The computational form of craving is a selective multiplication of economic value

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Craving is thought to be a specific desire state that biases choice toward the desired object, be it chocolate or drugs. A vast majority of people report having experienced craving of some kind. In its pathological form craving contributes to health outcomes in addiction and obesity. Yet despite its ubiquity and clinical relevance we still lack a basic neurocomputational understanding of craving. Here, using an instantaneous measure of subjective valuation and selective cue exposure, we identify a behavioral signature of a food craving-like state and advance a computational framework for understanding how this state might transform valuation to bias choice. We find desire induced by exposure to a specific high-calorie, high-fat/sugar snack good is expressed in subjects' momentary willingness to pay for this good. This effect is selective but not exclusive to the exposed good; rather, we find it generalizes to nonexposed goods in proportion to their subjective attribute similarity to the exposed ones. A second manipulation of reward size (number of snack units available for purchase) further suggested that a multiplicative gain mechanism supports the transformation of valuation during laboratory craving. These findings help explain how real-world food craving can result in behaviors inconsistent with preferences expressed in the absence of craving and open a path for the computational modeling of craving-like phenomena using a simple and repeatable experimental tool for assessing subjective states in economic terms.

craving | economic value | attribute similarity | multiplicative gain

There is growing interest across marketing, psychology, economics, and medicine in understanding how subjective and physiological states bias behavior. One such phenomenon that has received much attention is craving. Defined as a strong desire for a particular substance, craving is widely recognized as important for the maintenance and treatment of addiction (1) and is beginning to gain importance in our understanding of eating disorders and obesity as well (2). Craving leads to a type of myopia for the craved substance that can result in its consumption even after long abstinence periods or overt efforts to avoid it.

While the clinical significance of craving cannot be understated, craving is a dimensional construct and in its nonpathological form, food craving in particular, is extremely common (3). A vast majority of people (>90%) report having experienced craving of some kind (4, 5), suggesting this subjective state might operate on general processes that shape and maintain individual preferences. Craving might reflect a specific, temporally limited change in an individual's internal valuation process, a change in how individuals experience the subjective value of the object of their craving. There is compelling evidence in support of this hypothesis. From data on real-world behavior, we know, often against competing goals, people who experience craving (or psychological desires consistent with what one might call craving) are more likely to spend (6) or eat (7, 8) more than intended and fall off their diet (9, 10). From passive cue reactivity studies (11–13), we know canonical valuation regions are robustly engaged during food craving. Most notably, from behavioral economic studies, we know that the subjective values of high-calorie, high-fat foods increase following exposure to these foods (14), with similar findings observed in smokers and problem drinkers with cue-exposure–induced drug craving (15–18). A related line of work focused on attention, a known subcomponent process of craving (19, 20), finds that manipulations with shared features to these cue-exposure manipulations, such as extended viewing time (21) or increased physical salience of choice options (22), also reliably lead to enhanced valuation of the attended options.

Despite evidence that craving as well as its subcomponent processes (e.g., attention) and subjective valuation are intertwined, many unanswered questions remain. First, the number of controlled studies examining the effect of food cue exposure on economic behavior is small, and these studies typically operationalize craving broadly, often as desire for a diverse set of foods. This makes it difficult to distinguish specific cravings from more general states like hunger and thirst. By definition, unlike these "need" states, craving is thought to represent a very specific desire experienced as a self-limited state that can emerge and dissipate spontaneously, upon exposure to a tempting stimulus or through more cognitive mechanisms (e.g., memory, cognitive control). Thus, separating craving from hunger is necessary to address questions regarding one of craving's most distinguishing features: its presumed selectivity for the object of craving.

A second consideration for the study of any transient subjective phenomenon including craving deals with how best to capture its momentariness. In traditional experimental economic approaches to quantifying valuation, incentives are somewhat delayed, as they are typically realized at the end of an experimental session (if at all). This imposed delay can have consequences for valuation such as susceptibility to temporal discounting. Repeated, nonconsequential subjective desire ratings have

Significance

Craving is a specific desire state that biases choice toward the desired object. Although extremely common, and in its pathological form a major contributor to negative health outcomes as in addiction and obesity, craving is not well understood. In a laboratory model of craving, we find "craving" is reflected in people's momentary willingness to pay for the things they desire, and for subjectively similar things, consistent with a transient, good-selective change in subjective valuation. We further find the value of the desired goods increases multiplicatively, which might explain several escalation behaviors associated with craving in real-world environments. This opens more lines of research regarding the computational form of craving in health and disease, with implications for marketing actions and consumer choice.

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been used as a means to address this issue but these do not allow for an explicit quantification of value in a way that ensures these judgments are minimally influenced by a desire to be self-consistent or by experimenter demand effects.

