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Resource scarcity compromises explore-exploit decision-making☆

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ABSTRACT

Residents living in neighborhoods marked by concentrated disadvantage (i.e., poverty, joblessness, residential segregation) contend with resource scarcity. Theories indicate that competition for resources from an insufficient pool within the context of concentrated disadvantage may be one factor that promotes social norm violations. A limited body of experimental research has explored the impact of concentrated disadvantage on decision-making about obtaining resources, and in other research, the potential connection between concentrated disadvantage and engagement in social norm violation. Participants ($N = 112$) completed patch-foraging tasks in resource-rich and resource-depleted (i.e., scarce) environments. Participants then completed a social norm foraging task where they could trespass and forage on their neighbor's land, which was resource-rich compared to their own. Computational modeling was used to evaluate explore-exploit decision-making in the resource-rich and resource-depleted environments. The frequency of crossing and foraging was used to capture social norm violations. Results indicated that individuals who experience higher levels of concentrated disadvantage in the real-world made fewer resource-maximizing decisions in resource-rich and resource-depleted environments. Model fits revealed that the performance difference in the resource-rich and resource-depleted environments for individuals higher on concentrated disadvantage was due to difficulty in discriminating between competing choice options and not due to a general bias toward exploring or exploiting. Finally, when foraging in a relatively depleted environment compared to the enriched environment of their neighbor, the majority of participants, regardless of experienced real-world concentrated disadvantage, engaged in social norm violations. Overall, resource scarcity, whether in the real world or experimental context, affects cognition and behavior.

Nearly a quarter of households in the United States are located in census tracts, or neighborhoods, characterized by high levels of concentrated disadvantage (United Health Foundation, 2020). Beyond having a disproportionately high percentage of residents who live below the poverty line, neighborhoods characterized by concentrated disadvantage are further defined by a high percentage of residents who claim unemployment, high rates of housing vacancy, low rates of change in jobs or business establishments, as well as a deterioration of physical infrastructure and spatial and social segregation (Massey & Denton, 1989; Sampson, Sharkey, & Raudenbush, 2008). Residents in neighborhoods with high levels of concentrated disadvantage face a host of socio-economic challenges (i.e., unemployment, reliance on public assistance, exposure to crime) and consequently are at risk for poorer physical health, mental health difficulties, and involvement in the criminal justice system (see Freedman & Woods, 2013 for review). These adverse effects highlight the importance of examining how the experience of concentrated disadvantage affects the behavior of its residents.

Residents of neighborhoods marked by concentrated disadvantage commonly are faced with decisions about how and where to meet their basic needs. Sentiments such as "you have to hunt for the fruits, the vegetables, the bottled water…" (Zenk et al., 2011, p.285) or "… I might settle for what they [local stores] have at that particular point in time" (Zenk et al., 2011, p.287), indicate that residents who experience concentrated disadvantage develop strategies to obtain limited resources in order to survive (Ball et al., 2015; Clifton, 2004; Hernández, 2016; Wilson, 2012). Previous experimental research suggests that resource scarcity induces a "scarcity mindset," wherein attention narrows to focus on present needs (Shah, Mullainathan, & Shafir, 2012), resulting in the valuation of immediate rewards at the expense of future ones (Amir, Jordan, & Rand, 2018; Griskevicius et al., 2013). Thus,

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neighborhoods with high levels of concentrated disadvantage may create environments, whereby residents must prioritize their immediate needs, potentially at the expense of longer-term planning (Griskevicius et al., 2013; Mani, Mullainathan, Shafir, & Zhao, 2013; Ong, Theseira, & Ng, 2019; Sheehy-Skeffington, 2020).

Theoretical models also suggest that resource scarcity promotes competition among residents for resources from an insufficient pool (Grossman & Mendoza, 2003; Mullainathan & Shafir, 2013; Ross, Mirowsky, & Pribesh, 2001). Both structural characteristics (i.e., concentrated disadvantage) and social factors (i.e., weakened social bonds) contribute to neighborhood environments wherein social norm violations are more likely to occur (Sampson, Morenoff, & Gannon-Rowley, 2002; Sampson, 2008; Shaw & McKay, 1942). In neighborhoods characterized by concentrated disadvantage, where resources and social connection are constrained, self-preservation may be amplified, resulting in some residents taking resources at the expense of their neighbors. Accordingly, neighborhoods marked by higher concentrated disadvantage have more incidents of general neighborhood crime (Pratt & Cullen, 2005) and residential burglary than neighborhoods lower in concentrated disadvantage (Bernasco & Nieuwbeerta, 2004; Chamberlain & Boggess, 2016; Kikuchi & Desmond, 2010). Thus, resource scarce environments may increase the likelihood for some individuals to engage in social norm violations.

While there has been some experimental research on the effects of resource scarcity on cognitive processes that support decision-making, there has been no experimental work examining how this experience might affect an individual's behavior when searching for resources. Nor has there been experimental work connecting the experience of concentrated disadvantage to engagement in social norm violations when there is an inequitable distribution of resources. Using experimental methods can be advantageous because they allow for more direct measurements of cognitive processes hypothesized to underlie real-world decision-making and investigation of when and in what context the cognitive process may become disrupted.

One area of research that examines cognitive processes implicated in decision-making across environments is found in studies of both non-human animals and humans that use what is called a patch-foraging task (Charnov, 1976; Constantino & Daw, 2015; Wolfe, 2013). Within these tasks, foraging decisions are continually made about whether to explore a new patch that may or may not be more fruitful or to exploit the current patch to harvest a resource that depletes over time. The decision to exploit the current patch or to explore a new patch is necessary for obtaining resources, and by extension, survival. An agent must know when to exploit the current patch and when it is more advantageous to move on and explore a new patch. This type of task provides a controlled experimental context for investigating how individuals obtain (i.e., forage) resources within patches of an environment.

Foraging behavior classically is investigated using the marginal value theorem (MVT; Charnov, 1976), which states that, to maximize long-term resource intake, individuals should explore a new patch whenever the rate of return from exploiting the current patch decreases below the environment's overall average rate of return (Charnov, 1976; Hayden, Pearson, & Platt, 2011). Research on foraging for food in animals (Charnov, 1976; Hayden et al., 2011) and humans (Constantino & Daw, 2015; Wolfe, 2013) demonstrates that foraging behavior is broadly consistent with the predictions of MVT. For example, research in humans shows that individuals explore patches as a function of the resources they are obtaining and the opportunity cost of time to travel between patches (Constantino et al., 2017; Constantino & Daw, 2015; Wolfe, 2013). Additionally, research using a Bayesian-based MVT model, which allows for the acknowledgment that individuals update their knowledge of environments as they forage (Biernaskie, Walker, & Gegear, 2009; Green, 1980; McNamara, Green, & Olsson, 2006), shows similar behavior patterns. For instance, Cain and colleagues demonstrate that individuals forage longer in environments where additional resources are likely but will leave an environment if additional resources are unlikely (Cain, Vul, Clark, & Mitroff, 2012). Accordingly, agents tend to make decisions about foraging to maximize resources.

However, research also shows that individuals can deviate from MVT as a function of psychological demands, such as the experience of stress (Lenow, Constantino, Daw, & Phelps, 2017). It is well-documented that individuals living in concentrated disadvantage generally experience high levels of stress (Brenner, Zimmerman, Bauermeister, & Caldwell, 2013; Hill, Ross, & Angel, 2005) and specifically, stress reflective of worry about resources (Shah, Zhao, Mullainathan, & Shafir, 2018). Therefore, it is reasonable to speculate that utilizing a patch foraging task and MVT-based modeling enhanced with Bayesian updating could uncover important insights into cognitive processes related to resource decision-making among individuals who experience higher levels of real-world concentrated disadvantage. However, no research has been conducted examining explore-exploit decision-making in relation to concentrated disadvantage.

The overarching goal of the present study was to investigate the association between resource decision-making and concentrated disadvantage using a patch-foraging framework. First, using a traditional foraging task that is on average resource-rich, we used a Bayesian-based MVT model to investigate variability in resource decision-making and related that to the experience of real-world concentrated disadvantage utilizing an objective census-based measure of concentrated disadvantage (Area Deprivation Index [ADI]; University of Wisconsin School of Medicine and Public Health, 2020). Second, manipulating the available resources in the environment to represent an on average resource-depleted environment, we modeled variability in resource decision-making and related that to the experience of real-world concentrated disadvantage. Based on previous research that indicates that experiencing resource scarcity leads to disruptions in decision-making, we hypothesized that individuals who experience higher real-world concentrated disadvantage compared to individuals who experience lower real-world concentrated disadvantage would make fewer resource-maximizing decisions as defined by our model in both the traditional and resource-depleted environments. In addition to examining the primary outcome of percentage of resource-maximizing decisions in each environment, we also investigated which potential cognitive processes, bias (degree to which participants value exploiting versus exploring) and imprecision (degree to which participants can discriminate between the value of exploiting versus exploring), may affect resource-maximizing decisions in relation to real-world concentrated disadvantage. While these parameters do not directly shed light on the cognitive mechanisms behind reductions in resource-maximizing decisions, they capture two important types of deviations. If participants deviate from MVT because they over- or under-value different aspects of the task, then their performance should align with MVT once their responses are corrected for bias. If, beyond a bias, participants also struggle in identifying the best choice, the magnitude of this effect can be captured with the imprecision parameter.

Finally, taking the basic structure of the depleted foraging task but adding an option to cross a fence to forage on a neighbor's land, we estimated the tendency to engage in social norm violation, particularly when one's own environmental resources were depleted compared to a neighbor's resources. The key manipulation of the participant having depleted resources compared to a neighbor was created to reflect the real-world conditions that many living in concentrated disadvantage experience: having relatively less compared to someone else in their environment. This final task provided an experimental context where *all* participants experienced the type of resource competition common in disadvantaged neighborhoods. The primary outcome of this task was measured by dividing the amount of time participants spent harvesting (i.e., stole) on their neighbor's land by the number of times participants crossed onto their neighbor's land (i.e., trespassed). Based on theoretical work linking concentrated disadvantage to social norm violations, we expected that most participants would engage in social norm violations by trespassing onto their neighbor's land and harvesting on that land. Additionally, we hypothesized that living in real-world concentrated disadvantage would further amplify the tendency to engage in social norm violations (i.e., trespass and take from the neighbor's land) during this period of relative inequality in resources.

