Personalization and the Decoy Effect

Short Paper

Nasim Mousavi
Emory University
Atlanta, GA, USA
nasim.mousavi@emory.edu

Jesse Bockstedt
Emory University
Atlanta, GA, USA
bockstedt@emory.edu

Panagiotis Adamopoulos
Emory University
Atlanta, GA, USA
panagiotis.adamopoulos@emory.edu

Abstract

In this paper, we study how the decoy effect, a well-established context effect, impacts the effectiveness of personalization systems. By conducting a controlled experiment and using a real-world movie recommendation system, we find different behavioral effects in personalized and non-personalized settings. Including a decoy item in a set of recommended items negatively impacts the effectiveness of the personalized recommendations, while it does not hurt the efficacy of a non-personalized one.

Keywords: Personalization, decoy effect, recommendation system, user behavior

Introduction

Technology advancement enables online retailers to track consumer browsing and purchasing behavior, predict their future needs, and show personalized offerings to them. In general, personalization is defined as adjusting content by considering consumers' needs and interests to optimize business opportunities, like sales, consumer engagement, satisfaction, and retention (Tam and Ho 2006). Personalization not only reduces information overload and helps consumers in the decision-making processes but also affects their behavior and preferences.

For instance, it has been shown that personalization increases consumers' engagement, purchasing likelihood, and willingness to pay while reducing search cost, improving decision quality, and increasing choice confidence and loyalty (Adomavicius et al. 2018; Häubl and Trifts 2000; Tam and Ho 2006; Xiao and Benbasat 2007). Moreover, Adomavicius et al. (2013) demonstrated that personalized systems can manipulate consumers' interests towards products. Such effects can have substantial business implications that still remain underexplored in the literature. Therefore, it is important to further investigate the effect of personalization systems on user behavior and investigate ways to improve their effectiveness.

To increase the effectiveness of the personalization systems, it is important to consider consumers' decision-making behavior. According to the literature in marketing, consumer preferences are constructive and context-dependent due to the vast amount of accessible information and the limited processing capacity of consumers (Bettman et al. 1998; Tam and Ho 2006). Scholars have studied contextual factors that might influence consumers' behavior toward a system. Factors such as the number of items suggested by a personalization system, algorithm types used for personalization, user location, a device used, and certain contextual factors have been recognized as important factors (Adamopoulos et al. 2021; Lee et al. 2020; Tam and Ho 2005). Although there is research in this stream, our understanding of the impact of contextual factors on the effectiveness of personalization is still limited.

In this paper, we focus on the theory of decoy (attraction) effect, one of the well-known context effects (Huber et al. 1982) and investigate how adding a decoy can impact the effectiveness of personalized product recommendations. The theory predicts that adding an inferior item (a decoy) to a set of options changes the selection likelihood of items in the set and increases the likelihood of selecting the item that is most similar to -but superior to- the decoy. The decoy effect has been widely studied in the context of regular product advertising and product offerings. However, to the best of our knowledge, no prior research has explored the decoy effect in the context of personalization. It is not clear how the inclusion of a decoy will affect consumer choice when personalized recommendations are provided. On the one hand, including a decoy could be beneficial for a personalization system as it could be used to drive demand to certain items by leveraging the standard decoy effect observed in prior literature (i.e., demand becomes focused toward the similar but superior product). On the other hand, the inclusion of an inferior item may call into question the efficacy of the personalization system, which may result in different consumer choice behavior. To reconcile these opposing views, we performed a randomized controlled choice experiment using a real-world movie recommendation system that provides personalized and non-personalized recommendations. We find that the nature of the decoy effect changes substantially in the context of personalization, and the inclusion of decoys in a set of recommended items can negatively impact the effectiveness of a personalized recommendation system.

Background

Decoy Effect

Individuals typically make judgments relatively, comparing a given item to other available options. To illustrate, in Figure 1, the middle circles in both images are equally sized. However, the circle surrounded by smaller circles seems bigger than the circle surrounded by bigger circles (Todorović 2010). In consumer decision-making, for instance, when selecting a restaurant, the quality of a restaurant is measured relative to other available restaurants (Huber et al. 1982). A restaurant can seem to be high quality among other lower-quality restaurants, while the same restaurant can seem to be a low-quality one among other higher-quality restaurants.

