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When Uncertainty in Social Contexts Increases Exploration and Decreases Obtained Rewards

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Similar decision-making situations often arise repeatedly, presenting tradeoffs between (i) acquiring new information to facilitate future-related decisions (exploration) and (ii) using existing information to secure expected outcomes (exploitation). Exploration choices have been well characterized in nonsocial contexts, however, choices to explore (or not) in social environments are less well understood. Social environments are of particular interest because a key factor that increases exploration in nonsocial contexts is environmental uncertainty, and the social world is generally appreciated to be highly uncertain. Although uncertainty sometimes must be reduced behaviorally (e.g., by trying something and seeing what happens), other times it may be reduced cognitively (e.g., by imagining possible outcomes). Across four experiments, participants searched for rewards in a series of grids that were either described as comprising real people distributing previously earned points (social context) or as the result of a computer algorithm or natural phenomenon (nonsocial context). In Experiments 1 and 2, participants explored more, and earned fewer rewards, in the social versus nonsocial context, suggesting that social uncertainty prompted behavioral exploration at the cost of task-relevant goals. In Experiments 3 and 4, we provided additional information about the people in the search space that could support social-cognitive approaches to uncertainty reduction, including relationships of the social agents distributing points (Experiment 3) and information relevant to social group membership (Experiment 4); exploration decreased in both instances. Taken together, these experiments highlight the approaches to, and tradeoffs of, uncertainty reduction in social contexts.

Public Significance Statement

When interacting with other people, we often face a high degree of uncertainty: we may not know how other people are feeling, their past experiences, or their future behaviors. We show that people resolve this uncertainty through behavioral exploration—that is, they seek out interactions with other people in order to learn about them. However, this exploration can come at the cost of other goals (in this case, earning rewards). People can sidestep the need for this costly exploration by employing other tools, such as their expectations about how people are similar to each other or themselves. Together, we demonstrate approaches that individuals use to guide social knowledge acquisition.

Keywords: exploration–exploitation, social context, uncertainty, ingroup, multiarmed-bandit task

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Many decisions in human life rely on the consideration of multiple choices with uncertain outcomes. From small decisions that are made on a regular basis (e.g., what to order at a restaurant) to larger decisions made more rarely (e.g., where to buy a home), choices can be broadly characterized as either consistent with exploitation or exploration (see Mehlhorn et al., 2015 for a review). Exploitation involves leveraging information one already has to garner more certain, desired outcomes. For example, during a workplace lunch, you

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might choose to engage in conversation with an old friend because you are confident that you will have an enjoyable time. Exploration, on the other hand, involves trying an alternative about which you know less. Initiating conversations with newer acquaintances (exploring new social connections) could result in a more or less enjoyable outcome, but either way, it provides you with previously unknown information that could potentially help you make predictions about your enjoyment of various lunchtime companions in the future. Exploration decisions might be especially complex in social situations, like this one, because the factors affecting different outcomes are associated with substantial uncertainty: the internal states that drive other people's behavior are hidden from view, dynamic, and responsive to the behavior of others (Berkay & Jenkins, 2023; Dennett, 1987; Fiske, 1993). Recent research provides evidence to suggest that there is a meaningful link between exploratory behavior and real-world social environments and networks (Saragosa-Harris et al., 2022), including that individuals from more diverse social environments forge connections between previously unconnected groups (Wood et al., 2023), and that individuals use statistical inference to infer the relatedness of these networks (which, might in turn influence exploration; Sehl et al., 2022).

While the benefits and costs of exploration have been well studied in nonsocial domains, and uncertainty is known to be a key factor that drives exploration, we know relatively less about how the social landscape affects choices to explore. Here we test predictions about when, and with what consequences, people explore in social contexts. We adapted a classic exploration paradigm (Wu et al., 2018) in which we presented participants with a series of grids comprised of tiles on which participants could click to reveal underlying point values that would be converted to monetary rewards. This simple paradigm is thought to isolate key elements of exploration in natural environments and provide a broad spatial layout to assess local sampling (Wu et al., 2018). To investigate how framing the context as a social one affects exploration, we told participants either that the tiles represented individual people who had allocated to them some reward or that the rewards were generated in a nonsocial fashion (by a computer in Experiment 1; by a natural phenomenon in Experiment 2). We investigated to what extent this simple framing of the context as social or nonsocial affected exploration behavior and reward receipt within the grids. The broad search space mirrors situations in which an individual may be presented with a number of potential social partners across a physical space (e.g., at a party, workplace, or classroom) and in which it may be useful to sample interactions with multiple people before spending more time with a given person.

Given its relevance to decision-making, both human and nonhuman animal behavior (e.g., foraging), and the cognitive processes that underlie these activities (e.g., memory search; Hills et al., 2015; Todd & Hills, 2020), there has been substantial interest in the factors that influence when, why, and for how long individuals engage in a behavioral exploration of nonsocial contexts (see Cohen et al., 2007; Mehlhorn et al., 2015 for reviews). Research suggests that preferences for exploration are not fixed (Mehlhorn et al., 2015) but instead reflect the interaction of multiple contextual considerations (Schulz et al., 2016, 2018), including the age of the learner (Plate et al., 2018), the time one has to potentially acquire information (Wilson et al., 2014), and an agent's goals (Mehlhorn et al., 2015). Indeed, uncertainty is one especially important factor known to increase exploration (Gershman, 2018, 2019; Speekenbrink & Konstantinidis, 2015). Exploration of uncertain environments can satisfy curiosity (Kidd & Hayden, 2015; Liquin et al., 2020), reduce boredom (Geana et al., 2016), and support the pursuit of knowledge to inform flexible changes in behavior (Sharot & Sunstein, 2020).

In the social domain, previous research has sought to understand exploration in collaborative and competitive group environments (e.g., Goldstone et al., 2005; Hills et al., 2015). For example, in group contexts, learning from others' outcomes reduces individuals' need to engage in exploration themselves (Toyokawa et al., 2014). At the same time, there can be a tendency to over rely on social information under uncertain learning conditions (Plate et al., 2021; Toyokawa et al., 2017), and overly local exploration can produce perceptions of differences between groups that do not in fact exist (i.e., stereotypes; Bai et al., 2022). Learners must balance the use of observed social outcomes with attention to structural features of the environment (including reward structure; Wu et al., 2021), which is reflected in dynamic behavior, even within a brief experimental session, as individuals pursue both individual exploration and social learning (Krafft et al., 2015; Plate et al., 2020). However, much remains unknown about exploratory behavior in social contexts, particularly given that individuals may weight social sources of uncertainty differently than nonsocial sources of uncertainty (Blount, 1995; Li et al., 2019; Rilling et al., 2008).

Relatively high unpredictability and ambiguity in the social world have been well documented (e.g., Berkay & Jenkins, 2023; FeldmanHall & Shenhav, 2019; Hertwig & Herzog, 2009; Jenkins & Mitchell, 2010). Individuals may need to turn to behavioral exploration to resolve this uncertainty in social contexts. In other words, they may need to interact with others to gather information that they could then employ to make inferences in the future. Decisions involving other people can involve heightened uncertainty because not only is the outcome itself uncertain (e.g., whether lunch with a new acquaintance would be enjoyable), but the social factors influencing that outcome are also uncertain (e.g., whether the acquaintance will be in a pleasant mood). On the one hand, uncertainty about the reward value of options may trigger exploration to a greater extent than would be expected in nonsocial contexts, in which the primary source of uncertainty is in the outcome itself. On the other hand, higher levels of exploration in social domains may come at the cost of obtaining desired outcomes if individuals attempt to gather information that is difficult and/or slow to acquire (e.g., because they lack access to the internal mental states of others), thereby highlighting the potentially complex interactions between reward, uncertainty, and social factors. Moreover, it is possible that some "types" of exploration will be especially critical in social contexts. *Directed exploration*—in which learners sample options that reduce the overall uncertainty of a search space (Wilson et al., 2014, 2021)—may be especially useful, as opposed to *random exploration* (i.e., sampling options, but not specifically those that can reduce uncertainty), for which the costs of exploration might outweigh the benefits. Finally, social and nonsocial contexts may differ in the availability of strategies for uncertainty reduction. Whereas uncertainty in nonsocial contexts might be disproportionately necessary to resolve through behavioral exploration of choice options, uncertainty in social contexts may sometimes be amenable to resolution via cognitive processes. In other words, the decision maker may employ social knowledge to sidestep the need for behavioral exploration. For instance, in one set of experiments, participants were randomly assigned to sample either the choices of others (social condition) or the outcomes of lotteries (nonsocial condition) in an ultimatum game before playing the game themselves, with the idea that viewing the outcomes could help participants decide their own future choices (Fleischhut et al., 2021). Participants sampled fewer choices of other people versus the lotteries. The authors reasoned that the participants engaged in less search in the social condition because they were using the social outcomes that they observed to engage social-cognitive processes not available in the context of the lottery, including self-projection (e.g., thinking about what they, themselves, would do in that situation) and norm-based reasoning (e.g., thinking about how social norms might recommend certain behaviors). This study is consistent with the possibility that exploration facilitates the accumulation of social knowledge that can be engaged later to reduce the need for additional behavioral exploration. Further evidence suggests that learners in social contexts rely more on top-down information about interaction partners (i.e., information that is known ahead of time), such as trait generosity than bottom-up cues to reward, such as the amount of reward given by the individual (Hackel et al., 2020). In these cases, the use of available social information to guide assumptions about others ostensibly reduces exploration.