Finally, although craving (and cue exposure more generally) is thought to act on valuation processes, virtually nothing is known about how this happens. We can speculate about three simple algorithmic processes that can tell us about what happens at the level of valuation systems. These are addition, multiplication, and exponentiation, and their distinction in other fields has proved important, e.g., for understanding the neurobiology of reinforcement learning (23) and efficient sensory coding (24, 25). In our case, addition could suggest craving is a separable signal independent of the underlying input–output value function for the desired object. The two nonadditive cases could instead suggest craving scales this function, linearly (gain control-like scaling) or nonlinearly (a fundamental change in value coding), respectively. Isolating the specific algorithmic process of craving is an important step toward narrowing the explanatory gap between basic neuroscience work on craving and work on the psychological construct of craving.

Using a selective, multisensory, food-exposure manipulation and a variant of the Becker–DeGroot–Marschak (BDM) auction procedure (26) designed to elicit true momentary valuations, here we answer three related questions about craving, which we defined in our laboratory model as a transient exposure-induced increase in psychological desire for the exposed food. These are the following: (*i*) Is there an increase in subjective valuation due to changes in desire for specific foods? (*ii*) Is this increase selective for the exposed food, and, if so, what does this selectivity depend on? And (*iii*) what is the algorithmic process at play? We find exposure transiently increases subjective valuation, but this increase is proportional to a given option's subjective attribute similarity to the exposed food. Furthermore, the change in valuation during peak effects is best captured by multiplication—a linear good-selective scaling of the underlying value function.

Results

Study 1. Four-hour fasted nondieters (n = 44) indicated their momentary subjective value in the form of a monetary bid, as well as concurrent desire, for 15 snack foods spanning three categories (sweet, savory, drinks; Fig. 1*A*). In each bid trial, subjects indicated the maximum they would pay out of a $5 endowment in the current moment for the good offered on that trial. In each desire trial, subjects indicated their current desire for the good offered. The latter served as scaffolding for the psychological process of bidding and a manipulation check for cue exposure. Bid trials were interleaved with desire trials and clustered in blocks. The task could end with 2% probability after each block at which point a single bid trial from the last completed block was realized. Thus, subjects knew that their bids "now" could determine which if any snack they could have now. After two blocks (baseline), and before resuming the task for up to 20 additional blocks (postexposure), subjects underwent a brief multisensory cue exposure previously shown to induce food craving (14, 27–30) (Fig. 1*B* and *Materials and Methods*). Subjects were randomly assigned to undergo exposure for Snickers (a nut and chocolate candy bar, n = 16), Cheetos (cheese corn puffs, n = 14), or Coke (a soft drink, n = 14). These goods were chosen based on their temptation level (high-calorie, high-fat/sugar content) and relationship to risk for overeating, as their baseline value correlated with increased subject body mass index (BMI) (Fig. S2 and *SI Materials and Methods*). These features resulted in a subjective experience that, compared with other active control exposures, was most akin to a craving-like state. Further, exposure was tailored to a particular good with a particular set of attributes to allow us to test for the selectivity of postexposure changes in valuation. The multiple postexposure blocks also allowed us to examine any temporal modulation of these effects.

Postexposure desire. Postexposure desire for the exposed good (in the first and all postblocks; *SI Results*) was higher relative to baseline, confirming the success of the manipulation at inducing a craving-like desire state as in prior work (14, 27–30) and consistent with our operationalization of this state.

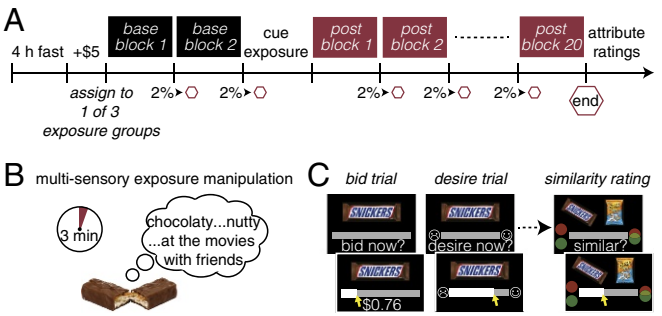

Fig. 1. Experimental procedures. (*A*) Timeline of the economic decision-making task, exposure, and ratings procedures. (*B*) During the 3-min selective exposure, subjects were sensorially exposed to one snack good (randomly assigned Snickers, Cheetos, or Coke) while recalling a memory of consuming that particular good. (*C*) Example bid, desire, and similarity rating trials.

