LESS IS MORE? TWO ESSAYS ON CONSUMER PERCEPTIONS OF SIMPLICITY AND COMPLEXITY

by

NICHOLAS LIGHT

M.A., University of Chicago, 2010
B.A., University of Vermont, 2009

A dissertation submitted to the faculty of the University of Colorado Leeds School of Business in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

Marketing Division

2021

Committee Members:

Philip Fernbach

John Lynch

Margaret Campbell

Nicholas Reinholtz

Ellen R. K. Evers

Abstract

Light, Nicholas (Ph.D., Business Administration, Division of Marketing)

Less Is More? Two Essays on Consumer Perceptions of Simplicity and Complexity

Dissertation committee chaired by Associate Professor Philip Fernbach

Marketers like simplicity in brands, and think consumers do too. Trying to get consumers to associate a brand or product with the idea of simplicity is a very popular marketing strategy. However, the effect this strategy might have on consumers' perceptions of those brands and products has never been formally tested. Furthermore, whereas practitioners have touted this simplicity strategy as something approaching a panacea, this dissertation demonstrates that such a strategy comes with hidden pitfalls. Essay 1 argues that when marketing is successful at convincing consumers that a brand is simple, their perceptions of the likelihood of product or service failures is lowered, which leads to significant dissatisfaction and anger in the event of a failure. Essay 2 demonstrates that consumer perceptions of the simplicity or complexity of products can also be manipulated by marketing, and tests whether consumers' believe there is a tradeoff between product reliability and maximum performance, as a function of product complexity. Essay 2 concludes by comparing consumers' default mental models of product complexity against real-world models of complexity (and their associated levels of risk and performance), in order to test the appropriateness of consumers' complexity-to-risk and complexity-to-performance inferences.

TABLE OF CONTENTS

List of Figures

Figure

List of Tables

Table

"Everything should be made as simple as possible, but no simpler."
-Albert Einstein

"Simple can be harder than complex."
-Steve Jobs

1) Introduction

Simplify. *Run Simple*. *Life Simplified*. Consumers regularly encounter marketing messages like these, which are created by marketing practitioners specifically to convey feelings of simplicity. Many practitioners advocate using simplicity in marketing, which has become an increasingly popular strategy in the last decade. For example, marketing thought leadership articles in *Fast Company* and *Think with Google* have referred to simplicity as "the most powerful branding principle," and "the difference [between] an award-winning ad and an ad that brings in the results" (Ahto 2015; Meyer 2012; also see Horst 2018; Molloy 2015). Practitioners attempt to convey simplicity in multiple ways, by explicitly mentioning the words "simple" or "simplicity" in marketing communications, with visually simple branding and imagery, and by projecting simplicity in the design of products and packaging. Hill City, a men's athleisure brand owned by Gap Inc., launched in 2018 with three brand values prominently displayed on its website, one of which is *Simplify*. The design firm IDEO, famous for its work with Apple, "seeks simplicity in product and branding design to the nth degree" (personal communication: B. Crosier, October 24, 2018). One relatively well-known example of this strategy is direct-to-consumer mattress brand Casper, which gained legions of fanatic customers and hundreds of copycats with its sparse illustrated ads, simple website, and crisp blue and white boxes (Dolan 2017; Griffith 2017).

The reason some practitioners seek to convey simplicity in marketing is that they believe consumers are overloaded with marketing information. One *Harvard Business Review* article titled, "To Keep Your Customers, Keep it Simple," wrote that "for many consumers, the rising volume of marketing messages isn't empowering—it's overwhelming" (Spenner and Freeman 2012). IDEO co-founder Tom Kelley wrote that "companies today understand that what people want is more integration and simplicity" (Kelley and Littman 2001). The idea is that by projecting simplicity and making marketing communications simpler, brands will be better able to reach consumers through the clutter and more effectively communicate their unique value propositions. Marketing practitioners also believe that consumers like simple-seeming brands; branding agency Siegel+Gale has published a Global Brand Simplicity Index of the world's simplest brands annually since 2009, arguing that simpler brands perform better financially, gain more trust, and inspire more customer loyalty (Belk and Rafferty 2012; Siegel+Gale 2018).

Despite the increasing importance of simplicity as a strategy for practitioners, the critical role that brands play in marketing, and the extensive academic literature on brand perceptions, it is not well understood how consumers' perceptions of the simplicity (or complexity) of brands and their products influence downstream outcomes for consumers and firms. Part of the problem is that the seeming intuitiveness of the simplicity-complexity construct has led to inconsistent and imprecise definitions and operationalizations. This in turn has made the triangulation of effects and formation of predictions on the topic difficult. In spite of this lack of cohesion, research in psychology and marketing suggests that the correlates of simplicity and complexity are a *who's who* of phenomena that matter in decision making: perceived understanding (Rozenblit and Keil 2002), attention (Pieters, Wedel, and Batra 2010), motivation and effort (Swait and Adamowicz 2001), and extremity of evaluations (Fernbach, Rogers, et al. 2013), for example. Additional research on the topic is clearly warranted.

In an effort to better understand consumers' perceptions of simplicity and complexity, and to lay the foundation for a research program on the topic, this dissertation examines the downstream effects of marketers' attempts to convey simplicity. Two essays explore the antecedents of consumers' judgments of the simplicity and complexity of brands and their products, as well as the effects of those judgments on perceptions of risk, liking, and performance. In essay 1 I argue that consumers' perceptions of brand simplicity can lead to unexpected dissatisfaction by giving them unrealistically low expectations of the risk of product failures. Marketers generally assume that simpler brands are better liked. If true, liking should have positive consequences on trial and choice. However, essay 1 shows that even if brands perceived to be simpler are better liked than ones perceived to be complex, consumers think simplicity means there is less opportunity for simpler brands' products and services to fail. When failures inevitably occur, consumers become more upset than they would have in the absence of perceptions of brand simplicity. Essay 1 also attempts to better conceptualize consumers' judgments of the simplicity of brands by examining antecedents via structural equation modeling. In this dissertation I discuss seven completed studies for essay 1.

In essay 2 I examine the inferences consumers make about products they perceive to be complex. Although marketing suggesting simplicity has become more common, some practitioners may choose not to use this strategy. They may even convey complexity (deliberately or not) through the communication of features, technologies, or the R&D process, in marketing materials. Essay 2 examines what product complexity means to consumers, as well as their beliefs about the reliability and performance of complex products. I argue that consumers believe complex products are more likely to fail, but also have a higher performance ceiling. I test these predictions in seven more studies.

2) Essay 1: Consumer Perceptions of Brand Simplicity and Risk

2.1 What is Brand Simplicity?

I conceptualize brand simplicity as a consumer's overall gestalt feeling of simplicity associated with a brand, formed by the totality of its marketing communications. Given the importance of simplicity to marketing practitioners it is surprising that there is little research on consumer perceptions of the simplicity or complexity of brands in the academic literature. The challenge for academics interested in making predictions about consumer behavior based on findings about simplicity and complexity is that researchers appear to be talking about different constructs when they use the words *simplicity, simple*, *complexity* or *complex*. Even when restricting the scope to work exclusively in marketing or psychology journals, cohesion is lacking, and definitions are rare. Some describe complexity in terms of the existence of more—more images, more information, more labels, or more options (Conway et al. 2008; Dellaert and Stremersch 2005; Linville 1982; Pacer and Lombrozo 2017). Others describe simplicity or complexity in terms of ease or difficulty, as in a complex decision, proof, or product that is difficult to understand, use, or categorize (Bettman, Luce, and Payne 1998; Chernev 2003; Payne 1976; Rogers 2003). Somewhere in between are those who describe complexity as interconnectedness, such as interdependent units in a business or antecedents and consequences in a network (Bar-Yam 2002; Grandjean 2019). There are still more operationalizations that use mathematical approaches to quantify information or computation required to process a document or run a program (Chater and Loewenstein 2016; Evers, Inbar, and Zeelenberg 2014; Mizerski 1978). More recent research discusses two kinds of visual complexity in advertisements: "feature complexity" and "design complexity" (Pieters, Wedel, and Batra 2010). The distinction between these two is not one of varying objectivity, but between two types of objective visual complexity – one measured by less redundancy in adjacent pixels and another by less consistency and similarity in shapes, textures, and colors.