1. Methods

1.1. Participants

Participants were recruited using flyers distributed throughout New Haven County, an environment which contains areas ranked in the lowest and in the highest state percentiles of neighborhood disadvantage, as measured by the ADI (University of Wisconsin School of Medicine and Public Health, 2020). Participants completed a prescreen phone interview and an in-person clinical assessment. Individuals who were younger than 18 or over 75, had performed below a fourth-grade level on a standardized measure of reading (WRAT-III; Wilkinson, 1993), had performed below 70 on a brief measure of IQ (Shipley; Zachary, 1986), who had diagnoses of schizophrenia, bipolar disorder, or psychosis and not otherwise specified, or who had a history of certain medical problems (e.g., uncorrectable auditory or visual deficits, seizures, head injury with lost consciousness of 30 min or more, color blindness) that may impact their comprehension of materials or performance on the task were excluded. A total of 75 participants were excluded (64 at the prescreen phone interview [31 had diagnoses of schizophrenia, bipolar disorder, or psychosis and not otherwise specified; 33 had a history of certain medical problems that may impact their comprehension of materials or performance on the task] and 11at the in-person assessment [8 endorsed psychotic symptoms; 1 failed to complete neuropsychological measures; 2 had a history of certain medical problems that impacted ability to perform the task]). All participants provided informed consent and experimental procedures were approved by the Yale University Human Investigation Committee. Participants were paid \$10/h for completion of the self-report measure and experimental tasks. Participants were also paid a bonus based on their performance in the experimental tasks. Data and modeling code are available upon request to the corresponding author.

Participants who met inclusion criteria ranged in age from 18 to 73 years ($M = 40.61$, $SD = 14.46$). The racial composition of the sample included 48.21% of participants identifying as White, 43.75% as Black, 3.57% as Asian, and as 4.46% Other/Multiracial. The majority of the participants identified as non-Hispanic (95.54%), and 4.46% identified as Hispanic. In relation to educational attainment, 2.68% of participants completed Junior High/Middle School or below, 16.07% completed partial high school education, 27.68% completed high school, 29.46% completed partial college, 16.96% completed college, and 7.14% completed a graduate degree. Approximately 35% of the sample reported earning an individual annual income of less than \$1000, 20.54% of participants reported earning between \$5000 through \$11,999, 8.04% reported earning between \$12,000 through \$15,999, 10.71% reported earning between \$16,000 through \$24,999, 10.71% reported earning between \$25,000 through \$34,999, 7.14% reported earning between \$35,000 through \$49,999, 3.57% reported earning between \$50,000 through \$74,999, and 4.46% reported earning between \$75,000 through \$99,999. See Table 1 for a summary of sample characteristics and zero-order correlations among primary variables.

Across studies that included multiple foraging conditions (Constantino & Daw, 2015; Lenow et al., 2017; Wolfe, 2013; Zhang, Gong, Fougnie, & Wolfe, 2015) effect sizes were generally small. Based on this, we calculated an a priori power analysis before any data analysis began using the pwr package (Champely, 2020) in R (R Core Team, 2020) that estimated a small effect size (Cohen's d = 0.20) for a one predictor regression, which indicated that a sample size of approximately 110 participants will result in sufficient (80%) power.

1.2. Measures

1.2.1. Area deprivation index (ADI; University of Wisconsin School of Medicine and Public Health, 2020)

The ADI is an index of disadvantage at the neighborhood level derived from the 2011–2015 5-year estimates from the US Census' Community Survey and represents neighborhoods at the Census Block Group. The ADI has been used extensively to investigate how

Table 1
Final sample characteristics and zero-order correlations among primary variables.

Variable	n (%)	M	SD	4	5	6	7	8	9	10
1. Age	112	40.61	14.46							
2. Sex										
Male	75 (66.96)									
3. Race										
Black	49 (43.75)									
White	54 (48.21)									
Asian	4 (3.57)									
Other/Mutiracial	5 (4.46)									
4. ADI	112	7.45	2.65	–						
5. Percent resource-maximizing decisions in traditional foraging task	112	64.57	13.64	−0.28**	–					
6. Bias parameter in traditional foraging task	103	0.25	1.43	−0.00	0.30**	–				
7. Imprecision parameter in traditional foraging task	103	0.75	0.97	0.21*	−0.35***	−0.04	–			
8. Percent resource-maximizing decisions in depleted foraging task	112	61.71	12.81	−0.31***	0.79***	0.31**	−0.35***	–		
9. Bias parameter in depleted foraging task	96	0.37	1.61	0.16	0.08	0.58***	−0.18	0.11	–	
10. Imprecision parameter in depleted foraging task	96	0.75	1.15	0.24*	−0.26*	0.45***	0.31**	−0.31**	0.37	–
11. Tendency to engage in social norm violation in the social norm foraging task (total amount of time spent on Logan's land/number of times crossed over to Logan's land)	112	178.30	173.71	−0.14	0.29**	0.05	−0.15	0.21*	−0.00	−0.16**

Note. ADI = Area Deprivation Index.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

neighborhood-level disadvantage predicts individual differences in various outcomes, including risk for Alzheimer's disease neuropathology (Powell et al., 2020), hospital readmission (Jencks et al., 2019; Kind et al., 2014), neuromorphology (Hunt et al., 2020; Vargas, Damme, & Mittal, 2020), and neural circuitry (Mullins, Campbell, & Hogeveen, 2020). The ADI reflects a composite score created via principal components analysis of 17 measures taken from the Census data. Examples of these measures include percentage of families below the poverty level, percentage of population aged ≥25 years with <9 years of education, percentage of population aged ≥25 years with at least a high school diploma, median family income, and percentage of employed persons aged ≥16 years in white collar occupations. Scores were obtained utilizing the address on the participant's photo identification or self-report of the address at which they had lived for the longest period of time as an adult if their photo identification did not include an address. Addresses were entered into the Neighborhood Atlas website (University of Wisconsin School of Medicine and Public Health, 2020) to determine ADI scores. ADI scores have been transformed into state percentile rankings, ranging from 1 to 10. Higher scores on the ADI represent greater neighborhood disadvantage and scores in this sample ranged from 1 to 10 in all analyses (see Fig. 1). Average ADI scores from the city where the study was conducted was 6, and average ADI scores for surrounding cities included 2, 4, 5, and 8.

1.3. Experimental tasks

1.3.1. Traditional foraging task

Participants were informed that they would be making a series of decisions that would allow them to earn money. In the instructions, it was emphasized that the goal of the game was to harvest as many apples as possible because the total number of apples harvested over the course of the task would be converted into a monetary bonus.

Participants began the task by seeing an aerial overview of the number of apples on the trees on their land. The mean of the distribution of apples on the trees was 10, which reflected the mean of the distribution from which initial tree richness was initialized (see Table 2 for experimental parameters). Participants indicated which quartile of their land to begin harvesting by pressing the number key corresponding to the labeled quartile (see Fig. 2). Although participants were given the choice of where to begin foraging to promote participants feeling a sense of agency over their decisions, the trial order was fixed, such that all participants encountered trees in the same order. Participants then viewed a single tree at a time and could choose to harvest the current tree (exploit) for apples or to go to a new tree on their land (explore). At the start of each trial, participants saw a bare tree by itself. After 500 ms, participants were prompted to select one of two key presses: 1) to harvest the current tree by pressing the 'S' key or 2) to go to the next tree on their land by pressing the 'K' key.

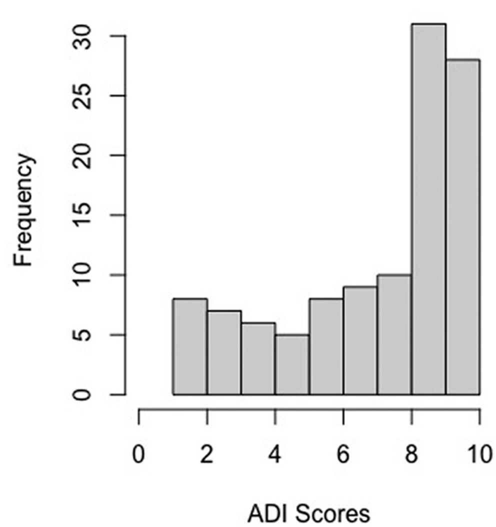

Fig. 1. Histogram of ADI Scores.

Table 2
Parameter values defining the task environments.

Environment	h (s)	d (s)	k, σ_k	S_0, σ_s
Traditional foraging task	3 s	6 s	0.88, 0.07	10,1
Depleted foraging task	3 s	6 s	0.88, 0.07	6,1
Social norm foraging task (participant's land)	3 s	6 s	0.88, 0.07	5,1
Social norm foraging task (Logan's land)	3 s	6 s	0.88, 0.07	10,1

Note. h = harvest time, d = travel time, k = mean of distribution of depletion rate per harvest, σ_k = standard deviation of distribution of depletion rate per harvest, S_0 = mean of distribution of initial tree richness, σ_s = standard deviation of distribution of initial tree richness. These experimental parameters were selected based on pilot data of 10 participants, as well as, modeled off of the paradigm used by (Constantino & Daw, 2015).

If participants decided to harvest the current tree, the number of apples from that harvest decision was revealed underneath the tree for the length of the harvest time delay (3 s). If participants decided to go to the next tree, a 'traveling' screen appeared for the duration of the travel time delay (6 s). The reaction time for each decision was counted within the harvest or travel delay, so that reaction time did not influence the overall reward rate of the environment. Participants had 1.5 s to decide to harvest the current tree or go to the next tree before the response options left the screen. If they failed to decide before the options left the screen, a warning message was displayed, during which participants could not enter any decisions. This warning lasted for 1.5 s in order for the length of the trial to match the length of a harvest delay (3 s). Participants then faced the same decision (i.e., explore-or-exploit) at the next trial (see Fig. 3 for a task schematic).

Participants did not have a priori knowledge of the parameters defining the environment. They simply were informed that repeatedly harvesting a tree would yield fewer apples each time and that each new tree had never been harvested before, thus a new tree had a full supply of apples. Additionally, participants were informed that once a decision was made to go to the next tree, it was not possible to return to that exact same tree. It was emphasized that participants could earn different amounts of money by paying attention to how harvesting was depleting apples on a tree. They were told that they would be paid 0.00125 of a cent per apple collected. Participants were informed that they would be completing the first phase of the task for 20 min. The task paused after 20 min, marking the end of the traditional foraging task.