In the present experiments, we asked how uncertainty in social (vs. nonsocial) contexts influences exploration. Participants searched for rewards across tiles in a grid in which rewards were either supposedly generated by other people (social context) or by the physical environment (nonsocial context). In Experiments 1 and 2, we provided little information about the individuals in the social context to test whether the elevated uncertainty inherent in a social, compared to a nonsocial, environment would increase exploration. In Experiments 3 and 4, we provided additional information about the individuals in the search space, including their degree of trait similarity to each other (Experiment 3) and their social group membership (Experiment 4) to test whether participants would reduce exploration in social contexts when information is available that could potentially be employed in the service of cognitive uncertainty reduction. To assess the consequences of different search approaches, we measured the rewarding outcomes participants received during their search. Across all experiments, we manipulated environmental smoothness (defined as the degree to which rewards cluster together in the search space) to assess whether comparisons between the social and nonsocial contexts mirror comparisons between environments that vary in degree of uncertainty with regard to the distribution of underlying rewards.

Experiment 1

In Experiment 1, we asked to what extent patterns of exploration differ when the search context is social versus nonsocial, under conditions of minimal information and holding constant the underlying reward structure across contexts. We compared the degree of exploration in social and nonsocial contexts. To characterize the type of exploration participants adopted, we used a modeling approach to compare the extent to which participants engaged in *directed exploration* (i.e., selecting options that will reduce the overall uncertainty of the search space), and the extent to which participants engaged in *random exploration* (i.e., not specifically targeting options that will reduce the overall uncertainty) in social and nonsocial contexts. To the extent that participants associate the social context with higher uncertainty than the nonsocial one, they should demonstrate more exploration (specifically, directed exploration, which would indicate targeted uncertainty reduction; Wilson et al., 2014) in the social context. We additionally measured the impact on reward receipt. While exploration may be pursued in the service of garnering rewards in the long term (e.g., Wilson et al., 2014), it is possible that there may be tradeoffs with reward receipt in the short term.

Method

Transparency and Openness

The experiment, de-identified datasets, and analysis scripts for all experiments are available online at Open Science Framework (https://osf.io/2mj3y/; Plate et al., 2022). R version 3.6.3 was used for all analyses (R Core Team, 2019). We used the tidyverse package (Wickham et al., 2019) for data organization, lme4 package (Bates et al., 2014) for linear mixed effect models, DEoptim package for fitting the Gaussian process model (Mullen et al., 2011), and ggplot2 package (Wickham, 2016) for visualization. The experimental task was adapted from Wu et al. (2018) in JavaScript and hosted on Pavlovia (pavlovia.org). We report how we determined our sample size, all data exclusions, all manipulations, and all measures in the experiments. The experimental design and analyses were not preregistered with the exception of Experiment 5 (presented in the online supplemental materials, preregistration at https://aspredicted.org/uh9yw.pdf).

Participants

Participants were 155 adults recruited via Amazon's Mechanical Turk (MTurk). Thirteen participants were excluded for earning a bonus of less than \$0.50 (indicating low engagement in the task) or bot-like responses (i.e., text provided in open response questions regarding strategy approach and general comments appeared to be sourced from website content or was identical for multiple participants), leaving data from 142 participants for analysis (51 women, 87 men, 4 self-described or did not provide gender information; 14 participants were 18–25-year-old, 76 participants were 26–35-year-old, 36 participants were 36–50-year-old, and 16 participants were older than 50-year-old). For all experiments, we aimed for a final sample size of at least 120 participants for consistency with previous research (Wu et al., 2018), and we oversampled participants to account for exclusions. Participants received \$0.50 for their participation in the 10-min task. We restricted participation to MTurk workers with Human Intelligence Task acceptance rates >97% who were located in the United States. All participants provided informed consent and participated in a manner approved by the Institutional Review Board at the University of Pennsylvania.

Design and Procedure

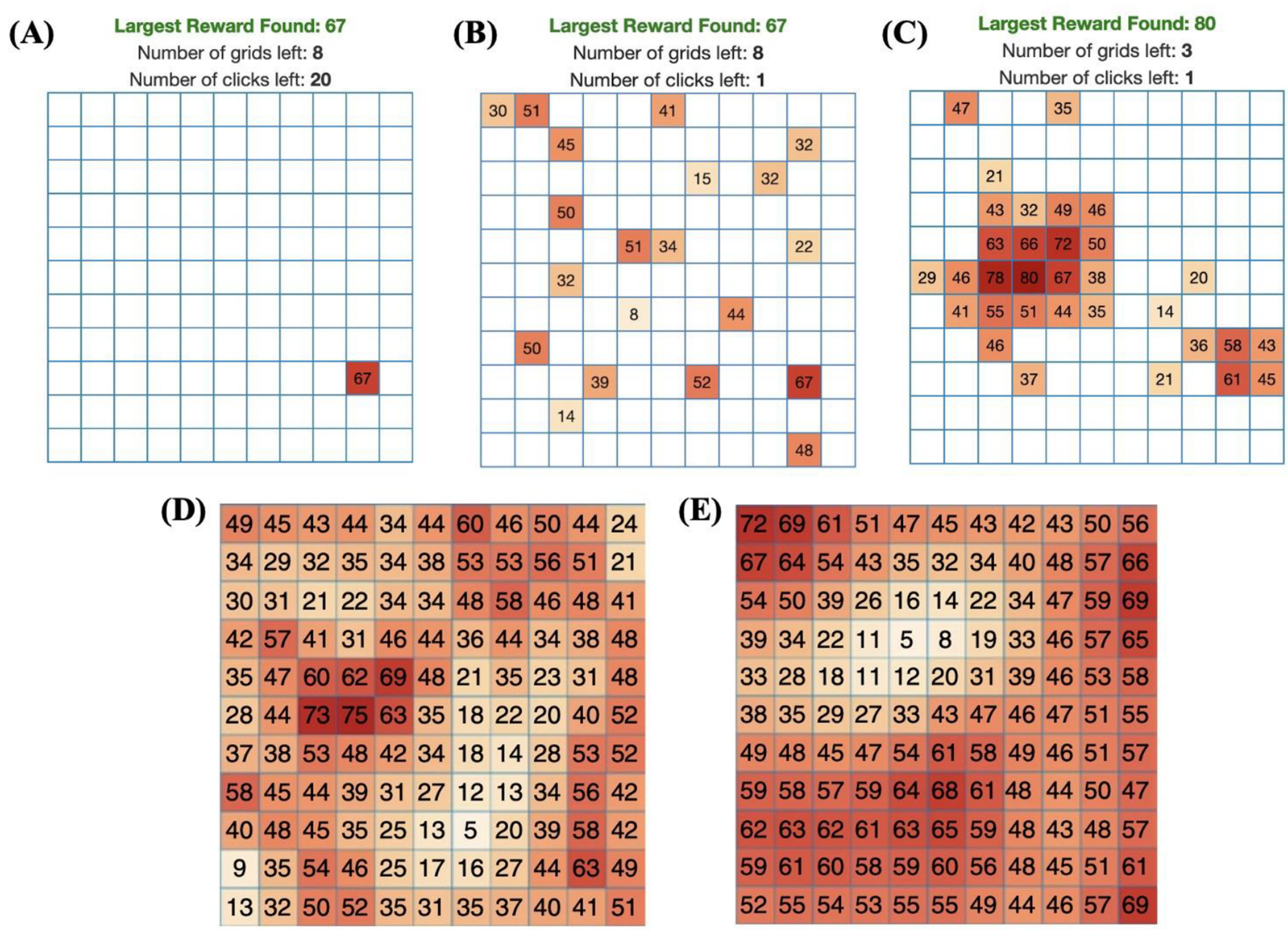
The experimental task was adapted from Experiment 2 of Wu et al. (2018). While there are many experimental paradigms that set up a tension between exploration and exploitation, we had three additional goals that influenced our task selection, namely to: (a) include a large landscape for possible exploration in order to capture the complexity of many, varied options, as are present in the social world; (b) use the same task structure across social and nonsocial contexts; and (3) be well-established in the literature, particularly with regard to model-based analysis. The Wu et al. (2018) "grid task" satisfied these conditions. In the task, participants searched for points in a series of eight grids, presented sequentially, each containing 121 tiles. In Experiment 1, participants were randomly assigned to one of four between-subjects conditions in a 2 (Context: social, nonsocial) × 2 (Environment: rough, smooth) design (post-exclusion N rough, social = 36; N smooth, social = 39; N rough, nonsocial = 29; N smooth, nonsocial = 38). Participants in the social context read,

> Each tile on the grid represents an MTurk worker who previously played this game. At the end of the game they were able to allocate a proportion of the points THEY earned on each click to YOU. By clicking on an MTurk worker tile in the grid, you reveal points that MTurk worker gave out.