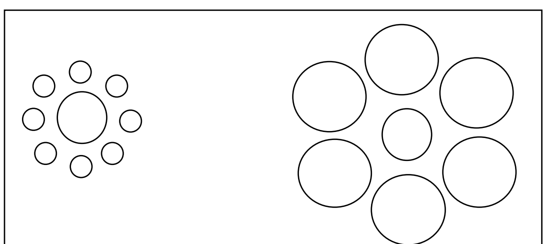

Figure 1. Example of Context Effect

Therefore, when analyzing consumer behavior, it is important to also consider contextual factors. One important factor that can impact consumer judgments and their decisions is the relationships between a focal item and other items in a choice set (Tversky and Simonson 1993). For instance, in the literature on consumer behavior, it has been shown that the presence of an inferior item in a choice set changes the market share of items in that choice set. The effect is called the decoy or attraction effect. Specifically, Huber et al. (1982) conducted multiple experiments using different products, such as cars, restaurants, beers, films. They designed a set of options containing three items: a target item, a competitor, and a decoy item. When the decoy is not present, the choice is between the target and the competitor, and each option has attractive attributes, so demand is often split between these items. However, when a third item that is dominated by the target item (i.e., the decoy) is added to the choice set, we see a shift in demand toward the target item.

Even though the third option is irrelevant as it would not be chosen based on its attributes, its presence can shift consumer preferences because of relative comparisons to the existing items (Luce 1977).

In general, comparing items in a choice set can be a complex decision process that can often result in the deferment of the item selection (Dhar 1997; Tversky and Shafir 1992). Additionally, even when consumers select an available option, the likelihood that they regret their choice is high (Chernev et al. 2015). Adding a decoy to a choice set makes one of the items clearly superior in 'consumers' eyes and creates the opportunity for a decision heuristic, which makes the decision-making easier for consumers, and the final choice becomes more justifiable, thus reducing regret (Huber et al. 1982; Simonson 1989; Pechtl 2009).

Personalization

The decoy effect has been demonstrated in many contexts, with the Economist subscription experiment[1] as one of the most famous examples (Ariely 2009). However, no prior research has considered how the role of the decoy might change in the context of personalization. Since, increasingly, the content and product choices shown to consumers are driven by personalization systems, it is a worthwhile pursuit to investigate how the introduction of decoys influences consumer choice in such settings.

Personalization as a marketing strategy has changed consumers' information processing and decision-making processes by reducing search costs and improving decision quality (Häubl and Trifts 2000; Hostler et al. 2005; Pathak et al. 2010). However, the effectiveness of personalization systems can be also influenced by contextual factors that are outside of the system, such as the order of personalized content, time, location, presence of others. For instance, Tam and Ho (2005) showed that a larger set of personalized recommended items attracts more user attention towards the personalized contents. Moreover, to examine the impact of time and crowd pressure, Kawaguchi et al. (2019) conducted a field experiment using beverage vending machines in train stations and showed that time pressure negatively impacts the effectiveness of product recommendations. Moreover, crowd pressure can slightly increase the effectiveness. Furthermore, Adamopoulos et al. (2021) illustrated contextual factors, such as traffic, weather, mobile networks, etc., can impact the effectiveness of the recommendation system in the mobile channel. For instance, their findings revealed that traffic levels impact the effectiveness of recommendation system by impacting consumer mood. In a lower traffic level, people are in a more positive mood and are more responsive to the recommendation systems.

Hypothesis

Using personalization systems and choosing an item from a set generally involves a certain level of cognitive load for customers. This load is typically a function of how complex it is to compare and evaluate the alternative items. When customers are offered a list of equally attractive items, they need to compare them across multiple dimensions and values. Since there are no clear contrasts or clearly superior items, customers may engage in an exhaustive search. Studies have found that the inclusion of a decoy item can simplify the choice by creating clear contrasts between some items, requiring less cognitive burden and increasing higher satisfaction and confidence (Huber et al. 1982; Simonson 1989).