1.3.2. Depleted foraging task

Participants were then shown a 'current' aerial overview of the number of apples on the trees on their land for 3 s. The mean of the distribution of apples on the trees in this overview was 6, in order to represent a depleted environment. Participants were told that the task would resume exactly as before and that the goal of the game was to continue to harvest as many apples as possible, therefore earning as much bonus as possible. Participants were informed that they would be completing this phase of the task for 10 min. Compared to the traditional foraging task, the length of the depleted foraging task was shorter since participants were harvesting apples within a more restricted range of initial tree richness. This restricted range resulted in participants seeing fewer types of trees in the depleted environment. Thus, the depleted foraging task was shortened because there were fewer types of trees for

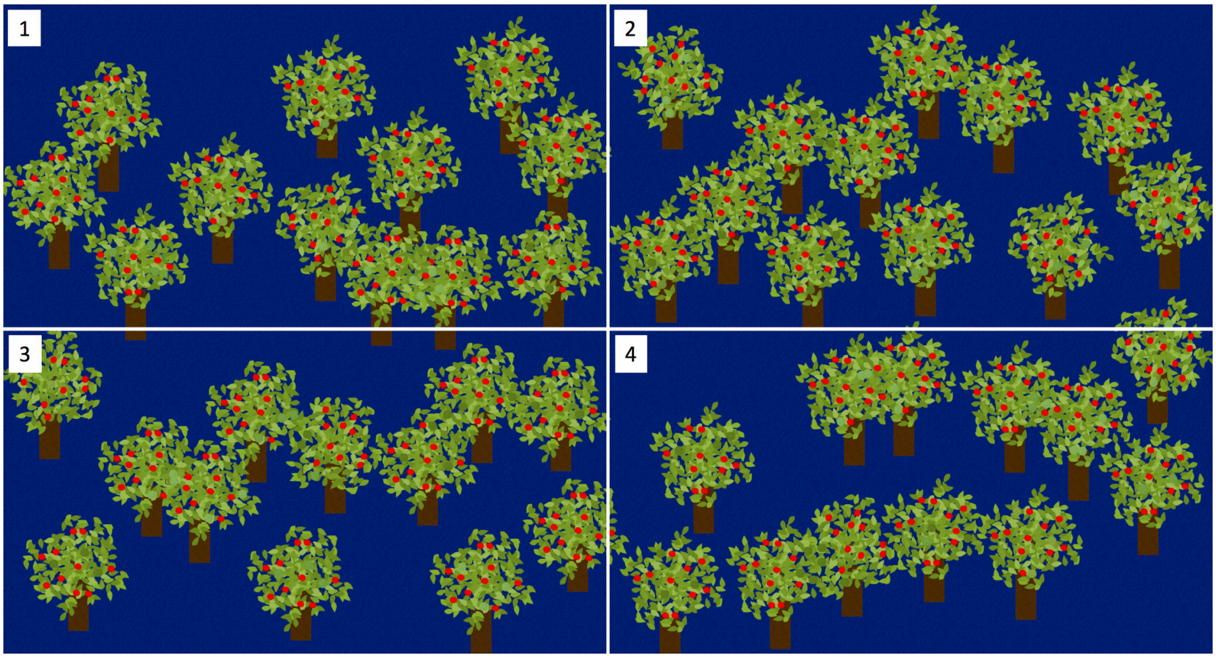

Fig. 2. Aerial overview of the traditional foraging task.
Note. The aerial view shows the number of apples on the trees on their land. The mean of the distribution of apples on the trees was 10, which reflected the mean of the distribution from which initial tree richness was initialized.

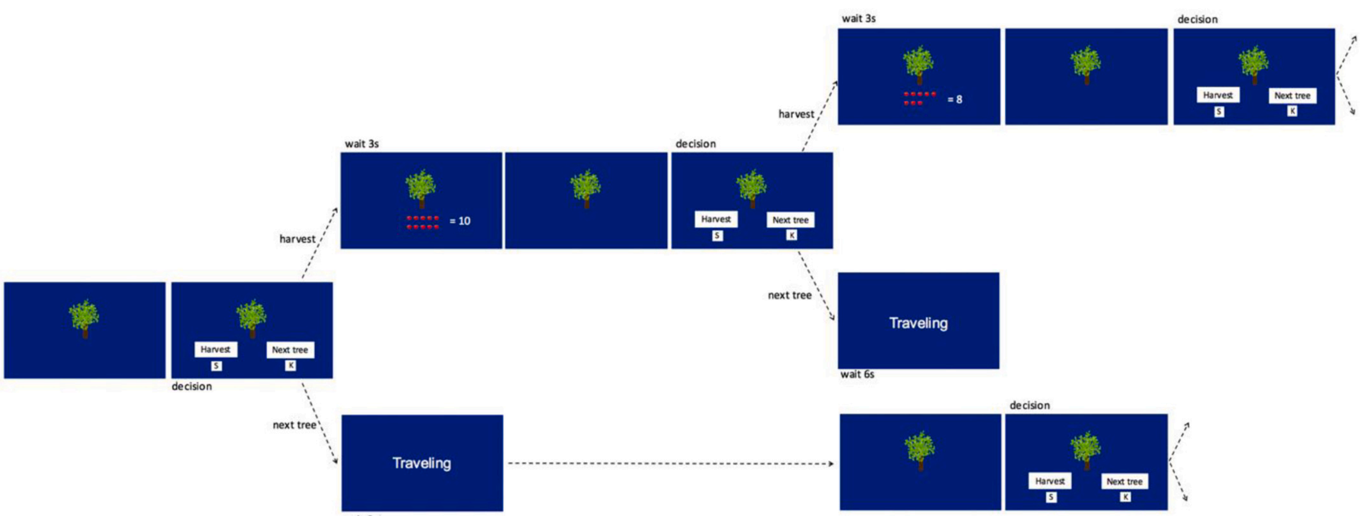

Fig. 3. Schematic of the traditional foraging task.
Note: In the task, participants made a series of decisions to harvest (exploit) a currently displayed tree or to travel to a new tree to harvest (explore). Trees yielded fewer apples with each successive harvest. Traveling to a new tree incurred a time cost but resulted in the opportunity to harvest at a new tree.

participants to encounter.[2]

1.3.3. *Social norm foraging task*

The structure of the social norm foraging task was the same as the traditional foraging task, except participants now had the option of harvesting apples on their own land, as well as on their neighbor, Logan's, land. Participants began the social norm foraging task by viewing an aerial image of the number of apples on the trees on their land, as well as on Logan's land for 5 s (see Fig. 4). The mean of the distribution from which initial tree richness was initialized on the participant's land was 5, and the mean of the distribution from which initial tree richness was initialized on Logan's land was 10. The background color denoted whose land they were on. The participant's land was blue, and Logan's Land was purple. Participants always began the task on their land and viewed a single tree at a time. Participants could choose to harvest the current tree for apples, to go to a new tree on the current land, or to cross the fence and go to a new tree on the opposite land. At the start of each trial, participants viewed a tree that did not display the number of apples. After 500 ms, participants were prompted to select

[2] The results of our analyses do not change if only the first 10 min of the traditional foraging task (as opposed to the full 20 min) are examined to match the length of the depleted foraging task. We still see a significant effect of ADI on percentage of resource-maximizing decisions in the traditional foraging task, $R^2 = 0.08$, $b = -1.48$, $t(110) = -3.02$, $p = .003$, 95% CI [-2.45, -0.51].

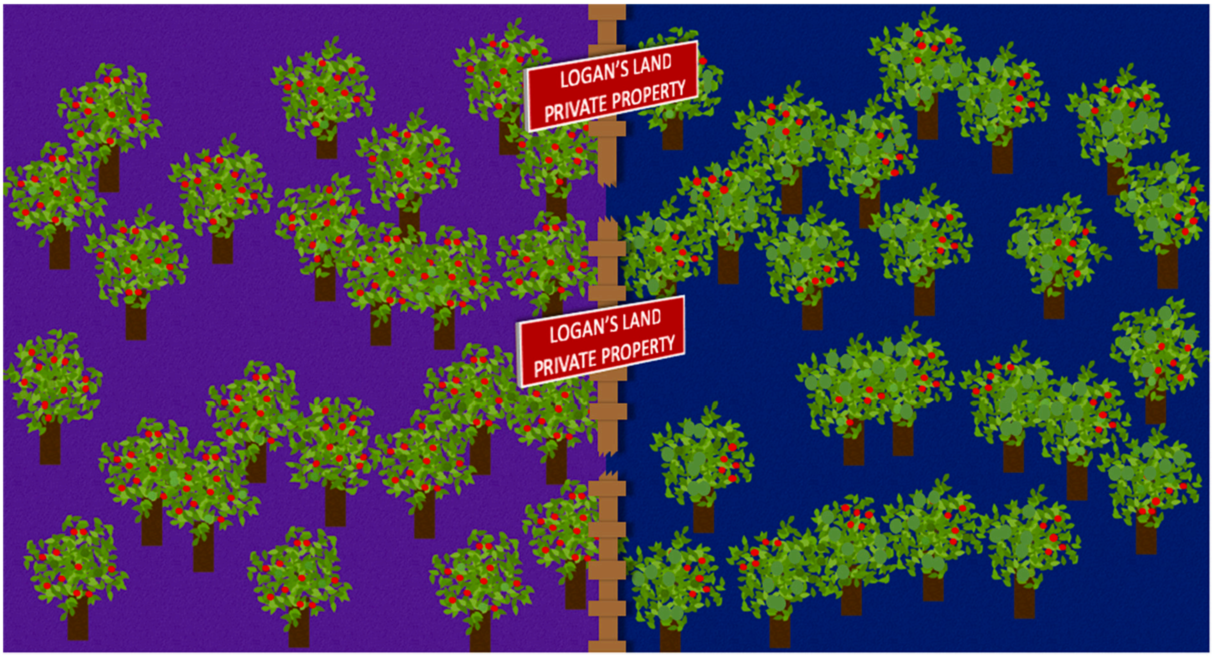

Fig. 4. Aerial overview of the social norm foraging task.
Note: The aerial view shows the number of apples on the trees on the participant's land (blue background), as well as on Logan's land (purple background). The mean of the distribution from which initial tree richness was initialized on the participant's land was 5, and the mean of the distribution from which initial tree richness was initialized on Logan's land was 10.

one of three key presses: 1) to harvest the current tree by pressing the 'S' key 2) to go to the next tree on the current land by pressing the 'K' key, or 3) to cross the fence to go to a new tree on the opposite land by pressing the 'G' key.

