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Does greater product information actually inform consumer decisions? The relationship between product information quantity and diversity of consumer decisions

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ABSTRACT

For many consumer goods, the advent of online markets dramatically increases the amount of information available about products' different features and qualities. Although numerous studies have investigated the effects of information quantity on individual-level decisions, it is still unknown how the amount of attribute information affects group-level patterns of behavior, particularly when consumers are also aware of a choice's popularity. In the present studies, we hypothesized that when attribute information increases, it may exceed the individual's cognitive capacity to process this information, and as a result conformity – choosing the most popular item – becomes more likely. In this study, we first examined empirical data collected from human subject experiments in a simulated online shopping experience, and then developed an agent-based model (ABM) to explore this behavioral clustering. Both studies confirmed our primary hypotheses, and the ABM shows promise as a tool for exploring extensions of these ideas.

1. Introduction

With the rise of the internet and online shopping, consumers confront an unprecedented amount of information when purchasing even the most mundane products. How do consumers react to this richness of available information? Classical economic theories predict that more information will lead to a greater diversity of decisions, reflecting the diversity of individuals' needs and preferences. These theories often assume that consumers are rational and that their information-processing capacity is unlimited—whatever information is available about products will be used fully and efficiently (e.g. Becker, 1976). The behavior of real human agents falls short of this ideal, however. Many empirical studies suggest human cognitive

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processing is limited (Bettman, 1979; Cowan, 2000; Miller, 1956; Streufert & Driver, 1965), thus the quantity of information available can sometimes exceed processing capacity. In this state, which we will refer to as a state of cognitive overload (Schroder, Driver, & Streufert, 1967; Schwartz, 2005), decision-makers focus on only a few facets of the information available and frequently rely on mental shortcuts and simpler strategies (Einhorn, 1970; Grether & Wilde, 1983; Tversky, 1972). One such strategy for simplifying the decision process is to rely on what other people have chosen, often called ''social learning'' (Boyd & Richerson, 1982, 1985; Efferson, Lalive, Richerson, McElreath, & Lubell, 2008).

If a sufficiently large proportion of individuals rely on a social learning strategy, the group will tend to converge on one behavior; as more people adopt the behaviors of those who came before, the group as a whole will come to favor the same choice. For instance, in the well-known ''sky-watching'' experiment conducted by Milgram, Bickman, and Berkowitz (1969), a few confederates stood on a sidewalk and looked up at the sky. As passersby adopted a ''social learning'' strategy – looking up at the sky as well – the group converged on sky-watching, and the researchers had to stop the experiment because the crowd began to block the entire street. Because popularity information and a large quantity of product information are available on many online shopping sites (e.g., Amazon.com) today, many consumers may conform to the choices of others. As a result, more information will lead consumers' decisions to become less – not more – diverse.

By converging on a single product, however, consumers may fail to choose the highest quality option (Arthur, 1989). For instance, the sky-watching experiment above shows that many pedestrians will follow others and look up the sky even when there is nothing to look at. Likewise, as information increases and more consumers experience cognitive overload, switching to a social learning strategy, the group should become more likely to converge on objectively poorer products. This prediction stands in contrast to classical economic theories, which assume that because all information is considered for decisions, more information will lead consumers to make better choices.

In the current research we explored the interaction of information quantity and product popularity in two ways. First, we conducted an experiment with human subjects in a simulated online shopping experiment to test the hypothesis that large amounts of product information lead consumers to conform to the choices of others. We then simulated this scenario with an agent-based model (ABM), a technique that facilitates scientific exploration of how group-level patterns of behavioral clustering can emerge from individual-level decisions (Goldstone & Janssen, 2005). In particular, the ABM allowed us to observe how information quantity affected the quality of consumer choices because we could control agent preferences and then measure how well they were satisfied.

2. Study 1: Human performance in a simulated online shopping environment

We first conducted an empirical study that put real participants in a simulated online shopping situation. Two independent variables were manipulated: product information quantity (moderate or high), and the presence or absence of information depicting the popularity of the items (we will refer to these two separate conditions as the ''public'' and ''private'' environments). We hypothesized that when the product information quantity was high, and participants had access to popularity information (i.e., in the public environment), the participants would rely on this information and ''herd'' to the most popular choice.