The decoy effect has only been studied in non-personalized settings (e.g., Huber et al. 1982, Simonson 1989, Simonson and Tversky 1992). However, personalized settings have unique characteristics that might alter customer behavior and expectation, rendering the decoy less effective. Particularly, in the personalized setting, customers expect to see relevant items that strongly match their needs and interests. They also expect the system to be credible and reliable enough to help them in the decision-making process (Briggs et al. 2002; Xiao and Benbasat 2007).

To examine what these differences between personalized and non-personalized settings mean for the effect of including a decoy item, we use persuasion theory (Cialdini and Cialdini 2007). Persuasion theory is particularly applicable in our context because personalization is a communication channel through which

[1] (Ariely 2009) conducted an experiment to encourage subscription of the magazine, with the options of online ($59), print ($125), and print & online ($125). The results showed that including the print ($125) option as the decoy one, increased the demand for print & online ($125).

companies communicate messages with their customers (Tam and Ho 2005). To have an effective communication, the personalization system needs to provide a persuasive message to attract consumers' attention.

According to the persuasion theory, source credibility and message quality are the two main factors that impact persuasion (Kumkale et al. 2010; Petty 2018). Source credibility demonstrates the expertise and reliability of an advocator. Encountering a message from a reliable source increases consumers' attention and confidence and enhances the chance of message acceptance (Petty 2018; Pornpitakpan 2004). Message quality is the other determinant of persuasion (Petty 2018). High-quality messages create favorable thoughts and feelings for users (Areni and Lutz 1988). Importantly, consumers' reliance on source credibility and message quality is different based on issue relevance (Petty and Cacioppo 1979, 1984). In high-relevant conditions, consumers desire more accurate information to make the optimal decision (Petty 2018), and observing low-quality information creates a negative expectation disconfirmation, decreasing the acceptance of the information (Xiao and Benbasat 2007).

This dynamic helps explain how the decoy effect might work differently in a personalized context as compared to a non-personalized context. In the personalized setting, the contents are more fit and relevant to consumers' needs and interests compared to non-personalized settings. Thus, the system's credibility and the quality of recommendations play a more important role in the acceptance of the recommendations. Customers expect the system to know their needs and interests and offer products and services without any bias or manipulation. Including a decoy item with a low chance to match consumers' needs may signal that the system does not have enough knowledge about the consumers' interests, undermining the system's credibility and reliability. Low-quality items can also be a signal for manipulation and biasedness of the system, jeopardizing the user's trust in the system, which is one of the fundamental elements of the acceptance of personalization. Based on the above arguments, we expect that adding an inferior item to a personalized list of items hurts system's credibility and content quality. We hypothesize that:

Hypothesis: In comparison with a non-personalized setting, the decoy effect is weaker in the personalized setting.

Methodology

Experiment

To test the hypothesis, we conducted a controlled lab experiment with 255 participants who were undergraduate students in a leading U.S. business school. The participants' age ranged from 18 to 34 with a mean of 19, and 136 were women. We built a real movie recommendation system using the MovieTweetings dataset[2] (Dooms et al. 2013). In particular, to measure the decoy effect in the personalized setting and compare it with a non-personalized one, we designed a platform that can offer both personalized and non-personalized recommendations. The personalized recommendations are based on a collaborative filtering algorithm (Herlocker et al. 2004) and ratings of movies provided by our experiment participants. The non-personalized recommendations are based on the popularity of movies, measured by the number of reviews and average rating for each movie from the MovieTweetings database.