The timing related to harvesting the current tree, going to the next tree, and making a decision was the same as the traditional and depleted foraging tasks. The only difference was that when participants crossed the fence to go to a new tree on the opposite land (incurring a travel time delay of 6 s), the background color of the environment changed (see Fig. 5 a task schematic). Instructions regarding repeated harvesting at a

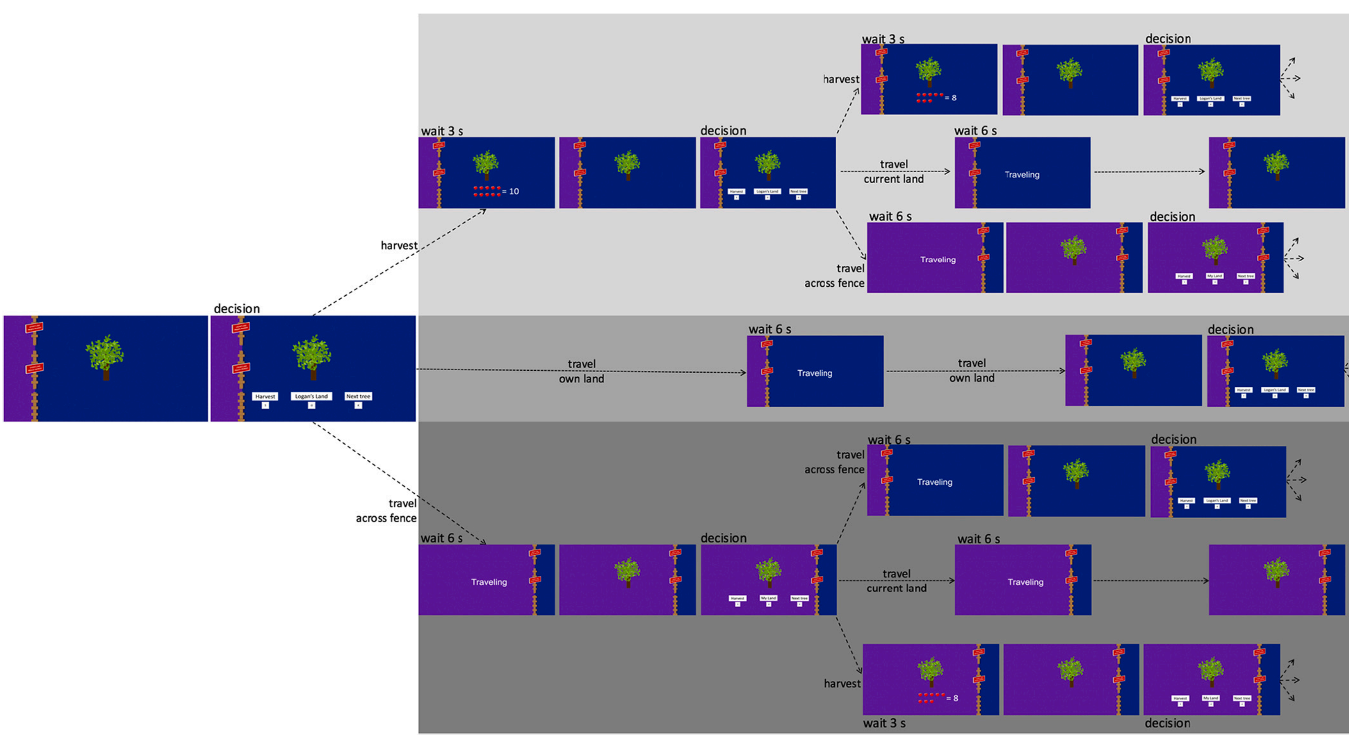

Fig. 5. Schematic of the social norm foraging task.
Note. In the task, participants made a series of decisions to harvest the currently displayed tree (shown in the top light gray panel), to travel to a new tree on the current land to harvest (shown in the middle panel), or to cross the fence to travel to a new tree on the opposite land (shown in the bottom darkest gray panel). Trees yielded fewer apples with each successive harvest. Traveling to a new tree incurred a time cost but resulted in the opportunity to harvest at a new tree.

tree and the goal of the game (to harvest as many apples as possible) were the same as the traditional and depleted foraging tasks. Participants were informed that they would be completing this phase of the foraging task for 15 min.

1.4. Experiment parameters

Each foraging environment was defined by four factors: the distribution of the tree's initial richness (modeled through a normal distribution with mean S_0 and standard deviation σ_s), the distribution of depletion rates across trees (modeled through a Beta distribution with mean k and standard deviation σ_k), travel time d, and harvest time h. The state (or number of apples available for the next harvest) of a tree at trial i, is denoted as s_i. Each travel decision led to a tree initialized with a state of variable quality $s_i \sim N(S_0, \sigma_s)$, and a depletion factor, $k_i \sim \mathrm{Beta}(S0, \sigma s)$. By varying the distribution of a tree's initial state of quality and the applied depletion factor at each tree, environments of different quality trees varying in richness of apples were created, with each tree having a different possible reward path.

The parameters for the environments in the traditional foraging task, the depleted foraging task, and the social norm foraging task are shown in Table 2. In the traditional foraging task, the mean of the average initial tree richness was 10, and the task lasted for 20 min. In the depleted foraging task, the mean of the average initial tree richness was decreased to 6 in order to simulate foraging in an environment akin to the experience of concentrated disadvantage, and this lasted for 10 min. In the social norm foraging task, the mean of the average initial tree richness on the participant's land was 5, while the mean of the average initial tree richness on Logan's land was 10, in order to simulate the experience of having depleted resources compared to a neighbor's resources. The social norm foraging task lasted for 15 min.

1.5. Procedure

Participants came into the lab for two visits. On visit 1, each participant's ADI score was obtained and participants completed a clinical and neuropsychological assessment, as well as a questionnaire measuring engagement in social norm violations (e.g., aggressive behavior, criminal activity). On visit 2, participants completed the foraging tasks. Before beginning the traditional foraging task, the experimenter read instructions aloud to the participants, and participants completed a practice round. Apples harvested during the practice round were not included in the calculation of the participant's final number of apples harvested over the course of the task. Following the practice round, participants were given the opportunity to ask the experimenter for clarification before starting the actual task. When the traditional foraging task ended, participants were given a 30 s break. Following the break, participants received instructions on the screen and resumed with the depleted foraging task. When the depleted foraging task ended, the experimenter re-entered the testing room to read the instructions for the social norm foraging task aloud to the participants. Participants had the opportunity to ask questions before beginning the social norm foraging task. There was no practice round before the social norm foraging task. *Note*: The experimenter never explicitly stated that the participant could steal from Logan. The experimenter just showed the view of Logan's land and the option to cross the fence. Signs stating "Logan's Land Private Property" flanking the right or left side of the screen were displayed for the entire social norm foraging task. All participants completed the foraging tasks in the following order: traditional foraging task, depleted foraging task, and social norm foraging task. We report all measures, manipulations, and exclusions in this study.

1.6. Computational framework

Building on previous models of human foraging (e.g., Constantino & Daw, 2015), we implemented a computational model of foraging behavior that made decisions based on the principles of MVT, enhanced with a human-like Bayesian learning mechanism of environmental depletion (Payzan-LeNestour & Bossaerts, 2011; Yu, 2007). While previous work has used MVT as a model of human behavior (i.e., treating the computations occurring in MVT as representing the computations occurring in the brain), here we treat it as an ideal observer model (Anderson, 1990; Chater & Oaksford, 1999). Under this approach, MVT is not treated as a literal model of human cognition. Instead, it provides a method to determine the best possible choice that participants could make at each point in order to maximize resources (as well as how difficult it is to identify the best choice). Equipped with this model, we can quantify how often people make the best possible resource-gathering decisions and reveal how deviations happen as a function of environmental factors. Ideal-observer models have a long history in areas such as vision and sensorimotor learning (e.g., Geisler, 2003; Körding & Wolpert, 2004), and have gained recent prominence across psychology more broadly thanks to their success in helping explain high-level cognition (see Gershman, Horvitz, & Tenenbaum, 2015; Tenenbaum, Kemp, Griffiths, & Goodman, 2011 for reviews).

Formally, in line with MVT, our model tracks the return rate of the current tree the participant is harvesting, given by $r_{exploit} = v_{exploit}/h$ for exploiting the current tree and compares it to the long-run reward rate obtained so far in the environment, given by $r_{total} = v_{total}/h_{total}$ (where v_{total} is the total number of apples harvested in the entire task, and h_{total} is the total time spent in the task).

We fixed h to 3 (as participants in our experiment knew the harvest time) in order to estimate the expected return rate for staying. The remaining variable, $v_{exploit}$, represents the number of apples that the participant expected to obtain by harvesting the same tree again (exploiting). After harvesting s_i apples, harvesting the same tree again would yield ks_i apples, where k is the tree's depletion rate. When a tree has only been harvested once, its depletion rate k is unknown, and thus estimated using the overall distribution of depletion rates that the participant has observed so far. We obtained this estimate by assuming that participants began the task with no knowledge about the depletion rates (i.e., a uniform distribution over the range 0–1), but that they updated this knowledge throughout the task using Bayesian inference (see Supplemental Material for details). When participants chose to exploit a tree a second time, the difference between the first and second returns revealed the tree's true depletion rate, and we thus assumed that participants could accurately predict the next returns using the tree's now known depletion rate k (*note*: this assumption might be too strong, therefore below we present an extended model that relaxes this expectation).

According to MVT, to maximize long-term resource intake, people should continue harvesting the same resource until $r_{total} < r_{exploit}$. When this happens, people should switch to exploring a new resource patch. We also implemented an alternative version of this model as a robustness check to help us ensure that our results are not affected by these modeling choices. In all cases, our results were qualitatively identical (see Supplement for details and results using the alternative model).

1.6.1. Resource decision-making parameters

The model described above allowed us to calculate the percentage of decisions where participants choose the option consistent with classical MVT. However, we are not only interested in testing whether people adhere to classical MVT, but also uncovering in what ways they deviate from this hypothetical best performance. To do this, we extended the classical MVT model to capture three possible deviations that different participants might exhibit. First, some participants may struggle to make the right decision when confronted with a difficult choice (i.e., making more errors as $r_{exploit}$ and r_{total} become more similar). This could be due to a variety of factors, such as difficulty in estimating the exact return rate associated with exploring and exploiting, or a tendency to choose randomly when the value of exploring and exploiting is similar. Second, some participants may have a tendency to deplete resource patches more so than predicted by classical MVT. This could stem from a variety of reasons, such as an aversion to exploration (perhaps due to the uncertainty associated with it), an optimistic assessment of the expected return rate for depleting a resource, or a pessimistic assessment of what might happen in a novel context. Finally, a third possibility is that some participants explore more than is predicted by classical MVT. These participants may have a tendency to prefer exploration either because they believe it is more likely to yield higher resources or because they under-estimate the potential gains from exploiting a current resource.