One reason for the lack of brand simplicity research in marketing may be that the notion of brand simplicity does not naturally fit into the most influential frameworks that treat brands as possessing human characteristics, or consumer-brand interaction as analogous to human relationships (Aaker 1997; Aaker, Fournier, and Brasel 2004; Fournier 1998). However, the idea of consumers judging the simplicity or complexity of brands is not inconsistent with influential branding research. Specifically, it is consistent with the role of brand associations in Keller's customer-based model of brand equity, in which consumers associate brands with any number of different ideas, feelings, and concepts (Keller 1993, 2012). Consumer perceptions of brand simplicity can therefore be thought of as the strength of association between a brand and simplicity in consumers' brains. However, in order to gain a better understanding of consumers' judgments of brand simplicity, study 1 uses structural equation modeling to identify potential antecedents of those perceptions, in order to be able to subsequently manipulate the construct in a data-driven way.

2.2 Consequences of Brand Simplicity Judgments

Why might projecting simplicity in marketing be a good idea? One of the strongest arguments in its favor is that people generally like simple things. Research from cognitive psychology has shown that humans seek the simplest representations and briefest explanations of incoming information that still allow them to make sense of the world. This fundamental sense-making behavior manifests itself in a general preference for simple things (Chater 1999; Chater and Loewenstein 2016; Chater and Vitányi 2003; Hahn, Chater, and Richardson 2003). Several findings from the marketing literature support this insight. Consumers prefer ads that are lower in visual complexity (Pieters et al. 2010). Difficulty in comprehension (driven by complexity) is a barrier to new product adoption, and consumers downgrade products they feel they do not understand well (Jhang, Grant, and Campbell 2012; Rogers 2003a). Most consumers also prefer using simpler products (Eytam, Tractinsky, and Lowengart 2017) and prefer simpler explanations of new products (Fernbach, Sloman, et al. 2013).

However, several findings from both psychology and marketing research suggest a more nuanced relationship between simplicity and liking, with complexity actually being preferred in some contexts. For example, psychologist Daniel Berlyne hypothesized that when people see a more novel, complex, or irregular object, they become more aroused and attempt to reduce the arousal by exploring the object (Berlyne 1958). Relatedly, a series of studies on fluency and ad evaluations shows that evaluations of complex ads become more positive with additional exposures, while evaluations of simple ads do not (Cox and Cox 1988). There is also evidence that consumers prefer more complexity in products when it is framed in terms of additional features. In evaluating and choosing products, consumers have been shown to value a product’s features more than its usability before making a purchase, which results in choosing complex products that are hard to use once purchased, which makes them unhappy and causes “feature fatigue” (Thompson, Hamilton, and Rust 2005). Finally, Brighton and Gigerenzer (2015) argue that many researchers attempting to model complex phenomena prefer models higher in complexity even though simpler models often perform comparably in minimizing bias and much better in minimizing variance across samples (Brighton and Gigerenzer 2015; Briscoe and

Feldman 2011).

Given the inconsistency of these findings, in essay 1 I test marketing practitioners' assumption that simplicity in marketing is good for brand liking, but do not make a specific prediction about the relationship. I argue that, though brand simplicity could increase liking, it may also have its drawbacks. According to the expectation-confirmation theory of consumer satisfaction, consumer evaluations of an experience depend both on the quality of the experience itself and the gap between the experience and the consumer's expectation prior to the experience (Oliver 1980). Thus, an equally poor experience will yield more dissatisfaction if expectations are higher *a priori*. This prediction has been confirmed in numerous marketing studies (Diehl and Poynor 2010; Oliver 1993; Spreng, MacKenzie, and Olshavsky 1996; Swan and Trawick 1981). I hypothesize that brand simplicity establishes an expectation of minimal risk, and that simplicity as a marketing strategy can therefore create the conditions for increased consumer dissatisfaction when something goes wrong. Additionally, because the common marketing strategy of suggesting simplicity frequently also includes suggestions of ease (either explicitly or implicitly), and because several research definitions of simplicity mention ease, I also explore whether perceptions of brand simplicity might create expectations of a brand's products being easier to use, obtain, understand, or make, which would also cause additional dissatisfaction or anger in the event of an unexpected failure or difficulty.

Risk has been defined in multiple ways across different literatures. One tradition in the behavioral sciences has attempted to pinpoint the qualitative features of events that make them feel risky (Fischhoff et al. 1978; Slovic 1987). Slovic (1987) categorized risks into two dimensions: "unknown risk" and "dread risk." Unknown risk is defined in terms of unknowable hazards, while dread risk is characterized by a fear of negative consequences and perceptions of a high likelihood of loss. Most real-world hazards have aspects of both dread and unknown risk. A different approach in the decision-theory and judgment and decision making literatures has defined risk perceptions in terms of summary statistics of outcome distributions, like mean and variance (March and Shapira 1987; Weber, Shafir, and Blais 2004). Perceptions of risk are higher both when variance is higher and when mean is lower. An investment opportunity is judged risky, for instance, when the distribution of possible outcomes is dispersed and when the probability of losing money is relatively high. Here in essay 1 I decided to operationalize risk judgments in line with the qualitative tradition. I opted for an elicitation that blends dread and unknown risk by asking participants to judge the likelihood of something unexpected happening "that would cause a consumer to return something, post a negative review, or contact customer service for any reason."

The link between simplicity and risk, defined this way, makes intuitive sense. If a system is more complex it has more potential points of failure and it would be perfectly reasonable to infer greater risk. I argue however that simple marketing can create unrealistic expectations, leading to miscalibrated risk perceptions. One reason for this is that people tend to underestimate complexity in general, believing things to be simpler than they are (until they are asked to explain them; Fernbach, Rogers, et al. 2013; Rozenblit and Keil 2002). Similarly, consumers report higher probability judgments of future failures when they mentally unpack potential reasons for failures, compared to consumers who do not undertake an unpacking task (Biswas, Keller, and Burman 2012), suggesting that they underestimate potential sources of failure *a priori.* Simple marketing has the potential to reinforce or exacerbate these tendencies.

A related phenomenon was demonstrated by Long, Fernbach, and de Langhe (2018) in the context of investing. Investors judged companies they felt they understood better to be less risky investments. For instance, one might think that Starbucks is a safe investment because their business, serving coffee, seems easy to understand. Of course, evaluating the investment risk of a company is much more complicated than a simple assessment of one's understanding of what they do. Indeed, investors' perceived understanding judgments had no predictive value for actual investment risk in Long et al.'s studies. If consumers believe they understand simpler brands better, they may also believe them to be lower risk.