Postexposure bids. Critically, the induced desire state was reflected in subjective valuation. We focus first on the two postexposure blocks because we expected effects to be dynamic and to peak immediately. Repeated-measures ANOVA with time (baseline, immediately postexposure) as within-subjects factor and exposure group (Snickers, Cheetos, and Coke) as between-subjects factor revealed a main effect of time [$F(1,41) = 29.64$, $P = 3.0 \times 10^{-6}$, $\eta_p^2 = 0.42$; Fig. 2*A*], no effect of exposure group ($P = 0.68$), and no exposure group $\times$ time interaction ($P = 0.64$). Thus, exposure-induced bid increases did not depend on the identity of the exposed good, consistent with our selection of these goods as all highly tempting. We therefore combined the groups for all further analyses. In the combined group, subject bids increased by $0.66 (or 38%), indicating a substantial willingness to overpay for the exposed goods postexposure relative to before exposure.

We also explored if there were changes not only in absolute value but also in relative value, a rank-order change indicative of preference reversals. Such reversals were indeed observed: Whereas the exposed goods assumed all possible rank-order positions between the least and most valuable based on bid amount among all goods at baseline (median position: 8 of 15), postexposure, these same items were now part of the top one-third most preferred goods in the choice set (median position: 4 of 15, $Z = 4.52$, $P = 6.13 \times 10^{-6}$, Wilcoxon signed-rank test; Fig. 2*B*).

Selectivity. In addition to preference reversals, the rank-order data show exposure did not increase subjective valuation globally. To quantify the degree of selectivity, or alternatively generalization, of the induced state, we examined postexposure bids for nonexposed goods. For this analysis, we used posttask similarity ratings: individual subject estimates of the degree of subjective similarity between good pairs (Fig. 1*C* and *SI Materials and Methods*). While the broad snack categories were a strong predictor of these similarity judgments, subject-specific, cross-category attributes such as tastiness and healthiness explained additional variance, suggesting these judgments contained additional idiosyncratic information about the relational structure of the choice set (Fig. S3). As shown for an example subject (Fig. 3*A*), these similarity judgments predicted the degree of bid change postexposure for the full choice set. Postexposure bids increased for nonexposed goods rated as subjectively similar for this subject to the exposed good (in this case, Coke). In contrast, bids were unchanged or below-baseline levels for dissimilar goods. We examined the similarity effect for the group in a linear mixed model (LMM) where we expressed the change in subject bids postexposure as a function of the degree of similarity of each good i to the exposed good for a given subject j, assuming a random intercept (b_{0j}) and random slope (b_{1j}) varying by subject: $\Delta bid_{ij} = \beta_0 + \beta_1 sim_{ij} + b_{0j} + b_{1j} sim_{ij} + \varepsilon_{ij}$. The

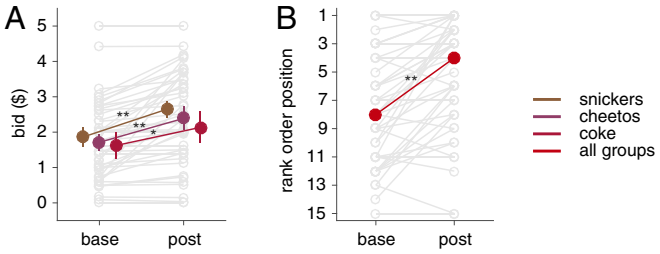

Fig. 2. Effect of selective exposure on subjective valuation. (*A*) Average bids, by group, for the exposed good at the two baseline blocks and at the two postexposure blocks. (*B*) Median rank, based on bid amount, of the exposed good (the three groups combined) relative to all other goods at the same time points (baseline and postexposure), showing preference reversals following exposure. Individual subject data are shown in gray. Values are means ± SE. $*P < 0.05$, $**P < 0.01$.

fixed effect was significant [unstandardized $\beta_1 = 0.44$ (SE = 0.096), standardized $\beta^*_1 = 0.26$, $t(658) = 4.55$, $P = 6.26 \times 10^{-6}$; Fig. 3*B* and Table S1], indicating similarity had a small to medium-sized effect on postexposure bids across the group. In a follow-up exploratory/control analysis (Table S1), we confirmed these results remained after excluding the exposed good from the analysis ($P = 0.039$)—an arguably more powerful demonstration of this effect. Specifically, bids increased significantly postexposure for the single most (89.5 ± 15.5%) similar nonexposed good (+$0.26, $P = 0.015$), but not for the single least (6.7 ± 11.3%) similar nonexposed good (+$0.03, $P = 0.61$). See Fig. S4 and Table S2 for snack identities ordered by similarity. Taken together, these data indicate a degree of exposure-induced generalization in valuation that depends on similarity.

