vector space, we used a word representation model of vector embeddings pre-trained on a large English language corpus of Wikipedia articles[22]. Similar models have been used to model human judgement and decision making in other domains[23]. The elements' word vectors were used as inputs to two feedforward neural networks. The first model was a link prediction model, which predicted which element combinations were likely to succeed. The second model was an element prediction model, which assigned probabilities to each of the 720 possible elements, stating how likely the respective element was to result from the given combination. Both neural networks were trained on subparts of the true underlying game tree, by dividing the possible 259,560 combinations into a training, validation and test dataset. We used ten-fold cross-validation such that each element combination was part of a test set at least once. For all further analysis, we only used the predicted probabilities of combinations that were not part of the training set. These probabilities were used to form a new basis for our empowerment model. We created new empowerment values for each possible combination by multiplying its success probability with the outcome probabilities of all elements times their specific empowerment values—how many unique elements it is likely to create (for more details, see Supplementary Information). Thus, combinations that had a high probability to succeed and a high probability to result in an element that can create more elements in the future had a high empowerment value, predicted by the two models in unison. These values are naturally still based on the underlying true game tree. Therefore, there exists a substantial correlation between the empowerment values of each element according to the model and according to the true underlying game tree ($r = 0.83$, $P < 0.001$; for a visualization, see Supplementary Information). However, the model's predictions seem to match people's intuitions according to our additional experiments (for details, see Supplementary Information).

Regression analysis

We compared how well the different models described the actual behaviour of all players. Because players' inventory grows over time, it becomes difficult to compare across all possible choices. Therefore,

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we decided to use a simpler method to compare the different models' predictions, which was to create a dataset comparing the value of a combination chosen by a player according to the current model with the value of a randomly sampled combination that the player could have chosen but did not based on his current inventory. We then fed the differences of these two value predictions into a logistic mixed-effects regression[6], allowing us to regress participants' choices onto model predictions (for further details on including potential confounding factors, as well as multiple recovery analyses, see Supplementary Information).

We compared several models of players' gameplay, while also controlling for the number of trials different players played, as well as interaction effects between the models and the trial number. We found that the model best describing choices was a combination of empowerment ($\beta = 0.38$, $z = 369.22$, $P < 0.001$) and uncertainty-guided ($\beta = 0.22$, $z = 204.44$, $P < 0.001$) exploration (Fig. 2d; for full model comparison, see Supplementary Information). Importantly, the effect of empowerment was larger than the effect of uncertainty-guided exploration ($\beta = 0.118$, $z = 86.46$, $P < 0.001$). Although there was a positive effect of uncertainty-guided exploration, our model recovery results showed that we cannot fully distinguish between uncertainty-guided and random exploration. Thus, participants were driven mostly by the attempt to create elements that empowered them to create even more elements.

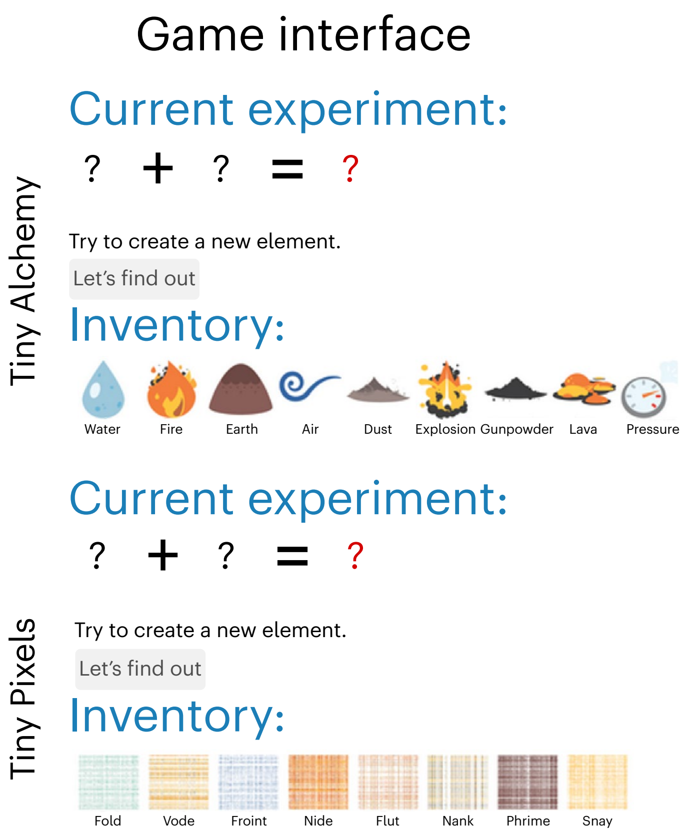

Fig. 3 | Experiment setup of 'Tiny Alchemy' and 'Tiny Pixels'. 'Tiny Alchemy' is an experimental version of 'Little Alchemy 2'. 'Tiny Pixels' is based on 'Tiny Alchemy' but does not contain any semantic information.