To summarize, I argue that simplicity in branding may act as a promise that risk is low. This could be beneficial if lower risk perceptions are positive for consideration and choice (or if consumers generally like simpler things). However, there is a danger if simplicity perceptions create unrealistic expectations. Some marketers may not intend for simple marketing to be a promise. They may choose simple marketing because it is fashionable or because they are focused on liking and trial, without thinking about potential dangers later in the customer lifecycle. In fact, I conducted a short survey of marketing practitioners ($N = 25$) from two marketing agencies and one in-house team, which revealed that they believe consumers like simpler brands more than complex ones ($p < .001$) and think consumers view simpler brands as less risky (in terms of failures; $p < .001$). However, in spite of being prompted to consider risk perceptions by the previous question, not one practitioner mentioned increased consumer dissatisfaction in response to failures in their responses to an open-ended question asking them to list any potential downsides of projecting simplicity in marketing. Thus, the predictions tested here have important, novel, and non-obvious implications for marketers.

2.3 Essay 1 Studies

2.3.1 Summary of Studies

In study 1 I use structural equation modeling to identify antecedents of consumers' judgments of brand simplicity. In study 2 I use real advertisements and company websites in tests of the relationships between perceived brand simplicity, pre-purchase liking, risk perceptions, and the important potential confound of perceived brand premiumness. I find that participants believe simpler brands are less risky, controlling for how premium the brand is perceived to be and how much they like it. However, study 2 data provide mixed results in terms of the effect of simplicity on liking. In studies 3a and 3b I manipulate perceived simplicity by altering the visual appearance of advertisements for fictitious brands, and replicate the pattern of results for risk from study 2, controlling for the additional confounds of perceived professionalism, luxury, and size of the company. Contrary to study 2, however, studies 3a and 3b provide evidence in support of a positive relationship between simplicity and liking. In study 4 I manipulate the perceived simplicity of a focal brand in a between-subjects experiment by contrasting it with either a visually simpler or more complex competitor brand's marketing image. In the condition where the focal brand is made to seem simpler, participants report lower risk perceptions, and more liking. In study 5 I turn to proprietary *Consumer Reports* customer survey data on product reliability and satisfaction to test the prediction that brands perceived to be simpler are penalized more for product and service failures. Study 6 conceptually replicates study 5's findings using experimental manipulations of simplicity and failure, and by testing all of the paths in the essay's conceptual model. Finally, study 7 examines the relationships between consumers' perceptions of overall brand simplicity, perceptual simplicity, and ease, as well as how those different simplicity types may be differently associated with risk in consumers' minds.

2.3.2 Study 1: Antecedents of Brand Simplicity Judgments

The idea of brand simplicity is novel, and investigating its potential antecedents has not yet been attempted. I therefore conducted a conceptual study using structural equation modeling to better understand what drives consumer perceptions of brand simplicity, with a view to manipulating it in later studies. A secondary aim of study 1 is to determine if meaningful and intuitive variation exists in consumer perceptions of simplicity between well-known brands.

In order to conceptualize a model structure with latent factors predicting overall perceptions of the simplicity of brands, I first assembled a total of 19 indicator items, derived from relevant research (including work on diffusion of innovations, fluency, understanding, attention, and cognitive complexity). I attempted to identify elements, situations, or inferences that could potentially influence consumers' perceptions of the simplicity of brands (or that are referred to in extant research as being—or contributing to—simplicity or complexity), particularly those that could be observed or inferred by consumers in an online setting. For example, work on visual simplicity/complexity and fluency has discussed the number of non-redundant pixels, edges, or objects in a marketing image, as well as how difficult a product name is to pronounce (Janiszewski and Meyvis 2001; Pieters et al. 2010; Song and Schwarz 2009). Research on consumer acceptance of innovations has characterized complexity as "the degree to which an innovation is perceived to be difficult to understand and use" (Rogers 2003, 257), and judgments of complexity as potentially arising from marketers' communications about how—or in what contexts—a product is used (Wood and Moreau 2006). Lastly, research on cognitive complexity and research on constructed preferences have characterized simpler mental representations of objects and lower task or choice complexity as arising from fewer dimensions or options (Bettman et al. 1998; Chernev 2003; Linville 1982). With this research in mind, six items were designed to capture Perceptual Simplicity, seven to capture Process Simplicity, and three to capture Dimensionality (see table 1 below for all items and factors). I also created three items to measure participants' overall evaluations of brand simplicity, which acts as the dependent factor in the structural equation model.

TABLE 1: STUDY 1 ITEMS AND ANTECEDENT FACTORS

Item Number	Statement	Hypothesized Model Factor	Final Model Factor
1	Visually, the [brand] website is sparse/uncluttered.	Perceptual	Perceptual
2	Visually, [brand] ads are sparse/uncluttered	Perceptual	Perceptual
3	The words on [brand] ads are easy to understand.	Perceptual	Perceptual
4	In general, the physical design of [brand] products is simple	Perceptual	Perceptual
5	In general, [brand] product packaging is simple.	Perceptual	Perceptual
6	The name [brand] is simple.	Perceptual	Perceptual
7	I have a good understanding of how [brand] products work.	Process	Conceptual
8	It would take a short amount of time to learn how to use [brand] products.	Process	Conceptual
9	In general, [brand] products are easy to make.	Process	Conceptual
10	The process of purchasing [brand] products is simple.	Process	Conceptual
11	The process of deciding on which [brand] product to purchase would be simple.	Process	Conceptual
12	From the point when a customer decides to buy some [brand] product, the customer would have access to the product quickly.	Process	Conceptual
13	Getting set up to use [brand] products after a customer has one is easy.	Process	Conceptual
14	[Brand] offers very few products.	Dimensionality	--
15	In general, [brand] products have very few uses.	Dimensionality	--
16	In general, when promoting their products, [brand] lists many features of those products.	Dimensionality	--
17	Overall, I think 'simple' is a good word to describe [brand].	Overall Simplicity Dependent Factor	Overall Simplicity Dependent Factor
18	[Brand] has an aura of simplicity.	Overall Simplicity Dependent Factor	Overall Simplicity Dependent Factor

19	Compared to other companies, [brand] is one of the simplest.	Overall Simplicity Dependent Factor	Overall Simplicity Dependent Factor

Method

550 Amazon Mechanical Turk participants were recruited through Cloud Research (Litman, Robinson, and Abberbock 2017) and paid $.60 for completing a Qualtrics survey. Eleven participants asked to have their data removed, eight admitted to not viewing study stimuli, and 19 took less than 2.5 minutes to complete the survey.[1] These participants' data were removed before data analysis, resulting in a final *N* of 512. The survey contained 40 brand-conditions, and each participant was randomly assigned to only one brand-condition per session. The 40 brands in the survey included five brands each from eight different product categories: cars, mattresses, athletic shoes, mobile phones, financial services, insurance, hair products, and headphones. The categories and brands were selected in order for the set to have broad appeal across consumers, variance in predicted simplicity/complexity, and if multiple recent print advertisements could be found for at least five brands in a category.

Participants were first directed to view the condition-specific brand's home webpage and answer all items not specific to ads in random order. They then viewed up to five real print or billboard advertisements published by the brand between 2012 and 2017, before answering the advertising-specific items. The procedure mimics how consumers search and evaluate products in the real world, but is not an excessive time burden and can be completed entirely online.

[1] The mean completion time of the remaining 512 participants was 7 minutes, 11 seconds.