2.1. Methods

2.1.1. Participants

Four hundred ninety-four undergraduates (223 male, 258 female, and 13 gender-unidentified) at Arizona State University participated in this experiment in exchange for extra course credit. The majority (91%) were recruited from an introductory psychology course. The others were recruited from an upper division social psychology class.

2.1.2. Products

Five product categories (digital cameras, headphones, music CDs, books and detergents) were used in this experiment. Five fictional products were created for each product category. The descriptions of all items were selected from online shopping web sites, such that all products in each category had somewhat similar qualities, but neither actual brand information nor pictures of the products was included. Each product was presented with either a large or moderate amount of information concerning its attributes. For the digital camera, headphones and detergent categories, a large amount of information was operationalized as 20–25 items in the product description, while moderate amounts for these categories included only 7–9 pieces of information. For the CD and book categories, a large amount of information was operationalized as including 800–1000 words of reviews for each product, while a moderate amount of information was operationalized as 200–300 words.

2.1.3. Design and procedure

This experiment was a 2×2 mixed factorial design, varying both the environments (between-subject: private versus public) and the information quantity for each product (within-subject: moderate versus large). Participants were randomly assigned to either the private or public decision-making environments. In the public environment, participants were able to view a bar graph indicating how many people had chosen each of the products, while in the private environment this

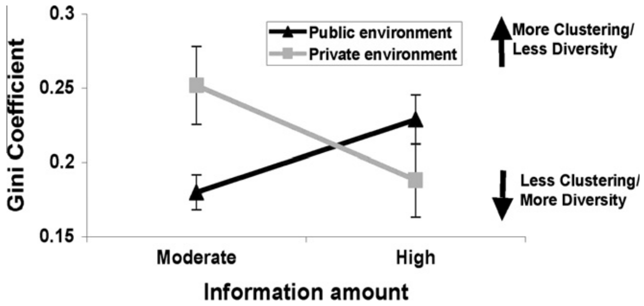

Fig. 1. Gini coefficient and quantity of information for online experiment, the vertical axis indicates clustering levels; higher Gini coefficients mean higher clustering levels. The bars represent ±1 standard errors of the mean.

information was not available. To give their choices real consequences, participants were informed that they would have a chance to win a real version of the products that they chose in this experiment at the end of the semester.

At the onset of each trial, the screen displayed the message "in the next session, you must choose one digital camera (or headphone/music CD/book/detergent) among five". Once each trial started, one of the five product categories was displayed, and information for the five products in that category was shown on the screen. Both the order of the product categories and the presentation of products within the categories were randomized across participants. In the public environment, participants were also presented with a link that, once clicked, displayed the popularity of each product as a bar graph on a separate page. Participants made their final decision by clicking on a check box with the corresponding product name and submitted their choices by clicking on the submit button on the bottom of the page. They then proceeded in the same fashion for the other four products. After all the trials had been completed, participants were debriefed and dismissed. The experiment lasted about 15–20 min.

2.1.4. Analysis

Because our interest was in behavioral clustering, we conducted our analysis at the aggregate level, using each of the five product types as the unit of analysis. A 2×2 mixed factor Analysis of Variance (ANOVA) was conducted by calculating the degree of clustering of choices for each product type within each condition: public vs. private environment (between-subjects factor) and large vs. moderate information quantity (within-subjects factor).

We used the Gini coefficient to characterize the degree of behavioral clustering for each product. The Gini coefficient is a measure of statistical dispersion, often used to measure inequity of income distribution among and within countries (Gini, 1921). The range of this coefficient is 0–1[1]; a low Gini coefficient (close to 0) indicates choices spread more equally across the options, while a high Gini coefficient (close to 1) indicates a greater degree of clustering and hence a lower diversity of choices. Clustering is a group-level behavior; the Gini coefficient is calculated for each product category (e.g., a separate calculation for cameras, for CDs, etc.) as a function of participants' choices. For the current analyses, therefore, the product category's Gini coefficients become the unit of analysis, instead of the participants' individual choices of those products.