Recency model

An additional factor that could have an influence on people's playing behaviour is recency—the number of trials since an element was last chosen. We checked whether players displayed a recency bias in their decisions by constructing a recency model. This model chooses elements based on the number of trials since their last usage. The value of a combination in the recency model is calculated by taking the negative value of the sum of the individual recency values, which are defined as the number of trials since the element was last used, divided by the total number of trials played so far. We found that recency had a significant positive effect ($\beta = 1.76$, $z = 508.93$, $P < 0.001$). This means that players preferred to use elements they just used again. This result can be partly explained by the interface design—elements that have just been used unsuccessfully stay in the play area—which pushes players into the direction of re-using just used elements. However, even when running an experiment that is similar to the original game (see 'Tiny Alchemy' in Supplementary Information), but does not include a play area, recency still shows a significant positive effect ($\beta = 0.68$, $z = 44.00$, $P < 0.001$). Therefore, it seems like players were more likely to choose elements that they recently used. This effect has been observed in multiple experiments[24]. However, even when including the recency model, as well as its interaction effect with the number of trials, empowerment still had a significant effect on players' behaviour in the original regression model ($\beta = 0.40$, $z = 354.14$, $P < 0.001$; for full regression results, see Supplementary Information).

Empowerment versus success only

Since our model formalizing exploration as empowerment consists of two components—a link prediction and an element prediction component—one might ask if the link prediction component alone might already be enough to explain human behaviour in 'Little Alchemy 2'. This would correspond to players only caring about whether or not a combination can successfully create new elements. However, the link prediction component is not straightforwardly comparable with our empowerment model, as the empowerment model contains a link prediction component. Because unsuccessful combinations cannot be empowering, the two models are correlated in their predictions. To further tease apart the two concepts, we performed two additional analyses.

In the first analysis, we manipulated our regression analysis by matching the success of the randomly sampled combination with the combination chosen by the player. For the main regression reported, we had simply matched the chosen pairs with randomly sampled pairs. Here, we manipulated this sampling by matching the sampled pair such that it was successful if the chosen pair was successful and unsuccessful if the chosen pair was unsuccessful. This essentially nullified the contribution of success to this regression. Our oracle model, which was based on the true game tree, was therefore—by design—not capable of predicting human decisions. However, the empowerment model based on the true game tree was still able to significantly explain variance in human behaviour ($\beta = 0.08$, $z = 61.54$, $P < 0.001$), even when adding the uncertainty (empowerment: $\beta = 0.07$, $z = 49.37$, $P < 0.001$) or the recency component to the regression analysis (empowerment: $\beta = 0.06$, $z = 37.17$, $P < 0.001$; for full regression results, see Supplementary Information).

In a second analysis, we created a new empowerment model, which was directly trained on the empowerment values of the successful combinations according to the underlying game tree (see Supplementary Information for further details). As this method does not use the link prediction component to calculate the empowerment value, this reduced the correlation between the two models. In the corresponding regression analysis, in which we included the new empowerment model, as well as the link prediction component—corresponding to a success-only model based on the neural network approximations—we found that empowerment explained a significant amount of variance in human behaviour when controlling for the link prediction component ($\beta = 0.12$, $z = 126.49$, $P < 0.001$), even when additionally controlling for the uncertainty (empowerment: $\beta = 0.13$, $z = 131.37$, $P < 0.001$) or the recency component (empowerment: $\beta = 0.13$, $z = 119.91$, $P < 0.001$; for full regression results, see Supplementary Information).

