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BRIEF REPORT

Hurry Up and Decide: Empirical Tests of the Choice Overload Effect Using Cognitive Process Models

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The choice overload effect emerged as a rebuttal to the notion that having more options from which to choose is always preferable. Jessup, Veinott, Todd, and Busemeyer (2009) used a modified version of decision field theory, a cognitive process model of choice, to generate multiple mechanisms based on psychological principles for the choice overload effect as it pertains to choice probability. Here we experimentally tested 2 of these mechanisms—time out and preference change—in a virtual hiring task to see whether participants hired more applicants when choosing from small relative to large sets of applicants. We further wanted to observe how the distribution of options affected choice. The choice overload effect replicated. More importantly, we observed that the time out mechanism did indeed account for choice overload effects, whereas the conflict-based preference change mechanism did not. Model fitting via simulation provided converging support because the time-out model provided a superior fit relative to the preference change model. This further demonstrates the value of utilizing models that incorporate underlying cognitive processes when exploring behaviors of interest to psychology, marketing, economics, and other related disciplines.

Keywords: choice overload, hiring, consumer choice, time pressure, conflict

Supplemental materials: http://dx.doi.org/10.1037/dec0000115.supp

In the summer of 2012, Apple's Genius Training Student Workbook, a manual for new Apple store employees, was leaked to the public. Nestled among old sales techniques is advice based on more recent research: never present more than three options at once (Biddle, 2012). This is just one example of the popularization of research on choice overload, due in no small part to Schwartz's (2004) *The Paradox of Choice*.

Standard economic models predict that an abundance of options will increase the likelihood of a purchase (Baumol & Ide, 1956). Curiously, Iyengar and Lepper (2000) demonstrated the opposite effect, finding that customers purchased more exotic jams from a display of six compared with 24 options. This effect of choice overload has been demonstrated with a wide variety of choices (Gourville & Soman, 2005; Haynes, 2009; Iyengar, Huberman, & Jiang, 2004; Iyengar et al., 2000; Ketcham, Lucarelli, Miravete, & Roebuck, 2012; Morrin, Broniarczyk, Inman, & Broussard, 2008; Park & Jang, 2013; Reutskaja & Hogarth, 2009).

Two recent meta-analyses of this literature have yielded conflicting results. Scheibehenne, Greifeneder, and Todd (2010) examined pub-

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lished and unpublished data and concluded that chance might best explain the effect because the effect often failed to replicate. However, they stated that particular moderator variables might provoke the effect and the lack of theory-driven approaches may have hampered reliable observations of it. The more recent meta-analysis considered more data sets—all published—and explicitly tested the effects of four variables: decision task difficulty, choice set complexity, preference uncertainty, and decision goal, observing that all four moderate assortment size-based choice overload effects (Chernev, Böckenholt, & Goodman, 2015). However, because they were limited by previous research, their moderator categories were rather broad. For example, they classified both time pressure and conflict within the decision difficulty moderator. Yet these two causes elicit phenomenologically different feelings, as in, one can feel extreme time pressure but very little conflict; or, as in the case of a marriage decision, little time pressure but much conflict.

Most choice overload research has primarily involved observation of the effect, followed by the establishment of boundary conditions regarding the circumstances in which the effect will occur. Jessup et al. (2009) introduced a unique approach: They took an existing process model of choice that yields behavior based on underlying cognitive mechanisms and extended it to the no-choice domain (see Bhatia & Mullett, 2016 for a similar approach). The utility of their approach is that it views the problem in terms of why and how rather than what. Moreover, the answers to these questions generate new and testable predictions.

Jessup et al. (2009) began with decision field theory (Busemeyer & Townsend, 1993), a dynamic and stochastic model of choice within a class of cognitive process models that explains a wide array of decision phenomena in the consumer (Roe, Busemeyer, & Townsend, 2001), psychological (Busemeyer et al., 1993; Johnson & Busemeyer, 2005), and economic literature (Diederich & Busemeyer, 1999; Rieskamp, Busemeyer, & Mellers, 2006). Decision field theory can be considered a dynamic version of signal detection theory uniting expected utility with Bayesian inference (Green & Swets, 1966). In decision field theory, attention shifts back and forth between the attributes at each time step to generate momentary evaluations for each option. These evaluations accumulate into preferences for each option, which necessarily drift over time. When preference for an option hits a predetermined decision threshold θ, the choice process ends and that option is selected (see Figure 1). As written, this model always results in the selection of an option. To account for choice overload effects, Jessup et al. (2009) proposed three independent modifications—each grounded in psychological principles—to convert decision field theory from a forced choice model to one that could elect not to choose.

The three mechanisms were labeled preference change, time out, and the no-choice option. Although the last of these successfully predicted not choosing in other consumer situations (Busemeyer, Johnson, & Jessup, 2006), it did not predict the choice overload effect. However, the other two did.

The first mechanism, preference change, depends on the elements of conflict and dynamic preferences. In a situation with high conflict, a decision maker might vacillate between alternatives (e.g., at one moment option 1 is most preferred and at the next moment option 2 is most preferred). The dynamic and stochastic nature of decision field theory naturally produces such effects, wherein the most preferred (or lead) option can change repeatedly. The relevant proposed modification was to add a lead change threshold θ_δ. If the number of changes of the most preferred option hits that threshold, then the decision maker exits the choice process and makes no selection, essentially declaring that this choice is too difficult (see Figure 2). Effectively, this might represent one mathematical instantiation of other conflict-based mechanisms for choice deferral (Dhar, 1997; Tversky & Shafir, 1992).

The second mechanism, time out, derives from the idea that decision makers might feel time pressure and so set a time limit for themselves when deciding. Because preferences in decision field theory evolve over time, this represents a natural extension to the theory. The relevant proposed modification was to add a temporal threshold θ_τ. If the deliberation process arrives at θ_τ before an option is selected, then the process ends and no option is selected (see Figure 3). Effectively, the decision maker declares that this choice takes too long. This might represent a mathematical implementation of explanations for choice deferral based on time pressure (Dhar & Nowlis, 1999; Haynes, 2009).