Temporal dynamics. The above findings demonstrate an immediate effect of cue exposure, but induced laboratory craving is expected to dissipate within minutes or hours (29, 31). We therefore examined how bids for the exposed good evolved over postexposure block number i for a given subject j as follows: $\Delta bid_{ij} = \beta_0 + \beta_1 block_{ij} + b_{0j} + b_{1j} block_{ij} + \varepsilon_{ij}$. The linear block fixed effect was negative and significant [$\beta_1 = -0.013$ (SE = 0.006), $\beta^*_1 = -0.074$, $t(792) = -2.27$, $P = 0.02$; Fig. 3*C* and Table S1], showing the expected decline in bids with time. Considering time in minutes yielded similar results ($P = 0.03$, Table S1). These rates predict a full return to baseline in ≈48 blocks or ≈117 min, such that we captured just under half of the total predicted time course of the exposure effect in valuation (41.7% drop). Further exploratory/control analyses showed alternative (e.g., exponential decay) models did not provide a better fit (*SI Results*).

These data show the induced subjective state, while fairly long lasting, is dynamic and support an effect along a similarity gradient. In a follow-up analysis, we explored how these features relate. If a single latent process drives dynamic changes in valuation for the exposed good and nonexposed goods as a function of similarity between the two, then we expect stronger time-course correlations between subjects' bids for the more similar than for the less similar nonexposed goods and their bids for the exposed good. To test this prediction, we first correlated subjects' bids for each good (g) with those for the exposed good (Δ *bid* in the full postexposure window; see Fig. 3*D* for an example) and asked whether the correlation strengths (R_i coefficients) were ordered by similarity for a given subject j as follows: R (*good g* vs. *exposed*)$_{ij} = \beta_0 + \beta_1 sim_{ij} + b_{0j} + \varepsilon_{ij}$. As with overall bidding behavior, the fixed effect was significant [$\beta_1 = 0.17$ (SE = 0.04), $\beta^*_1 = 0.14$, $t(593) = 3.84$, $P = 0.0001$; Fig. 3*E* and Table S1], with a higher degree of similarity predicting stronger temporal coupling between a given nonexposed good's postexposure value and that of the exposed good. This supports the idea that a single underlying process dynamically drives both the similarity and temporal effects in valuation.

Study 2. So far, we find specific desires affect subjective valuation, but we do not yet know how. Borrowing from methods in computational neuroscience (23, 24), in study 2 we tested three possible algorithmic processes that could explain the change in subjects' internal value representation: addition, multiplication, and exponentiation (Fig. 4*A*). An independent sample of 45 subjects completed the same procedures but now had the opportunity to bid for 1 unit, 2 units, 3 units, 5 units, or 8 units of the exposed good ($n = 24$ Snickers, $n = 21$ Cheetos) as well as two other goods (Snickers or Cheetos, depending on which one was not assigned for exposure, and nut and chocolate trail mix; Fig. S5 and *Materials and Methods*).

Postexposure desire. Postexposure desire for the exposed good (in the first and all postblocks; *SI Results*) was higher relative to baseline, again confirming the success of the manipulation.

Postexposure bids. First, to directly compare results across studies, we analyzed bids for quantity = 1, the only quantity offered in study 1. A repeated-measures ANOVA with time (baseline, immediately postexposure) and exposure group (Snickers, Cheetos) as factors revealed a main effect of time [$F(1,43) = 13.65$, $P = 6.19 \times 10^{-4}$, $\eta_p^2 = 0.24$], no effect of exposure group ($P = 0.35$), and no exposure group × time interaction ($P = 0.11$), replicating results of study 1. Significant main effects of time (all $P < 0.015$, $\eta_p^2 > 0.13$) and nonsignificant effects of exposure group and its interaction with time (all $P > 0.33$) were also observed for each of the other quantities separately (2, 3, 5, 8).

Algorithmic process. Importantly, our design in study 2 allowed us to, for each subject, good, and moment, construct a function mapping objective (quantity offered) to subjective value (the relative increase in bid with quantity), which for simplicity we refer to as a "utility function." Our primary analysis tested for differences in this function consistent with addition, multiplication, or exponentiation at the two postexposure blocks (where the exposure effect peaked in study 1) relative to baseline.