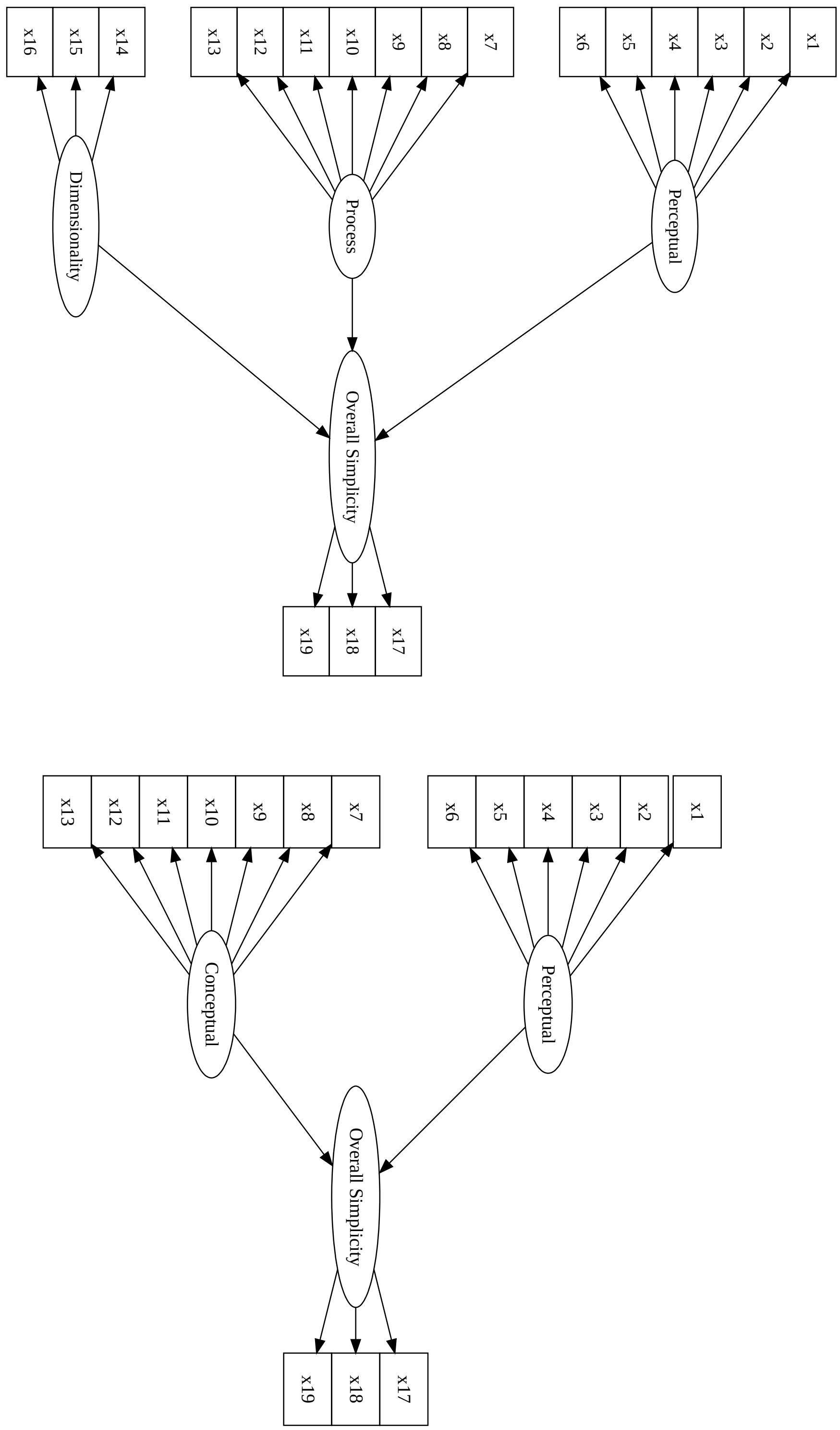
Because the stimulus brands are real, I expected participants to have differing levels of brand knowledge and exposure. This procedure thus represents a middle ground between simply measuring unaided judgments and asking online participants to undertake a complex procedure (that still allowed a modicum of control over participants' exposure to the stimuli). After answering the ad- and website-specific questions, participants were then shown the three items intended to capture perceptions of overall simplicity of the brand. They were asked to indicate the degree to which they agreed with each statement on a seven-point scale from "strongly agree" to "strongly disagree." All 19 items were phrased in the same direction in order to avoid the formation of a method factor.

Results and Discussion

I used structural equation modeling to examine what branding elements form latent antecedent constructs of consumers' overall perceptions of brand simplicity. I also compared the differential degree to which those constructs predict consumers' overall brand simplicity perceptions. I began with the theoretically-derived model which I subsequently refined (see model visualizations in figure 1).

Before modeling began in earnest, I examined zero-order correlations between all variables, which revealed that all three questions from the hypothesized Dimensionality factor *([brand] offers very few products; In general, [brand] products have very few uses; In general, when promoting their products, [brand] lists many features of those products*) all had near-zero correlations (all *r*s $\leq$ .18, mean = .05) with the three Overall Simplicity items. Because the goal of the study was to learn how the indicators form latent antecedent factors of overall perceptions of brand simplicity, I removed those three items prior to analysis, and renamed the Process factor "Conceptual Simplicity." These changes resulted in a refined hypothesized model with only two antecedent factors, as well as one Overall Simplicity dependent factor, shown below in figure 1.

FIGURE 1: STUDY 1 HYPOTHESIZED (TOP) AND FINAL (BOTTOM) STRUCTURAL EQUATION MODELS



Note: Correlations between antecedent factors and between indicator error terms have been left off for clarity. Models are reflective, meaning that each latent construct is the common cause of participants' answers on the indicators.

Model 1 was analyzed in Mplus Version 8 (Muthén and Muthén 2017) using robust weight least squares (WLSMV) estimation, which does not assume normally distributed variables (Brown 2015). Though there is significant disagreement on the usefulness and appropriate cutoff values of different model fit indices, I report several of the most common for structural equation models. In addition to the Chi Square (with lower values indicating better fit), I report Root Mean Square Error of Approximation (RMSEA), an absolute measure of fit, with .01, .05, and .08 indicating excellent, good, and mediocre fit, respectively (for a thoughtful discussion of SEM fit indices, see Kenny 2015). I also report the Comparative Fit Index (CFI) and Tucker Lewis Index (TLI), which both penalize model complexity, are usually highly correlated, and should be .90 or higher to indicate good fit.

The refined model fit the data fairly but not exceptionally well (χ^2 (101) = 438.35, $p < .001$, RMSEA = .081, CFI = .953, TLI = .944). The standardized coefficient for the effect of the Perceptual factor on the Overall Simplicity factor was .50 ($p < .001$), and the effect of the Conceptual factor was .26, ($p < .001$). In running this model, I included syntax for model modification indices in the analysis, and Mplus modification suggestions included adding three pairs of within-factor indicator residual correlations, which were added to the next iteration of the model. These residual correlations suggest unmodeled sources of covariance between each pair of indicators that are not systematically related to that of the latent antecedent factor onto which they load. Therefore, allowing these residual correlations improves model fit, but does not necessarily help or hurt the theoretical validity of the model itself. Several complex (cross-factor) loadings were also suggested by Mplus modification indices, but could not be justified theoretically, and therefore were not added to the subsequent model.