2.1.5. Results

There was a significant two-way interaction of product information density (within-subjects factor) and whether participants had access to popularity information (between-subjects factor) ($F(1, 9) = 22.17$, $p < .01$). Simple effects tests showed that participants in the public environment tended to choose more similar products given a large amount of information compared to a moderate amount (two-tailed paired t-test: $t(4) = 2.65$, $p = .057$). In contrast, the participants in the private environment chose more similar products when a moderate amount of information was available compared to a high amount (two-tailed paired t-test: $t(4) = 4.19$, $p = .014$) (Fig. 1).

These differences in diversity of choices strongly support our hypothesis that participants in the public environment chose the item that was most popular at the time of their decision, whereas those in the private environment did not. To confirm this, we examined the proportion of people choosing the most popular item in each of the five product categories, and then proportions were compared across the large and moderate information conditions within each environment (using a paired t-test, which corresponds to the simple effect reported above). As predicted, in the private environment, more people in the large information condition chose the most popular product relative to the moderate information condition (two-tailed paired t-test: $t(4) = 3.60$, $p = .027$). In the private condition, the effect was in the opposite direction, with more participants choosing the most popular item given moderate amounts of information vs. large amounts (two-tailed paired t-test: $t(4) = 2.52$, $p = .067$). These results confirm the Gini coefficient results: The participants chose the most popular option in the public environment, while they did not in the private environment. The summary of these results is presented in Table 1.

[1] With a limited number of product options, as was the case in this experiment, the upper limit for the Gini coefficient is actually lower—around 0.8—but the relative differences remain meaningful because this upper limit is constant across experimental conditions.

Table 1
Number and proportion of participants choosing each item (most popular to least) within each product category in (a) public and (b) private environments, with Gini coefficients (*G*).

Information amount	Most popular			Least popular		
(a) Public						
Camera						*G*
High	53(39%)	26(19%)	25(18%)	21(15%)	11(8%)	0.25
Moderate	38(35%)	24(22%)	22(20%)	15(14%)	10(9%)	0.22
Headphones						*G*
High	49(39%)	26(21%)	22(18%)	16(13%)	12(10%)	0.27
Moderate	37(31%)	25(21%)	23(19%)	21(18%)	13(11%)	0.17
Detergent						*G*
High	39(30%)	32(25%)	22(17%)	21(16%)	15(12%)	0.18
Moderate	31(27%)	27(24%)	24(21%)	18(16%)	13(12%)	0.16
Music						*G*
High	36(31%)	30(26%)	28(24%)	12(10%)	10(9%)	0.25
Moderate	37(30%)	27(22%)	27(22%)	19(15%)	15(12%)	0.15
Book						*G*
High	39(38%)	19(18%)	16(15%)	16(15%)	14(13%)	0.2
Moderate	47(34%)	28(20%)	25(18%)	24(17%)	15(11%)	0.2
(b) Private						
Camera						*G*
High	41(36%)	28(25%)	20(18%)	15(13%)	9(8%)	0.25
Moderate	44(38%)	35(30%)	19(16%)	12(10%)	6(5%)	0.34
Headphones						*G*
High	40(34%)	23(19%)	21(18%)	20(17%)	15(13%)	0.17
Moderate	38(36%)	28(27%)	15(14%)	14(13%)	10(10%)	0.26
Detergent						*G*
High	32(28%)	26(23%)	21(18%)	18(16%)	17(15%)	0.14
Moderate	33(30%)	25(23%)	21(19%)	20(18%)	10(9%)	0.18
Music						*G*
High	30(28%)	23(21%)	22(21%)	19(18%)	13(12%)	0.14
Moderate	38(32%)	31(26%)	20(17%)	18(15%)	11(9%)	0.22
Book						*G*
High	44(41%)	19(18%)	19(18%)	14(13%)	12(11%)	0.24
Moderate	46(40%)	22(19%)	19(17%)	16(14%)	12(10%)	0.26

2.1.6. Discussion

We predicted that providing too much information about consumer products would lead participants to rely on popularity information, which would in turn increase the clustering of consumers' choices on the most popular item. The online shopping experiment showed precisely this. It also showed an unexpected effect: despite the absence of popularity information, participants in the moderate information condition were more likely to choose the most popular item relative to those in the large information condition. This may suggest that at manageable levels of product information amount, participants converge on similar decisions because they have similar preferences. However, without being able to observe consumer preferences (let alone whether cognitive capacities were exceeded), it is difficult to draw any clear conclusions about the nature of this unpredicted effect in the private environment. Note, however, that this unexpected finding does not in any way negate the deleterious effects of a large amount of information on the diversity of choices made in the public environment, which is the primary interest of this investigation.