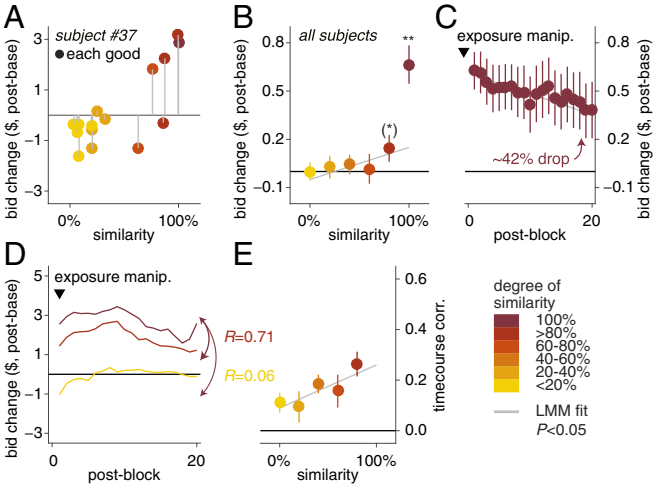

Fig. 3. Postexposure changes in valuation are proportional to subjective attribute similarity to exposed good. (*A*) Example subject's data showing bid increases postexposure depend on similarity of each good to the exposed (in this case Coke, shown at 100% similarity). (*B*) Monotonic ordering of population bids by similarity. (*) denotes significant bid increases postexposure for the single most similar nonexposed good within the >80% similar set of nonexposed goods. (*C*) Moving average (size = 3) of the data in *B* over block number postexposure showing the effect dissipates with time at a rate at which a full return to baseline is predicted within ≈48 blocks or ≈2 h. (*D*) The same example subject's data as in *A*, over block number, for the exposed and the most (>80%) and least (<20%) similar nonexposed goods. The time courses of bids for the exposed and for the most similar goods are tightly coupled, but not for the exposed and the least similar. (*E*) Monotonic ordering of population correlation coefficients (*R* values) by similarity, showing the same underlying process explains both the similarity and temporal effects in valuation. Values are means ± SE. $*P < 0.05$, $**P < 0.01$.

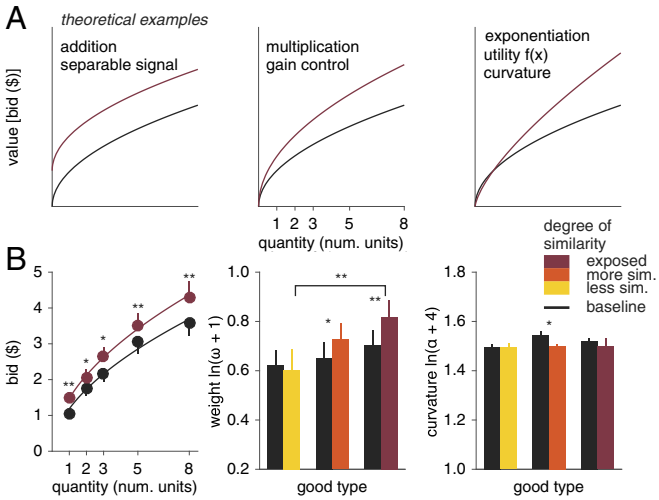

Fig. 4. Algorithmic process. (*A*) Illustrative examples of three possible transformations of valuation following exposure: addition, multiplication, and exponentiation. (*B*) Empirical data in study 2 showing a specific increase in a linear weight term (ω) but not curvature (α) of the utility function for the exposed good postexposure and a smaller increase in the same parameter for nonexposed but similar goods, consistent with multiplication. Values are means ± SE. $^*P < 0.05$, $^{**}P < 0.01$.

We first examined the form of exposure-induced change, using a "model-free" approach without assumptions about the shape of subjects' utility functions. For each subject and each quantity of the exposed good, we subtracted baseline bids from postexposure bids (Fig. S6 and Table S1). We then tested in a LMM whether the differences fell on a horizontal line (slope = 0, indicating an equal-magnitude increase in value irrespective of quantity consistent with addition) or on a monotonically increasing/decreasing line (with slope $\neq 0$ consistent with a nonadditive process). We observed some evidence for the latter, a monotonic increase, such that bids tended to increase more for the higher quantities of the exposed good. These data suggest that exposure does not transform valuation via a purely additive process.

Next, we performed a more detailed "model-based" analysis of the shape of the utility function for the exposed good in an effort to arbitrate between the two nonadditive possibilities: multiplication vs. exponentiation. We fitted a power function to individual subject bid data using nonlinear least-squares regression: $bid_i = B_0 + \omega\ quantity_i^{\alpha} + \varepsilon_i$, where ω and α represent a weight (gain) term and the curvature of this function, respectively. We fitted separate models to the postexposure and baseline bid data (four parameters in total), with the simplifying assumption that the intercept (B_0) was the same at the two time points (here set to 0, although other values produced similar results). We then tested for group-level changes in each of the two parameters after natural-log transformation (to approximate normal distributions). A shift in ω would indicate multiplicative (linear) scaling, whereas a shift in α would indicate exponential (nonlinear) scaling. We found evidence only for a shift in ω, with ω increasing postexposure relative to baseline [$t(44) = 2.95, P = 0.005, d = 0.44$; Fig. 4*B*]. In contrast, and consistent with theory and prior work, both functions were concave ($\alpha < 1$), showing similar rates of diminishing marginal value/utility with increasing reward size at baseline and postexposure [$t(44) = -0.88, P = 0.38, d = 0.13$].