After making these changes, the newly refined model was then re-analyzed in Mplus. The two models are non-nested, so significance testing for model comparison is not feasible. However, the newly refined model saw improvements over the previous model on all fit statistics (χ^2 (98) = 363.39, $p < .001$, RMSEA = .073, CFI = .963, TLI = .955). The standardized coefficient for the effect of the Perceptual factor on the Overall Simplicity factor was .61 ($p <$ .001), while that of the Conceptual factor became .20 ($p = .018$). As a measure of effect size, the standardized estimate of residual variance in the Overall Simplicity factor was .47, indicating that the two antecedent factors explained approximately 53% of the Overall Simplicity factor's variance. No further model modifications were made.

Study 1 identifies branding elements that form latent antecedent factors of participants' overall brand simplicity judgments. Specifically, the perceived sparseness of ads and websites, the perceived simplicity of a product, its packaging, and the brand name, and the ease of understanding the copy of ads combined in a Perceptual factor to positively predict the perceived simplicity of companies in general. The effect of this factor was stronger than the Conceptual factor. I believe this reflects the difference in salience between perceptual and conceptual elements of branding. There are two possible explanations for this difference. The first is that perceptual cues have a larger effect than conceptual ones on judgments of overall simplicity of companies in the real world. The other is that there was something about the methodology that increased the relative salience of perceptual cues compared to their salience in the real world. Regardless of which explanation is correct (and since I did not predict the differential effects *a priori*), what is important is that both the Perceptual and Conceptual factors had an effect on overall simplicity perceptions. In study 2 I manipulate Perceptual Simplicity because it shows a stronger effect and is therefore likely to produce larger effect sizes, and because manipulating perceptual branding elements in an internally valid way is more straightforward.

2.3.3 Study 2: Effects of Simplicity on Risk and Liking

I hypothesized that, ceteris paribus, perceptions of brand simplicity decrease perceptions of product or service failure risk. In study 2 I test this prediction using stimuli from study 1. I also test the simplicity-liking relationship. I chose a subset of the brands from the study 1 that differed in rated simplicity, had participants view their websites and visual advertisements, and then judge risk and liking. I predicted that the simpler-rated brands would be deemed lower risk. Manipulation of perceived brand simplicity was accomplished via stimulus selection. I considered two plausible alternative explanations for an association between perceived simplicity and risk. First, participants may see simpler brands as more premium and more premium brands as lower risk. Second, it could be the case that risk judgments do not depend on simplicity per se, but instead are fully mediated by liking. That is, participants may like simpler brands better and deem things they like to be lower risk. If this were true, it would mean that anything that increases liking should decrease risk, without a theoretically interesting place for simplicity. To test these alternatives, I included a measure of brand premiumness and controlled both for it and for liking when assessing the effect of simplicity on risk.

Method

204 Amazon Mechanical Turk participants completed a Qualtrics survey via Cloud Research for $2.00. Data from 11 participants who admitted not viewing study stimuli and three participants who took less than five minutes to complete the survey[2] were deleted from the data set before analysis began, resulting in 190 complete responses.

Study 2 used a fully within-subjects design. I took pairs of brands—the simplest and the most complex from four of the eight product categories in study 1 (based on average simplicity judgments). The brands were Sleep Number and Casper (mattresses), Aetna and Oscar (insurance), Charles Schwab and SoFi (financial services), and OGX and Suave (hair products). All participants viewed the websites and advertisements of all eight brands (with order of website or ads first counterbalanced), which were identical to the study 1 stimuli for those brands. After viewing the website and advertisements of a brand, participants then answered questions on four key variables. The first variable of interest was liking ("How much do you like the company [brand]?"). This was measured on a six-point "Do not like at all" to "Like very much" scale. The second variable was simplicity/complexity ("In your opinion, how simple or complex is the company [brand]?"), which was measured on an eight-point "Extremely simple" to "Extremely complex" scale.[3] The third was premiumness ("Please rate how much you agree disagree with the following statement: I think of [brand] as a high-end brand."), measured on a six-point "Strongly disagree" to "Strongly agree" scale. Finally, participants indicated perceived

[2] The mean completion time for the remaining 190 participants was 21 minutes, 20 seconds. Participants could not, in good faith, complete the survey in less than five minutes because they were instructed to visit the websites of 8 brands, spend several minutes on each, view multiple advertisements by those brands, and answer more than 50 questions in total.

[3] Because Cronbach's α on the three items used to measure Overall Simplicity in study 1 was .89, and in order to measure the construct with multiple operationalizations, I chose a slightly different one-item measure of simplicity/complexity in this study.

risk on a seven-point “Extremely low risk” to “Extremely high risk” scale in response to the following statement:

> “When buying something or interacting with a company, sometimes consumers experience issues that they didn't expect. These issues include anything that would cause a consumer to return something, post a negative review, or contact customer service for any reason. In your opinion, what is the risk of this kind of issue happening with [brand]?”

These four measures were always presented in random order, as was the order in which participants saw the eight brand survey blocks. Participants then answered a question asking them if they actually viewed all eight of the brand websites, or if they skipped one or more. They answered demographic questions before ending the survey.

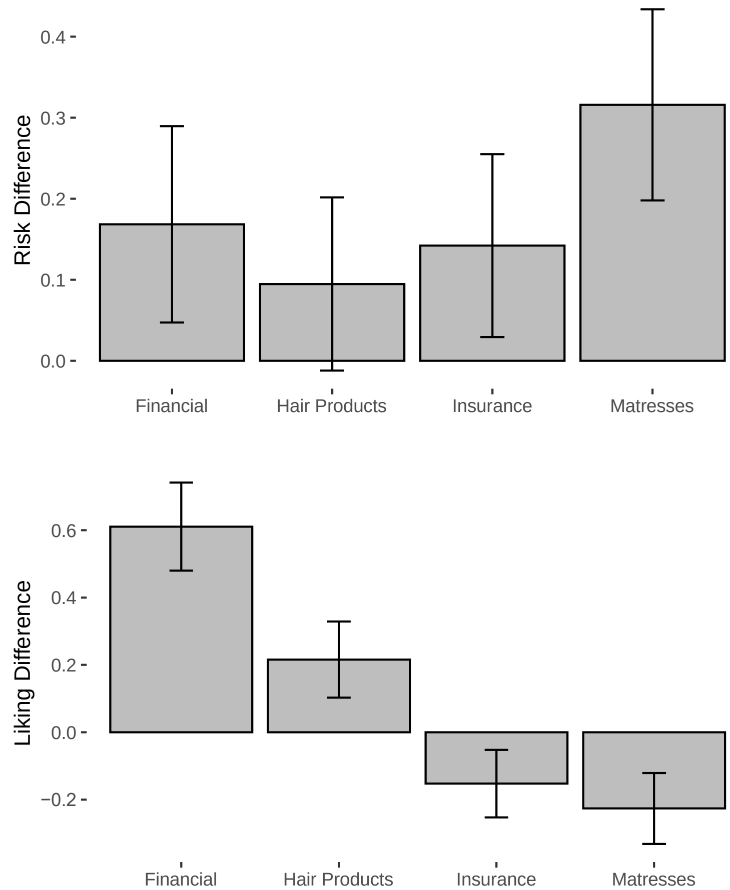
Results and Discussion

I first checked for meaningful differences in perceived complexity between the simple and complex brands in each product category, replicating the perceived differences from study 1. I tested if the within-subject differences between the simple and complex brands were significantly different from zero on average, and confirmed that the brands perceived to be simpler or more complex in study 1 were significantly so in study 2 in each product category (all ps $< .001$).