Taken together, we conclude that while the expected success of a combination influenced people's choices, it was not the only strategy

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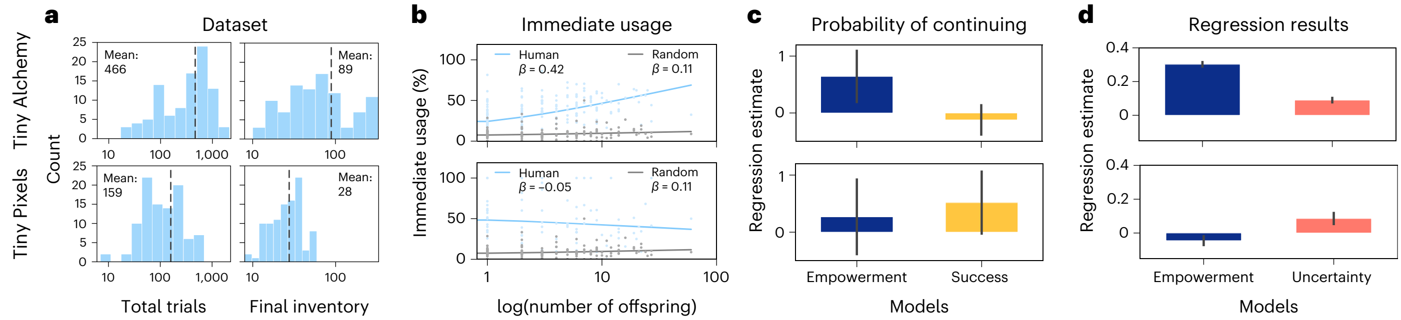

Fig. 4 | Importance of richly structured game semantics. a, In 'Tiny Alchemy', 97 participants played for 466 trials and created 89 elements on average. In 'Tiny Pixels', 98 participants played for 159 trials and created 28 elements on average. **b**, While participants were more likely to immediately use empowering elements in 'Tiny Alchemy', this was not the case for participants in 'Tiny Pixels'. **c**, While the empowerment value of recently discovered combinations had an influence on participants' continuation behaviour in 'Tiny Alchemy', this was not the case in 'Tiny Pixels'. **d**, Regression coefficients of empowerment plus uncertainty model. Whereas empowerment and uncertainty both significantly related to participants' choices in 'Tiny Alchemy', only uncertainty-guided exploration—and not empowerment—did for 'Tiny Pixels'. Error bars indicate the standard error of the mean.

they used. Rather, it is very likely that players additionally took the empowerment value of elements into account.

The importance of semantic structure

We argued that richly structured environments should be used to study more sophisticated exploration strategies than are typically found in simpler paradigms such as multi-armed bandit tasks. In particular, we believe that 'Little Alchemy 2' is richer than multi-armed bandits on two axes. First, multi-armed bandits are flat with only very few options, while our game has many possible nodes and ways in which an exploring player can go. Second, multi-armed bandits are also blank because they do not assume any prior knowledge, while our game requires a rich semantic understanding of how different elements could be combined. We hypothesized that people explore by trying to empower themselves in the game, not only because the game contains a rich game tree, but also because of the rich semantics underlying the tree. To further probe this hypothesis, we checked if stripping away the semantics of the game changed players' exploration strategies. For that purpose, we created our own two versions of the game which we termed 'Tiny Alchemy' and 'Tiny Pixels'. Both versions are based on the game tree of 'Little Alchemy 1', the predecessor of 'Little Alchemy 2'. The game 'Tiny Alchemy' contains 540 elements and has a similarly rich semantic structure as the original game. We simplified the game even further, resulting in 345 discoverable elements. The game 'Tiny Pixels' has the same underlying game tree but we eliminated the semantics by randomly repositioning the pixels in the pictures of the elements and adding uninformative names usually used in memory tasks (Fig. 3). With the semantic structure removed, the game is still rich (because it is not flat), but we expected it not to be rich in the right way (because it was now blank). We also expected this manipulation to make the game more difficult for the participants, as they would not be able to use their intuition to make decisions. We collected data for both games on Amazon Mechanical Turk, gathering 97 participants for 'Tiny Alchemy' and 98 participants for 'Tiny Pixels'. The resulting dataset allowed us to assess how much our finding of exploration as empowerment was indeed driven by the semantics of the game.