Selectivity. Following the results of study 1, we tested for any spillover by similarity in ω and α in repeated-measures ANOVAs with time and good type (exposed, more similar, less similar) as within-subjects factors. A similarity effect was supported by a good × time interaction for ω [$F(2,88) = 5.57, P = 0.005, \eta_p^2 = 0.11$]. There was also a time main effect [$F(1,44) = 5.71, P = 0.02, \eta_p^2 = 0.12$] but no good type effect ($P = 0.07$). As with the exposed good, ω increased for the more similar [$t(44) = 2.22, P = 0.03, d = 0.33$], but not for the less similar [$t(44) = -0.52, P = 0.61, d = 0.08$], of the two nonexposed goods (Fig. 4*B*). See Table S3 for good identities ordered by similarity. No significant main or interaction effects were observed for α ($F < 2.93, P > 0.09, \eta_p^2 < 0.06$). Altogether, these data suggest the exposure-induced state transforms valuation nonadditively and the specific form of this transformation is multiplicative—a linear scaling of the underlying value function that depends on similarity.

Discussion

In a laboratory model of food craving as a model for craving more generally, we found that selective exposure increased psychological desire for the exposed good and, importantly, its subjective value, consistent with prior work on specific drug cravings (15–18) and craving for a range of high-calorie, high-fat foods (14). Additionally, owing to the use of a constant probability that signaled limited opportunities to purchase the desired snack options (a fixed hazard function in time) and a fairly broad menu, we were able to show the change in valuation was transient, and it generalized on a subjective similarity dimension to other nonexposed goods. Probing the underlying algorithmic process, we further found multiplicative scaling best accounted for the change in subjective valuation. This craving-like state is, this suggests, a positive and good-selective linear reweighing of an individual's internal value representation. These findings could help explain how craving can result in behaviors inconsistent with expressed preferences in the absence of craving and open a path for the computational modeling of craving.

Importantly, the exposure-induced changes in valuation were indicative of preference reversals. The exposed options overtook options ranked higher preexposure, which at an economic level suggests craving-like desire can be viewed as a context-dependent change in preference order and understood with existing models of choice. From a health behaviors perspective, preference reversals of this kind imply that even if people strive to eat healthier or endorse drug-free lifestyles, craving could overshadow the value of health by boosting the value of unhealthy foods or drugs, in line with previous suggestions (6, 7, 9, 10, 32), although see ref. 33. This was manifest even in our nondieter sample. The "healthier" options were rated as subjectively dissimilar to the high-calorie, high-fat/sugar content exposure snacks (Table S2) and were those that exhibited unchanged, and in some instances below-baseline, postexposure values (while the tempting options had consistently higher postexposure values).

These preference order data underscore a second main finding of our study: The selectivity of the exposure effect depended on the subjective similarity of a given option to the desired, exposed options. This suggests desire for Snickers does not make one hungrier; it makes one desire Snickers and to some degree subjectively similar goods, such as its closest substitutes. This is seemingly at odds with an alternative, and equally intuitive, perspective that predicts more similar goods should be less appealing once attention is focused on a target good, perhaps because the discriminability between the two is enhanced. Our data heavily weigh against this possibility. Other data supporting this possibility have been observed (34), however, only when the most similar available good is of lower value than the target/exposed good (e.g., generic or store brand version). In our study, the exposed and most similar goods had comparable values.

The similarity effect also argues against the possibility that our results are driven by experimenter demand or mere exposure. Although subjects were not exposed to the most similar goods, their value increased. In directly comparing our manipulation to two control manipulations with similar experimenter demands (*SI Materials and Methods*), (*i*) a physically identical exposure for a less tempting food and (*ii*) a picture-viewing–only exposure, we found that, in fact, exposure alone is not sufficient to induce the specific changes in desire or valuation that we observed. These changes instead depended on the subjective experience of the exposure—how positively intense it was for the subject. This is consistent with prior work showing that exposure effects on

willingness to pay and choice depend on the physical salience of the exposed stimulus (22) and its valence (21), with attention to appetitive vs. aversive goods leading to opposite choice biases. Although in these prior studies subjective experience was not assessed, these studies together with our data support a more active account of exposure effects in value-based choice whereby changes in subjective valuation depend on how positively evocative a stimulus is for the subject, rather than a more passive effect whereby exposure directly primes approach behavior.