Participants were also informed that each grid was comprised of a *new* group of MTurk workers and that MTurk workers were required to give at least some of their points, so that they could expect that all payoffs are greater than zero (but were also told that the maximum payoff differed based on the MTurk workers). Participants in the nonsocial context were told that the point values were determined via a computer algorithm and also informed that the minimum payoff is greater than zero and the maximum payoff is variable (see "Task Instructions" in the online supplemental materials for full instructions).

Grids in the rough environments were sampled from a Gaussian process prior with radial basis having $\lambda_{\text{correlation\_decay}} = 1$ and grids in the smooth environments were sampled from a Gaussian process prior with $\lambda_{\text{correlation\_decay}} = 2$, where $\lambda_{\text{correlation\_decay}}$ is a length-scale parameter that indicates how quickly the correlation between rewards in the grid decreases across the spatial layout of the grid (see Figure 1 for task illustration). The greater the lambda value, the slower the correlation decays as distance increases, which can be interpreted psychologically as a greater extent to which people generalize spatially the reward information of observed tiles to unobserved tiles (and may indicate less uncertainty about neighboring rewards; see "Details of Modeling Framework" in the online

Figure 1
Depiction of Experimental Task Grids



Note. (A) Display of grid prior to participant's first choice. (B) More explorative search paths are characterized by searching locations farther from the previously selected location. (C) Less explorative search paths are characterized by searching locations closer to the previously selected location. (D) Rough environment ($\lambda = 1$). (E) Smooth environment ($\lambda = 2$). Task adapted and stimuli from Wu et al. (2018). See the online article for the color version of this figure.

supplemental materials). Therefore, the social manipulation provided participants with explicit information about the task context whereas the environmental smoothness had to be gleaned over time in an exclusively "bottom-up" fashion. Specifically, participants were not told the range of values that could appear in the grids (up to 100), nor were they told whether (or to what extent) nearby tiles could have similar values. Therefore, participants' knowledge of these factors could only be obtained through behavioral exploration.

Because time horizon has previously been found to modulate directed and random exploration (Wilson et al., 2014), we varied the time horizon for exploration across the grids in a within-subjects manner, but this manipulation was not central to our hypotheses. Specifically, for four of the grids, participants had 20 clicks ("short search horizon") to search for points before proceeding to the next grid; for the other four grids, participants had 40 clicks ("long search horizon"). In the instructions, participants were told, "you will have either 20 or 40 clicks, with the number of remaining clicks displayed above the grid" (see "Task Instructions" in the online supplemental materials). The order of the short and long search horizons alternated during the task, and we counterbalanced which search horizon was assigned to the first grid. Participants could select any tile on each of their clicks, including tiles they had visited previously. For example, they were told, "Previously revealed MTurkers can also be reselected and there may be changes in the point values based on how many points they donated from each of their clicks" and "Previously revealed tiles can also be reselected and there may be changes in the point value" in the social and nonsocial conditions, respectively (rates of reclicking were $<25\%$ in all conditions and experiments). Participants were instructed to find as many points as possible and told that the magnitude of their bonus (up to \$1.50) was dependent on how many points they found. Participants had unlimited time to make their responses.

Deception

In Experiment 1 (and subsequent experiments), participants encountered deception in the task instructions. Specifically, participants were given false information about how rewards were generated (e.g., by another player); in fact, all rewards were generated via the experiment task design. We employed deception in order to maintain strict control and consistency over the underlying reward structure to examine how framing might lead to different behavior within the same search environments. All participants had the opportunity to read a debriefing form (see "Debrief Forms" in the online supplemental materials) that disclosed the deception.

Data Analysis

Model-Free Analysis of Exploration. First, we used a *t* test to examine rates of exploration and exploitation in the social versus nonsocial context. Exploration was defined as the average number of times participants selected a "new" (i.e., previously unselected) tile within a round. Exploitation was defined as the average number of times participants reselected the highest-rewarded tile observed within a round. Additionally, to take advantage of the foraging-style task (that affords the ability to measure spatial exploration across a physical space defined by a specified underlying reward structure), multitrial design, and to connect to research on how individuals navigate their spatial social environments (Wood et al., 2023), we regressed the distance (using Manhattan distance) from the previously selected tile on environmental smoothness (smooth $= -.5$, rough $= .5$) and context (nonsocial $= -.5$, social $= .5$) using a linear mixed-effects model with random intercepts for participant, horizon, and search environment (i.e., the specific spatial distribution of underlying rewards). We included the interaction between predictors to test whether context differences might emerge under some environmental structures but not others (e.g., because some reward structures might better match actual or expected human behavior). Because time-related constraints can influence the degree of exploration (Wilson et al., 2014), we examined whether the effects of exploration held for each of the short and the long horizons individually. We also examined the extent to which the magnitude of the reward received from the previously selected tile was associated with exploration on the subsequent trial and present these results in the online supplemental materials. In brief, participants were more willing to explore in the social condition and in rough environments following a previously highly rewarded selection than in the nonsocial condition and smooth environments (see "Magnitude of Previous Reward" in the online supplemental materials).

Model-Based Analysis of Exploration. To further disentangle the factors contributing to how people explore differently in social versus nonsocial contexts, we fit our data with a computational model that decomposes the search behavior into three components: generalization, directed exploration, and random exploration (Schulz et al., 2019, Wu et al., 2018). Generalization aims to capture the mechanism through which people generalize from the rewards of the observed tiles to all tiles. It is formulated as a Gaussian process regression (Quinonero-Candela et al., 2007) with the radial-basis function as kernel. The kernel has a *length-scale* parameter λ governing how fast the reward correlation decays as the distance between two tiles increases, which is a free parameter we fit to the data to capture participants' degree of generalization. Directed exploration aims to assign a subjective value to each tile that will guide which tile to choose next. From generalization, we can extract two pieces of information: the expected value and standard deviation of reward in each tile. The subjective value of a tile is obtained by combining them using upper-confidence-bound sampling (Srinivas et al., 2009), where a free parameter β controls how much the standard deviation contributes to the subjective value, and thus encodes how much the exploration tendency is directed by the degree of reward uncertainty. Random exploration converts the values of each tile into a probability distribution over all tiles from which the next choice will be sampled (i.e., a behavioral policy). It is achieved by using the *softmax* function with a temperature parameter τ capturing how much exploration happens simply due to behavioral stochasticity. In sum, this computational modeling framework is able to tease apart three factors contributing to a participant's choice of which tile to click next: generalization (embodied by λ), directed exploration (embodied by β), and random exploration (embodied by τ). We used Mann–Whitney *U* tests to assess whether generalization, directed exploration, and random exploration differed by context and environmental uncertainty.

Model-Free Analysis of Reward. We examined the rewards that participants found during the task in two ways. First, we examined whether context and environmental smoothness influenced participants' overall rewards by regressing the average reward received on environmental smoothness (smooth $= -.5$, rough $= .5$), context (nonsocial = −.5, social = .5), and their interaction using a linear mixed-effects model with random intercepts for participant, horizon, and search environment. We ran a mediation analysis using the mediation package (Tingley et al., 2014) to evaluate whether the amount of exploration (i.e., using the Manhattan distance between previous and subsequent tile selections) mediated the relationship between context and reward receipt. Second, we ran the linear mixed-effects model with the maximum (rather than average) reward found to test whether there were any differences in participants' ability to find the highest reward presented in each of the grids.

Assessment of Task Expectations

In addition to examining choice behavior on the task, we were interested in whether participant expectations about the social and nonsocial versions of the task differed simply after reading the instructions. It is possible that differences in motivation or interest across contexts could affect search behavior. Therefore, to accompany each experiment, we collected data from an independent sample of participants to assess expectations for each context regarding task difficulty (i.e., average reward the participant would earn in the task; average reward the typical MTurk worker would earn in the task; a highest and lowest reward that could be earned), enjoyment (i.e., desire to complete the task), and structure (i.e., whether repeat selections of a tile location would be an acceptable strategy; distribution of rewards). Participants in these samples read the task instructions but did not complete the experimental task. The full method and results for these studies are available in "Assessment of Task Expectations" in the online supplemental materials.

Results

Participants Explore More in Social Contexts

The first question of interest was how the social (vs. nonsocial) context affected exploration behavior. Participants explored more in the social ($M = 87\%$ of selections were to new tiles) than the nonsocial ($M = 76\%$ of selections were to new tiles) context, $t(111.95) = -2.58$, $p = .01$, $d = -.44$. Participants also show lower exploitation in social versus nonsocial contexts (Table 1). Model-based analyses made it possible to disentangle two possible sources of exploratory behavior: exploration that reduces uncertainty (directed exploration: β) and choosing tiles at random (random exploration: τ). We found that only the directed exploration parameter β was higher in the social context than the nonsocial context ($U = 3073$, $p = .022$), showing that elevated exploration in the social context was driven by motives to reduce uncertainty (means and medians for all parameter estimates are in Table S2 in the online supplemental materials). The random exploration parameter τ and a generalization parameter λ did not differ between contexts ($U =$ 2,633, $p = .624$; $U =$ 2,566, $p = .829$), meaning that participants did not explore tiles more randomly or infer a stronger reward correlation between tiles in one context compared to the other (see Table 3 for contrasts based on uncertainty and Figure S1 in the online supplemental materials for visualization). Together, these patterns are consistent with the idea that uncertainty is heightened in social contexts, and, in the absence of information about the social context that could support the cognitive resolution of uncertainty, participants turned to behavioral exploration to reduce it.