To generate our personalized recommendations, we provided participants with a list of one hundred movies at the beginning of the experiment and asked them to rate at least 20 movies. For each movie, related information such as name, year, picture, a brief description, and a link to YouTube trailer was provided. Using a within-subject experiment design, users were then randomly assigned to one of the four conditions. In each condition users presented with a list of 5 recommended movies, which were sorted based on prediction scores (for the personalized) or average user ratings (for the non-personalized). In each round, the movies have different genres. For each movie on a recommendations page, an image, a brief description, and a link to the YouTube trailer were provided. At the end of each page, the participants were asked which of the recommended movies they most are interested in watching. We also included a no-choice option as an

[2] We used the updated 2018 version of the dataset. In the dataset, on average, users rated 12 movies. And all users have rated at least 1 movie. We calculated the sparsity as the number of zero elements divided by the total number of elements. And the results show that the sparsity of the dataset is 99.5%.

outside option for when users did not wish to watch any of the movies in the recommendation list. After completing all treatment conditions, participants answered a survey of demographic and control questions.

When we introduce a decoy, we select a movie with a low prediction score in the personalized setting and a low average rating in the non-personalized setting. Moreover, prior studies (e.g., Huber et al. 1982, Simonson and Tversky 1992) have shown that the decoy effect is more considerable when the attributes of a decoy are comparable and similar to a target item. In other words, the more comparable a decoy is to the target item, the more likely that demand will shift to the target item. Thus, the decoys we introduce are randomly selected but have the same genre as the first movie in the list and placed it as the second item in the list. The first movie on the list is thus our target. The experiment thus had four treatment conditions: personalized recommendations (with and without decoy) and non-personalized (with and without decoy).

In each condition, we are interested in the relative selection likelihood of each option with and without a decoy. Thus, we ensured that except for the decoy, all other movies were randomly distributed in the with and without decoy situations. In each condition, we also conducted a regression analysis to statistically test the distribution of the prediction scores/aggregate ratings. The result shows that in both conditions, there are not any significant differences between the distribution of the scores in the with/out decoy.

Results

As the first step in our analysis, we look at how personalization[3] and the decoy effect interact to affect the likelihood of the no-choice option. Figure 2 shows that the presence of the decoy item in the personalized recommendations condition dramatically increases the selection likelihood of the no-choice, outside option. However, the same effect is not present in the non-personalized condition. This suggests that personalization significantly alters the decoy effect. The traditional decoy effect predicts that the presence of the decoy would move demand to the target item; however, the presence of the decoy in the personalized setting shifts demand to the outside, no-choice option. Moreover, as we can see in Figure 2, adding a decoy in the non-personalized setting generates the traditional decoy effect, with demand shifting to the target item. However, in the personalized condition, the opposite occurs. Adding a decoy reduces demand for the target item. We see a significant decrease in the selection likelihood of the target item from the non-decoy to decoy situation(p-value<0.01). However, for the non-personalized condition, the difference is not significant (p-value=0.12).

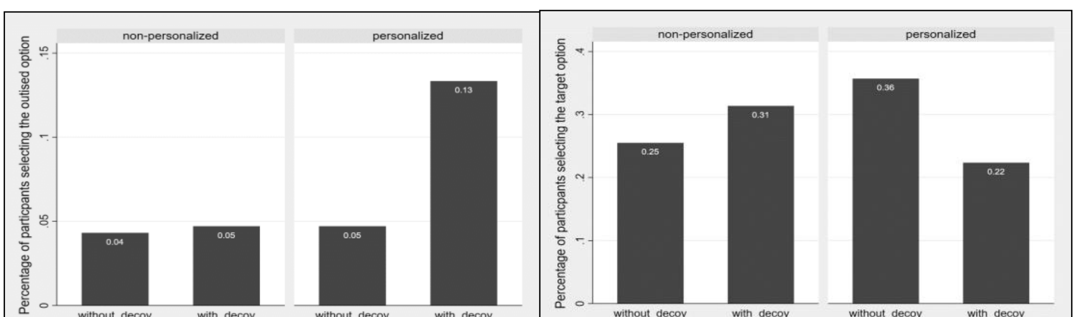

Figure 2. The Decoy Effect in Personalized vs. Non-personalized Settings

To assess the statistical significance of the change in the non-choice and the target options, we ran a participant fixed-effect logit model with the choice of the outside and the target options as the dependent variables and experiment conditions as the independent variables. As Table 1 demonstrates[4], adding a decoy significantly increases the selection likelihood of the no-choice option. In other words, having a decoy

[3] To check manipulation of personalization, at the end of each condition, we asked users a Likert-type question with a 1 to 7 scale: “The recommended movies were personalized for me”. The result of the fixed-effect model shows, on average, the perceived personalization was higher than in the personalized condition than the non-personalized one (p<0.001).