Behavioural differences

We first investigated simple behavioural differences between the two games under the assumption that 'Tiny Pixels' would be more difficult for players than 'Tiny Alchemy'. We found that players of the game 'Tiny Alchemy' played on average longer ($t(193) = 7.12$, $P < 0.001$, $d = 1.02$) and discovered more elements ($t(193) = 7.21$, $P < 0.001$, $d = 1.03$) than players of the game 'Tiny Pixels' (Fig. 4a; 'Tiny Alchemy': mean number of trials 465.55, s.d. 397.71; mean number of elements 89.07, s.d. 83.76; 'Tiny Pixels': mean number of trials 159.44, s.d. 150.99; mean number of elements 27.5, s.d. 11.67).

Next, we compared the frequency of immediately using a newly created element based on its empowerment value—the ability to create new elements later on. In 'Tiny Alchemy', players were more likely to use empowering elements immediately than in 'Tiny Pixels' (Fig. 4b; $\beta = 0.47$, $t = 4.73$, $P < 0.001$; 'Tiny Alchemy' human: $\beta = 0.42$, $t = 8.51$, $P < 0.001$; 'Tiny Pixels' human: $\beta = -0.05$, $t = -0.55$, $P = 0.58$; random: $\beta = 0.11$, $t = 1.83$, $P = 0.07$; for details, see Supplementary Information).

We again compared the influence of success and empowerment values of recent combinations on players' probability of continuing the game. In 'Tiny Alchemy', players were more likely to continue the game when they had recently discovered empowering elements ($\beta = 0.64$, $z = 2.69$, $P = 0.007$), but were not when we just looked at the success of recent combinations ($\beta = -0.12$, $z = 0.14$, $p = 0.39$). We also found no evidence of the success value as in the original dataset. In 'Tiny Pixels', we found no evidence of either model on participants' decision to continue the game (Fig. 4c, empowerment: $\beta = 0.27$, $z = 0.78$, $P = 0.43$; success: $\beta = 0.52$, $z = 1.80$, $P = 0.07$).

Regression analysis for experimental data

We conducted a similar regression analysis as for the online data from before. However, we combined the 'Tiny Alchemy' and 'Tiny Pixels' datasets and included a variable indicating which version a player played. We again included the number of trials and the interactions of model predictions with the number of trials in our regression analysis to account for the unequal length of the datasets. For 'Tiny Alchemy', players were best explained by a combination between exploration as empowerment ($\beta = 0.30$, $z = 29.68$, $P < 0.001$) and uncertainty-guided exploration ($\beta = 0.09$, $z = 8.86$, $P < 0.001$), with the effect of empowerment being stronger than the effect of uncertainty-guided exploration ($\beta = 0.28$, $z = 19.91$, $P < 0.001$). For 'Tiny Pixels', players' choices were only significantly positively influenced by uncertainty ($\beta = 0.09$, $z = 4.26$, $P < 0.001$), but we found no evidence for empowerment (Fig. 4d, $\beta = -0.05$, $z = -2.71$, $P = 0.007$), leading to a higher effect of uncertainty-guided exploration over empowerment ($\beta = -0.21$, $z = -9.31$, $P < 0.001$). These results further strengthen our idea that rich environments are necessary to study complex explorations strategies such as success-oriented or empowerment strategies and that players' exploration looks more like what has been frequently found in traditional multi-armed bandits paradigms when the rich structure of the game is removed.

Discussion

We have studied human exploration in a richly structured online game using a large dataset of human playing behaviour. We showed that players' behaviour appears to be driven by more than previously shown motivations grounded in external reward signals—such as an attempt to produce successful outcomes—or well-researched internal reward signals—such as uncertainty and recency. Their behaviour is also driven by an intrinsic motivation for empowerment—people seem to take into account how empowering the outcomes of their actions are. Detailed computational modelling showed that these patterns could be captured quantitatively. Our results suggest that people use richly structured and semantically meaningful exploration strategies in the game, resembling other strategies observed in the real world such as children's playing behaviour or scientific methods of discovery.

As mentioned in the results, a success-only model, based on the link prediction component of the empowerment model, described human play behaviour well. However, we were able to show with multiple extra analyses that players additionally took the empowerment value of combinations into account. Nevertheless, in future investigations, we would like to compare both models in more detail using other paradigms, to further study the value of empowerment.