When examining the Manhattan distance, we also found a main effect of context on exploration, $b = 0.40$, $X^2(1) = 4.76$, $p = .029$, 95% CI [0.04, 0.76]; Figure 2, such that participants explored more broadly (spatially) in the social context than in the nonsocial context. There was also a main effect of environmental smoothness on exploration, $b = 0.44$, $X^2(1) = 5.72$, $p = .017$, 95% CI [0.08, 0.80], such that participants explored more in rough than smooth environments across contexts. The Context × Environmental Smoothness interaction was not significant, $b = -0.18$, $X^2(1) =$ 0.25, $p = .617$, 95% CI [−0.90, 0.54]. These findings also held both for short and long horizon grids (Table 2; horizon did not interact with uncertainty or context, $ps > .50$), indicating that participants engaged in more exploration in the social (vs. nonsocial) context regardless of the actual level of spatial smoothness in the environment and even when a short time window for obtaining rewards limits explorations' instrumental benefits.

To examine the possibility that differences in exploration across social and nonsocial contexts may have arisen due to differences in participants' expectations about the maximum obtainable reward magnitude in those contexts, we examined data from an independent sample of participants, who only read the task instructions and reported their expectations. We found no differences in expectations between contexts, suggesting that differences in participants' behavior across contexts are unlikely to have been driven by differences in their expectations (see the online supplemental materials).

Table 1
Exploration and Exploitation (Defined by Rates of Reclicking Previously Selected Tiles) by Context and Experiment

Exploration and exploitation	Social	Nonsocial	*t* test
Experiment 1			
% Exploration	87	76	$t(111.95) = -2.58$, $p = .01$, $d = .44$
% Exploitation	2	4	$t(110.15) = 2.25$, $p = .03$, $d = .38$
Experiment 2			
% Exploration	90	81	$t(110.15) = -2.22$, $p = .03$, $d = -.38$
% Exploitation	2	4	$t(106.68) = 2.25$, $p = .03$, $d = .39$
Experiment 3			
% Exploration	84	79	$t(151) = -1.12$ $p = .26$, $d = -.18$
% Exploitation	3	4	$t(151) = 0.64$, $p = .52$, $d = .10$

Note. Percentage of exploration and exploitation trials and *t* test reported. The top row for each experiment is the percentage of trials in which a tile was not reclicked ("exploration"). The bottom row for each experiment is the percentage of trials in which the highest-rewarded tile observed was reselected (but does not require consecutive selection, "exploitation").

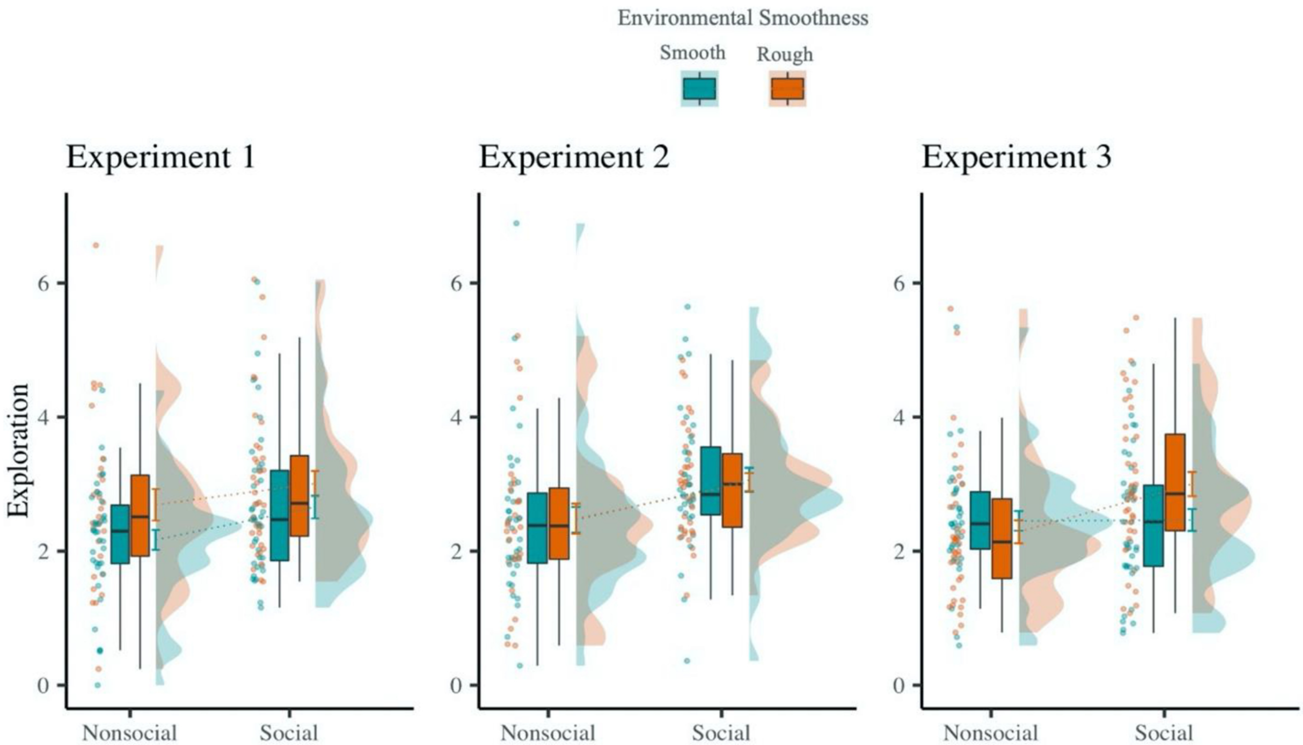
Participants Earn Fewer Rewards in Social Contexts

The second question of interest was how the social (vs. nonsocial) context affected participants' reward earnings. Analysis of the average rewards participants garnered during the task (i.e., across all grids) revealed a main effect of social context, $b = -3.15$, $\chi^2(1) = 3.81$, $p = .051$, 95% CI [−6.31, −0.01], with participants earning lower rewards in the social context. Participants also earned lower rewards in rough (vs. smooth) environments, $b = -8.27$, $\chi^2(1) = 26.26$, $p < .001$, 95% CI [−11.43, −5.11]. The interaction was not significant, $b = 2.09$, $\chi^2(1) = 0.42$, $p = .519$, 95% CI [−4.24, 8.42].

Moreover, the relationship between context and reward receipt was mediated by exploration, $b = -0.57$, $p = .017$, 95% CI

Figure 2

Exploration by Context and Environmental Smoothness for Experiments 1–3



Note. Raincloud plot of exploration behavior across Experiments 1–3. Exploration was defined as the distance from the previous selection. Each point is the mean Manhattan distance for each participant. Boxplot and standard error bars are depicted along with the density of the individual points. Participants explored more in the social versus nonsocial contexts in Experiments 1 and 2. In Experiment 3, this difference was specific to the rough environments. See the online article for the color version of this figure.

[−1.05, −0.09], Figure S2 in the online supplemental materials). This provides evidence that the social manipulation acted on patterns of exploration, which in turn influenced reward receipt. In other words, pursuing additional information about the social context to reduce uncertainty was done at the detriment of reward receipt, which is notable considering that participants in this task could earn a monetary bonus based on the rewards they found.

Participants' lower reward earnings in the social context could derive from at least two possible sources: a lower success rate in finding as highly rewarding tiles in the social context (compared to the nonsocial context) or a greater tendency to continue exploring even after finding highly rewarding tiles in the social context (compared to the nonsocial context). To investigate these possibilities, we examined the magnitude of the highest reward found throughout the task. This analysis revealed no effect of context on the highest reward found by participants, $b = 0.07$, $\chi^2(1) = 0.007$, $p = .933$, 95% CI [−1.69, 1.84]. We observed only an effect of environmental smoothness, such that participants found higher rewards in smooth, versus rough, environments, $b = -2.58$, $\chi^2(1) = 8.24$, $p = .004$, 95% CI [−4.34, −0.82], which is expected given that the distribution of rewards was less predictable in the rough environments. The interaction between context and environmental uncertainty was not significant, $b = -1.46$, $\chi^2(1) = 0.66$, $p = .418$, 95% CI [−4.98, 2.07]. Together, these results show that participants in both contexts had the opportunity to exploit high-reward tiles, but those in the social context were less likely to do so.