As noted above, one implication of the primary result is that a reliance on popularity information may undermine the degree to which consumers choose products that actually map onto their preferences. Previous studies have found that more information leads to suboptimal choices (Chewning & Harrell, 1990; Cook, 1993; Griffeth, Carson, & Wilde, 1985; Lee & Lee, 2004; Scammon, 1977; Schroder et al., 1967; Swain & Haka, 2000). With real human subjects, it is difficult to assess how successfully choices map onto preferences, because satisfaction with the product is usually hard to observe. Simulating the agents in an online shopping environment gave us the opportunity to control these factors and more fully explore how the quantity of information affected reliance on popularity information.

3. Study 2: Agent-based computer simulation

Study 2 used an agent-based model to simulate the online shopping process observed in Study 1. We generated populations of consumer agents, each with a specific cognitive capacity for processing information. An agent's probability of picking the best option declined once product information content exceeded its cognitive capacity. If the agent had access to popularity information, it could compensate for this cognitive overload by using a social learning strategy. We used the model to determine how behavioral clustering and decision performance varied with the amount of product information and with the agents' access to popularity information.

3.1. Products

In each model run, 500 agents chose among five product options. In order to allow diversity in preferences, products were characterized by 10 features. The value of each feature was randomly determined to be a number between 1 and 100, with higher values indicating better quality. For each agent, one of 10 features was randomly chosen as the preferred feature, so the product with the highest value in that feature was the best one for her. Therefore, the "best" product could be different for different agents. In addition to these features, we characterized the total amount of product information that was available to agents. We treated the number of features and the information amount as independent variables and manipulated only the amount of information across simulations. This allowed us to maintain the same underlying diversity of preferences while manipulating the agents' information-processing burden. Thus, in all simulations the number of product features was ten, but the amount of available information varied from moderate to high.

3.2. Cognitive capacity of agents

Each agent had a randomly determined cognitive capacity, operationalized as a function representing the probability that the agent makes the best choice given a certain amount of information.

$$F(x) = \frac{2\left(\frac{x}{M}\right)}{1 + \left(\frac{x}{M}\right)^2} \tag{1}$$

The parameter x is the amount of product information, and the parameter M is the optimal amount of information. These two parameters determine $F(x)$, the probability of making the best choice given a certain amount of information (Fig. 2). This probability increases with x until it reaches the optimal value M. Performance then declines with still higher values of x, reflecting the agent's inability to process this amount of information adequately. For each agent, M was chosen from a normal distribution with a mean of 5 and standard deviation of 1; we chose this mean arbitrarily, though note that choosing a different number would not qualitatively change the results of the simulation. For comparison, we also developed "rational-economic" agents that had unlimited cognitive capacities; that is, they always chose the best option regardless of the amount of information.

3.3. Decision-making in public and private environments

The agents' decision-making strategies depended on whether they were in a public or private environment. In the private environment, agents had to rely solely on their individual learning strategies no matter how much information was available. In the public environment, they turned to a social learning strategy when information exceeded their comfort zones: They chose the most popular product and thus conformed to the majority's decision. We defined the comfort zone as the *range of information quantities* that would produce a probability of 0.85 of choosing the right product. The limits of this zone varied among agents. For example, if the agent with the cognitive capacity function illustrated in Fig. 2 (with $M = 5$) were given an information amount larger than 9 in the public environment, it would use the social learning strategy. Note that since the rational-economic agents could always choose the best option by themselves (i.e. $F(x) = 1$), and they never used the social learning strategy, no matter how much information was available.