While the neurobiological mechanism supporting the similarity effect is unknown, one possibility, assuming values for similar goods are represented in physically adjacent brain regions, as some studies have shown (35), is that exposure enhances the value of the exposed, desired good and collaterally the value of goods represented nearby in cortical space, in a manner reminiscent of spatial attention's distribution in visual cortex. Of course value can be encoded on a more abstract representational dimension and exposure could act indirectly on these representations, for example, by triggering memories for related goods (36) or by enhancing the weight of a particular attribute (or set of attributes) common to the desired and similar goods—a type of reshaping of a subject's attentional priority map. From a basic science perspective, these data suggest we could take advantage of selective cue exposure as a tool to better understand the organization of value representation in the brain. For example, like devaluation, which dampens identity-specific values (37), such manipulations could be used instead to show selective hypervaluation.

A central aim of computational approaches to psychiatry is obtaining a theoretical, mechanistic, understanding of psychological phenomena (38). Here we aimed to identify the algorithmic process by which laboratory craving is expressed in valuation. Identifying this process is important because the behavioral motifs associated with specific algorithmic computations can have different neurobiological implementations (39). We compared three such possible algorithmic processes, addition, multiplication, and exponentiation, and found multiplicative scaling of subjective valuation best captured the algorithmic process of laboratory craving. Multiplication is one of the most common algorithmic computations throughout neural systems (25) and is observed in valuation systems as well (40). Given that the valuation system, composed of the ventromedial prefrontal cortex and the striatum (41), is a candidate neurobiological substrate of craving (11–13) and animal (42, 43) and in vivo human imaging (44, 45) work linking dopamine in this system to behavior and/or subjective experience consistent with craving, we speculate that craving is a gain control-like scaling of valuation signals that might involve dopamine, although as noted this is highly speculative. Nevertheless the particular bidding procedure we used is implemented in the brain's valuation system (46); as such, we expect to be able to directly measure changes in this system that reflect changes in subjective valuation and that will allow us to test this hypothesis. This is also an important next step in linking our findings to real-world behavior as some studies have suggested that neural measures might be more predictive of these behaviors than corresponding behavioral or self-report laboratory measures, particularly at longer timescales (47).

In addition to providing testable predictions for future neurobiological work, multiplication can also help explain a number of observations. For example, because of the nature of multiplicative scaling, exposure-induced changes in valuation should be larger for things generally of higher value (e.g., those high in tastiness and/or low in healthiness). Consistent with this, the most frequently craved foods in the general population are rich in sugar and fat (4, 5). Also because of the nature of multiplicative scaling, when we desire something, we should want more of it. This could translate into seeking increasing amounts of a desired good, which might explain why people plan to (27) and eventually do (48) consume more of a desired food in laboratory studies and certain eating escalation behaviors in real-world environments (7).

Some methodological considerations and potential avenues for future research are worth noting. First, although we used a nondieter community sample to ensure a distribution of exposure effects for food, it remains an open question whether the phenotype we observed in our laboratory model of craving is the same in dieters and in individuals who experience pathological levels of craving. Future studies should examine how generalizable our findings are to the full range of craving intensity. Future work should also test the boundary conditions of the time course of this subjective state and the mechanisms underlying its dynamics in valuation. In our estimation, effects should fully dissipate in 2 h. But this is in the context of repeated exposure to the opportunity to obtain the desired good. When this good is not available, or when a person engages in self-regulation, this time course may be shorter. Additional (e.g., memory decay) processes could also play a role and require further investigation.

In summary, we find exposure increases subjective valuation in a selective, but not exclusive, manner. These changes appear to respect underlying relationships among choice options (e.g., based on similarity) and established individual preferences. Our data also shed light on the underlying algorithmic process, showing the induced subjective state operates through a multiplicative/gain-control like mechanism, the neural implementation of which is an important target for future research.

Materials and Methods

Subjects. Forty-four adults (34 female, ages 18–55 y [24.9 (SD = 7.7)]) participated in study 1 and 45 adults (27 female, ages 18–59 y [24.1 (SD = 8.7)]) participated in study 2 after giving informed consent. New York University's Committee on Activities Involving Human Subjects approved all procedures.

Because dietary goals affect how food cues influence consumption behaviors (3), we only recruited nondieters. Subjects were invited to participate if they rated their current dietary goals in the contemplative or below range on a diet questionnaire, were not diabetic, and did not report any relevant food allergies or restrictions. Because of the restricted choice set in study 2 (see below), additional exclusion criteria for this study included a prestudy desirability rating for Snickers and Cheetos $\geq$3 (out of 10). These ratings were completed as part of prescreening before scheduling subjects for their session. A total of 12 subjects who completed study procedures were excluded from all analyses because they (*i*) did not understand or did not comply with the study instructions (n = 4 from study 1, n = 5 from study 2) or (*ii*) reported post hoc dietary or medical restrictions not disclosed at the time of screening that would have made them ineligible for the study (n = 3 from study 2). In addition, the task ended before the exposure manipulation for n = 1 subject from study 2. Data from the remaining 89 subjects are reported.