Table 2

Full Model Output for Effects of Uncertainty, Context, and the Interaction Based on Horizon, Experiment 1

	Short horizon (20 clicks)					Long horizon (40 clicks)				
Predictor	*b*	*SE*	CI	*t*	*p*	*b*	*SE*	CI	*t*	*p*
(Intercept)	2.76	0.11	[2.54, 2.98]	24.85	<.001	2.57	0.1	[2.39, 2.76]	26.85	<.001
Environment	0.5	0.2	[0.10, 0.90]	2.46	.014	0.42	0.19	[0.05, 0.78]	2.25	.024
Context	0.39	0.2	[−0.01, 0.80]	1.93	.054	0.41	0.19	[0.05, 0.77]	2.21	.027
Environment × Context	−0.16	0.41	[−0.96, 0.64]	−0.39	.696	−0.19	0.37	[−0.91, 0.54]	−0.51	.613

Table 3
Full Parameter Comparisons With Mann–Whitney U *Tests for Experiments 1–3*

Predictor	λ *U*	λ *p*	β *U*	β *p*	τ *U*	τ *p*
Experiment 1						
Context	2,566	.829	3,073	.022	2,633	.62
Environment	2,519	.948	3,064	.022	3,116	.01
Context (Rough)	543	.788	622	.191	498	.76
Context (Smooth)	756	.883	908	.09	835	.34
Experiment 2						
Context	2,516	.552	2,875	.034	3,030	.01
Environment	2,116	.275	2,250	.603	2,272	.67
Context (Rough)	628	.148	620	.18	683	.03
Context (Smooth)	624	.657	820	.088	808	.12
Experiment 3						
Context	3,179	.351	3,117	.48	3,296	.17
Environment	3,021	.722	3,110	.496	3,661	.01
Context (Rough)	876	.351	997	.033	935	.13
Context (Smooth)	717	.714	515	.07	754	.44

Interim Discussion

In Experiment 1, participants explored more when they thought that the points associated with the grid tiles were determined by human individuals than when they thought the points were determined by a computer algorithm. In particular, the social context specifically increased directed (as opposed to random) exploration, which targets uncertainty reduction. This suggests that the mere knowledge that rewards have been generated by social agents may be sufficient to produce heightened exploration in social contexts at the cost of short-term reward receipt.

At the same time, one principal limitation in Experiment 1 is the difference in instructions for the social and nonsocial contexts, which leaves open the possibility that the observed difference in exploration between contexts could have arisen due to factors other than the social versus nonsocial context per se. For example, participants might have expected that the points generated from the computer were random but that the points coming from other people were associated with more systematic patterns, which particularly may have influenced the differences observed with our Manhattan distance metric of spatial exploration. In particular, although we selected the Wu et al. (2018) task for many desirable features, including the vastness of the search space and its established place in the literature, this foraging-style task may have introduced a confound with a condition in participants' expectations about the reward distributions. If spatial correlations are less expected in the social context, this could in part explain differences between the conditions. Such a difference is plausible; participants may not expect that individuals associated with adjacent tiles would issue similar rewards, instead inferring that individual motivations could influence the social generation of rewards (Wilke et al., 2015). We address this issue in Experiment 2 by providing an explanation in both conditions as to why there may be spatial relationships between the tiles.

Another limitation is that the experiences of participants completing the task itself might have differed across contexts. For example, participants could have encoded observed rewards differently across conditions. To assess the replicability of the observed patterns of elevated exploration in social (vs. nonsocial) contexts in a new sample while addressing these considerations, we adapted our social and nonsocial conditions to be even more comparable in structure in Experiment 2.

Experiment 2

Method

The method of Experiment 2 was identical to that of Experiment 1, with the following exceptions. First, we changed the descriptions of the social and nonsocial contexts to make them more parallel. Participants in the social context read that each tile represented an MTurk worker who shared a portion of their points from when the MTurk worker played the game in 2020. Unlike Study 1, participants also read that the tiles were arranged based on the MTurk worker's geographic location. Furthermore, in the nonsocial context, participants read that each tile represented a plot of land and that the points corresponded to the crop yield from that plot of land in 2020. As in the social context, participants read that the tiles were arranged based on the plot of land's geographic location. However, we did not specify the scale of this organization (e.g., city, county, or state) in either the social or nonsocial context (full instructions in the online supplemental materials).

Second, we wanted to understand whether participants had different expectations and/or experiences of the possible rewards in the social and nonsocial contexts. At the end of the task, we asked participants to report the highest and the lowest reward that they thought was present overall (i.e., across all of the grids they saw). Finally, we revised the bonus structure such that the top 50 point-earning participants would earn a bonus of \$0.50. Participants were 138 adults (N rough, social = 37; N smooth, social = 35; N rough, nonsocial = 28; N smooth, nonsocial = 38) recruited via Amazon's MTurk (61 women, 76 men, one participant did not report gender, nine participants were 18–25-year-old, 54 participants were 26–35-year-old, 56 participants were 36–50-year-old, and 19 participants were older than 50-year-old). Sixty-eight additional participants were excluded for earning a bonus of less than \$0.50 (indicating low engagement in the task), and estimating the highest reward as <50 or the lowest reward as >50 (which would be highly inconsistent with the grid displays, where the lowest rewards observed by participants ranged from 3 to 17 and the highest ranged from 69 to 87) or bot-like responses.

Results

Participants Explore More in Social Contexts

We replicated the findings that participants explore more in the social ($M = 90\%$) versus nonsocial ($M = 81\%$) context, $t(111.38) = -2.22$, $p = .03$, $d = -.38$; and exploit less, Table 1. Also replicating the modeling results of Experiment 1, the directed exploration parameter β was higher in the social context than nonsocial context ($U = 2{,}875$, $p = .034$; Table S2 in the online supplemental materials for means and medians of parameter estimates), suggesting participants valued the reduction of uncertainty more if told that rewards were generated from other people than contingent on crop yield. Unlike Experiment 1, there was also a difference in the random exploration τ parameter ($U = 3{,}030$, $p = .01$; generalization was not significant, $U = 2{,}516$, $p = .55$; Table 3 and Figure S1 in the online supplemental materials).

Using the Manhattan distance, we show the main effect of the social context, $b = 0.57$, $\chi^2(1) = 9.54$, $p = .002$, 95% CI [0.21, 0.93]; Figure 2, but the effect of environmental smoothness, $b = -0.0009$, $\chi^2(1) = 0.00$, $p = .996$, 95% CI [−0.36, 0.36], and the interaction, $\chi^2(1) = 0.05$, $p = .823$, were not significant. These results were consistent across both the short and long time horizons (Table 4). As in Experiment 1, there were no differences in the independent sample of participants in ratings of expected task difficulty, enjoyment, or structure across contexts (see the online supplemental materials).

Participants Earn Fewer Rewards in Social Contexts

As in Experiment 1, there was a main effect of social context, $b = -5.18$, $\chi^2(1) = 13.24$, $p < .001$, 95% CI [−7.96, −2.39], on average reward, with participants earning lower rewards under the social context. Participants also earned lower rewards in rough environments, $b = -7.71$, $\chi^2(1) = 29.37$, $p < .001$, 95% CI [−10.50, −4.92]. The interaction was not significant, $\chi^2(1) = 0.200$, $p = .655$. Moreover, exploration again mediated the relationship between context and reward receipt, $b = -0.98$, $p = .001$, 95% CI [−1.59, −0.36]; Figure S3 in the online supplemental materials). Finally, we replicated the finding from Experiment 1 that environmental smoothness, but not social context, affected the magnitude of the highest reward found. Participants found higher rewards in the smooth environments, $b = -3.55$, $\chi^2(1) = 25.68$, $p < .001$, 95% CI [−4.92, −2.18], but neither the effect of context, $\chi^2(1) = 1.05$, $p = .306$, nor the interaction, $\chi^2(1) = 0.04$, $p = .839$, was significant.

Participant Estimates of Reward Do Not Differ Between Contexts

In Experiment 2, we included additional questions at the end of the experiment to test whether participants had different experiences of the rewards between contexts that could explain differences in exploration behavior. Participant estimates of the highest rewards available were related to the highest rewards that they, themselves, earned during the task, $r = 0.37$, $t(136) = 4.63$, $p < .001$, 95% CI [0.22, 0.50], indicating that participants were accurate at tracking rewards. In taking the difference score between the actual and estimated rewards, there were no differences based on social context, $t(134) = -1.42$, $p = .159$, environmental smoothness, $t(134) = 0.43$, $p = .670$, or their interaction, $t(134) = -0.55$, $p = .586$. This evidence suggests that explicit differences in expectations and/or experiences of reward distributions cannot account for differences in participant behavior across contexts.

Interim Discussion

In Experiment 2, we replicated the differences in exploration between the social and nonsocial contexts. Critically, in Experiment 2, we provided a scenario in which participants could infer a spatial correlation between tiles, namely that the tiles representing MTurk workers were arranged geographically. There are many social features that cluster along geographic lines, including race and socioeconomic status (Lichter et al., 2015), political orientation (McGovern, 2022), as well as other factors (e.g., preference for a type of weather or terrain), which could influence participants' expectations about how more generous and less generous individuals might cluster together (e.g., Farwell & Weiner, 2000). Therefore, participants could (but were not required to) draw on naturalistic correlations to make inferences during the task. We again found that participants explored more broadly spatially in the social, relative to nonsocial context. This is in contrast to finding no difference in exploration distance in rough and smooth environments (as we found in Experiment 1), suggesting that framing the geographic relations between the tiles may have influenced attention to the underlying reward distribution generally.