The predicted effect of perceived simplicity on perceived risk was supported by the data. I ran a linear mixed-effects model with a within-subject risk difference score (complex minus simple) as the dependent variable. Because this measure represents each participant’s difference in perceived risk between the complex and simple brand within each category, I can test if the model intercept is significantly different from zero in order to probe the effect of simplicity on risk. The model also included zero-centered difference score variables to control for the effects of brand liking and perceived brand premiumness, as well as mean-centered participant demographic variables (age, gender, and income) and random intercepts for product category and participant (see appendix for construct correlations). A positive and significant intercept indicated that participants believe simpler companies to be lower risk (simplicity coded with higher numbers indicating more complexity; $\beta_0 = .36$, $t(5.56) = 5.60$, $p = .002$, 2.77% of range[4]). The next analysis examined the effect of perceived simplicity on liking judgments. I ran a model with the same demographic controls and random intercepts predicting within-subject differences in brand liking. The model revealed a positive intercept ($\beta_0 = .11$, $t(3.23) = .54$, $p = .63$), indicating more liking for the complex brands than the simple ones (though this intercept was not statistically significant). Further examination revealed that the simple brands were liked more than the complex brands in two of the four product categories (insurance and mattresses), but not in the other two (financial services and hair products; see figure 2 below).

[4] There is significant debate regarding the appropriateness of standardized effect size statistics in linear mixed-effects models. Therefore, because I use many linear mixed-effects models in this paper, I report instead an easily interpretable statistic representing a parameter's effect in terms of percent change in the dependent variable's scale range. For example, a coefficient (or slope) of 1 on an eight-point DV range would be reported here as "12.5% of range."

FIGURE 2: STUDY 2 WITHIN-SUBJECT DIFFERENCES IN RISK AND LIKING BETWEEN COMPLEX AND SIMPLE BRANDS ACROSS FOUR PRODUCT CATEGORIES (WITH STANDARD ERRORS)



Note: All difference score measures were constructed by subtracting an individual's judgment of a simple brand from that of a complex brand. Positive values on these measures indicate more risk, liking, etc. for complex brands.

Across eight brands from four product categories, participants demonstrated that they believe that simpler brands are less likely to experience unexpected issues than complex brands, after controlling for liking and perceived premiumness. However, the practitioner assumption that participants like brands perceived to be simpler more than those perceived to be complex was not supported. In fact, the data showed more liking for the complex brands on average, though this effect was driven by more liking for the complex brands in two of the four categories. As a result, study 2's evidence on the relationship between simplicity and liking has to be considered inconclusive.

2.3.4 Studies 3a And 3b: Manipulating Perceptual Simplicity

Although study 2 uses a good representative design because it uses real brands and has participants interact with real ads and websites, one potential criticism is that simpler branding could reflect brands that are actually simpler, in which case consumers would be correct to predict lower risk. Study 2 also has weaker internal validity because the manipulation is based on stimulus selection, with extraneous variables differing between brands within a given category. I designed study 3 to address these concerns by showing that merely the visual appearance of a marketing image can make consumers feel that there is a difference in risk between simpler and complex brands, even if other important factors about the brands are held constant. I tried to alleviate concerns about confounding factors in study 2 by controlling for perceived premiumness and liking, but it is possible the measures do not perfectly control for the confounded constructs, and there may be other confounds that I did not think of. In order to address these concerns in study 3 I manipulate perceived brand simplicity by varying the visual complexity of advertisements. I chose this manipulation in order to both maximize internal validity (since it is easy to manipulate visuals of an ad without changing other characteristics) and because perceptual elements were revealed to be strong antecedents of brand simplicity judgments in the study 1. I also strengthen the interpretation of the risk results by including additional control measures for perceived company size, luxury, professionalism, and liking, and re-test the simplicity-liking relationship in a more internally valid experiment. What follows is a full discussion of study 3a, with differences and motivations for running study 3b in the Results and Discussion section below.

Method

617 Amazon Mechanical Turk participants who were diverted from an unrelated study completed a Qualtrics survey via Cloud Research for $.80. Like study 2, study 3a used pairs of brands, but this time in five product categories: software development, financial services, bicycles, food, and apparel. Each participant was randomly assigned to view only one of the five categories, and each category included two fictional brands, one with a simple marketing image and one with a complex one.

The images were manipulated in line with findings from study 1 and Pieters et al. (2010). Complexity was increased by including additional images, edges, textures, colors, and copy, and reducing empty space. The simple stimulus in each category was black and white only, and included a stylized hourglass graphic, the company name, and three category-specific words, as well as a large amount of white space, reflecting takeaways from the study 1 about visual sparseness and the ease of understanding marketing copy. Across product categories, the images and company names were the same within simplicity levels, but the copy on the stimuli was changed to reflect the appropriate category. For example, the simple apparel company condition copy read, “Streetwear. Workwear. Simplicity,” while the simple financial services condition copy read, “Investing. Planning. Simplicity,” even though both brands used the same visuals and names. As discussed in the introduction, using the term “simple” or “simplicity” is a very common tactic when attempting to project simplicity, so I added Simplicity as the third word for all companies in the simple condition in order to strengthen this study's external validity. It is also important to note that because this is a within-subjects experiment, the simple and complex companies had to have different names and copy. Examples of simple and complex stimuli are shown in figure 3 and all study stimuli can be found in the supplemental materials.

I am primarily interested in participants' subjective perceptions of simplicity. However, because all stimulus images used in the experiment were the same height, width, and file format, objective visual complexity of the stimuli could be assessed by the size of each image file (for an excellent discussion on image compression, complexity, and file size, see Pieters et al. 2010). Across the five categories, the average file size of the complex condition stimuli (M_{Complex} = 372.92 kilobytes) was significantly larger than that of the simple condition stimuli (M_{Simple} = 30.97 kilobytes, $p_{\text{difference}} < .001$).

FIGURE 3: STUDY 3A EXAMPLE STIMULI FOR SIMPLE AND COMPLEX BRAND CONDITIONS

After being randomly assigned to a category condition, participants were then randomly assigned to one of two presentation order conditions (simple first or complex first). They viewed either the simple or complex marketing stimulus in their assigned category, evaluated the perceived simplicity of the company (using the same measure as in study 2), then answered three questions about important potential confounding factors in random order. The first was size of the company ("In your opinion, how small or large is this company?"), measured on a six-point "Very small" to "Very large" scale. The second was luxury ("Please rate how much you agree/disagree with the following statement: I think of this company as a luxury company."), measured on a six-point scale from "Strongly disagree" to "Strongly agree." The third was professionalism ("In your opinion, how professional is this company?"), measured on a six-point "Not professional at all" to "Very professional" scale. Participants then viewed the equivalent stimulus and answered questions for the other brand / level of simplicity in their assigned category. Participants were re-shown both stimuli and were asked to evaluate whether consumers of company A or company B (simple-complex counterbalanced across conditions) would be more likely to experience unexpected product or service issues. The wording of the first half of this risk measure was the same as in study 2, but the second half read, "Based on what you know, are consumers of Company A or Company B more likely to experience these kinds of issues? Please indicate your answer below. Feel free to look at the screenshots again if you need to." The key difference in this risk dependent variable compared to study 2 was that it was a direct-comparison six-point measure from "Consumers of Company A much more likely to experience issues" to "Consumers of Company B much more likely to experience issues." Lastly, participants answered the same demographic questions from study 2 before ending the experiment.