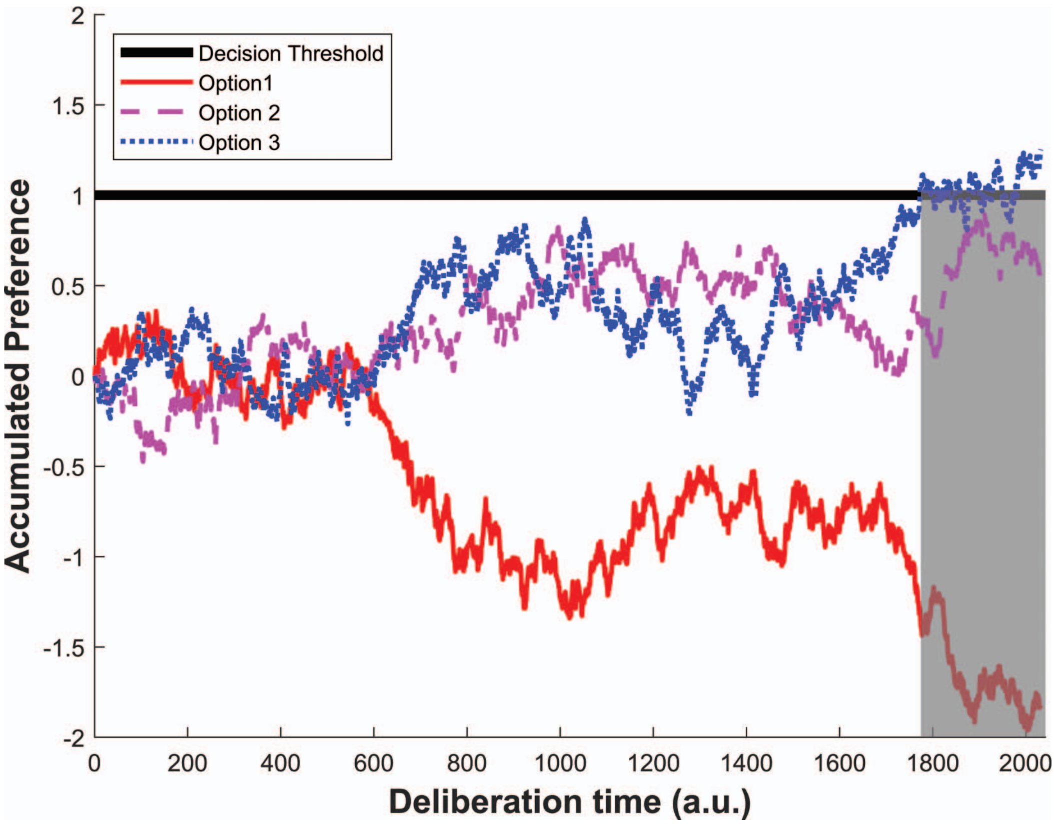

Figure 1. Process illustration of decision field theory. The vertical axis represents the preference state (i.e., accumulated preference) and the horizontal axis represents decision time in arbitrary units. In this example showing three options (1, 2, and 3), preference for each option accumulates across time, and the first option to reach the decision threshold (black horizontal line at y = 1) is chosen. Here option 3 (dotted blue line) is chosen at approximately time step 1,780. If the decision threshold were reduced to 0.25, then option 1 would instead be chosen at approximately time step 100. The gray shaded area denotes that the choice process has been exited. See the online article for the color version of this figure.

Critically, Jessup, et al. (2009) further considered the impact of the option set distribution, considering both uniformly (where there is much conflict) and exponentially distributed option sets (in which an option dominates). They then used simulations to test these modifications and their interactions with the two-option set distributions, yielding three predictions. First, the preference change mechanism predicted the presence of a choice overload effect when options were uniformly but not exponentially distributed. Second, the time-out mechanism predicted the presence of a choice overload effect in both distribution types among individuals under time pressure. Third, the time-out mechanism predicted that exponentially distributed option sets may exacerbate the choice overload effect among individuals under time pressure. In this study we experimentally test these two competing mechanisms, both classified within the decision difficulty moderator of Chernev et al. (2015).

Method

Participants

Ninety participants—49 female and 41 male—were recruited using flyers and ads placed throughout the university campus or received course credit for participation in addition

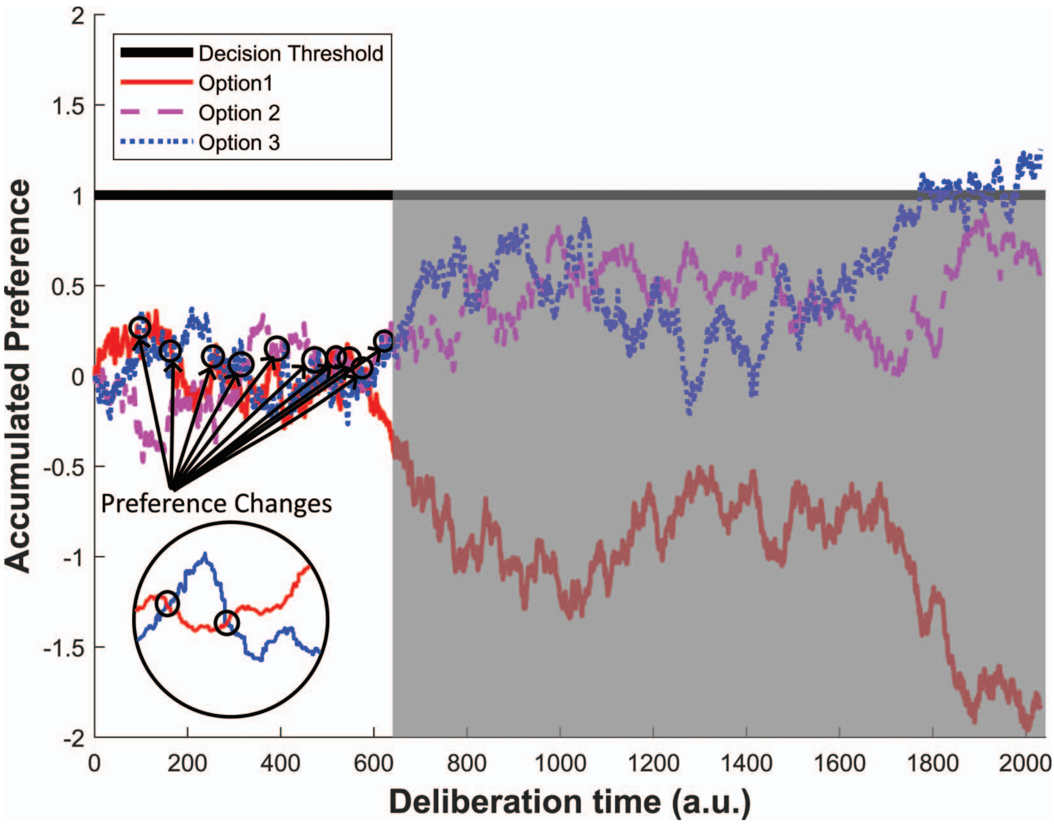

Figure 2. Preference change mechanism implemented in decision field theory. The vertical axis represents the preference state (i.e., accumulated preference) and the horizontal axis represents decision time in arbitrary units. For every time step on which a different option becomes most preferred (denoted by the circles), the preference change counter is incremented. If this counter value reaches the tolerance threshold for preference changes before an option reaches the decision threshold, then the process will stop and no option will be selected. Here the tolerance threshold was set to a value of 10 and reached at approximately time step 650. The lower left quadrant presents a hypothetical close-up of two preference changes. The gray shaded area denotes that the choice process has been exited. See the online article for the color version of this figure.

to financial incentives (described below). All of the participants from 1 day were removed because they were obtained using a nonstandard sampling procedure, 11 in total.[1] However, all statistical conclusions regarding our hypotheses were identical when using all participants in the analysis. In total, we sought to collect data from approximately 80–90 participants; our stopping rule was driven by the amount of money we had available to pay participants.