In terms of reward receipt, as in Experiment 1, participants garnered fewer rewards on average in the social context as compared to the nonsocial context as a result of increased exploration. To better interpret the differences in reward receipt between contexts, we asked participants to report on the highest and lowest rewards attainable across the grids. Participants were accurate in their estimates, and these estimates did not differ based on context, which aligned with findings from the independent sample of participants who only read the task instructions before making their ratings. Taken together, this evidence is consistent with the possibility that the patterns of behavioral differences between the social and nonsocial contexts in Experiment 1 arise from the assumptions participants bring to a social versus nonsocial exploration environment.

In Experiments 3 and 4, we test the idea that providing participants with more information about the social context will prompt engagement in the social-cognitive process to reduce uncertainty and therefore reduce behavioral exploration in the social context. First, in Experiment 3, we give participants a reason to believe that the MTurk workers represented in the grid vary (spatially) in the degree of similarity to each other. We predict that inducing an expectation of similarity will result in reduced exploration.

Experiment 3

Method

The method of Experiment 3 was the same as Experiment 2, with the following additions to the descriptions read by the participants in

Table 4
Full Model Output for Effects of Uncertainty, Context, and the Interaction Based on Horizon, Experiment 2

Predictor	Short horizon (20 clicks)					Long horizon (40 clicks)				
	b	*SE*	CI	*t*	*p*	*b*	*SE*	CI	*t*	*p*
(Intercept)	2.87	0.12	[2.64, 3.11]	24.18	<.001	2.71	0.1	[2.51, 2.91]	26.98	<.001
Environment	−0.04	0.2	[−0.43–0.35]	−0.19	.847	0.02	0.19	[−0.35, 0.39]	0.1	.922
Context	0.62	0.2	[0.23, 1.01]	3.12	.002	0.53	0.19	[0.16, 0.90]	2.8	.005
Environment × Context	0.15	0.4	[−0.63, 0.93]	0.38	.702	−0.22	0.38	[−0.96, 0.52]	−0.58	.56

order to provide information relevant to the social manipulation. In the social context, participants read that the tiles represented MTurk workers across counties in a single state (with each new grid representing a new state). Participants also read that we had previously collected generosity ratings from the workers and that people from nearby counties tend to (but do not always) have similar levels of generosity. In the nonsocial context, tiles were also said to be arranged according to counties; participants read that we collected ratings of soil fertility and that soil from nearby counties tends to (but does not always) have similar levels of fertility. Full instructions are in the online supplemental materials. Participants were 254 adults recruited via Amazon's MTurk. A total of 102 additional participants were excluded for earning a bonus of less than \$0.50 (indicating low engagement in the task), estimating the highest reward as <50 or lowest reward as >50, or bot-like responses, leaving 152 participants for analysis (63 women, 87 men, three self-described or did not provide gender information; 11 participants were 18–25-year-old, 61 participants were 26–35-year-old, 52 participants were 36–50-year-old, and 27 participants were older than 50-year-old; N rough, social = 40; N smooth, social = 39; N rough, nonsocial = 39; N smooth, nonsocial = 35).

Results

Participants Explore More in Social Contexts When Environment Is Rough

Contrary to Experiments 1 and 2, there was no difference in exploration rates by context, M social = 84%, M nonsocial = 79%, $t(151) = -1.12$, $p = .26$, $d = -.18$; nor was there a difference in exploitation (Table 1). Consistent with the model-free findings, we found that the directed exploration β was not higher in the social (vs. nonsocial) context for Experiment 3 ($U = 3{,}117$, $p = .48$; Table 3 and Table S2 and Figure S4 in the online supplemental materials).

As in Experiments 1 and 2, participants explored more broadly in the social, versus nonsocial, context, $b = 0.37$, $\chi^2(1) = 4.91$, $p = .027$, 95% CI [0.04, 0.70]; Figure 2. However, under these conditions of information that could plausibly support cognitive uncertainty reduction, the difference between the social and nonsocial contexts was unique to rough environments, interaction between environmental smoothness and context, $b = 0.69$, $\chi^2(1) = 4.19$, $p = .041$, 95% CI [0.03, 1.35], the main effect of environmental smoothness was not significant, $\chi^2(1) = 1.15$, $p = .284$. In other words, when the statistical distribution of rewards matched our cover story—that is, the spatial relationships between tiles were indeed meaningful—participants explored equally in the social and nonsocial contexts. However, when the statistical distribution of rewards did not match our cover story as well, and rewards were distributed more randomly, participants explored more broadly in the social, as compared to the nonsocial context. Furthermore, this effect appeared to emerge as participants learned more about the degree of environmental smoothness: it was specific to the longer time horizon, interaction: $b = 0.79$, $\chi^2(1) = 5.45$, $p = .020$, 95% CI [0.13, 1.45]; main effect of context: $b = 0.35$, $\chi^2(1) = 4.19$, $p = .041$, 95% CI [0.01, 0.86]; main effect of environmental smoothness, $\chi^2(1) = 0.56$, $p = .456$, and was not significant in the short horizon, interaction: $\chi^2(1) = 2.20$, $p = .138$; main effect of context: $b = 0.40$, $\chi^2(1) = 4.61$, $p = .032$, 95% CI [0.04, 0.77]; main effect of environmental smoothness, $\chi^2(1) = 2.13$, $p = .145$. That this pattern emerged only for long horizon grids suggests that participants adjusted their behavior over time based on how well the bottom-up evidence matched the top-down information provided in the instructions. Therefore, when social information was available, participants demonstrated less behavioral exploration; however, social information specifically affected behavioral exploration when the underlying rewards were consistent with the social information *and* when participants had a longer time to learn the environment structure.

As in Experiments 1 and 2, there were no differences in the independent sample of participants in rating expected task difficulty, enjoyment, or structure.

Participants Earn Fewer Rewards in Social Context When Environment Is Rough

When participants had additional information about the social agents in the search space, there was no difference in reward receipt between social and nonsocial contexts, $\chi^2(1) = 1.87$, $p = .172$. Participants still earned fewer rewards, on average, in the rough versus smooth environments, $b = -10.69$, $\chi^2(1) = 48.94$, $p < .001$, 95% CI [−13.68, −7.69]. These effects were qualified by an interaction. Participants received fewer rewards in the social context, as compared to the nonsocial context in rough environments, $b = -6.17$, $\chi^2(1) = 4.07$, $p = .044$, 95% CI [−12.16, −0.18], but there was no difference in reward receipt between the social and nonsocial contexts in smooth environments. Because there was only a relationship between social manipulation and exploration in rough environments, we examined mediation in rough environments only. In rough environments, exploration mediated the relationship between social manipulation and reward receipt, $b = -1.12$, $p = .002$, 95% CI [−1.89, −0.35]; Figure S5 in the online supplemental materials. Therefore, participants in the social context were able to obtain comparable rewards to those in the nonsocial context, but only in smooth environments. As in Experiments 1 and 2, there was only an effect of environmental smoothness in the magnitude of the highest reward found, $b = -4.57$, $\chi^2(1) = 47.52$, $p < .001$, 95% CI [−5.87, −3.27]; effect of social context: $\chi^2(1) = 0.33$, $p = .568$; interaction: $\chi^2(1) = 0.16$, $p = .689$.

Participant Estimates of Reward Do Not Differ in Social and Rough Environments

We included the same questions regarding rewards at the end of the experiment as in Experiment 2 and all effects were replicated. Specifically, participants' estimates of the highest reward available aligned with the rewards they encountered in the task, $r = 0.26$, $t(151) = 3.37$, $p < .001$, 95% CI [0.11, 0.41]. The difference between the actual and estimated reward receipt did not differ based on environmental smoothness, $t(149) = 0.26$, $p = .795$, social context, $t(149) = -1.04$, $p = .302$, or their interaction, $t(149) = 0.11$, $p = .912$.

Interim Discussion

In Experiment 3, we provided participants with explicit information intended to reduce uncertainty in the social context, specifically that the relationships between individuals represented in nearby tiles may indicate similarity. It is possible that participants used the generosity information to infer similarity between neighboring tiles, therefore sidestepping the need for behavioral exploration (FeldmanHall & Shenhav, 2019). The use of generosity information could have been explicit, with participants making conscious choices not to explore further once they found a high-reward cluster, choosing instead to select nearby tiles. Indeed, in the social context, participants more broadly explored after discovering a highly rewarded tile in comparison to the nonsocial context (as reported in "Magnitude of Previous Reward" in the online supplemental materials). Alternatively, the use of generosity information could have affected behavior without awareness on the part of the participant. Future research is needed to distinguish these possibilities empirically, particularly to make predictions about whether or how participants might reciprocate the generosity if given the opportunity (Delton et al., 2011; Schmid et al., 2021; Whitham, 2021).