To model these deviations from classical MVT, we extended our model to include a bias for each choice, such that the rate for either choice (explore or exploit) is given by $r_{choice} + \beta_{choice}$. Here, β_{choice} is the participant's bias for a particular choice (a positive value meaning that the participant over-values the choice, and a negative value meaning that the participant undervalues it). Because a negative bias for one choice is equivalent to a positive bias for the competing choice, we set $\beta_{explore}$ to 0 and only fit $\beta_{exploit}$ to participant judgments. Next, to model people's propensity to make errors as a function of decision difficulty, we softmaxed the return-rates. Formally, the probability of exploring and exploiting as the softmax of potentially biased estimates is given by

$$p(choice) \propto exp\left(\frac{(r_{choice} + \beta_{choice})}{\tau}\right)$$

where, τ is a parameter capturing the participant's imprecision.[3] When τ is low, the model always selects the best choice, even when the expected return rates are nearly identical. As τ increases, the model captures the idea that participants have difficulty distinguishing between comparable return rates for exploiting the current tree and exploring the next tree but can continue to identify the best choices when the return rate for staying and leaving is noticeably different. Note that under this formulation, classical MVT is a special case where $\beta_{choice} = 0$ and $\tau \sim 0$.

1.7. Experimental task key variables

Participants were excluded from all analyses if they failed to respond on greater than 25% of their trials, as this indicated a lack of engagement in the task. This resulted in the exclusion of data from two participants. Analyses are presented on 112 subjects unless otherwise specified below.

1.7.1. Traditional and depleted foraging task

Each participants' explore-or-exploit decisions in the traditional and depleted foraging tasks were compared against the classical MVT model predictions using the environment's parameters. Each decision that was greater than or equal to 0.5 as defined by our model prediction was considered to be resource-maximizing. This allowed us to calculate the percentage of explore-or-exploit decisions the participant made that were adherent to the resource-maximizing predictions of our model in the traditional and depleted foraging tasks, respectively. The higher the percentage, the more often the participant chose the resource-maximizing option when foraging.

1.7.2. Resource-decision making parameters

Bias and imprecision were fit to each participant individually through maximum likelihood. For each participant, we calculated the probability that their responses would be generated by our softmaxed model under each parameter combination (given by the product of the probability of making each choice throughout the task), and we then selected the parameters with the highest probability. For the traditional and depleted foraging tasks, we searched over the parameter space using a simple discretization, testing bias values over the range [−7 7] (using jumps of 0.1). This range was selected to be wide enough that it included biases extreme enough to outweigh any expected foraging rate that could appear in the task (i.e., this range allows a bias as strong as the equivalent of a return rate of 7 apples per second, which could never be reached in the task). Imprecision values were tested over the range [010] (using jumps of 0.02). This range was determined to ensure that the model included imprecision values where the model always selects the best possible choices, and values where the model fails at even the simplest choices. Higher τ parameters indicate greater imprecision of discrimination between the probability (i.e., value) of exploiting versus exploring, whereas τ parameters closer to 0 indicate greater precision discriminating between the value of exploiting versus exploring. That is, when τ is close to 0, softmaxing always assigns probability 1 to the option with the highest value (therefore becoming equivalent to classical MVT). As τ increases, softmaxing transforms classical MVT into a uniform distribution (random performance). Thus, although τ can take on any positive value between 0 and infinity, most of these values simply predict distributions that are close to chance performance, and it was necessary to restrict the range of τ values we fit to participants. Participants who only made "exploit" decisions were excluded from these analyses (traditional foraging task $n = 1$, depleted foraging task $n = 2$) because the model would interpret behavior like this as a strong exploit bias or poor imprecision, while in reality the decision only to exploit could reflect a lack of engagement with the task. Additionally, participants whose fitted bias or imprecision parameters were at the upper or lower bounds of the range tested were excluded from analyses (traditional foraging task $n = 6$, depleted foraging task $n = 11$).

Studentized t regression outliers, leverage, and influence diagnostics on bias and imprecision were then examined in order to identify potential outliers. Applying a joint exclusion criterion, only participants that were defined as outliers on more than one diagnostic test for both bias and imprecision parameters were excluded from analyses (traditional foraging task $n = 0$, depleted foraging task n = 1). A total of 103 participants remained in the traditional foraging task and a total of 96 participants remained in the depleted foraging task. The final ranges of fitted parameters were [−5.1 6.8] for bias and [0.04 9.96] for imprecision.

1.7.3. Social norm foraging task

To examine the tendency to engage in social norm violation, the total amount of time spent on Logan's land (i.e., stealing behavior) in seconds was divided by the number of times the participant chose to cross over to Logan's land (i.e., trespassing behavior). This variable was created because a measure only reflecting time spent harvesting on Logan's land fails to differentiate between participants who spend equal amounts of time harvesting (i.e., stealing) over the course of the task but differ in the number of times they crossed (i.e., trespassed) to Logan's land in order to steal. Additionally, increased crossing onto Logan's land does not account for what the participant does once crossed, such as the amount of harvesting (stealing apples) on Logan's land. Further, while crossing is a social norm violation (i.e., trespassing), in the context of the task, it is also a significant time investment, so an increased number of crossings is potentially disadvantageous and would consequently decrease the time left for harvesting (i.e., stealing). Thus, we opted to divide the amount of time spent on Logan's land by the number of fence crossings to account for the two ways people can engage in social norm violations in this task: trespassing and taking apples from Logan. This metric allowed us to discern between someone who spent the entire phase stealing from Logan and therefore was less likely to cross repeatedly (most severe social norm transgression [more stealing but less time spent trespassing]) and someone who stole from Logan but crossed lands multiple times (less severe social norm transgression [less stealing but more time spent trespassing]). The higher the value of this variable, the greater the participant's engagement in social norm violation in the context of the task. To establish construct validity, we correlated behavior on the social norm violation foraging task with self-reported questionnaire assessing real-world social norm violations (e.g.,

[3] This parameter is often called the rationality or temperature parameter.

shoplifting, destroyed property, threatened someone, robbed someone, stole money) administered during visit 1 (Sadeh & Baskin-Sommers, 2017), $r(110) = 0.25$, $p = .009$, 95% CI [0.07, 0.41].

2. Results

2.1. Traditional foraging task

In the traditional foraging task, participants made an average of 303 explore-or-exploit decisions and visited an average of 65 trees. On average, participants failed to make a response in the allotted time on 4 trials (0.02% of trials). Participants harvested an average of 1558 apples ($SD = 313$), earning on average a bonus of \$1.95 ($SD =$ \$0.36). On average, 65% ($SD = 13.64\%$) of decisions made by participants were resource-maximizing as defined by the classical model.

To examine the effect of real-world levels of concentrated disadvantage on foraging behavior, percentage of decisions that were resource-maximizing as defined by the classical MVT model in a generally resource-rich environment were entered in a robust linear regression with ADI as a continuous predictor. A robust linear regression was used because after a linear regression was conducted, diagnostic plots of Cook's distance identified 7 influential points. Results showed a significant effect of ADI on percentage of resource-maximizing decisions $R^2 = 0.08$, $b = -1.48$, $t(110) = -3.02$, $p = .003$, 95% CI [−2.45, −-0.51], suggesting that individuals who experience higher levels of concentrated disadvantage make fewer resource-maximizing decisions when foraging in a generally resource-rich environment (see Fig. 6).

2.2. Depleted foraging task

In the depleted foraging task, participants made an average of 145 explore-or-exploit decisions and visited an average of 37 trees. On average, participants failed to make a response in the allotted time on 2 trials (0.02% of trials). Participants harvested an average of 422 apples ($SD = 89$), earning on average a bonus of \$0.53 ($SD =$ \$0.11). On average, 62% ($SD = 13\%$) of decisions made by participants were resource-maximizing as defined by our model.

To examine the effect of real-world experience of concentrated disadvantage on foraging behavior, percentage of decisions that were resource-maximizing as defined by the classical MVT model in a generally resource-depleted environment were entered in a robust linear regression with ADI as a continuous predictor. Robust regression was used because Cook's distance measures of percentage of decisions that were resource-maximizing in a generally resource-depleted environment entered in a linear regression identified 7 influential points. Results showed a significant effect of ADI on percentage of resource-maximizing decisions $R^2 = 0.15$, $b = -1.79$, $t(110) = -3.56$, $p <$ .001, 95% CI [−2.79, −0.79], suggesting that individuals who experience higher levels of concentrated disadvantage make fewer resource-maximizing decisions when foraging in a generally resource-depleted environment (see Fig. 7).

2.3. Resource-maximizing decision-making across environments

To compare the relationship between ADI and resource-maximizing decisions in resource-rich and resource-depleted environments simultaneously, we entered the percentage of decisions that were resource-maximizing into a repeated measures General Linear Model with task (i.e., traditional or depleted) as a within-subjects factor and ADI as a continuous covariate. Results showed a significant within-subjects effect of task on percentage of resource-maximizing decisions $F(1,110) = 6.31$, $p = .014$, $\eta_p^2 = 0.058$. Participants, on average, made more resource-maximizing decisions in the traditional foraging task ($M = 64.57$, $SD = 13.64$) compared to the depleted foraging task ($M = 61.71$, $SD = 12.81$). Results showed no significant interaction between ADI and task on percentage of resource-maximizing decisions $F(9, 110) = 0.55$, $p =$ .833, $\eta_p^2 = 0.046$. Consistent with the results reported with the separate regressions and with the idea that living in real-world concentrated disadvantage disrupts resource-maximizing decision-making, there was a significant between-subjects effect of ADI on percentage of resource-maximizing decisions $F(1,110) = 11.84$, $p = .001$, $\eta_p^2 = 0.097$.