Procedure

Each participant gave informed consent and the study was approved by the university institutional review board. All participants then completed the Regret and Maximizer scale[2] (RAMS; Schwartz et al., 2002). They learned that they would complete a virtual hiring task

[1] Ten of 11 of these participants were studying where the experiment was to take place and so were asked to take part as well. After being informed of the $4 participation minimum, one of these individuals clarified, “You mean we get money, no matter what happens?” Because of the anonymizing procedure used, we were unable to determine which one participant volunteered under the standard protocol, so all 11 were removed.

[2] A recording error caused us to lose the last item on the scale for each participant.

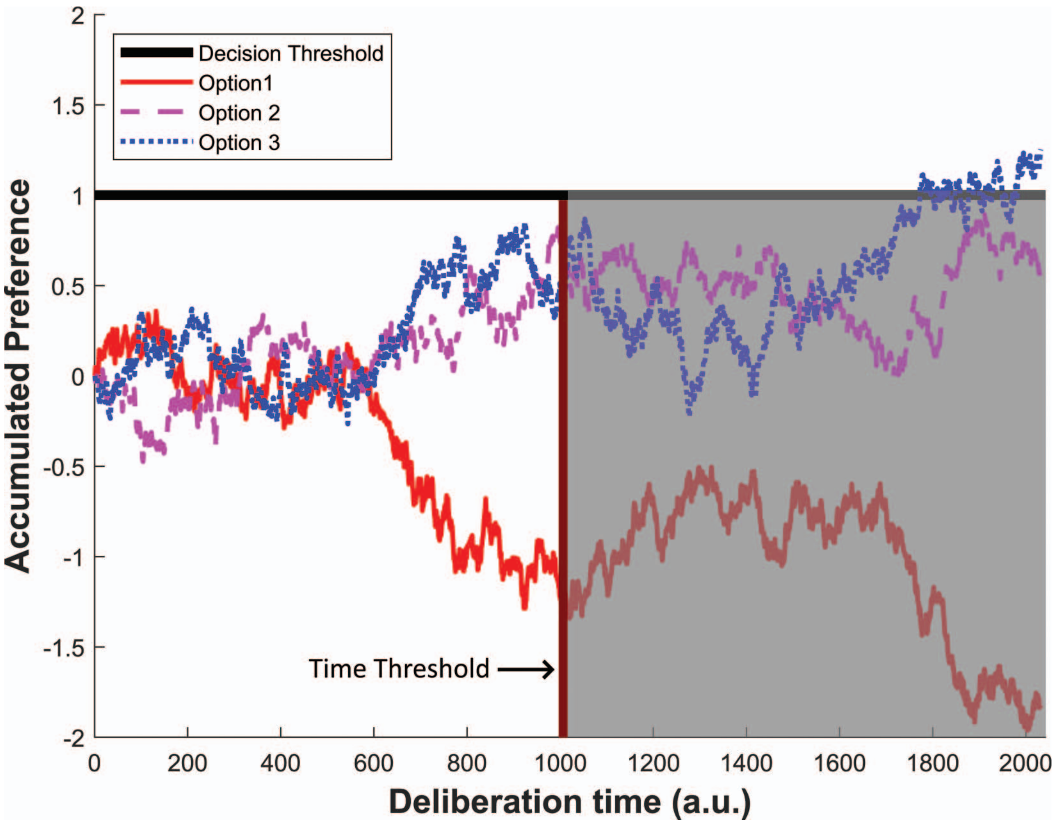

Figure 3. Time-out mechanism implemented in decision field theory. The vertical axis represents the preference state (i.e., accumulated preference) and the horizontal axis represents decision time in arbitrary units. If the time threshold (thick vertical line at approximately 1,000 time units) is reached before an option reaches the decision threshold, then the process will stop and no option will be selected. Here the process ended without any option being selected. The gray shaded area denotes that the choice process has been exited. See the online article for the color version of this figure.

and they received instructions. They were informed that they would either win or lose money on the basis of who they hired, and, critically, that if they were unsure on any trial about whom to hire, it was safest to hire no one. At the end of the experiment, participants received the greater of either $4 or the sum of the money they earned over all choices—divided by 1000— on the basis of their hiring decisions.

Participants then completed eight practice trials that were identical for all participants except for the time allowed. The first four showed 15 job candidates and advised the participants on the overall quality of the candidates; in one set they were told to reject all of the candidates and in another they were told that several were strong and they should select one. The second four practice trials consisted of one trial each from our two option set sizes and two different distribution types timed exactly as in the actual task with no feedback provided.

The task consisted of 80 hiring decisions. Participants could choose to hire any of the available applicants by pressing a corresponding button or they could choose none of the applicants. For the latter, they could either let the trial time out or press a button indicating they wanted to hire none of the current applicants.

We separated participants into two groups: no time pressure and high time pressure (120 or 5 s per decision, respectively). Each decision contained either a large (15) or small (three) set of job applicants. Applicant quality—which was demonstrated by four unique attributes relevant to personnel decisions (years of experience, standardized exam scores, college grade point average, and letter of recommendation quality)—was either exponentially or uniformly distributed. Each small option set contained the best, middle, and worst options from a corresponding large option set (see example in Figure 4), akin to the procedure used by Iyengar et al. (2000). Applicant quality was determined using a linear model using the attributes as inputs. (See the online supplemental materials for additional information concerning the determination of applicant quality and additional instructions).