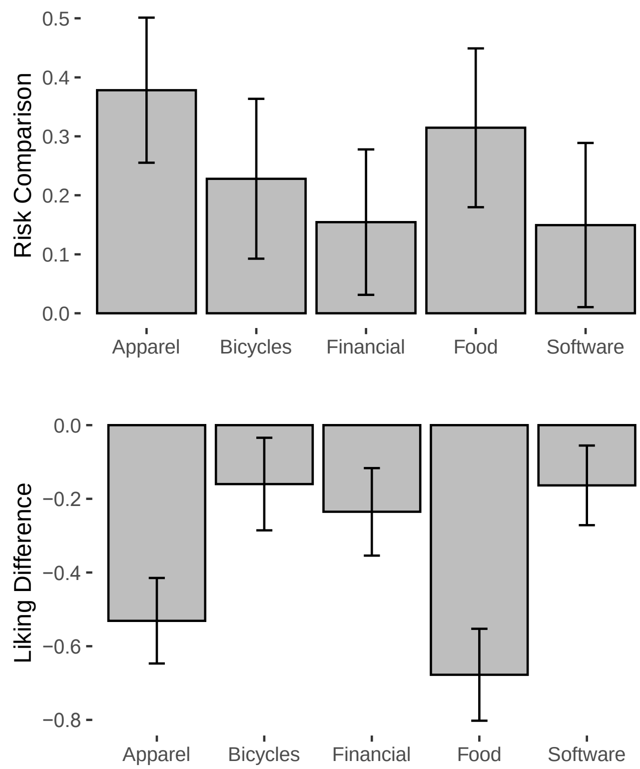
Results and Discussion

The simplicity manipulation was successful: the average within-subject difference in perceived simplicity between the simple and complex stimuli across the five product categories was 2.18 on an eight-point scale ($t(616) = 27.88$, $p <. 001$, 27.25% of range), and was significant for all five categories individually (all ps < .001).

Figure 3 shows differences in risk and liking between the simple and complex conditions by product category. To test significance, I used a linear mixed-effects model with random intercepts by category, four within-subject difference-score control variables (complex minus simple) for perceived size, luxury, professionalism, and liking, as well as a contrast-coded presentation order control variable, to test the effect of manipulated simplicity on perceived risk of unexpected issues. Because the dependent measure in the experiment was a single bipolar item, I zero-centered it at the midpoint of the scale. This allows me to easily interpret and test the significance of the model intercept, with positive intercept values indicating perceptions of more risk for the complex company, and negative indicating more risk for the simple company. As predicted, consumers judged the simpler brands to be less risky than the complex brands, over and above the effects of perceived differences in liking, luxury, professionalism, and size (β_0 = .21, $t(608) = 3.09$, $p = .002$, 3.50% of range; see appendix for all construct correlations).

I ran nine versions of the main model, first as a simple OLS test of the intercept, (model 1) then as linear mixed effects models with random intercepts by category, adding in a contrast-coded variable for presentation order (model 2), then with each control difference-score variable individually (models 3-6), with all four difference-score variables together (model 7), with difference-score and order variables (model 8), and with all previous variables plus gender, education, age, and income (model 9). Because I am testing the intercept in each model (which is meaningful only when all other independent variables have a value of zero), all difference-score and contrast-coded variables were zero-centered, and the four demographic variables were mean-centered at zero. The intercept in model 9, for example, can therefore be interpreted as the perceived difference in risk between the complex and simple brands for participants at the average age, income, education, and across genders, for whom there is no difference in perceived company size, premiumness, professionalism, or liking. See table 2 below for regression coefficients for all nine models. The value of the intercept is positive and significant, indicating less perceived risk for the simpler brands. The intercept fails to reach statistical significance in only one model, model 6, which includes liking as the only independent variable other than the intercept itself ($\beta_0 = .08$, $t(612) = 1.49$, $p = .14$, 1.33% of range).

FIGURE 3: STUDY 3A RISK AND LIKING ACROSS FIVE PRODUCT CATEGORIES (WITH STANDARD ERRORS)



Note: Higher values on Risk Comparison indicate higher perceived risk for more complex brands. Lower values on Liking Difference indicate less liking for complex brands.

Study 3a also provides support for the effect of simplicity on liking: the within-subject difference in liking between the complex and simple brands indicated more liking for the simpler brands (average within-subject difference on the six-point measure = .35, $t(613) = 6.50$, $p < .001$, 5.83% of range).

TABLE 2: REGRESSION COEFFICIENTS FOR ALL STUDY 3A MODELS TESTING THE EFFECT OF SIMPLICITY ON RISK

	Dependent variable: **Risk comparison (midpoint-centered)**								
	OLS (model 1)	*Linear mixed-effects (models 2-9)*							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Intercept	**.24*****	**.24*****	**.21*****	**.46*****	**.15****	**.08**	**.20***	**.21****	**.21****
Presentation Order		.09						.14	.14
Prof.diff			-.43***				-.22***	-.21***	-.20***
Size.diff				-.26***			-.10*	-.11**	-.11**
Lux.diff					-.24***		-.04	-.04	-.04
Like.diff						-.45***	-.28***	-.29***	-.30***
Male									-.02
Education									-.02
Age									.01
Income									.01

Notes: *p<.05, **p<.01, ***p<.001, dfs and ps estimated w/ Satterthwaite's method for models 2-9. Simplicity coded with higher values indicating more complexity.

Study 3a replicates the pattern of risk results from study 2 using a visual manipulation of perceived brand simplicity, providing additional support for the predicted effect after controlling for multiple potential confounding factors. However, the design of study 3a could have introduced other potential confounds. Specifically, the slogans and names used in the stimuli could have generated differential levels of feelings of risk, especially since the complex condition brand name was Float. The same could be said for the images themselves, one of which showed men climbing on scaffolding. To address these concerns, I ran study 3b.

Before launching study 3b, I conducted a pre-test (N = 201 participants via Prolific Academic) to test the potential new names and slogans in terms of perceptions of risk. The names were Sketch and Monarch, and the only change to the slogans from study 3a was that the term Simplicity in the simple condition was replaced with the company name, Sketch. For example, the new slogan in the financial category for the simple brand was "Investing. Planning. Sketch." Participants were not shown any images, and were asked to evaluate product failure risk on the same direct comparison measure from study 3a (one item for names and one for slogans), but with the added instructions to base their evaluations solely on the names and slogans (respectively). The pre-test revealed that Sketch was perceived to be marginally more associated with product risk than Monarch (difference in means = .19, $t(200) = 1.50$, $p = .14$), and the simple brand slogan significantly riskier than the complex one (difference in means = .60, $t(200) = 4.53$, $p < .001$). As a result, I launched study 3b with the riskier names and slogans used in the simple brand condition. This would work against the finding of the complex brand being perceived to riskier, so if the pattern of findings replicate in 2b, I believe this finding would strengthen my interpretation of the results.

Study 3b (N = 610 participants from Amazon Mechanical Turk via Cloud Research) used the same paradigm as study 3a. The only differences were the changes to the names, slogans, and images in the stimuli. The scaffolding background image from study 3a was replaced here with an abstract background of crisscrossing lines and hexagons. The pattern of results in study 3b were nearly identical to those in study 3a. Participants again judged the simpler brands to be less risky, over and above the effects of perceived differences in liking, luxury, professionalism, and size ($\beta_0 = .21$, $t(600) = 4.25$, $p < .001$, 3.50% of range). Study 3b also replicated study 3a's findings on the effect of simplicity on liking, with participants indicating more liking for the simpler brands (average within-subject difference on the six-point measure = .38, $t(604) = 7.18$, $p < .001$, 5.83% of range).