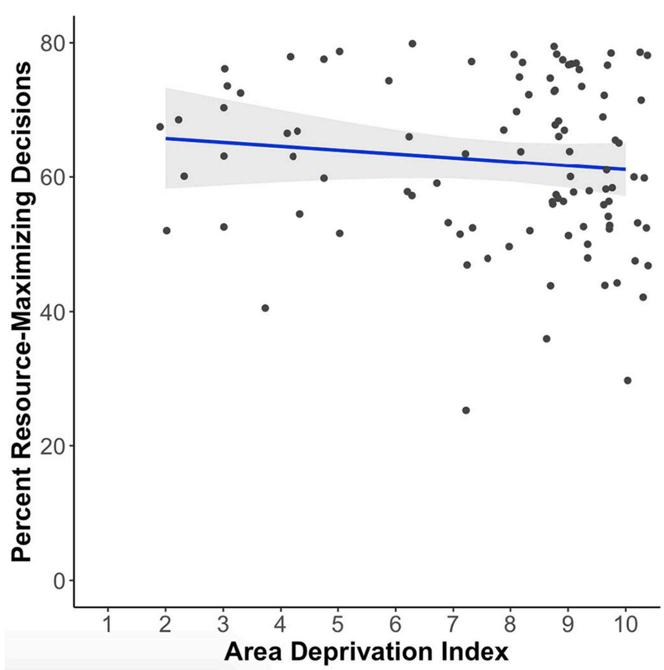

Fig. 6. Percentage of resource-maximizing decisions in a traditional foraging task as a function of ADI. *Note:* Error bands indicate 95% confidence intervals. Plot was generated using the stat_smooth function in the ggplot2 package (Wickham, 2016) in R (R Core Team, 2020).

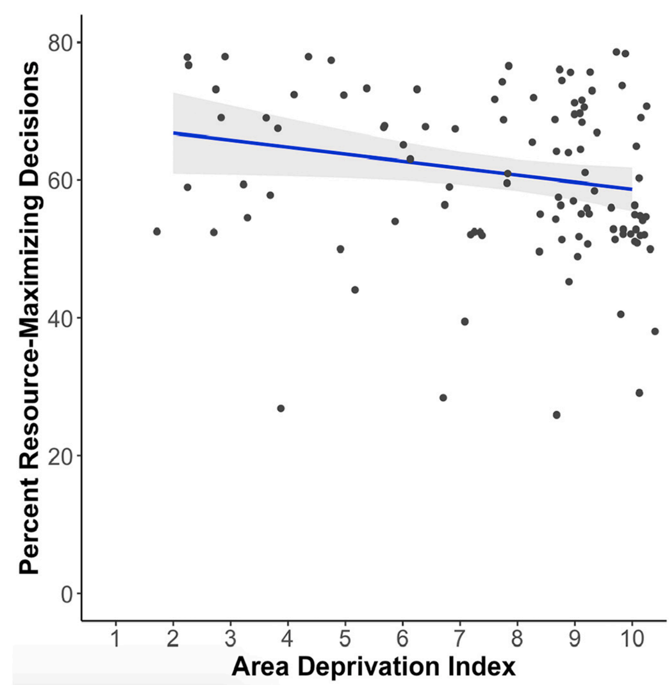

Fig. 7. Percentage of rate-maximizing decisions in a resource-depleted foraging task as a function of ADI.
Note: Error bands indicate 95% confidence intervals. Plot was generated using the stat_smooth function in the ggplot2 package (Wickham, 2016) in R (R Core Team, 2020).

Individuals higher on ADI made fewer resource-maximizing decisions across both tasks.

2.4. Robustness analyses

Foraging tasks place demand on multiple cognitive processes (e.g., attention, memory, inhibition), making it important to consider if some cognitive processes account for the capacity to make resource-maximizing decisions. Moreover, in relation to concentrated disadvantage, theories suggest that conditions of scarcity strain cognitive bandwidth, resulting in fewer mental resources to engage in executive control (Shah, Mullainathan, & Shafir, 2012). Experimental manipulations of scarcity have been shown to decrease response inhibition in individuals with greater real-world experiences of disadvantage (Shah, Mullainathan, & Shafir, 2012). Additionally, early experiences of disadvantage, such as low childhood socioeconomic status have been associated with deficits in working memory capacity (Evans & Schamberg, 2009; Farah et al., 2006; Noble, McCandliss, & Farah, 2007). Thus, inhibition and working memory are particularly relevant cognitive processes to control for in the context of studying resource scarcity and foraging behavior.

To ensure robustness of our results, we ran analyses controlling for the Color-Word Stroop task Inhibition/Switching vs. Word Reading contrast score (Stroop, 1935) and digit span backwards score (Delis, Kaplin, & Kramer, 2001) separately. Replicating the primary results, there was a significant negative effect of ADI on percentage of resource-maximizing decisions in a generally resource-rich environment ($p < .001$, 95% CI [−7.16, −2.02]) and in a generally resource-depleted environment ($p < .001$, 95% CI [−8.28, −3.88]) after controlling for response inhibition. There also remained a significant negative effect of ADI on percentage of resource-maximizing decisions in a generally resource-rich environment ($p = .039$, 95% CI [−5.49, −0.15]) and in a generally resource-depleted environment ($p = .007$, 95% CI [−6.59, −1.07]) after controlling for working memory (see Supplemental Tables 1 and 2 for full model results).

To further ensure robustness of our results, we also ran analyses controlling for biological sex and age separately, as these demographic factors have been shown to have an effect in a variety of foraging tasks (Bach, Moutoussis, Bowler, Neuroscience in Psychiatry Network Consortium, & Dolan, 2020; Lloyd, McKay, Sebastian, & Balsters, 2021; Mata, Wilke, & Czienskowski, 2009, 2013; Rosetti, Rodríguez, Pacheco-Cobos, & Hudson, 2016). Replicating the primary results, there was a significant negative effect of ADI on percentage of resource-maximizing decisions in a generally resource-rich environment ($p = .003$, 95% CI [−6.57, −1.41]) and in a generally resource-depleted environment ($p < .001$, 95% CI [−7.38, −2.16]) after controlling for biological sex. There also remained a significant negative effect of ADI on percentage of resource-maximizing decisions in a generally resource-rich environment ($p = .025$, 95% CI [−5.72, −1.27]) and in a generally resource-depleted environment ($p = .007$, 95% CI [−4.78, −0.85]) after controlling for age.

Finally, we ran analyses simultaneously controlling for Color-Word Stroop task Inhibition/Switching vs. Word Reading contrast score, digit span backwards, biological sex, and age. Once again, in line with the primary results, there was a significant effect of ADI on percentage of resource-maximizing decisions in a generally resource-rich environment ($p = .014$, 95% CI [−5.76, −0.65]) and on percentage of resource-maximizing decisions in a generally resource-depleted environment ($p < .001$, 95% CI [−7.67, −2.52]).

2.5. Resource decision-making parameters

We extended the classical MVT model to capture possible ways individuals deviate (i.e., bias and imprecision) from MVT. In this extended model, bias and imprecision parameters were fit to each participant through maximum likelihood. The average probability assigned to participant choices using this extended model was 74.30 ($SD = 13.32$) in the resource-rich environment and 69.69 ($SD = 10.84$) in the resource-depleted environment. On average, 80.44% ($SD = 11.60\%$) of decisions made by participants were resource-maximizing as defined by the extended model in the resource-rich environment. In the resource-depleted environment, an average of 77.25% ($SD = 10.17\%$) of decisions made by participants were defined as resource-maximizing by the extended model. Paired t-tests show that percentages of resource-maximizing decisions produced by the extended model were significantly higher than percentages of resource-maximizing decisions produced by the classical model in both the traditional $t(107) = -10.92$, $p < .001$, 95% CI [−0.18–0.13] and the depleted foraging tasks $t(107) = -10.55$, $p < .001$, 95% CI [−0.18–0.12] (see Fig. 8a and 8b), indicating that the extended model was an improved fit to participant choices.

Parameters of bias and imprecision were correlated with ADI to quantify how real-world experience of concentrated disadvantage might affect features involved in resource decision-making in both environments. Results showed no relationship between ADI and bias parameters in the resource-rich environment, $r(101) = -0.00$, $p = .987$, 95% CI [−0.20, 0.19] or in the resource-depleted environment, $r(94) = 0.16$, $p = .111$, 95% CI [−0.04, 0.35]. Results showed a significant positive relationship between ADI and the imprecision parameter in the resource-rich environment, $r(101) = 0.21$, $p = .033$, 95% CI [0.02, 0.39], as well as between ADI and the imprecision parameter in the resource-depleted environment, $r(94) = 0.24$, $p = .020$, 95% CI [0.04, 0.42].[4]

2.6. Social norm foraging task

In the social norm foraging task, participants had the option to forage on their own land, which was depleted in resources as compared to their neighbor, Logan's, land. On their own land, participants made an average of 45 explore-or-exploit-or-cross decisions and visited an average of 49 trees. On average, participants failed to make a response in the allotted time on 2 trials (0.01% of trials). Participants harvested an average of 139 apples ($SD = 159$), earning a mean bonus of \$0.15 ($SD = \$0.19$) on their own land. Participants also had the option to forage on their neighbor, Logan's, land, which was rich in resources in comparison to the participant's land. Participants made an average of 177 explore-or-exploit-or-cross decisions and visited an average of 34 trees on Logan's land. On average, participants failed to make a response in the allotted time on 2 trials (0.01% of trials). Participants harvested an average of 911 apples ($SD = 438$), equating to earning a mean bonus of \$1.14 ($SD = \$0.55$) on Logan's land.

Overall, 93% of participants engaged in at least one social norm violation by crossing over to their neighbor's land. To examine the effect of the real-world experience of concentrated disadvantage on the tendency to engage in social norm violation in an experimental context, our measure of tendency to engage in social norm violation was entered in a robust linear regression with ADI as a continuous predictor. Robust

[4] To confirm that our results remain consistent regardless of age and sex, we re-ran all analyses on bias, imprecision and ADI as partial correlations controlling for the effects of age and sex separately. All results replicated, showing no relationship between ADI and bias parameters controlling for age in the resource-rich ($p = .944$, 95% CI [−0.19, 0.20]) or resource-depleted environment ($p = .129$, 95% CI [−0.04, 0.35]). Results showed a significant positive relationship between ADI and the imprecision parameter controlling for age in the resource-rich environment, $r(101) = 0.22$, $p = .029$, 95% CI [0.02, 0.39] and in the resource-depleted environment, $r(94) = 0.21$, $p = .039$, 95% CI [0.01, 0.40]. Similarly, results showed no relationship between ADI and bias parameters controlling for sex in the resource-rich ($p = .933$, 95% CI [−0.20, 0.19]) or resource-depleted environment ($p = .114$, 95% CI [−0.04, 0.35]). Results showed a significant positive relationship between ADI and the imprecision parameter controlling for sex in the resource-rich environment, $r(101) = 0.21$, $p = .034$, 95% CI [0.02, 0.39] and in the resource-depleted environment, $r(94) = 0.24$, $p = .019$, 95% CI [0.04, 0.42].