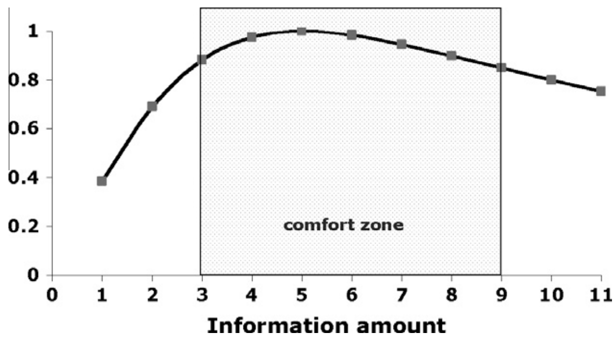

Fig. 2. Cognitive capacity function ($M = 5$).

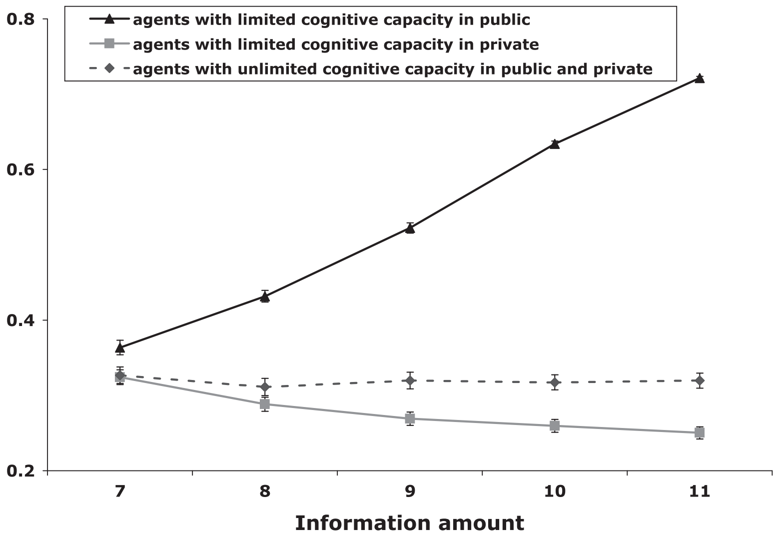

Fig. 3. Gini coefficient and amount of information for the computer simulations. The bars represent ±1 standard errors of the mean.

3.4. Process overview and scheduling

Simulations were run in two environments (private and public), and with five different amounts of information (x), ranging from 7 (moderate) to 11 (large) at integer steps. All information amounts were relatively high, since we were interested in effects of cognitive overload. Each combination of environment and information amount was simulated twice, once with 500 cognitively limited agents and once with 500 unlimited ones. Thus there were 20 simulation types in all, each of which was run 100 times. During each simulation, agents were randomly selected one at a time to choose among five products. The selected product's popularity value was increased for subsequent choices.

At the conclusion of each run, we assessed the degree of behavioral clustering with the Gini coefficient, as well as the overall quality of the choices. This ABM (and the code that produced it) is available online.[2]

3.5. Results and discussion

The results clearly replicate the patterns seen in the empirical study: As the amount of information increased, clustering of choices decreased in the private decision-making environment (linear regression: $\beta = -0.017$, $F(1, 498) = 38.95$, $p < 0.001$), whereas clustering increased in the public environment (linear regression: $\beta = 0.092$, $F(1, 498) = 1887$, $p < 0.001$; Fig. 3). The only difference between the environments was that in the private condition, the subjects had to use the individual learning strategy even when the amount of information exceeded their cognitive capacity, but in the public condition they were able to use the social learning strategy. In contrast to the results for the limited-capacity models, clustering in the rational economic model (in which cognitive capacities were unlimited) was unchanged by the amount of information and whether the environment was public or private (linear regression: $\beta = 0.001$, $F(1, 498) = 0.058$, $p = 0.81$) (Fig. 3). These findings provide corroborating evidence that behavioral clustering of actual consumers (as observed in Study 1) emerges when limited cognitive capacities confront large amounts of information, leading consumers to blindly follow, if possible, the majority's choice.

Because measures of clustering do not reflect choice quality, we next examined the overall quality of the choices made in the private and public environments. We determined the quality of each agent's choice using only its preferred feature. That is, the quality of each agent's choice was defined as the score of its preferred feature in the chosen product. The results show that for both the public and private environments, the quality of the choices decreased as the amount of information increased (linear regressions: $\beta = -6.95$, $F(1, 498) = 1223$, $p < 0.01$ for public environment and $\beta = -1.71$, $F(1, 498) = 162$, $p < 0.01$ for private environment) (Fig. 4). Moreover, the slope for the public environment was much steeper than the one for the private environment, meaning that a large amount of information significantly impaired the quality of choices more in a public than in a private environment (ANCOVA: $F(1, 996) = 475$, $p < 0.01$). This difference can be explained by the greater number of agents using the social learning strategy in a public environment.

