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## Replication

## Is there a mere categorization effect in investment decisions?☆

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## ABSTRACT

This study seeks to replicate and extend the work of Mogilner, Rudnick, and Iyengar (2008) on the mere categorization effect (i.e., placing choice options into categories – even uninformative ones – can increase perceived variety and choice satisfaction among novices). This effect did not extend to the context of investments. We suggest that decision complexity and intangibility are possible boundary conditions such that consumers expend additional cognitive effort rather than rely on heuristics such as perceptual variety cues.

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## 1. Introduction

Mogilner et al. (2008) observed a mere categorization effect wherein consumers unfamiliar with a choice context consider the number of categories as an indicator of variety. As a result, merely organizing choice options into categories – even uninformative ones – can increase perceived variety and choice satisfaction.

The original study considered relatively simple decisions regarding tangible goods (e.g., choosing among different types of coffee or magazines) with choice sets divided into one of four categorization conditions conveying different levels of information regarding the available choices (i.e. no categories, uninformative categories, semi-informative categories, and informative categories). The results revealed a significant interaction between expertise and categorization. Choosers with less expertise reported higher choice satisfaction with categorization relative to no categories; even in the case of uninformative categories. Choosers with more expertise reported no difference in choice satisfaction across the categorization conditions. Terming the effect “mere categorization”, the original study suggested that choosers with less expertise or familiarity with the choice set consider categorization to be an indicator for variety leading to increased choice satisfaction. The current research sought to replicate the mere categorization effect in the context of a more complex decision regarding an intangible service (namely choosing among different mutual funds). With a healthy debate continuing regarding dual process cognition theories (Evans & Stanovich, 2013), such as heuristic versus systematic processing, it is interesting to consider whether a change in context can alter the use and relevance of perceptual cues such as the mere categorization effect. For instance, do novice investors continue to use the number of categories as a cue for variety leading to increased satisfaction with choice? This research suggests possible boundary conditions to the mere categorization effect.

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## 2. Study design and measures

The current study involved a computer-based exercise of constructing a hypothetical investment portfolio (worth \$250,000) using a highly representative list of mutual funds. Three hundred forty-one participants were recruited from a volunteer pool of third year undergraduate business and economics students in a North American university and they received course credit for participation. The study was a 3(category type: no categories, uninformative categories, informative categories)  $\times$  2(chooser type: novices, experts) design. The stimuli were a list of 50 funds drawn from [www.morningstar.ca](http://www.morningstar.ca), an on-line database of actual mutual funds. Each list included information about the, 1-year, 3-year and 5-year percentage returns to indicate performance, and the standard deviation of returns to indicate volatility. The actual fund names were replaced with a descriptive name to avoid confounds. Random assignment placed respondents into one of the 3 category-type conditions. In the no categories condition, participants chose from a simple list of 50 mutual funds. The uninformative categories condition presented the same 50 mutual funds divided equally into 10 uninformative categories (Group A, B, C, etc.). The final condition provided 10 informative categories as labels (e.g., “U.S. Equity,” “Global Money Market,” etc., drawn from the actual category labels provided by Morningstar). As in Mogilner et al. (2008), participants reported their choice satisfaction, perceived variety, preference identification, self-determination and finally, familiarity with the choice set as a measure of expertise. In addition, participants reported on decision difficulty and confidence in their decision. As such, this replicates Mogilner et al.’s (2008) Study 2, which used 50 flavors of coffee as the stimuli (divided into no categories vs. 10 uninformative vs. 10 somewhat informative vs. 10 informative categories). See the Supplementary Online Appendix A for more details about the study design and stimuli.

## 3. Analysis and results

Mogilner et al. (2008) grouped respondents as experts or novices based on a dichotomization of expertise measured by 3 items regarding familiarity with the choice set. ANOVA results showed that dividing the available options into categories increased choice satisfaction due to increased perceived variety for novices but not for experts. Using the same method in the current study, pairwise comparisons in a 3(category type: none, uninformative, informative)  $\times$  2(chooser type: novices, experts) ANOVA on satisfaction showed novices reporting no significant difference in satisfaction for the uninformative categories condition ( $M = 4.23$ ) as compared to no categories ( $M = 4.25$ ;  $F(1, 335) = 0.01$ ;  $p = .92$ ; Table 1). There was also no significant difference for no categories compared to informative categories ( $M = 4.28$ ;  $F(1, 335) = 0.01$ ;  $p = .91$ ). For experts, there was also no significant difference in satisfaction between any category types. A manipulation check on the perceived informativeness of the category labels revealed that the manipulation was successful.