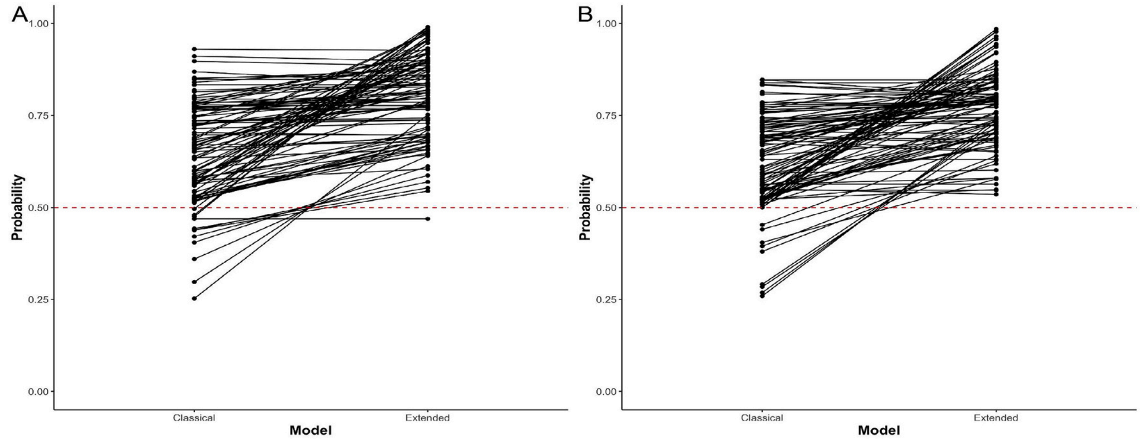

Fig. 8. Model fit comparison across tasks.
Note. Panel A compares probabilities assigned to participant choices by the classical model with the probabilities assigned to participant choices by the extended model in the traditional foraging task. Panel B compares probabilities assigned to participant choices by the classical model with the probabilities assigned to participant choices by the extended model in the depleted foraging task.

regression was used because Cook's distance measures of a linear regression identified 6 influential points. Results showed that ADI was not significantly related to engaging in social norm violations $R^2 = 0.06$, $b = -12.07$, $t(110) = -1.94$, $p = .056$, 95% CI [−24.43, 0.29] (see Fig. 9). This finding suggests that relative levels of real-world concentrated disadvantage did not further impact engagement in social norm violation when the participant's environment was depleted relative to their neighbor's.[5,6] See Supplement for additional analysis of the social norm foraging task based on moral licensing theory.

3. Discussion

Residents in neighborhoods marked by concentrated disadvantage experience economic, social, and physical resource scarcity (Boardman, Finch, Ellison, Williams, & Jackson, 2001; Sampson et al., 2008). These residents are continually faced with decisions about how best to meet their basic needs, including how to obtain food and money to securing housing and health care. The present study examines a previously unexplored decision-making propensity related to maximizing available resources in a resource-rich and a resource-depleted patch foraging environment, as well as tendency to engage in social norm violation in an experimental context where one's own environmental resources are depleted compared to a neighbor's resources. We find that decision-making related to obtaining resources in a rich and depleted environment is disrupted in individuals who experience real-world concentrated disadvantage. Further, when foraging in a resource-rich and a resource-depleted environment, disruption in resource-maximizing decisions is reflective of less precision in differentiating between the value of two competing choices. Finally, the majority of individuals, regardless of whether they experience real-world concentrated disadvantage, violate social norms when in an environment where inequality in resources relative to a neighbor's resources is amplified. Taken together, these findings contribute to a body of research that indicates that experiences of relative resource scarcity, both in the real world and in an experimental context, impact cognition and shape decision-making (Griskevicius et al., 2013; Shah et al., 2012).

Mullainathan and Shafir (2013) propose that exposure to a scarcity of resources (e.g., time, money) triggers a "scarcity mindset" in all individuals. In line with this research, we find that overall, being in a resource-depleted environment compared to a resource-rich environment leads to decreased resource-maximizing decisions across all participants. Further, we find that individuals who experience higher levels of real-world concentrated disadvantage make fewer resource-maximizing decisions across both resource-rich and resource-depleted environments. Our finding that real-world concentrated disadvantage is associated with making fewer resource-maximizing decisions in resource-rich and resource-depleted environments is especially interesting given prior research that indicates increased exposure to real-world scarcity is associated with steeper delay discounting (i.e., the tendency to value immediate rewards over delayed rewards), decreased response inhibition, and increased risk-taking behavior (Griskevicius et al., 2013; Johansson, 2020; Mani, Mullainathan, Shafir, & Zhao, 2020). This pattern of decision-making for individuals living in concentrated disadvantage may make decisions appear adaptive in the short term– addressing an immediate need based on the information in hand. However, this pattern of decision-making that reflects a prioritization of present information and not maximizing choice behavior over time may have long-term consequences—ineffectively considering the compounding impact of decisions and weighing alternatives. Thus, decision-making strategies that diminish resource-maximizing behavior over time (i.e., adapt to a short-term need at the expense of long-term gains) may further perpetuate experiences of hardship for individuals living in concentrated disadvantage (Frankenhuis, Panchanathan, & Nettle, 2016; Mani et al., 2020).

Prior research shows that real-world experiences of disadvantage are associated with reductions in functioning in an array of cognitive

[5] To control for resource-maximizing decision-making on the relationship between tendency to engage in social norm violation and real-world experience of concentrated disadvantage, we entered our measure of tendency to engage in social norm violation (the total amount of time spent on Logan's land divided by the number of times the participant chose to cross over to Logan's land) in a robust linear regression with ADI and percentage of resource-maximizing decisions in a resource-rich environment as defined by our model as continuous predictors. In line with our findings, we find no significant effect of ADI on tendency to engage in social norm violations $R^2 = 0.11$, $b = -20.54$, $t(109) = -1.10$, $p = .273$, 95% CI [−57.51, 16.43], nor was there a significant effect of resource-maximizing decision-making on tendency to engage in social norm violations $b = 35.82$, $t(109) = 1.60$, $p = .113$, 95% CI [−8.63, 80.26].

[6] The Behavioral Inhibition and Activation Scale (BIS/BAS; Carver & White, 1994) was administered at visit 1. Our results remain the same after including the reward responsiveness subscale of the BAS scale as a covariate. There remains a significant effect of ADI on percentage of resource-maximizing decisions in a resource-rich environment $R^2 = 0.09$, $b = -3.80$, $t(109) = -2.99$, $p = .003$, 95% CI [−6.32, −1.28], a significant effect of ADI on percentage of resource-maximizing decisions in a resource-depleted environment, $R^2 = 0.15$, $b = -4.64$, $t(109) = -3.39$, $p = .001$, 95% CI [−7.35, −1.93], and no significant effect of ADI on tendency to engage in social norm violations $R^2 = 0.08$, $b = -31.52$, $t(109) = -1.97$, $p = .052$, 95% CI [−63.31, 0.27].

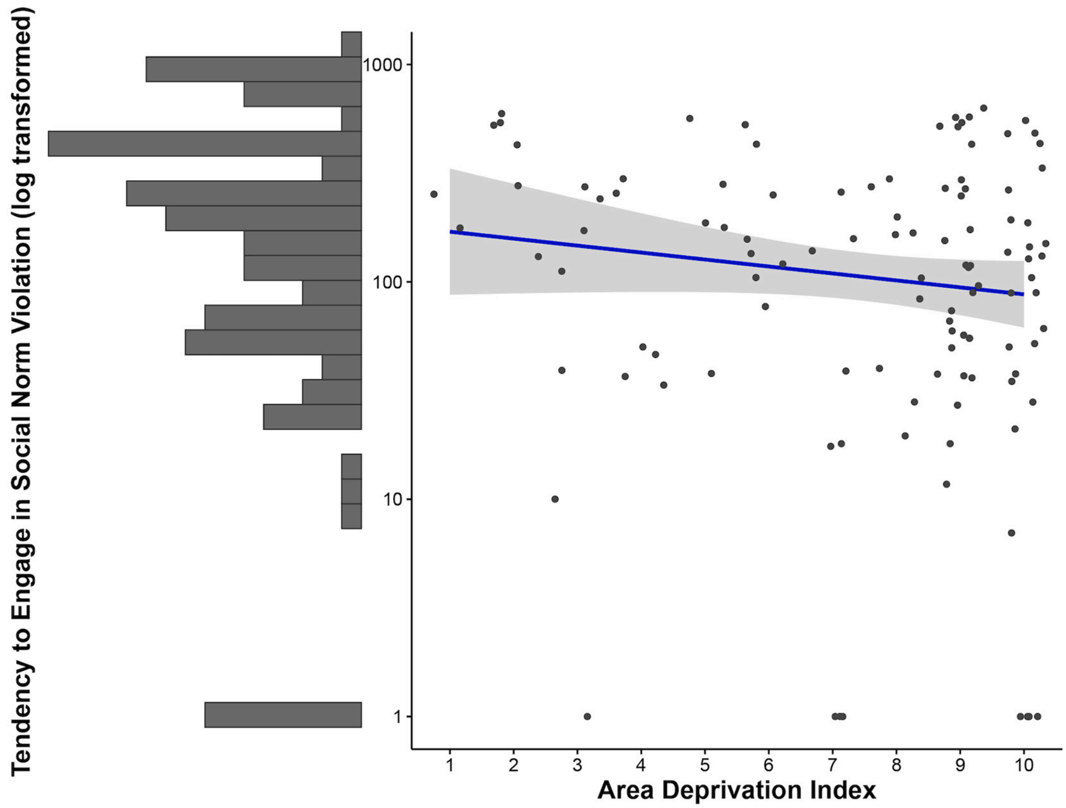

Fig. 9. Engagement in social norm violations as a function of ADI.
Note. For visualization, a value of 1 was added to the variable tendency to engage in social norm violation (total amount of time spent on Logan's land/number of times crossed over to Logan's land) and then log transformed. The value 1 represents participants who did not engage in social norm violations and 1000 represents participants who engaged in the most social norm violation in the context of the experiment. On the left is a histogram displaying the distribution of tendency to engage in social norm violations. On the right is a scatterplot of the relationship between ADI and tendency to engage in social norm violation. Error bands indicate 95% confidence intervals. Plot was generated using the stat_smooth function in the ggplot2 package (Wickham, 2016) in R (R Core Team, 2020).

processes (Dean, Schilbach, & Schofield, 2017; Mani et al., 2013). It is possible that impairments in cognitive functioning, reflective of the stress of living in disadvantaged environments, underlie the reduction in resource-maximizing decisions observed among those living in higher real-world disadvantage. In the present study, however, we find that real-world experience of concentrated disadvantage predicts reduced resource-maximizing decision-making even after controlling for response inhibition and working memory capacity. These results leave open the question of what cognitive process(es) may be supporting the decision-making differences among people living in higher real-world disadvantage?