[4] p-values; ^ p<0.10, * p<0.05, ** p<0.01, *** p<0.001 (standard errors in parentheses)

increases the odds of selecting the no-choice option by 110% (e^0.780=2.1). The interaction model demonstrates that the decoy increases demand for the no-choice option in the personalized setting but does not significantly change the likelihood of selecting that option in the non-personalization condition (Decoy x Personalization β_3=1.103, p<0.1).

	Main Effect	Interaction
Decoy	0.780*** (0.271)	0.094 (0.434)
Personalized	0.780*** (0.271)	0.094 (0.434)
Decoy X Personalized		1.103^ (0.564)
Log-likelihood	-77	-75
AIC	159	157
N	240	240

Table 1. The Decoy Effect on the Outside Option (No-choice)

Moreover, as the main model in Table 2 shows, adding a decoy does not significantly change the selection likelihood of the target item. However, the results of the interaction model demonstrate that although the decoy does not change the demand for the target item in the non-personalized setting, it decreases the likelihood of selecting the target item in the personalization context (Decoy x Personalization $\beta_3 = -0.968$, p<0.001). This behavior could be because the presence of the decoy item suggests to the participant that the system is less knowledgeable and less reliable. Especially since the target item has more similar attributes to the decoy, matched genre in our case, the decoy item could be tainting its attribute space and other items that have similar attributes, thus decreasing their selection likelihood (Frederick et al. 2014; Simonson 2014; Yang and Lynn 2014).

	Main Effect	Interaction
Decoy	-0.187 (0.140)	0.297 (0.199)
Personalized	0.029 (0.139)	0.497** (0.197)
Decoy X Personalized		-0.968*** (0.284)
Log-likelihood	-280	-274
AIC	563	553
N	732	732

Table 2. The Decoy Effect on the Target Option

Mechanism: Post Hoc Analysis

We believe the mechanism behind our findings might be that adding a decoy can negatively impact the perceived credibility and reliability of the system, reducing consumers' trust. Personalization systems as intelligent agents are expected to understand customers' needs and interests and help them in their decision-making processes, reducing the difficulty in making choices and increasing decision confidence (Xiao and Benbasat 2007). The presence of a decoy, which is not highly aligned with consumers' needs and interests, may decrease the average perceived quality of the set of recommended items, which could negatively impact the credibility and reliability of the system and reduce the users' trust. As a post hoc analysis, we examined how the decoy item impacts the system's reliability and users' trust. We specifically asked users two Likert-type questions with a 1 to 7 scale: "I rely on the system for deciding what movies to watch", and "The system is able to identify good movies" (Komiak and Benbasat 2006).

To test the perceived credibility of the system, we ran a fixed-effect model. The results in Table 3 demonstrate that, on average, adding a decoy significantly decreases the perceived credibility of the system ($\beta_1 = -0.628, p < 0.001$). Moreover, the interaction model shows that although the decoy negatively impacts the perceived credibility of the system in non-personalized system, the negative impact is stronger in the personalized condition.