Of course, our current empowerment model is just one formalization of exploration in richly structured environments such as games. Even though we found our model to match well with both people's actual gameplaying behaviour and their intuitions in a validation experiment, other strategies of exploration could also be assessed using our data. One such strategy is powerplay[25], which attempts to train one's model of the world as much as possible and would predict that players not only create elements to empower themselves, but also to learn more about the game mechanics in general. Another strategy is goal-conditioned exploration[26], which is setting yourself goals to accomplish within the game. For example, in 'Little Alchemy 2', having the goal of creating a solar cell would probably lead to a different exploration path through the game tree than the goal of creating chicken soup. There have also been several other studies on both the algorithmic[27–29] and behavioural[30,31] underpinnings of more sophisticated exploration strategies. All these exploration strategies have the potential to explain human behaviour in this dataset in addition to empowerment. In future investigations, we will attempt to further identify signatures of human behaviour in this dataset and use it to compare more elaborate strategies of exploration.

Relatedly, our current model does not incorporate any learning of the underlying structure and solely focuses on the exploration aspect of people's play. We believe that this is a good first step to understanding exploration as empowerment because people probably already have detailed intuitions about the different element pairs before the start of the game. Nonetheless, one of our future goals is to build models that update their intuitions while playing the game and thereby simulate people's learning progress.

Another concern is the fact that the underlying semantic structure of the game tree was designed by just one person, that is the creator of the game. Thus, one could argue that the game might not tell us much about people's general intuitions and exploration behaviour. We do not believe this to be the case for two reasons. First, we were able to show that these intuitions are shared among the players within our validation study. Second, games are generally designed to be natural for people—meaning they have to be learnable and are calibrated to people's intuitive theories in the first place. Thus, we believe that games such as 'Little Alchemy' can be used to reverse-engineer people's intuitive semantics and use them to model human exploration.

Finally, even though players participated in the online game 'Little Alchemy 2' without any external rewards, participants of our experimental versions of the game, 'Tiny Alchemy' and 'Tiny Pixels', were rewarded for generating new elements. This means that participants exploring the game intrinsically behaved similarly to participants who participated in our online experiments for monetary rewards. We used the experimental versions of the game to establish that stripping away the semantics of the game changed participants exploration strategies after having established intrinsic exploration strategies using data from the online game already. However, as we do not have a non-rewarded version of the game without semantics, we were not able to look at any behavioural changes external rewards might induce in the non-semantic case. Therefore, in future studies, we would like to further disentangle the effects of rewards on players' behaviour by also removing the semantics of the online game.

Taken together, our results advance our understanding of human intrinsic exploration behaviour and extend current research paradigms by using a large, complex, and richly structured dataset of an online game. One implication of our results could be that empowerment—or other more elaborate exploration strategies—may often drive people's decisions but are masked by the simple paradigms used in research on human exploration strategies. Perhaps more sophisticated strategies can simply not be found in easier paradigms or look like simpler strategies, such as uncertainty-guided exploration, when studied in reduced forms. Thus, we believe that our work demonstrates that using games as experimental paradigms can increase the complexity, robustness and ecological validity of psychological research.

Conclusion

We investigated the exploration behaviour of 29,493 players in the richly structured online game 'Little Alchemy 2'. We have shown that exploration is driven by multiple factors, some of which are familiar and well studied in behaviour, such as a drive for predictable success and recency, but one of which is novel and potentially a crucial factor in innovative discovery: a drive for empowerment. Using two additional games, we replicated our results in a controlled setting and showed that participants resorted to simpler exploration strategies when the semantic structure of the game was removed. Our results point to the necessity to use more complex experimental paradigms to study elaborate strategies of human exploration. We hope that our findings and model are a first step towards empowering our own theories of human exploration.

Methods

All experiments were approved by the Harvard internal review board. All statistical tests applied were two-sided. The modelling and data analysis were conducted in R and Python.

'Little Alchemy 2' dataset

The 'Little Alchemy 2' dataset was gathered over a duration of 3 weeks from 1 June to 21 June 2019 with the help of the game's developer. For all our analyses, we only included players who started to play the game within that time period and filtered out all repeated trials. This led to a dataset containing 29,493 players who tried 4,691,033 combinations in total. All included players consented to their anonymized data being used for scientific purposes.