After each set of 20 trials (containing 10 large option set trials and their matching small option set trials within a randomized order), participants received feedback concerning their choices, indicating their earnings for each trial, a value that represented a noisy estimate of the true underlying quality of the chosen applicant derived from the linear model mentioned above. The feedback screen merely listed the payoffs for each of the options selected during the block of 20 trials (ranging from 0 listed payoffs up to 20, if an option was selected on every trial). We used this approach to minimize the impact of feedback on choice throughout the experiment (Jessup, Bishara, & Busemeyer, 2008). (See the online supplemental materials for additional information concerning creation of the applicant distributions). Although our data are presented as a single experiment, the within-subjects nature of our design contains 80 trials per participant consisting of 20 replications for each of the four conditions. Hence, our design contains the same amount of data as 20 experiments using a between-subjects design, each with an N of $4 \times 79 = 316$ participants.[3]

Analysis and Predictions

The time-pressure manipulation was intended to force individuals to set a temporal threshold as implemented by the time-out explanation. The goal of this manipulation was to see whether, when setting such a threshold, individuals demonstrated the choice overload effect as predicted. The high-pressure group was contrasted with the no-pressure group, which served as a control. The different distribution within option sets was intended to test the preference change explanation. Here the uniform distribution of options is predicted to elicit choice overload, in contrast to exponentially distributed options which served as a control condition.

We analyzed the data using a $2 \times 2 \times 2$ mixed ANOVA with two within-subjects factors: distribution type (exponential or uniform) and set size (large or small), and one between-subjects factor: time pressure (no pressure or high pressure) using choice probability as the dependent variable. General support for choice overload would be demonstrated by a main effect of set size, with the smaller set yielding more choosing. A set size by time-pressure interaction in which the high-pressure group showed a larger choice overload effect than the no-pressure group would demonstrate the importance of time pressure in producing the effect, providing support for the time-out hypothesis. Lastly, a set size by distribution interaction in which the uniform (but not the exponential) distribution yielded a choice overload effect would demonstrate that conflict is an important component in generating the effect, thereby providing support for the preference change hypothesis. On the other hand, for the same interaction, if the exponential (but not the uniform) distribution yielded a choice overload effect, this might demonstrate that time pressure is an important component in generating the effect (given that the time-out explanation was stronger at producing the effect in exponential relative to uniform distributions in Jessup et al., 2009). This would be further strengthened if the three-way interaction between set size, distribution, and time pressure was significant, and the effect was more pronounced in the high-pressure group, thereby lending support to the time out hypothesis.

Results

All of the measures and conditions that we collected are reported here, except for information regarding the quality of choices, which will be presented in a different article. Unless otherwise noted, the widths of all confidence intervals (CI) indicate the 95th percentile of the difference between the contrasted means. The

[3] It should be noted that 20 studies with $N = 316$—if the studies do not involve the same participants—will have independent data, whereas our data are not all independent.

Figure 4. Experimental choice display. Participants were presented with either 15 or three job applicants, each rated on four attributes, indicated by the bars. If they wanted to hire an applicant, participants would push the button on the left corresponding with the chosen applicant. If they did not want to hire any of the applicants, then participants could either wait until the trial timed out or push the button labeled "select none of these." See the online article for the color version of this figure.

overall probability of making a choice was .58 (SD = .22) and the median response time was 4.21 s (SD = 2.58). Table 1 shows the percent of trials on which those in the high pressure group ran out of time, conditioned on no option being selected. There was no trial on which participants in the no-pressure group ran out of time. Even though the expected value of the task was negative if selecting at random (see online supplemental materials), all but four participants earned more than the minimum win amount of $4, and only one had a negative win amount; this suggests that participants were sufficiently motivated.

Behavioral Results

Manipulation checks. A first manipulation check was to see whether there was a higher choice probability in the exponential distribution condition, consistent with prior research. There was a higher choice probability in the exponential distribution condition. This was tested using the 2 × 2 × 2 mixed ANOVA described in *Method*, with a significant main effect for distribution type (CI [0.06, 0.17], F[1, 77] = 16.48, $p < .001$). The probability of selecting an option in the exponential condition was .64 compared with .52 in the uniform condition. We ran a second manipulation check to verify that individuals were less likely to make a choice when options were more conflicting. They were less likely. This was tested with logistic regression using the participants' individual choice data on each trial as the dependent variable and our conflict measure as an independent variable, the result of which was significant (beta coefficient CI [0.012, 0.17], t[6318] = 10.64, $p < .001$). The conflict measure was represented by the percent of variance accounted for by the first principal component, obtained by running a principal components analysis on each observed option set, representing a multidimensional version of cosine similarity. Technically this indicates similarity (i.e., 1 – conflict). Thus, the less conflicting an option set is, the more likely one is to select an option.

A third manipulation check indicated that the median response time statistically differed between the time pressure groups (CI [2.16, 3.71], F[1, 77] = 57.20, $p < .001$), tested via a one-way ANOVA comparing the median response time of individuals in the high-pressure to no-pressure group. As expected, the no-pressure group had statistically longer response times (no-pressure group: M = 5.51 s, SE = 0.37; high-pressure group: M = 2.57, SE = 0.10). This indicates that our time pressure manipulation operated as designed. Response time distributions are shown separately for the no-pressure and high-pressure groups in Figures 5 and 6, respectively.

Choice overload effect. We tested the following hypotheses using the 2 × 2 × 2 mixed ANOVA described in *Method*. We first wanted to know whether individuals selected an option more when choosing from small option sets than from large option sets, thereby replicating

Table 1
Percent of Trials on Which High-Pressure Group Ran Out of Time Among Those on Which No Option Was Selected, Separated by Distribution and Set Size