We speculate that violating the expectation of similarity (in the rough environments) may have prompted a similar situation as in Experiments 1 and 2. Without access to a social-cognitive route to uncertainty reduction, participants turned to behavioral exploration (which was heightened in the social context). Future research should investigate situations in which there is a mismatch between expectations and the social environment (as might have been the case in the rough social condition or in a situation in which an individual goes to a party thinking everyone will know each other but many people are strangers). Indeed, it is likely that social environments present a range of expected (and experienced) uncertainty. We investigate one such situation in Experiment 4. Specifically, in addition to attending to the relationships between others, individuals may project their own expected behavior onto others to reason about individuals (i.e., "What would I do in this situation?"; Fleischhut et al., 2021; Tarantola et al., 2017). Evidence suggests that the extent to which individuals engage in this self-projection depends on the individuals or groups about whom they are attempting to reason. For instance, reasoning about ingroup members—perceived as similar to the self—has been associated with self-projection (Ames, 2004; Jenkins et al., 2008; Mitchell, 2004; Mitchell et al., 2006). Enhanced ability to self-project for members of one's ingroup may disproportionately facilitate cognitive resolution of uncertainty for ingroup behavior (Hogg, 2000; Tamir & Mitchell, 2013). In Experiment 4, we test whether providing participants with information about the individuals who comprise tiles in the grids leads to differences in search behavior. We used political orientation to assess ingroup versus outgroup search because political orientation is a potent marker for group identification (Falk et al., 2012; Van Bavel & Pereira, 2018). Specifically, to the extent that evidence of similarity to self facilitates cognitive resolution of uncertainty (e.g., participants may predict ingroup members to behave in certain ways), we expect reduced behavioral exploration when there is a high degree of similarity between the participant's political orientation and the political orientation of the individuals represented in the grid.

Experiment 4

Method

Participants were 160 adults recruited via Amazon's MTurk. Sixty-three participants were excluded for not answering the political orientation questions at the end of the task, earning a bonus of less than \$0.50 (indicating low engagement in the task), estimating the highest reward as <50 or lowest reward as >50, or bot-like responses. The final sample included 97 participants (38 women, 56 men, three participants self-described or did not report gender, 12 participants were 18–25-year-old, 49 participants were 26–35-year-old, 21 participants were 36–50-year-old, and 10 participants were older than 50-year-old). Participants were randomly assigned to either rough ($N = 49$) or smooth ($N = 48$) environments. All participants received social context instructions, similar to those provided in Experiment 1; however, for half of the grids (i.e., four grids), participants read that the grids were comprised of individuals who identified as politically liberal (see the online supplemental materials, for precise description and full instructions), and for half of the grids, participants read that the grids were comprised of individuals who identified as politically conservative (order of presentation was counterbalanced).

We included additional questions at the end of the task to assess participants' own political orientation (i.e., "Politically, how liberal or conservative are your views on [social/economic] issues?"; Likert scale with 1 = *very liberal*, 3 = *neither liberal nor conservative*, 5 = *very conservative*), the extent to which participants identified with each liberal and conservative (i.e., "To what extent do you consider [liberals/conservatives] to be a part of your ingroup (i.e., a group of people who are similar to yourself and who share similar values and perspectives)?"; Likert scale with 1 = *not at all*, 5 = *extremely*), and participant expectations regarding the generosity of each group (i.e., "How generous do think that [liberals/conservatives] tend to be?"; Likert scale with 1 = *not at all generous*, 5 = *extremely generous*).

Analyses

As a measure of the participant's political affiliation, we created an average score of each participant's responses to the two political orientation questions. We first assessed how well this score related to questions about ingroup affiliation and expectations about group generosity. To do so, we regressed the averaged political orientation ratings on responses to the questions of identification with liberals as one's ingroup and identification with conservatives as one's ingroup (both variables were mean-centered). We ran the same model with responses to the questions regarding the generosity of liberals/conservatives as predictors.

Next, we coded the political orientation composite to represent an ingroup score consistent with the task block, that is, for the block in which participants were told that conservatives comprised the grids, scores higher on the political orientation measure (i.e., more conservative) were coded as higher on ingroupness. Similarly, for the block in which participants were told that liberals comprised the grids, scores lower on the political orientation measure (i.e., more liberal) were coded as higher on ingroupness. We will refer to this measure as "ingroup rating." We focus on the Manhattan distance as our primary exploration outcome variable to best take into account task features and to examine consistency in the patterns observed in Experiment 3, now regressing the outcome variable on uncertainty (smooth = −.5, rough = .5), ingroup rating (mean-centered), and their interaction. We included the composition of the grid (conservatives = −.5, liberals = .5) as a covariate and included by-participant, by-horizon, and by-environment random intercepts.

Results

Political Orientation Is Associated With Group Affiliation and Expectations About Generosity

First, we assessed how well the political orientation measure served as a marker of ingroup affiliation in our sample. Participants who rated their social and economic views as more conservative indeed identified more strongly with conservatives as members of their ingroup, $b = 0.44$, $F(1, 94) = 29.93$, $p < .001$. Similarly, those who rated their social and economic views as more liberal identified more strongly with liberals as members of their ingroup, $b = -0.19$, $F(1, 94) = 5.79$, $p = .018$. Political orientation was also associated with expectations for group-level generosity. Individuals with more conservative views expected conservatives to be more generous in general, $b = 0.37$, $F(1, 94) = 13.60$, $p < .001$, whereas those with more liberal views expected liberals to be more generous, $b = -0.23$, $F(1, 94) = 4.99$, $p = .028$. Therefore, we found that differences in ingroup judgments tracked with political orientation and that participants used political orientation to make social inferences in this context (i.e., about generosity).

Participants Explore Less in Ingroup Contexts When Environment Is Smooth

In support of the prediction that participants would explore less when grids were composed of ingroup members, there was a main effect of ingroup rating on exploration, $b = -0.05$, $\chi^2(1) = 8.23$, $p = .004$, 95% CI [−0.08, −0.01]. Additionally, there was an interaction between ingroup rating and environmental smoothness, $b = 0.10$, $\chi^2(1) = 9.44$, $p = .002$, 95% CI [0.04, 0.16]. The relationship between ingroup rating and exploration was only significant in smooth environments, $b = -0.09$, $\chi^2(1) = 15.52$, $p < .001$, 95% CI [−0.14, −0.05], and the relationship was not significant in rough environments, $\chi^2(1) = 0.02$, $p = .879$. This pattern was consistent with the findings of Experiment 3 in which differences in choice behavior between the social and nonsocial contexts were reduced only in smooth environments. These results provide support for the idea that individuals might engage in self-projection to make predictions about how others will act, and that this projection may be stronger for similar others (Hogg, 2000; Tamir & Mitchell, 2013). The main effects of environmental smoothness, $\chi^2(1) = 0.003$, $p = .955$, and grid composition, included as a covariate, $\chi^2(1) = 2.86$, $p = .091$, were not significant. Similar to the finding in Experiment 3, the interaction emerged for long horizon search only, long: $b = 0.17$, $\chi^2(1) = 19.29$, $p < .001$, 95% CI [0.10, 0.25]; short: $\chi^2(1) = 2.75$, $p = .098$; Table 5. Again, there were no overall differences in the independent sample of participants' ratings of expected task difficulty, enjoyment, or structure.

Finally, we examined the model-based results. Because ingroup rating is a continuous scale, we could not apply the Mann–Whitney U test to the modeling parameters. Instead, we assessed Kendall's correlation between ingroup rating and each estimated parameter value. None of the three parameters showed a significant correlation with ingroup rating (ps > 0.1; Table S3 in the online supplemental materials).

Participants Earn Similar Rewards Regardless of Ingroup Rating

When examining the average rewards earned, we observed only a main effect of environmental smoothness, such that participants garnered fewer rewards under rough conditions, $b = -8.60$, $\chi^2(1) = 16.52$, $p < .001$, 95% CI [−12.75, −4.45]. The effects of ingroup rating, $\chi^2(1) = 0.59$, $p = .443$, the interaction, $\chi^2(1) = 0.11$, $p = .738$, and the effect of grid composition, $\chi^2(1) = 3.03$, $p = .082$, were not significant. Because there was no relationship between ingroup rating and reward receipt, we did not conduct a mediation analysis.

When examining the maximum reward found, there was again a main effect of environmental smoothness, consistent with previous experiments, $b = -3.11$, $\chi^2(1) = 13.01$, $p < .001$, 95% CI [−4.81, −1.42]; the main effect of ingroup rating was not significant, $\chi^2(1) = 0.64$, $p = .424$. In addition, there was an interaction between ingroup rating and environmental smoothness, $b = 1.03$, $\chi^2(1) = 32.00$, $p < .001$, 95% CI [0.67, 1.38]. The relationship between ingroup rating and maximum reward found was positive in rough environments, $b = 0.61$, $\chi^2(1) = 22.52$, $p < .001$, 95% CI [0.36, 0.86], but negative in smooth environments, $b = -0.24$, $\chi^2(1) = 3.56$, $p = .059$, 95% CI [−0.49, −0.01]. That the findings regarding the maximum reward found differ in Experiment 4 from the previous experiments warrants future research to better understand how search strategies could affect discovering, versus exploiting, specific information.