	Main Effect	Interaction
Decoy	-0.628*** (-7.73)	-0.257* (-2.26)
Personalized	-0.309*** (-3.80)	0.063 (0.55)
Decoy X Personalized		-0.743*** (-4.63)
Constant	5.196*** (73.82)	5.010*** (62.46)
Log-likelihood	-1565	-1551
AIC	563	553
N	1020	1020

Table 3. The Decoy Effect on Users' Trust

Conclusion

Personalization has become one of the important marketing strategies for online retailers. So, it is crucial to investigate how firms can enhance the effectiveness of those systems. We have demonstrated that the decoy effect, a well-studied decision bias, can change in the context of personalization. Specifically, we show that when decoys are introduced in personalized lists of recommended items, the decoy effect is diminished, and demand is more focused on an outside, no-choice option. This is in contrast to the traditional decoy effect findings, where the presence of a decoy drives demand toward a similar but superior target item. We replicated the traditional decoy effect with non-personalized movie recommendations but show the effect changes dramatically when decoys are used within personalized recommendations. In the future, we will gather more observations by running two additional experiments: a lab experiment and a Mturk one. We will run the lab experiment to triangulate our results and an MTurk experiment to expand the size and heterogeneity of our sample. Moreover, to control for the possible ordering effect, we will randomize the position of the decoy in the recommended list of items.

References

Adamopoulos, P., Ghose, A., and Tuzhilin, A. 2021. "Heterogeneous Demand Effects of Recommendation Strategies in a Mobile Application: Evidence from Econometric Models and Machine-Learning Instruments," *MIS Quarterly (Forthcoming)*.

Adomavicius, G., Bockstedt, J. C., Curley, S. P., and Zhang, J. 2013. "Do Recommender Systems Manipulate Consumer Preferences? A Study of Anchoring Effects," *Information Systems Research* (24:4), pp. 956–975.

Adomavicius, G., Bockstedt, J. C., Curley, S. P., and Zhang, J. 2018. "Effects of Online Recommendations on Consumers' Willingness to Pay," *Information Systems Research* (29:1), pp. 84–102.

Areni, C. S., and Lutz, R. J. 1988. "The Role of Argument Quality in the Elaboration Likelihood Model," *ACR North American Advances*.

Ariely, D. 2009. *Predictably Irrational: The Hidden Forces That Shape Our Decisions*, HarperCollins Publishers.

Bettman, J. R., Luce, M. F., and Payne, J. W. 1998. "Constructive Consumer Choice Processes," *Journal of Consumer Research* (25:3), pp. 187–217.

Briggs, P., Burford, B., De Angeli, A., and Lynch, P. 2002. "Trust in Online Advice," *Social Science Computer Review* (20:3), pp. 321–332.

Chernev, A., Böckenholt, U., and Goodman, J. 2015. "Choice Overload: A Conceptual Review and Meta-Analysis," *Journal of Consumer Psychology* (25:2), pp. 333–358.

Cialdini, R. B., and Cialdini, R. B. 2007. Influence: The Psychology of Persuasion, , Collins New York.

Dhar, R. 1997. "Consumer Preference for a No-Choice Option," *Journal of Consumer Research* (24:2), pp. 215–231.

Dooms, S., De Pessemier, T., and Martens, L. 2013. MovieTweetings: A Movie Rating Dataset Collected From Twitter, in *Workshop on Crowdsourcing and human computation for recommender systems, CrowdRec at RecSys*, Hong Kong, CN, p.43.

Frederick, S., Lee, L., and Baskin, E. 2014. "The Limits of Attraction," *Journal of Marketing Research* (51:4), pp. 487–507.

Häubl, G., and Trifts, V. 2000. "Consumer Decision Making in Online Shopping Environments: The Effects of Interactive Decision Aids," *Marketing Science* (19:1), pp. 4–21.

Herlocker, J. L., Konstan, J. A., Terveen, L. G., and Riedl, J. T. 2004. "Evaluating Collaborative Filtering Recommender Systems," *ACM Transactions on Information Systems (TOIS)* (22:1), New York, NY, pp. 5–53.

Hostler, R. E., Yoon, V. Y., and Guimaraes, T. 2005. "Assessing the Impact of Internet Agent on End Users' Performance," *Decision Support Systems* (41:1), pp. 313–323.

Huber, J., Payne, J. W., and Puto, C. 1982. "Adding Asymmetrically Dominated Alternatives: Violations of Regularity and the Similarity Hypothesis," *Journal of Consumer Research* (9:1), pp. 90–98.