Variable	Small	Large
Exponential	.06%	.19%
Uniform	.36%	.66%

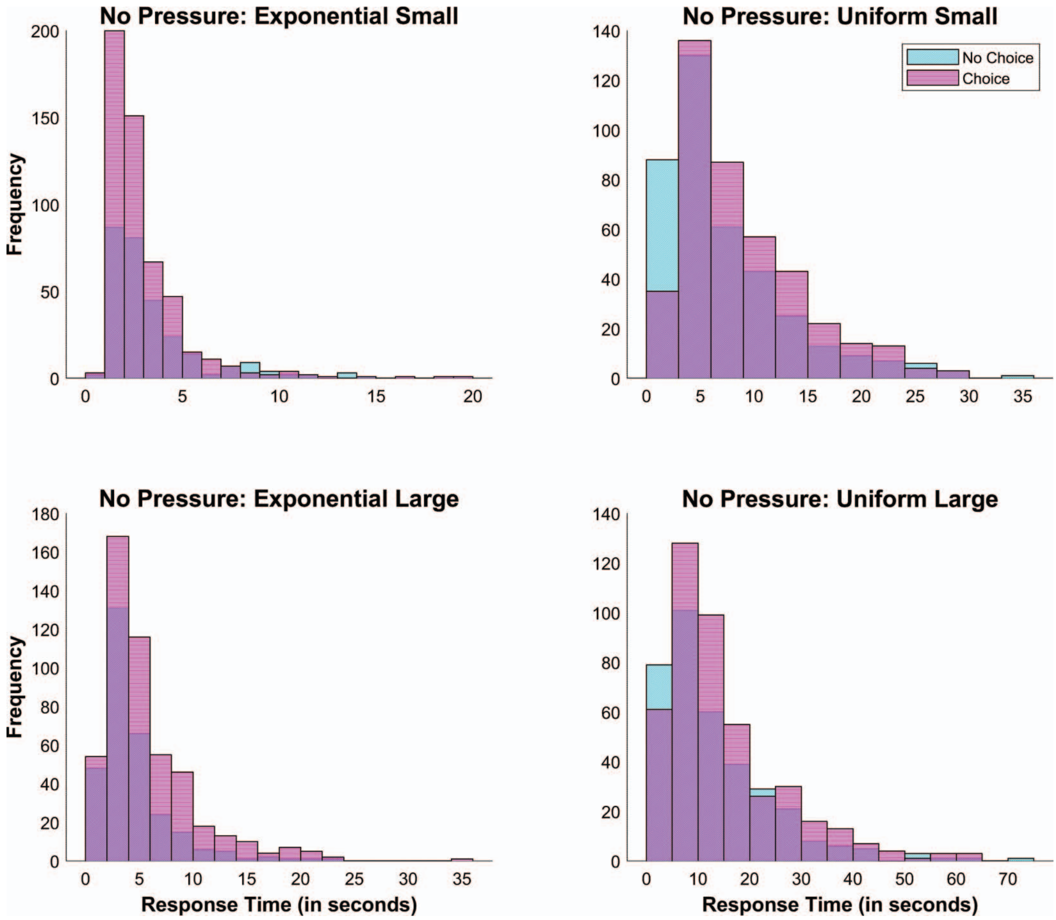

Figure 5. Response time distributions for no-pressure group are separated by distribution type and set size and no choice (cyan with diagonal pattern) or choice (magenta with horizontal pattern). The overlap is shown in purple with diagonal pattern. See the online article for the color version of this figure.

the choice overload effect according to choice probability. The effect replicated (set size main effect: CI [.02, .07], $F[1, 77] = 9.73$, $p < .003$). The choice probability for small option sets ($M = .60$, $SE = .03$) was higher than that for large option sets ($M = .56$, $SE = .02$). Continuing, we wanted to determine whether the preference change mechanism for the choice overload effect was supported by the choice probability data. It was not supported. Individuals were equally likely to make a choice when options were uniformly relative to exponentially distributed (Set Size × Distribution interaction: $F(1, 77) = 1.32$, $p < .255$).

Lastly, we wanted to determine whether the time-out mechanism for the choice overload effect was supported by the choice probability data. It was supported (Set Size × Time Pressure interaction: CI [.05, .16], $F(1, 77) = 14.19$, $p < .001$). As conveyed by Figure 7 and exactly in line with the time-out hypothesis, there was little difference in choice probability for the no pressure group, regardless of option set size, whereas the high-pressure group was substantially more likely to make a choice from a small compared with a large option set. This exact pattern of significant and nonsignificant effects also emerged from a 2 × 2 × 2 mixed ANOVA on participants' block 1 choices (see Table 2 for additional results from the ANOVA for which there were no a priori hypotheses).

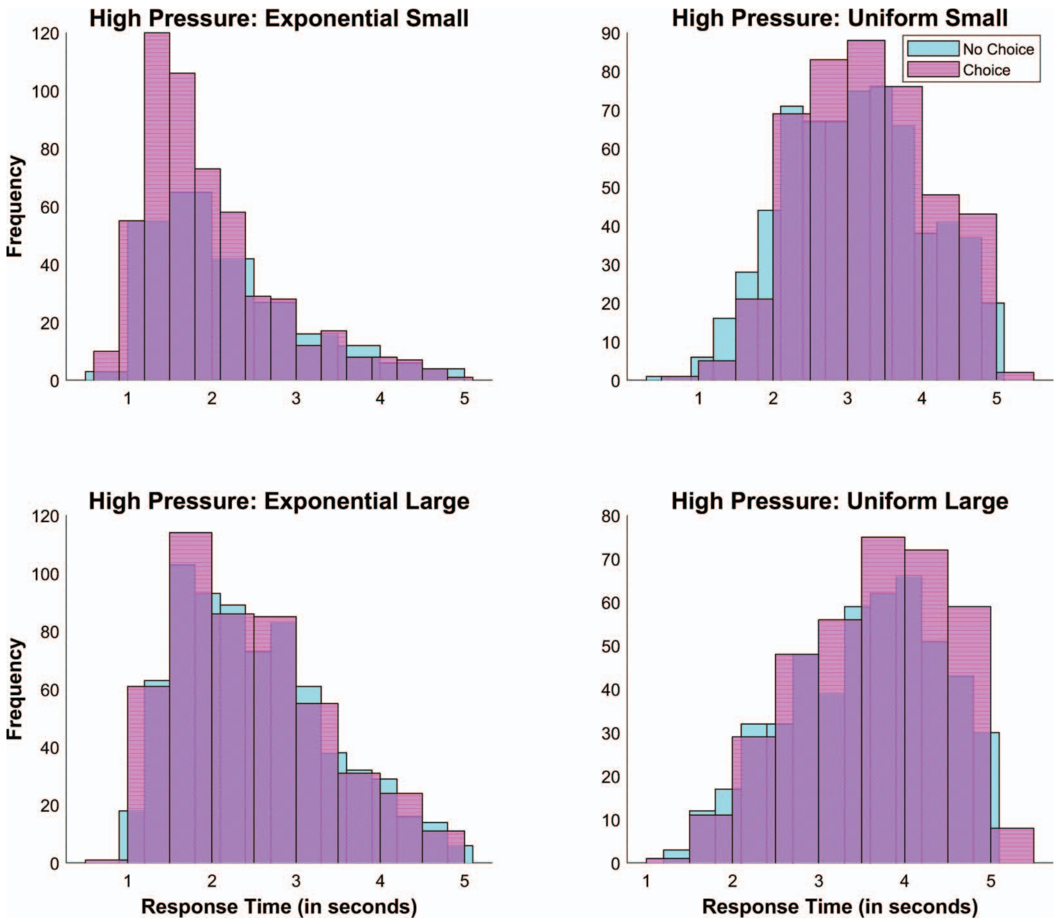

Figure 6. Response time distributions for high-pressure group are separated by distribution type and set size and no choice (cyan with diagonal pattern) or choice (magenta with horizontal pattern). The overlap is shown in purple with diagonal pattern. No-choice trials exclude trials on which the participant timed out. See the online article for the color version of this figure.