'Tiny Alchemy' and 'Tiny Pixels'

For the experimental versions of the game, that is 'Tiny Alchemy' and 'Tiny Pixels' we recreated the game with standard JavaScript using the game tree of 'Little Alchemy 1'. Whereas players of 'Tiny Alchemy' played the game with normal element pictures and names, 'Tiny Pixels' used element pictures with randomly positioned pixels and unrecognizable yet distinct names (Fig. 3). Players were paid US$0.10 for every discovered element and could play for as long as they wanted but only up to 2 h. We recruited participants from Amazon's Mechanical Turk. For 'Tiny Alchemy', we recruited 97 participants (48 females, mean age 32.68, s.d. 7.97). For 'Tiny Pixels', we recruited 98 participants (45 females, mean age 30.83, s.d. 8.78). All participants consented to their anonymized data being used for scientific purposes. All experiments were approved by Harvard's institutional review board.

Empowerment model

The empowerment model is based on how many distinct elements an element can produce by combination with any other element. As humans play according to their semantic intuitions, we attempted to recreate these and use them as a basis for our empowerment values. This process consisted of four steps: pre-processing the words by turning them into word vectors, prediction of the link probability, prediction of the resulting element, and the actual empowerment calculation step.

First, we used a pre-trained word representation model of word vector embeddings called fasttext[22]. Thereby, we got 300-dimensional word vectors for each of the elements. For each combination, we then concatenated the two vectors of the involved elements to use them as one combination vector.

Second, we used the vectors as input combinations for a link prediction model, which consisted of a fully connected neural net with one hidden layer. This model returned a link probability for the input combination vector. It was trained on subparts of the true game tree—all 259,560 possible combinations were split into a training, validation and test dataset. We used ten-fold cross-validation such that each element combination was part of a test set at least once. For our further analysis, we only used combinations' predicted probabilities that were not used in training. If a combination had a predicted value of higher than 50%, it was classified as a link.

Third, we used the concatenated word vectors as inputs for the element prediction model, which was another fully connected neural network with two hidden layers. This model returned the probability of being the resulting element for each of the 720 possible elements, based on the cosine similarity of the word vector. As before, training was conducted using ten-fold cross-validation.

Fourth, the resulting values of each combination were merged into an empowerment value by multiplying the predicted probability of success with the sum of the probabilities of each element multiplied with the expected empowerment value of an element—the number of distinct elements resulting from combinations involving the element with a predicted success greater or equal to 0.5.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

Anonymized participant data of the experiments and model simulation data are available at https://github.com/franziskabraendle/alchemy_empowerment (ref. 32). Third party data of participants playing the original game may be shared upon reasonable request (franziska.braendle@tuebingen.mpg.de).

Code availability

The code used for all experiments, models and analyses is available at https://github.com/franziskabraendle/alchemy_empowerment (ref. 32).

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Author contributions

F.B., L.J.S., S.J.G. and E.S. conceived the study. F.B. and E.S. collected the data. F.B., L.J.S. and E.S. performed the analyses. F.B., L.J.S., J.B.T., S.J.G. and E.S. wrote the paper.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41562-023-01661-2.

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☒	☐	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
☒	☐	For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
☐	☒	Estimates of effect sizes (e.g. Cohen's d, Pearson's r), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	Data was collected via the game "Little Alchemy 2" and via the Amazon Mechanical Turk Platform using standard javascript.
Data analysis	Behavioral data was analyzed using R (3.6.2) and Python (3.8.1). The model simulations were implemented in Python (3.8.1). The code of the analyses can be found at https://github.com/franziskabraendle/alchemy_empowerment

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Anonymized participant data of the experiments and model simulation data are available at https://github.com/franziskabraendle/alchemy_empowerment. Third party data of participants playing the game may be shared upon reasonable request (franziska.braendle@tuebingen.mpg.de).

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Sample size	*Describe how sample size was determined, detailing any statistical methods used to predetermine sample size OR if no sample-size calculation was performed, describe how sample sizes were chosen and provide a rationale for why these sample sizes are sufficient.*
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Randomization	*Describe how samples/organisms/participants were allocated into experimental groups. If allocation was not random, describe how covariates were controlled OR if this is not relevant to your study, explain why.*
Blinding	*Describe whether the investigators were blinded to group allocation during data collection and/or analysis. If blinding was not possible, describe why OR explain why blinding was not relevant to your study.*

Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	We studied human choices in the online game "Little Alchemy 2", which could be accessed via a website and an app. We also ran several additional experiments using Amazon Mechanical Turk. In all experiments, we gathered quantitative data based on the participants' choices in each trial.
Research sample	The data sample of 29.493 participants were choices of players of the game "Little Alchemy 2". The participants of our additional experiments were recruited via Amazon Mechanical Turk. For ``Tiny Alchemy'', we recruited 97 participants. For ``Tiny Pixels'', we recruited 98 participants. For the Model validation experiment we recruited 104 participants. Participants were required to be from North America, as well as to have a past HIT completion rate of at least 99% with a minimum of 100 past completed HITs.
Sampling strategy	We used the data of all players of the online game over a period of three weeks in June 2019. We used random sampling for the experiments on the Amazon Mechanical Turk platform, with each sample size around 100 participants. The sample size was determined based on similar studies.
Data collection	The data of the game was gathered by the developer of "Little Alchemy 2" and sent to us already anonymized. Data was saved via javascript onto a local database. No researchers were present while gathering the data, as participants played the game / participated in the expeirments remotely from their own devices.
Timing	The data of players of the game was gathered over a period of three weeks from June 1st to June 21st 2019. The experiments on Amazon Mechanical turk took approximately one day each. The data of "Tiny Alchemy" was gathered in April 2019, of "Tiny Pixels" in August 2021 and of the Model validation experiment in November 2021.
Data exclusions	We excluded data of players who already started the game before their behavior was recorded.
Non-participation	Did not happen.
Randomization	There were no experimental groups.

Ecological, evolutionary & environmental sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	*Briefly describe the study. For quantitative data include treatment factors and interactions, design structure (e.g. factorial, nested, hierarchical), nature and number of experimental units and replicates.*

Research sample	*Describe the research sample (e.g. a group of tagged Passer domesticus, all Stenocereus thurberi within Organ Pipe Cactus National Monument), and provide a rationale for the sample choice. When relevant, describe the organism taxa, source, sex, age range and any manipulations. State what population the sample is meant to represent when applicable. For studies involving existing datasets, describe the data and its source.*
Sampling strategy	*Note the sampling procedure. Describe the statistical methods that were used to predetermine sample size OR if no sample-size calculation was performed, describe how sample sizes were chosen and provide a rationale for why these sample sizes are sufficient.*
Data collection	*Describe the data collection procedure, including who recorded the data and how.*
Timing and spatial scale	*Indicate the start and stop dates of data collection, noting the frequency and periodicity of sampling and providing a rationale for these choices. If there is a gap between collection periods, state the dates for each sample cohort. Specify the spatial scale from which the data are taken*
Data exclusions	*If no data were excluded from the analyses, state so OR if data were excluded, describe the exclusions and the rationale behind them, indicating whether exclusion criteria were pre-established.*
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Randomization	*Describe how samples/organisms/participants were allocated into groups. If allocation was not random, describe how covariates were controlled. If this is not relevant to your study, explain why.*
Blinding	*Describe the extent of blinding used during data acquisition and analysis. If blinding was not possible, describe why OR explain why blinding was not relevant to your study.*

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Access & import/export	*Describe the efforts you have made to access habitats and to collect and import/export your samples in a responsible manner and in compliance with local, national and international laws, noting any permits that were obtained (give the name of the issuing authority, the date of issue, and any identifying information).*
Disturbance	*Describe any disturbance caused by the study and how it was minimized.*

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Materials & experimental systems

n/a	Involved in the study	
☒	☐	Antibodies
☒	☐	Eukaryotic cell lines
☒	☐	Palaeontology and archaeology
☒	☐	Animals and other organisms
☐	☒	Human research participants
☒	☐	Clinical data
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Methods

n/a	Involved in the study	
☒	☐	ChIP-seq
☒	☐	Flow cytometry
☒	☐	MRI-based neuroimaging

Human research participants

Policy information about studies involving human research participants

Population characteristics	Main dataset: Players of the game "Little Alchemy 2" Three additional experiments: Amazon Mechanical Turk participants Tiny Alchemy: 97 participants, 48 females, mean age=32.68, SD=7.97 Tiny Pixels: 98 participants, 45 females, mean age=30.83, SD=8.78 Model Validation experiment: 103 participants, 86 females, mean age=37.1, SD=8.00
Recruitment	Players were recruited via the game website / app as well as on Amazon Mechanical Turk. Amazon Mechanical Turk

Recruitment	participants were required to be from North America, as well as to have a past HIT completion rate of at least 99% with a minimum of 100 past completed HITs.
Ethics oversight	Harvard Internal Review Board.

Note that full information on the approval of the study protocol must also be provided in the manuscript.