Theoretical papers have suggested that a group composed of individual and social learners (i.e. public group) performs better than a group composed only of individual learners (i.e. private group) when a majority of the public group uses the individual learning strategy (Rogers, 1988). However, when the majority uses the social learning strategy, the public

[2] http://www.openabm.org/model-archive/diversity_of_choices_for_different_amounts_of_product_information.

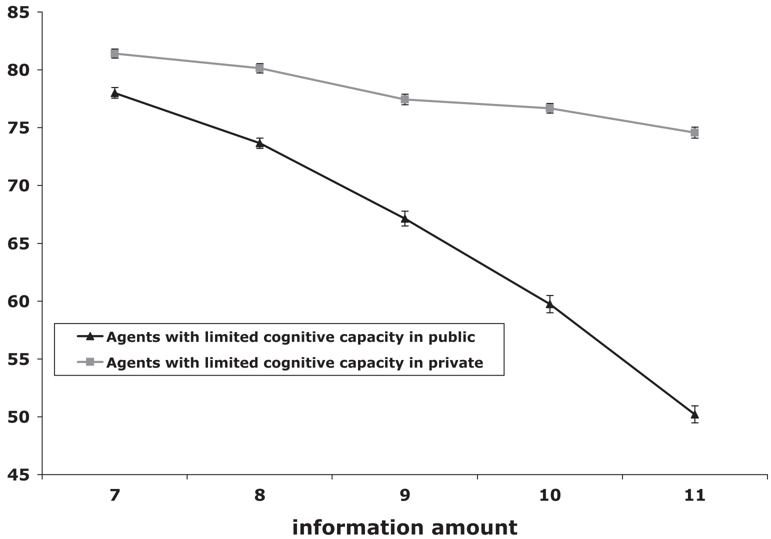

Fig. 4. Quality of choices and amount of information for the computer simulations. The bars represent ±1 standard errors of the mean.

group's performance is worse than the private group because as the number of social learners increases, so does the likelihood of clustering around a potentially suboptimal choice. In our simulation, as the amount of information increased, it exceeded the cognitive capacity of more and more agents, forcing them to use the social learning strategy (e.g., when $x = 7$ and 11, mean numbers of social learners were 69 and 435, respectively). As a result, a large amount of information impaired the quality of choices more in a public than in a private environment.

4. General discussion

Traditional economic theories would predict that if humans did not experience cognitive overload and always used an individual learning strategy, the diversity of choices should not be affected by the availability of social information. However, our experiments showed a clear effect of social information on the degree of behavioral clustering. Participants in the public environment tended to choose more similar products when given a high amount of product information than when given a moderate amount. In contrast, participants in the private environment showed the opposite pattern, choosing more similar products when given a moderate amount of product information. Our ABM results support the conclusion that these effects were due to reliance on product popularity when high information content caused cognitive overload.

Although overall patterns in the empirical data were consistent with the ABM data, the Gini coefficients obtained for human subjects in the public environment were slightly different from the ones in the ABM. For example, human subjects given moderate amounts of information showed a greater diversity of choices in the public than in the private condition. That is, subjects tended to choose different products from one another when they knew what others had chosen. The ABM predicted no difference in choice diversity between these two conditions. A possible explanation for this discrepancy is that some people engage in anti-conformity as a way of standing out from the crowd (Laland, 2004). For example, one experiment found that people in bars were more likely to choose different types of beer from each other if they ordered sequentially and their orders were publically known than if they ordered simultaneously and their orders are confidential (Ariely & Levav, 2000). Despite this particular discrepancy between the experiment and the ABM, we believe that the general picture that emerged was quite consistent.