Procedure. All sessions began between 11:00 AM and 12:30 PM or 4:00 PM and 5:30 PM and lasted ≈2 h. To increase motivation for the snack foods offered, subjects had to refrain from eating or drinking anything for 4 h (Fig. S1). Payment was $20/h plus a bonus. The bonus consisted of additional money, a snack, or both depending on individual bidding behavior. Subjects were extensively trained on the bidding procedure, including completion of practice trials and a comprehension quiz with the experimenter. The experimenter then left the room and subjects were alone for the remainder of the time and received all further instructions via the computer screen.

Economic Decision-Making Task. See *SI Materials and Methods* for a detailed description of the task development. The task included 15 snack foods and a maximum of 22 blocks (2 baseline + 20 postexposure blocks). Each block consisted of 30 trials (1 bid and 1 desire rating trial for each of the 15 goods). On each trial subjects saw a high-resolution color image depicting a good and below it a mouse-controlled slider bar used to register their bid (from $0 to $5 in $0.01 increments) or desire rating [from 0 to 8 in 0.016 arbitrary unit increments (same spacing as the bid bar)] for that good. The bid and desire rating trials were randomly interspersed except for in the first postexposure block, which always began with a desire rating for the exposed good. The task was self-paced, but most subjects took ≈3 min/block. After each block, an animated scrambler appeared on the screen for 10 s, signaling the possibility of the task ending in that moment (which was kept at 2%). When the task ended, only bids from the last completed block were eligible for realization (see *SI Materials and Methods* for details). Subjects were explicitly told this should help them think in the current moment, and pilot data showed this feature of the task helped minimize discounting/forecasting behavior. Data loss due to the 2% hazard rate was minimal (all subjects completed at least 2 postexposure blocks, and 84% completed all 22 blocks).

Exposure Manipulation. See *SI Materials and Methods* for a detailed description of the exposure manipulation and other control manipulations. After the second task block, the computer program was interrupted with written instructions to find and open a covered tray. The tray contained a Snickers bar, bag of Cheetos, or can of Coke (randomly assigned). Adapted from prior work (14, 27–30), the multisensory exposure included instructions to examine the item in the tray by opening or unwrapping it, breaking off a piece or pouring it into a cup, and smelling it. Subjects were instructed to imagine the taste and texture without actually tasting it, rather by recalling a memory of consuming this item last. To facilitate compliance with instructions and the maintenance of a continuous representation of the exposed good after the exposure, subjects were told they would later have to answer questions about the "activity." After 3 min had elapsed, subjects were instructed to place the item back in the tray, cover it, and resume the task.

Posttask Ratings. Immediately after bid realization, subjects were asked for a brief description of the memory called to mind during the exposure manipulation, how good or bad they felt, and the intensity of that feeling. They then completed a series of similarity and subjective attribute ratings (Fig. 1*C* and *SI Materials and Methods*).

Study 2. Procedures largely paralleled those of study 1 (Fig. S5). The changes implemented were aimed at testing the algorithmic process of the exposure effect in valuation. Instead of a single vending-machine–sized Snickers bar or a 3.5-oz bag of Cheetos, here we used instead fun-sized Snickers bars and 1-oz Cheetos bags offered in units of 1, 2, 3, 5, or 8. To simplify the choice set and reduce the number of trials we omitted drinks. A third mixture category snack (nut and chocolate trail mix, also offered in five quantities) was available instead, for a total of 15 unique options (3 snack goods $\times$ 5 quantities of each). Additional changes included (*i*) subject assignment to one of two exposure groups (Snickers or Cheetos); (*ii*) because of the repetitiveness of the three-item task, a maximum of 12 task blocks (2 baseline + 10 postexposure blocks); and (*iii*) an endowment for bidding of $10.

Analysis. Data were analyzed in Matlab R2015b (MathWorks) using the Statistics and Machine-Learning Toolbox and SPSS v.22 (IBM Corp.). Two classes of LMMs were fitted: (*i*) a priori hypothesis-driven models, as described in *Results*, and (*ii*) exploratory/control models (Table S1). Unless otherwise noted, all models included fixed-effect intercept and slopes and random intercept and slopes varying by subject and were fitted using fitglme in Matlab, assuming Gaussian distributions. Repeated-measures ANOVAs and *t* tests were used to examine the exposure main effect (both studies) and differences in the individually estimated parameters ω and α (study 2). Results were considered significant at $P < 0.05$, two tailed.

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