General Discussion

The aim of the current investigation was to further knowledge about how social context influences exploration. In Experiments 1 and 2, we showed that, when little information about the social environment is provided, participants demonstrated more exploration in a social versus nonsocial context. Enhanced exploration is consistent with the idea that social contexts present additional uncertainty

Table 5
Full Model Output for Effects of Uncertainty, Ingroup Rating, and the Interaction Based on Horizon, Experiment 4

Predictor	Short Horizon (20 clicks)					Long Horizon (40 clicks)				
	B	*SE*	CI	*t*	*p*	*b*	*SE*	CI	*t*	*p*
(Intercept)	2.83	0.14	[2.56, –3.10]	20.72	<.001	2.58	0.12	[2.35, 2.82]	21.47	<.001
Environment	−0.08	0.25	[−0.57, 0.41]	−0.31	.757	0.01	0.22	[−0.43, 0.44]	0.02	.982
Ingroup rating	−0.11	0.03	[−0.16, −0.05]	−3.69	<.001	−0.01	0.02	[−0.05, 0.03]	−0.44	.657
Grid composition	0.06	0.06	[−0.07, 0.18]	0.92	.358	0.08	0.04	[−0.01, 0.16]	1.78	.074
Environment × IIngroup rating	−0.09	0.06	[−0.21, 0.02]	−1.66	.098	0.17	0.04	[0.10, 0.25]	4.39	<.001

(Berkay & Jenkins, 2023) that, in the absence of other social information, learners attempt to resolve through search and sampling of options. In Experiments 3 and 4, we observed that enhanced exploration in a social context can be reduced by providing relevant social information. Specifically, we found no difference in exploration between social and nonsocial contexts when we provided participants with information regarding expected similarities between social agents represented by the tiles in the grids (Experiment 3) and when we provided participants with information that situated the social agents within or outside of the participant's ingroup (Experiment 4). However, when we compared patterns of search across the physical space, participants only explored less broadly under these conditions when the underlying uncertainty was low (i.e., in a "smooth" environment).

Our model-free results were further backed up by results from a computational model that defines exploration with mathematical precision as a form of information seeking and encapsulates it into one parameter β. Comparing the estimated β parameter yields a significant difference between the social and nonsocial contexts in Experiments 1 and 2 when participants do not have additional information relevant to the social context, but no significant difference in Experiments 3 and 4 when additional information was provided. In addition to differences in directed exploration, we did find differences in random exploration between contexts in Experiment 2. While individuals may use both types of exploration (e.g., Wilson et al., 2014), future research is needed to further understand when the use of directed and random exploration diverge in social contexts. These results highlight the complex interactions between features of the environment and call for additional research on exploration tradeoffs in social contexts.

Limitations and Future Directions

Given that this is one of the first investigations of exploration in social contexts outside of collaborative/competitive group environments, there are limitations that guide directions for future research. First, in order to best equate social and nonsocial contexts, the social scenarios presented in these experiments were highly pared down and therefore limited in ecological validity. Real-world social contexts undoubtedly provide additional cues that could influence when, why, and for how long individuals explore. For example, if participants were soliciting donations from a group of people, exploration may be influenced by the participant's relation to individual social agents, whether social agents present cues that promote approach (e.g., a pleasant facial expression), as well as norms (that can vary for different social groups) about whether it would be permissible to "exploit" an individual agent by asking for donations across multiple occasions. Relatedly, in the current experiments, the social agents purportedly distributing points did not know anything about the participant. However, introducing an additional layer of knowledge (i.e., meta-perception) could increase the complexity of the task, including the types of inferences participants might make and subsequent adjustments (conscious or not) to behavioral exploration. To allow participants to bring their own priors about social and nonsocial contexts to bear in the experiments, the instructions were intentionally brief and did not provide highly constrained details. For example, participants may have wondered about whether the features of the game that the "previous MTurk participants" played differed in any way from their own experience, or about whether the geographic organization in Experiment 2 was according to city, county, state, or something else (the scale was not specified in the instructions). As such, it is possible that there was some between-participant variance in participant expectations, goals, and approaches, which we see as features of ambiguity and individual differences in goals, expectations, and perspectives that learners encounter in the social world. These considerations also relate to our use of convenience samples collected online in the United States. Social expectations, goals, and norms for interacting may differ across social groups and cultures, particularly those that may expect higher interdependence among social partners (as was observed in Experiments 3 and 4).

Another limitation is that it may have been less plausible for participants to expect spatial correlations in the social context (particularly in Experiment 1 when there were no instructions to introduce this idea). To fully map the landscape of exploration in social environments, future research should leverage the many diverse tasks that tap into exploratory behavior and build a knowledge base that parallels and is integrated with, the vast research on exploration in nonsocial and collaborative contexts. In doing so, future research could also use reward structures that are in fact generated by social agents (e.g., Wilke et al., 2015) and therefore take into account the natural patterns and variations of reward generation in social contexts as well as further measure participant expectations about rewards generated by social agents as compared to those generated by nonsocial means.

Finally, while the current experiments examined the search for monetary rewards from social agents, a related but distinct set of questions concerns how people explore social landscapes for rewards that are themselves social (e.g., relationship value, emotional rewards; Cords & Aureli, 2000; de Waal, 1997; Kummer, 1978; Wittig et al., 2008) and navigate potential social costs (e.g., risk of interpersonal aggression, energy expenditure; de Waal & Davis, 2003; Mitani & Amsler, 2003). For example, research suggests that individuals would rather lose monetary reward because of a chance than because of another person (Blount, 1995; Bohnet & Zeckhauser, 2004) and that there may be social-specific risk aversion (Haux et al., 2021), consistent with the idea that intentional harm is more painful to experience (Gray & Wegner, 2008). Additionally, expanded search in social environments has the potential to benefit long-term social outcomes with research suggesting that longer time spent searching for a romantic partner predicted longer marriage duration (Cohen & Todd, 2018). Future research should consider other factors that influence exploration beyond uncertainty.

In concert, the limitations and future directions highlight the idea that there are likely many mechanisms underlying the differences between social and nonsocial contexts. In other words, the "socialness" of a context will contain myriad features, including heightened uncertainty (see Berkay & Jenkins, 2023 for an in-depth examination of this idea), but perhaps also heightened stakes for rewards receipt or other features. As one step to understanding additional features, we conducted one additional experiment—"Experiment 5" (see the online supplemental materials) to investigate a possible role in individuation of the reward-generating entities. That is, Experiments 1–4 varied in how "individuated" the nonsocial reward generator was (i.e., a computer algorithm generating rewards across all tiles may not have been considered as individuated as individual plots of land). Individuation could have played a role not only in observed differences across nonsocial conditions but also in the distinction between the social context, in which each tile represented an individual person and the nonsocial ones. Accordingly, in Experiment 5, we included an additional nonsocial condition in which participants read that rewards for each tile were generated by "individual computer algorithms." Ultimately, the results from this preregistered experiment provide inconclusive evidence as to whether individuated nonsocial contexts of this type are more similar to individuated social, or nonindividuated nonsocial, contexts. It is possible that the elevated exploration we observe in social contexts arises from the intersection of multiple "social" features, about which, at present, we can only speculate: for example, individuation plus dynamicity or contingent responding. A promising route for future research will be to capture not only the broad-level differences in behavior between contexts but also the mechanisms driving those differences. In doing so, we may weave our way through the complexities of understanding how social contexts influence human behavior.

Conclusion

Across four experiments, we characterize exploration as a means to reduce uncertainty in social contexts. Holding constant the underlying distribution of rewards across social and nonsocial contexts, we show that when contextual information is sparse, participants demonstrate more behavioral exploration in social as compared to nonsocial contexts, in line with patterns of behavior expected in high-uncertainty environments. Moreover, we find that the increased exploration in social relative to nonsocial contexts comes at the cost of short-term reward receipt. However, when additional social information was available (i.e., how social agents relate to each other or the participant), we found evidence that participants leveraged this information as a cognitive means to uncertainty reduction and reduced behavioral exploration (thereby increasing their receipt of desirable outcomes). Together, these experiments provide evidence consistent with the view that social settings uniquely influence exploration as social beings balance multiple routes to uncertainty reduction dependent on the information available.

Constraints on Generality

In addition to the constraints on generality discussed in the Limitations and Future Directions section, in all experiments, we used convenience samples collected online in the United States. Therefore, our participant characteristics (i.e., individuals in the United States in early mid adulthood with access to the internet and a computing device) limit our ability to make broadly generalizable claims about the phenomenon of interest. Social expectations, goals, and norms for interacting may differ across social groups and cultures, particularly those that may expect higher interdependence among social partners (as was observed in Experiments 3 and 4); therefore, patterns of exploration may differ across populations.

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