RAMS score as a predictor of choice. Finally, we wanted to know whether participants' probability of making a choice bore a relationship to their RAMS score, a measure of the extent to which one maximizes or satisfices. There was no relationship. We tested this by regressing their RAMS score onto the overall probability of making a choice, $F(1, 76) = 0.41$, $p < .527$, the probability difference in making a choice between the two set sizes within the uniform condition, $F(1, 76) = 0.76$, $p < .784$, and within the exponential condition, $F(1, 76) = 0.17$, $p < .679$, and the statistical interaction contrast between set size and time pressure, $F(1, 76) = 0.32$, $p < .576$. Thus, even though the RAMS score yielded a Cronbach's alpha = .78, a value that falls in the acceptable range (George & Mallery, 2003), we found no evidence that it predicted choice in our current setting.

Model Simulations

Following Jessup et al. (2009), we used simulations to conduct a grid search; here for each participant, we ran 100 simulations for each of their 80 trials using each parameter combination for each model we tested. Using the probabilistic response profile from the simulations, we identi-

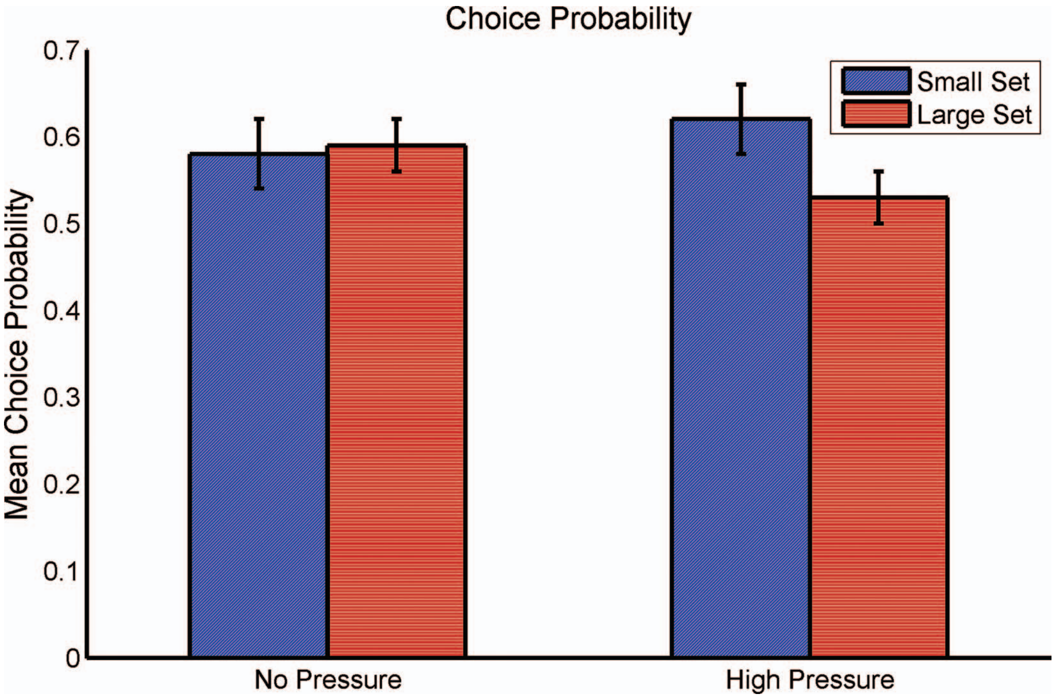

Figure 7. Statistical interaction between the time-pressure group and option set size, using choice probability as the dependent variable. Error bars indicate standard error of the mean. See the online article for the color version of this figure.

fied the tested parameters that maximized the likelihood of the data, given the models.

Three different models were tested: decision field theory with the time out exiting method, decision field theory with the preference change exiting method, and decision field theory with both the time out and the preference change exiting methods.

Decision field theory. Decision field theory evolves according to

$$\boldsymbol{P}(t+1) = \boldsymbol{S} \times \boldsymbol{P}(t) + \boldsymbol{V}(t) + \boldsymbol{E}(t) \tag{1}$$

where $\boldsymbol{P}(t)$ represents a $J \times 1$ preference state column vector, indicating the level of accumulated preference for each of the J options at time t. In decision field theory, option j is selected when the preference state for option j hits the preset decision threshold θ. S represents an $J \times J$ distance-dependent lateral inhibition matrix where cell $S_{2,5}$ indicates the similarity between option 2 and option 5. We used a euclidean distance measure scaled such that maximally distant (i.e., dissimilar) options had a value of 0 and maximally proximal options had a value of −.1. Effectively, these off-diagonal cells served to inhibit competing option preferences in a distance-dependent manner (i.e., the more similar the more the competitive inhibition). The main diagonal of matrix S represents temporal

Table 2
Additional Results From ANOVA for Which There Were No a Priori Hypotheses

Variable	$F(1, 77)$	p
Main effect: time pressure	.04	.84
Interaction: Distribution × Time Pressure	.41	.52
Interaction: Distribution × Set Size × Time Pressure	2.78	.10

decay for each option, and the value for each cell on the diagonal was set to .95. $E(t)$ is a normally distributed row vector of error at time t for each preference state according to $N(0,1)$. The matrix $V(t)$ is the $1 \times J$ valence vector at time t and is composed of

$$V(t) = \boldsymbol{C} \times \boldsymbol{M} \times \boldsymbol{w}(t). \tag{2}$$

$J \times J$ matrix C effectively represents a $1/J$ contrast matrix (having a value of 1 on the main diagonal) and is used to contrast the $J \times K$ motivational matrix M, where K represents the number of attributes, which was four in our study. In our simulations, the values in M were normalized to all of the options in our database, separated by distribution type (i.e., exponential or uniform) and then shifted such that the minimum value for each attribute was 0. The $K \times 1$ stochastic column vector $w(t)$ at time t determines which attribute is receiving attention at each individual time step. We gave each attribute an equal importance weight ($w_k = .25$ for all k); in practice, to speed the simulation process, we allowed for each attribute to be turned on at any moment, as opposed to limiting it to only one attribute at each time step t.