One potential process underlying decision-making that may contribute to the disrupted resource-maximizing behavior seen in individuals living in higher levels of concentrated disadvantage is reduced precision in discerning between the value of two competing choices. There are several plausible interpretations of the positive correlation between concentrated disadvantage and the model-based imprecision parameter in both resource-rich and resource-depleted environments. Past research suggests that experiencing resource scarcity generates cognitive load, which subsequently limits available cognitive bandwidth (Mani et al., 2013; Shah et al., 2012). For example, inducing thoughts of higher versus lower levels of financial scarcity results in reduced performance on cognitive tests for individuals with low-income but not for individuals with high-income (Mani et al., 2013). Additionally, for participants with relatively lower-income, thoughts related to money occur more spontaneously and are more difficult to suppress (Shah et al., 2018), suggesting that concerns related to a lack of resources occupy the mind, which can consequently reduce available cognitive capacity. Thus, while discriminating between similar options may be difficult for all individuals, the experience of concentrated disadvantage might sap cognitive bandwidth, making it harder to apply cognitive resources when choice behavior demands precision (Mani et al., 2013; Ong et al., 2019; Schilbach, Schofield, & Mullainathan, 2016).

An alternative interpretation of these results is that individuals who experience greater concentrated disadvantage forego discriminating between the value of two options in order to preserve energy or efficiency. In other words, individuals may decide that the benefit of making a less calculated choice outweighs the cost of the cognitive effort necessary to discern the value of two competing choices. Both qualitative and quantitative research suggest that experiencing resource scarcity is mentally taxing, which reduces individuals' cognitive capacity (Hernández, 2016; Nichols & Braimoh, 2016; Sheehy-Skeffington, 2020; Tach & Amorim, 2015; Zhao & Tomm, 2017). Appropriately, individuals who experience resource scarcity, whether it is experimentally induced (Shah et al., 2012) or in the real-world (i.e., food insecurity, low-income), adopt strategies that appear to prioritize efficiency, such as buying less perishable foods and in bulk to reduce trips to the store, which in turn conserves energy (Hernández, 2016; Nichols & Braimoh, 2016; Tach & Amorim, 2015). Thus, it is possible that for individuals who experience higher levels of real-world concentrated disadvantage, the appearance of less precision in discerning between the value of two competing choices reflects an effort to conserve energy and promote efficiency in the short-term (Hernández, 2016; Shah et al., 2012; Tach & Amorim, 2015).

While there is evidence that individuals living in concentrated disadvantage make fewer resource-maximizing decisions, the importance of context for promoting certain behaviors is essential to consider (e.g., foraging under competition; Mobbs et al., 2013). The social norm task in the present study highlights the role of context in facilitating social norm violations. Overall, the majority of participants trespass by crossing over to Logan's land and steal by harvesting apples on Logan's land when experiencing a context of relative deprivation. Notably, and contrary to our hypothesis, individuals living in higher real-world concentrated disadvantage are no more likely than individuals living in lower real-world concentrated disadvantage to engage in these social norm violations when individuals' resources are scarce in comparison to a neighbor. These results emphasize the role that experiencing relative deprivation in an experimental context plays in promoting social norm violation, irrespective of real-world experiences of concentrated disadvantage. Moreover, they provide experimental evidence for the theorized connection between neighborhoods with higher levels of concentrated disadvantage and increased social norm violation (Sampson, Raudenbush, & Earls, 1997; Shaw & McKay, 1942). For some individuals, resorting to illegal acts to obtain resources may stem from an environmental context that fosters and even necessitates this behavior, particularly if resources are scarce, and that for most individuals, relative deprivation might promote this behavior simply to maximize resources.

Several theoretical and methodological limitations should be noted. First, our tasks assessed whether or not an individual exhibited resource-maximizing behavior as defined by MVT. Note, however, that deviations from MVT do not necessarily imply that participants were behaving suboptimally. It is possible that all participants were making reasonable decisions based on expectations that were shaped by their environment (Kidd, Palmeri, & Aslin, 2013). For instance, the finding that people with greater ADI scores also had greater imprecision parameters might reflect a rational strategy, where these participants prefer not to invest too much time and effort on decisions that are likely to produce comparable outcomes.

A related second limitation is that our model does not reveal the underlying mechanisms causing differences in bias and imprecision. We therefore do not know if differences in these parameters stemmed from explicit beliefs in participants (e.g., an explicit belief that exploration is always risky, or a decision to not "overthink" difficult choices) or if they resulted from more basic cognitive mechanisms, such as differences in working memory, attention, or learning. Additionally, our model does not account for individual differences in learning and only compared participant decisions relative to the best possible choice if participants could instantly learn the depletion rate from consecutive foraging decisions of the same tree. Although this is a limitation, before investigating the role of learning while individuals forage in an environment, it was important to establish if individual variability in foraging behavior existed first, then whether or not this variability related to concentrated disadvantage. Having established in what ways participants deviate from MVT as a function of concentrated disadvantage, it would be important for future work to investigate the potential underlying mechanisms driving these differences, as well as other potential parameters, such as learning.

Third, we find that individuals who experience greater real-world concentrated disadvantage show reduced resource-maximizing decision-making in resource-rich and resource-deprived environments. The "scarcity mindset" (Mani et al., 2013, 2020) concept indicates that the experience of scarcity leads to an allocation of attention to the scarce resource, limiting cognitive capacity available to the individual. Based on this premise, some might hypothesize that individuals should not show reductions in resource-maximizing decision-making in the traditional foraging task because the environment is not scarce in resources (c.f. Amir et al., 2018; Griskevicius et al., 2013). However, several studies that experimentally manipulate experiences of scarcity in a lab utilize middle-class participants (Huijsmans et al., 2019; Mullainathan & Shafir, 2013; Shah et al., 2012), whereas participants in the present study ranged from living in the most to the least disadvantaged neighborhoods in the state. Therefore, participants in the present study experience a more persistent and severe form of resource scarcity compared to middle-class participants, which could impact the cognitive resources they bring to bear in various decision environments. Some studies supporting the "scarcity mindset" do use participants who experience persistent forms of resource scarcity (e.g., rice farmers) akin to concentrated disadvantage, and find that when tested after harvesting their crops, farmers' results on cognitive tests improve compared to when they have scarce resources before harvesting their crops (Mani et al., 2013). Of note, though, our task used a much more subtle manipulation of a scarce environment, which did not alleviate the participants' real-world experience of disadvantage. The differences in sample selection and research design make it difficult to compare directly the results of these studies. However, what remains consistent across all studies is a strong narrative showing that manipulating experiences of scarcity, whether in the lab or in the real-world, affects behavior and cognition. Moreover, our results align with research showing that experiences of real-world disadvantage, such as poverty or low socioeconomic status, are associated with patterns of present-focused decision-making (steeper delay discounting; Griskevicius et al., 2013; increased risk-taking; Johansson, 2020). Future research should continue to build on knowledge on the effects of scarcity by recruiting representative samples (Hill, 2020), considering length of time spent living in neighborhoods marked by concentrated disadvantage, and incorporating manipulations of scarcity in an experimental context.

Fourth, given that the majority of participants crossed to and foraged on the neighbor's land despite the presence of signs displaying "Logan's Land Private Property," one may think that participants did not view this behavior as a social norm violation. However, if participants did not consider foraging on the neighbor's land option as a social norm violation at all, then the rational strategy would have been to go and forage there for the entire time, since the neighbor's land was resource-rich compared to their own land. Instead, we saw that participants only spent about half of their time on the neighbor's land, suggesting that participants recognized they were not supposed to forage there. Additionally, behavior on this task positively correlated with real-world risky and impulsive behavior, providing some construct validity of the task behavior. To better address this limitation in future studies, a condition could be added where participants simultaneously choose to forage on their neighbor's resource rich land, their own resource rich land, or their own resource depleted land. This would more clearly show that choosing to forage on a neighbor's land represents a social norm violation as opposed to being influenced by the difference in the resource richness of the participant's land versus Logan's land.

Fifth, the selected task manipulations examined explore-exploit decisions in resource-rich and resource-depleted, as well as social norm decisions in a relatively depleted environment. Nonetheless, there are several other contexts and factors that may be important for further understanding the impact of living in concentrated disadvantage on decision-making. For example, other manipulations that change the distribution of resources may be used to model shifting circumstances or opportunities for upward mobility. Similarly, manipulating differences in social context, such as informal social control, should be considered since both structural and social characteristics of neighborhood relate to social norm violations (Sampson, 2008; Shaw & McKay, 1942). Social norm foraging tasks that have explicit probabilistic consequences for violations also might model potential contacts with the justice system that often plague residents in disadvantaged neighborhoods. The present study provides a foundation for building an experimental model that serves to connect individual decisional capabilities with neighborhood contexts.

The number of disadvantaged neighborhoods in the United States has grown by nearly three-quarters since the 2000's (Kneebone, 2014). The impact of concentrated disadvantage on individual well-being has garnered attention across several disciplines, including sociology, psychology, criminology, and public policy (Freedman & Woods, 2013; Rodriguez, 2011; Sampson et al., 2008). However, research has remained relatively discipline-specific, limiting our understanding of the processes through which experiencing concentrated disadvantage affects individual cognitions and behaviors. The present study combines research on neighborhood context and individual variability in cognition to better understand individual-level processes related to the perpetuation of disadvantage and the fostering of social norm violations. Adopting this interdisciplinary approach in future research might allow for the refinement of existing neighborhood-focused interventions, while also attempting to target individual-level cognitive processes in order to most effectively support members of communities most affected by concentrated disadvantage.

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Appendix A. Supplementary materials

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