Kawaguchi, K., Uetake, K., and Watanabe, Y. 2019. "Effectiveness of Product Recommendations Under Time and Crowd Pressures," *Marketing Science* (38:2), pp. 253–273.

Komiak, S. Y., and Benbasat, I. 2006. "The Effects of Personalization and Familiarity on Trust and Adoption of Recommendation Agents," *MIS Quarterly*, pp. 941–960.

Kumkale, G. T., Albarracín, D., and Seignourel, P. J. 2010. "The Effects of Source Credibility in the Presence or Absence of Prior Attitudes: Implications for the Design of Persuasive Communication Campaigns," *Journal of Applied Social Psychology* (40:6), pp. 1325–1356.

Lee, D., Gopal, A., and Park, S.-H. 2020. "Different but Equal? A Field Experiment on the Impact of Recommendation Systems on Mobile and Personal Computer Channels in Retail," *Information Systems Research* (31:3), pp. 892–912.

Luce, R. D. 1977. "The Choice Axiom after Twenty Years," *Journal of Mathematical Psychology* (15:3), pp. 215–233.

Pathak, B., Garfinkel, R., Gopal, R. D., Venkatesan, R., and Yin, F. 2010. "Empirical Analysis of the Impact of Recommender Systems on Sales," *Journal of Management Information Systems* (27:2), pp. 159–188.

Pechtl, H. 2009. "Value Structures in a Decoy and Compromise Effect Experiment," *Psychology & Marketing* (26:8), pp. 736–759.

Petty, R. E. 2018. *Attitudes and Persuasion: Classic and Contemporary Approaches*, Routledge.

Petty, R. E., and Cacioppo, J. T. 1979. "Issue Involvement Can Increase or Decrease Persuasion by Enhancing Message-Relevant Cognitive Responses.," *Journal of Personality and Social Psychology* (37:10), p. 1915.

Petty, R. E., and Cacioppo, J. T. 1984. "The Effects of Involvement on Responses to Argument Quantity and Quality: Central and Peripheral Routes to Persuasion.," *Journal of Personality and Social Psychology* (46:1), p. 69.

Pornpitakpan, C. 2004. "The Persuasiveness of Source Credibility: A Critical Review of Five Decades' Evidence," *Journal of Applied Social Psychology* (34:2), pp. 243–281.

Simonson, I. 1989. "Choice Based on Reasons: The Case of Attraction and Compromise Effects," *Journal of Consumer Research* (16:2), pp. 158–174.

Simonson, I. 2014. "Vices and Virtues of Misguided Replications: The Case of Asymmetric Dominance," *Journal of Marketing Research* (51:4), pp. 514–519.

Simonson, I., and Tversky, A. 1992. "Choice in Context: Tradeoff Contrast and Extremeness Aversion," *Journal of Marketing Research* (29:3), pp. 281–295.

Tam, K. Y., and Ho, S. Y. 2005. "Web Personalization as a Persuasion Strategy: An Elaboration Likelihood Model Perspective," *Information Systems Research* (16:3), pp. 271–291.

Tam, K. Y., and Ho, S. Y. 2006. "Understanding the Impact of Web Personalization on User Information Processing and Decision Outcomes," *MIS Quarterly* (30:4), pp. 865–890.

Todorović, D. 2010. "Context Effects in Visual Perception and Their Explanations," *Review of Psychology* (17:1), pp. 17–32.
Tversky, A., and Shafir, E. 1992. "Choice under Conflict: The Dynamics of Deferred Decision," P*sychological Science* (3:6), pp. 358–361.
Tversky, A., and Simonson, I. 1993. "Context-Dependent Preferences," *Management Science* (39:10), pp. 1179–1189.
Xiao, B., and Benbasat, I. 2007. "E-Commerce Product Recommendation Agents: Use, Characteristics, and Impact," *MIS Quarterly* (31:1), pp. 137–209.
Yang, S., and Lynn, M. 2014. "More Evidence Challenging the Robustness and Usefulness of the Attraction Effect," *Journal of Marketing Research* (51:4), pp. 508–513.