Time out, preference change, and combined model. To allow decision field theory to not select an option, an additional component must be added. For the time-out method, a temporal threshold θ_τ is set such that when the elapsed number of timepoints reaches θ_τ without an option being selected, then the decision process is exited and no options are selected. In practice, we used a probabilistic θ_τ, which was referred to at every time step t. This probabilistic threshold should yield the same effects as Jessup et al. (2009) while retaining the dynamic and stochastic modeling spirit of decision field theory.

For the preference-change method, a preference change threshold θ_δ was used such that we counted every time step t on which a different option became most preferred relative to the previous time step $t - 1$. When this counter reached θ_δ, the decision process exited and no option was selected. As with the time-out method, in practice, we used a probabilistic version of θ_δ such that on every time step on which a new option became preferred, there was some nonzero probability of exiting the choice process.

The combined model utilized both the probabilistic time-out threshold θ_τ as well as the probabilistic preference change threshold θ_δ in the same model.

The grid search ranged from 1 to 20 in increments of .25 for the decision threshold θ, totaling 77 values for the first dimension. For the next dimension(s), the probabilistic exit thresholds (θ_τ or θ_δ or both in the combined model) ranged from .001 to .999 at the extremes and otherwise ranged from .02 to .98 in increments of .02, yielding 51 values. Hence, there were two free parameters in the first two models and three free parameters in the combined model.

Model comparison. Each of the three above models were examined using four different versions for finding the optimal parameter combinations. The first version sought the best parameter combination for each participant over all 80 trials. The second version sought the best-fitting parameter combination for the model, separated by distribution type, yielding 40 trials for each parameter combination. The third version sought the best-fitting parameter combination for the model, separated by set size, also yielding 40 trials for each parameter combination. The fourth version sought the best parameter combination for each set size and distribution type, yielding four different parameter combinations total, one combination each for every 20 trials.

The models were compared using Bayesian Information Criterion (BIC; Schwartz, 2004), a method that penalizes models for additional parameters. BIC is computed as

$$BIC_m = -2 \cdot ln(L_m) + (p_m \cdot ln(n)) \tag{3}$$

where L_m represents the likelihood of model m, p_m represents the degrees of freedom (number of free parameters) in model m, and n indicates the number of data points to which the p_m degrees of freedom are applied. The terms after the addition sign compose the penalty for additional parameters. Because versions 2–4 of our models applied the free parameters to restricted subsets of the data points as opposed to all of them simultaneously, we used a version of BIC modified accordingly:

$$BIC_m = -2 \cdot ln(L_m) + k \cdot (p_m \cdot ln(n)). \tag{4}$$

Here k represents the number of restricted subsets to which the free parameters were applied (note that this formulation assumes that the same number of data points are used for each parameter combination of the same size). Consequently, the penalty for version one of the time-out model is $1 \cdot (2 \cdot ln[80]) = 8.76$ because there were 80 trials to which two free parameters were applied, all in a single subset. Comparatively, the penalty for version four of the combined model is $4 \cdot (3 \cdot ln[20]) = 35.95$ because three free parameters were separately applied to each subset containing 20 data points and four total subsets.

Each version of each model was compared with a 0-parameter baseline model, which assumed that participants merely selected options (or selected no option) at random. Hence, for an experimental model to outperform the baseline model, (a) participants must act in a nonrandom manner (b) that the experimental model is able to detect. The BIC of this 0-baseline model is the same for all participants and is

$$BIC_{Baseline0} = -2 \cdot [40 \cdot ln(1/4) + 40 \cdot \ln(1/16)] = 332.71. \qquad (5)$$

In the formulation used in this paper, the model performance increases as the BIC value decreases.

Simulation results. Statistics from the model simulations are shown in Table 3. As one can see, the BIC values for each version of each model outperforms the baseline model which has a BIC value of 332.71. Hence, participants did not merely choose at random, and every model version of decision field theory was able to detect this nonrandomness and adjust accordingly. The best BIC was obtained by version 4 of the time-out model and the second best was obtained by version 2 of the same model (although several other versions of the other models do nearly as well). Nonetheless, consistent with the conclusions from our behavioral results, the time-out model appears to be a superior predictor of choice overload effects when compared with the preference change model. Table 4 presents the median best-fitting parameter values for version 4 of the time-out model, separated by pressure group. We further wanted to know whether these best-fitting parameters differed between our pressure groups. There was one difference. This was tested using a two-tailed Wilcoxon's rank sum test for each between-group pair of parameter values. The θ_τ

Table 3
Simulation Statistics

Model	Version	Mean $-2 \times \ln(L_m)$	Penalty	BIC	Percent best fit
Time out					49.4%
	1	161.91	8.76	170.67	11.4%
	2	149.97	14.76	164.73	10.1%
	3	153.99	14.76	168.75	10.1%
	4	138.85	23.97	162.82	17.7%
Preference change					40.5%
	1	161.31	8.76	170.07	10.1%
	2	151.71	14.76	166.47	21.5%
	3	154.76	14.76	169.52	5.1%
	4	143.59	23.97	167.56	3.8%
Combined					10.1%
	1	154.30	13.15	167.45	8.9%
	2	143.29	22.13	165.42	.0%
	3	146.43	22.13	168.56	1.2%
	4	133.14	35.95	169.09	.0%

Note. BIC = Bayesian Information Criterion. Each version of each model was optimized to the data at the individual participant level using a grid search over parameter values by maximizing $-2 \times$ log likelihood of each model, given the data (see main text for differences in versions and tested value ranges). BIC penalizes models for additional free parameters and equals $-2 \times \mathrm{Ln}(L_M)$ + penalty; the BIC values may not sum correctly with the other values in the table because of rounding error. Lower values of BIC indicate superior performance.

Table 4
Median Best-Fitting Parameters for the Best-Fitting Model: Time Out Version 4

Group	Set size	Distribution	θ	θ_τ
No pressure				
	Small	Exponential	9.75	.36
	Small	Uniform	17.00	.11
	Large	Exponential	9.37	.38
	Large	Uniform	10.75	.53
High pressure				
	Small	Exponential	9.75	.28
	Small	Uniform	15.75	.12
	Large	Exponential	7.00	.40
	Large	Uniform	10.25	.70

Note. θ controls the extent to which individuals accumulate more preference before a choice; higher values indicate more preference required before selecting an option. θ_τ controls the extent to which individuals probabilistically exit from the decision process without selecting an option; higher values indicate an increased likelihood of exiting the decision process without selecting an option, holding θ constant.

for the high-pressure group in the large uniform condition was significantly higher than its respective counterpart for the no-pressure group ($z = -2.06$, $p < .040$), indicating that the model best fit the former group by setting a significantly more urgent time-out threshold relative to the no-pressure group. Interestingly, this occurred without any response time data used in the model fitting.