Extending the analysis further with floodlight analysis (Spiller, Fitzsimons, Lynch, & McClelland, 2013), we also treated expertise as a continuous variable to avoid reducing the statistical power and also to avoid possible spurious significant results (Fitzsimons, 2008). Regressing satisfaction on category type (none, uninformative, informative), expertise ( $M = 3.33$ ,  $SD = 1.37$ ,  $min = 1$ ,  $max = 6.67$ ), and their interaction revealed no significant effect for uninformative categories versus no categories as the control ( $t(335) = 0.73$ ,  $p = .47$ ), and no significant interaction ( $t(335) = -1.22$ ,  $p = .22$ ). To decompose the results, we used the Johnson–Neyman technique to identify the range(s) of expertise for which the simple effect of uninformative categories was significant. This analysis revealed that there is no significant effect of uninformative categories (vs. no categories) on satisfaction for any levels of expertise (See Fig. 1).

Repeating the above floodlight analysis for perceived variety as the dependent variable revealed no significant effect for uninformative categories ( $t(335) = 0.86$ ,  $p = .39$ ) and no significant interaction ( $t(335) = -0.26$ ,  $p = .79$ ). The Johnson–Neyman technique revealed no level of expertise where the effect of uninformative categories (vs. no categories) on perceived variety was significant (see Supplementary Online Appendix B for details).

To further examine the relationship between categorization, expertise and satisfaction, analysis was conducted on expertise, the difficulty of the decision, and confidence in the decision. Expertise significantly predicted satisfaction,  $B = 0.358$ ,  $t(339) = 7.87$ ,  $p < .001$  and explained a significant proportion of variance in satisfaction,  $R^2 = .15$ ,  $F(1, 339) = 62.00$ ,  $p < .001$ . Expertise also significantly decreased decision difficulty,  $B = -0.29$ ,  $t(339) = -5.77$ ,  $p < .001$  and explained a significant proportion of variance in difficulty,  $R^2 = .09$ ,  $F(1, 339) = 33.34$ ,  $p < .001$ . A floodlight analysis with decision difficulty as the dependent variable revealed no

**Table 1**  
Experiment Results.

	Zero categories		Ten categories			
	Novice	Expert	Uninformative		Informative	
			Novice	Expert	Novice	Expert
Satisfaction	4.25 <sup>a</sup> (1.48)	5.16 <sup>a</sup> (1.09)	4.23 <sup>b</sup> (1.11)	4.84 <sup>b</sup> (1.20)	4.28 <sup>c</sup> (1.11)	5.12 <sup>c</sup> (1.08)
Perceived variety	4.22 <sup>a</sup> (0.95)	4.56 <sup>a</sup> (1.01)	4.34 <sup>b</sup> (0.88)	4.83 <sup>b</sup> (0.90)	4.40 (0.86)	4.63 (0.93)
Preference Identification	3.16 <sup>a</sup> (1.04)	4.05 <sup>a</sup> (1.17)	3.47 <sup>b</sup> (1.23)	3.99 <sup>b</sup> (1.24)	3.55 <sup>c</sup> (1.33)	4.13 <sup>c</sup> (1.31)
Confidence	3.51 <sup>a</sup> (1.44)	4.76 <sup>a</sup> (1.11)	3.56 <sup>b</sup> (1.35)	4.48 <sup>b</sup> (1.26)	3.50 <sup>c</sup> (1.25)	4.72 <sup>c</sup> (1.22)
Difficulty	4.81 <sup>a</sup> (1.29)	4.24 <sup>a</sup> (1.40)	4.92 <sup>b</sup> (1.20)	4.21 <sup>b</sup> (1.24)	5.02 <sup>c</sup> (1.32)	4.20 <sup>c</sup> (1.27)

Note: Numbers in parenthesis are standard deviations. Within each row, means are compared to all other means – matching superscripted letters are significantly different at  $p \leq .05$  significance level.

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