To the best of our knowledge, this is the first study using ABMs to investigate consumer decision making as a function of the amount of product information and the availability of popularity information. Our results are relevant to advertising, marketing, and especially online markets where the amount of information is usually high. Today, online stores typically provide highly detailed information about products to help consumers satisfy their unique preferences. Ironically, our results suggest that as we have more information about products, one product is more likely to gain market dominance over others regardless our different preferences, a phenomenon known as "lock-in" (Arthur, 1989). Furthermore, the product that wins this popularity contest is not necessarily the best one available. In future research, it will be important to explore how the amount of information affects this lock-in tendency, and the ABM developed here is a promising tool to do so.

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References

Ariely, D., & Levav, J. (2000). Sequential choice in group settings: Taking the road less traveled and less enjoyed. *Journal of Consumer Research, 27*(3), 279–290.
Arthur, W. B. (1989). Competing technologies, increasing returns, and lock-in by historical events. *The Economic Journal, 99*, 116–131.
Becker, G. S. (1976). The Economic Approach to Human Behavior. Chicago: University of Chicago Press.
Bettman, J. R. (1979). *An information processing theory of consumer choice*. MA: Addison-Wesley.
Boyd, R., & Richerson, P. J. (1982). Cultural transmission and the evolution of cooperative behavior. *Human Ecology, 10*(3), 325–351.
Boyd, R., & Richerson, P. J. (1985). *Culture and the evolutionary process*. Chicago: The University of Chicago Press.
Chewning, E. C., Jr., & Harrell, A. M. (1990). The effect of information load on decision maker's cue utilization levels and decision quality in a financial distress decision task. *Accounting, Organizations and Society, 15*, 527–542.
Cook, G. J. (1993). An empirical investigation of information search strategies with implications for decision support system design. *Decision Sciences, 24*, 683–699.
Cowan, N. (2000). The magical number 4 in short-term memory: A reconsideration of mental storage capacity. *Behavioral Brain Science, 24*, 87–185.
Efferson, C., Lalive, R., Richerson, P. J., McElreath, R., & Lubell, M. (2008). Conformists and mavericks: The empirics of frequency-dependent cultural transmission. *Evolution and Human Behavior, 29*, 56–64.
Einhorn, H. J. (1970). The use of nonlinear, noncompensatory models in decision making. *Psychological Bulletin, 73*, 211–230.
Gini, C. (1921). Measurement of inequality and incomes. *The Economic Journal, 31*, 124–126.
Goldstone, R. L., & Janssen, M. A. (2005). Computational models of collective behaviour. *Trends in Cognitive Science, 9*(9), 424–430.
Grether, D. M., & Wilde, L. L. (1983). Consumer choice and information: New experimental evidence. *Information Economics and Policy, 1*, 115–144.
Griffeth, R. W., Carson, K. D., & Wilde, L. (1985). The irrelevance of information overload: An analysis of search and disclosure. *Southern California Management Review, 59*, 277–303.
Laland, K. N. (2004). Social learning strategies. *Learning and Behavior, 32*, 4–14.
Lee, B., & Lee, W. (2004). The effect of information overload on consumer choice quality in an on-line environment. *Psychology & Marketing, 21*(3), 159–183.
Milgram, S., Bickman, L., & Berkowitz, L. (1969). Note on the drawing power of crowds of different size. *Journal of Personality and Social Psychology, 13*, 79–82.
Miller, G. A. (1956). The Magical Number Seven or Minus Two: Some Limits on Our Capacity of Processing Information. *Psychological Review, 63*, 81–97.
Rogers, A. R. (1988). Does biology constrain culture? *American Anthropology, 90*(4), 819–831.
Scammon, D. L. (1977). 'Information load' and consumers. *Journal of Consumer Research, 4*, 148–156.
Schroder, H. M., Driver, M. J., & Streufert, S. (1967). *Human information processing—Individuals and groups functioning in complex social situations*. New York: Holt, Rinehart, & Winston.
Schwartz, B. (2005). *The paradox of choice. Why more is less*. NY: HarperCollins.
Streufert, S., & Driver, M. J. (1965). Conceptual structure, information load and perceptual complexity. *Psychonomic Science, 3*, 249–250.
Swain, M. R., & Haka, S. F. (2000). Effects of information load on capital budgeting decisions. *Behavioral Research in Accounting, 12*, 171–199.
Tversky, Amos. (1972). Choice by elimination. *Journal of Mathematical Psychology, 9*, 341–367.