Figure 8 plots the probability of making a choice as predicted by version 4 of the time-out model, separated by distribution, set size, and pressure condition together with the mean observed probabilities and the standard error for

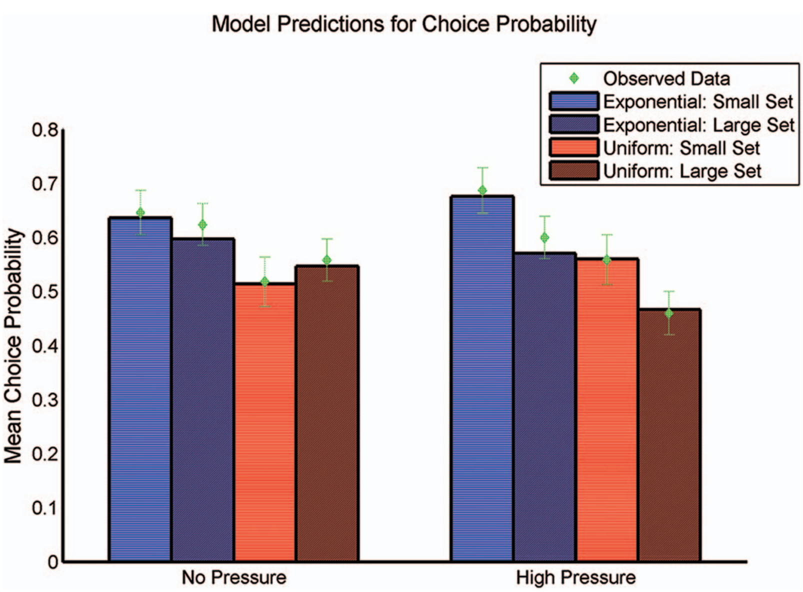

Figure 8. Model simulations showing the mean choice probability from the time-out mechanism, separated by distribution type, option set size, and pressure group. Error bars indicate standard error of the mean for the observed choice probability data from participants, centered on the mean. See the online article for the color version of this figure.

each observed choice probability. As can be observed, version 4 of the time-out model sufficiently predicts the overall probability of making or, more importantly, the probability of not making a choice.

Discussion

First, the fact that we replicated the choice overload effect is noteworthy. The overall effect is rather small—as denoted by the confidence intervals—rendering the conflicting meta-analyses more understandable. Moreover, interpretation of this main effect is tempered by the observation of statistical interaction effects from our other analyses.

Second, only one of the two potential cognitive mechanisms from Jessup et al. (2009) was supported, despite both being classified within the decision difficulty moderator (Chernev et al., 2015). Interestingly, the preference change mechanism of decision field theory received no support despite the fact that it encompassed the notion of conflict overwhelming individuals thereby precluding choice, an idea central to many of the initial observations and reports of the choice overload and other similar deferral effects (Iyengar et al., 2000; Schwartz, 2004; Tversky et al., 1992). Nonetheless, the effect on choice deferral of alignable and nonalignable sets (Gourville et al., 2005), represented in our data as similarity (or the inverse of conflict), is supported via our second manipulation check. One resolution to this apparent conflict in results is that the flaw may be in the preference change mechanism as presently implemented by decision field theory. Perhaps individuals alter their behavior beyond the underlying assumptions of decision field theory, depending on the different factors that were tested here. If the assumptions of the preference change mechanism are wrong, then the choice overload effect may fail to materialize where predicted. Probing this represents one of many avenues of future exploration exposed by the present work.

We found strong support for the time-out mechanism of decision field theory for choice overload, that is, individuals under time pressure are less likely to make a choice from large (relative to small) sets of options. This is also consistent with other recent findings that many choice deferral effects can be explained by a dynamic model that incorporates deferral via a temporal threshold (Bhatia & Mullett, 2016).

Haynes (2009) also tested time pressure as a potential mechanism for the choice overload effect. Yet he examined a fundamentally different set of dependent variables and his findings were rather mixed. Dhar et al. (1999) narrowly examined the effect that time pressure exerts on choice deferral but their study differed from ours in significant aspects, including only one set size (two) and a time-pressure condition that was more similar in time allowed for choosing to our no-pressure condition. Their work highlights some effect of time pressure in small sets, whereas we show support for the effect across both small and large sets.

Third, modeling via simulations add to the behavioral findings. Although the tested models predicted the effect (Jessup et al., 2009), their predictions were no guarantee (a) that the effect would emerge (Scheibehenne et al., 2010) or (b) emerge in a manner consistent with the models. Nonetheless, the model fitting results supported the behavioral results and the comparison of best-fitting parameter values, demonstrating that the model incorporated notions of time pressure despite not receiving any explicit information regarding time pressure beyond the options considered and the choice made.

It is possible that the choice overload effects that we observed were driven by learning, rather than decision, effects; such learning effects were possible because of the repeated nature of our design. The fact that our results were identical, even when considering the first block of responses (i.e., before feedback was given), suggests that the effects did emerge rather quickly, and, if because of learning, then the learning occurred in the absence of feedback.

It is also possible that the usage of visually presented bars made dominance easier to detect (see Figure 4) in our experimental task relative to typical tasks. Because of the lack of high-density process data (e.g., eye tracking), it is difficult to know for certain what participants were considering when making their selections; when asked to describe their strategy, 60% of participants mentioned that they examined the attributes with approximately two thirds of these reporting that they focused on one to two attributes (the attributes in focus differed between participants).

Although the particular application of time pressure in the present task was rather unrealistic, the goal of this manipulation was to effectively force this experimental group to act in accordance with the time-out explanation to see whether it could produce the effect. More ecologically valid efforts could be attempted in future work (e.g., finding individuals who are already in a hurry, etc.).

We did not find support for the hypothesis that the extent to which one is a maximizer, as indicated by one's RAMS score, influenced the prevalence of choice overload. A more thorough examination might have revealed an effect, but this was not a primary concern so we chose not to pursue it.

We believe that, consistent with Scheibehenne et al. (2010), the choice overload effect probably does not emerge very often. Here in contrived experimental circumstances meant to elicit the effect, we found a small one at the overall level (Cohen's d = .18). When under time pressure, the effect increases (Cohen's d = .42) to a medium effect size. Both of the above points are important: The effect is small but time pressure exacerbates it. Taken as a whole, our findings lend credence to an approach for understanding consumer choice via underlying cognitive processes, representing yet another successful foray of cognitive models such as decision field theory into the consumer choice field (Roe et al., 2001).

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