2.3.5 Study 4: Between-Subjects Contrast Effects

Studies 3a and 3b show a nearly identical pattern of results, which provide further support for the predicted relationship between perceived simplicity and perceived risk. However, both studies were within-subjects experiments in which simplicity and brand were necessarily confounded. For this reason, study 4 tests the simplicity-risk relationship in a between-subjects experiment.

Method

604 participants were recruited from Amazon Mechanical Turk via Cloud Research and completed a Qualtrics survey in exchange for $.40. They were assigned to one of two between-subjects conditions. In one condition, the focal brand, a fictional apparel company, was made to seem simple by comparison. In the other, the same focal brand was made to seem complex by comparison. In each condition the same marketing image from the focal brand was presented next to either a very visually simple or complex fictional competitor brand's marketing image.

Participants then proceeded to the three main variables of interest, reporting perceived simplicity, risk of failures, and liking for both the focal and competitor brand in their assigned condition. The items were similar but not identical to those in studies 3a and 3b. The simplicity items asked, "In your opinion, based on the marketing images above, how simple or complex are the two companies?" (matrix, 8-point scales from "Extremely simple" to "Extremely complex"). The first part of the risk items were the same as those in studies 2a and 2b, but then asked, "Based on the marketing images above, how likely are consumers of each of the two companies to experience these kinds of issues?" (matrix, 8-point scales from "Extremely likely" to "Extremely unlikely"). The liking items asked, "In your opinion, based on the marketing images above, how much do you like the two companies?" (matrix, 6-point scales from "Do not like at all" to "Like very much"). As with the previous studies, participants finished the survey by answering age, education, and gender questions for completeness.

Results and Discussion

Because participants in both conditions viewed and evaluated the identical image from the same focal brand (with only its competitor brand varying between them), I tested for between-condition differences in perceived simplicity, risk, and liking for the focal brand. The contrast-effect simplicity manipulation was successful: when paired with a competitor brand's very visually complex marketing image, the focal brand seemed simpler than when paired with a very visually simple competitor ($M_{\text{simple-by-comparison}} = 3.12$, $M_{\text{complex-by-comparison}} = 4.37$, $t(602) = 11.77$, $p < .001$, 15.50% of range; lower values indicate more simplicity). As hypothesized, these differences also extended to participants' perceptions of the risk of unexpected issues, with participants rating the focal brand as less risky when it seemed simpler ($M_{\text{simple-by-comparison}} = 4.15$, $M_{\text{complex-by-comparison}} = 4.46$, $t(602) = 2.83$, $p = .005$, 3.88% of range; lower values indicate less risk). Finally, replicating studies 2a and 2b, participants in the simple-by-comparison condition reported more liking for the focal brand than those in the complex-by-comparison condition

($M_{\text{simple-by-comparison}}$ = 3.62, $M_{\text{complex-by-comparison}}$ = 3.06, $t(602) = 5.32$, $p < .001$, 9.33% of range; higher values indicate more liking). Importantly, in a model predicting risk with condition and a control variable for liking, the complex condition was still perceived to be significantly riskier than the simple condition ($t(601) = 2.38$, $p = .02$).

Study 4 provides additional support for the hypothesized effects of perceived brand simplicity on perceived risk of failures in a between-subjects experiment with good internal validity. When the same focal brand seemed simpler to participants, they rated its customers as less likely to experience unexpected issues, compared to when it seemed more complex. Study 4 also provided support for the practitioner assumption that simpler brands are better liked than complex ones, given that the focal brand was liked more in the condition where it appeared to be simpler.

2.3.6 Study 5: Evidence for Consumer Response To Failures in Secondary Data

We hypothesized that by lowering risk perceptions, marketing simplicity can increase consumer dissatisfaction in the event of product or service failures. This prediction is nearly impossible to test in a general way in the lab or in a field experiment. A laboratory study would be constrained by achievable sample sizes, and would be limited to one or a small number of products. Manipulating product failure in a field experiment would be infeasible and would also be limited in coverage of product categories. I therefore tested this prediction using proprietary secondary data. As part of their product evaluation process, product testing and rating organization *Consumer Reports* conducts extensive consumer experience surveys. I were given access to the consumer survey data for 2018 in four product categories: blenders, grills, mowers, and vacuums.

This dataset was perfect because it includes measures of both an overall evaluation (recommendation likelihood) and a report of how many problems the consumer experienced with the product. *Consumer Reports* does not measure brand simplicity in its consumer experience surveys. Therefore, I collected brand simplicity judgments from an independent sample for the brands in the *Consumer Reports* data. The key prediction was an interaction between experienced problems and perceived brand simplicity on recommendation likelihood, such that simple brands are penalized more than complex ones when problems occur.

Consumer Reports Data

Consumer Reports' product reliability and satisfaction data is based on responses to their annual, quarterly surveys. Their Spring survey is emailed to a census sample of about 3 million *Consumer Reports* members, while their Winter, Summer, and Fall surveys utilize probability samples of these same people. Combined, these online surveys generate more than 800,000 responses per year. The data are representative of *Consumer Reports* members and the products they own. Each product category, aside from cars, is surveyed once per year.

We obtained data from the 2018 survey year for blenders, grills, mowers, and vacuums. The original dataset consisted of 171,059 customer surveys. I excluded incomplete responses and brands with fewer than 100 observations (because I wanted to have a tractable number of brands for which to collect simplicity scores). After these exclusions, the final dataset consisted of 147,460 observations across 63 brands. (Blenders: 12 brands, 26,727 observations; Grills: 12

brands, 33,360 observations; Mowers: 20 brands, 35,742 observations; Vacuums: 19 brands, 51,631 observations). The median number of observations per brand was 677.

The first key variable of interest was recommendation likelihood (“How likely is it that you would recommend a/an [brand, category] to your friends or family?”). This was measured on a 4-point “Extremely likely” to “Extremely unlikely” scale, which I recoded so that higher numbers indicated greater recommendation likelihood. The second key variable was number of problems experienced. For grills, mowers, and vacuums the question was, “…how many times did it break or stop working as well as it should?” and was measured on a 4-point ordinal scale (None,” “Once,” “Twice,” “Three or more times”). For blenders the question was, “In total, how many problems have you had with this blender since you've owned it,” and was measured on a 6-point scale (“None,” “1,” “2,” “3,” “4,” “5 or more”). For consistency across categories and because there were very few observations of “4” and “5 or more,” I collapsed them into one bucket with “3,” to create a 4-point scale, like the other categories.

In addition to the key variables I included controls for age of the product and price (as a proxy for premiumness). Age was measured by asking participants what year they purchased the product, and I recoded it to represent number of years since purchase. Price was measured by selecting a price-range bucket from a list. Though this scale is technically ordinal, for simplicity I include it as a continuous covariate in the main model. Treating this variable as categorical does not substantively affect the results but does make the model much more complex and difficult to interpret.

Simplicity Scores

I supplemented the *Consumer Reports* data with average brand simplicity scores that I collected from an independent sample via Prolific Academic. Five hundred participants were diverted from an unrelated study and completed a Qualtrics survey in exchange for $1.90. Data from 22 participants who admitted not following directions were excluded, leaving 478 in the final dataset.

Each participant was randomly assigned to one of the four product categories, then again to a random subset of up to 12 brands within the category, which they evaluated in random order. For each brand, participants were instructed to browse its website (via a link I provided) for several minutes before answering the three overall simplicity questions from study 1.[5] This gave me one measure of simplicity per brand per participant, which I averaged across participants to provide a mean simplicity score for each brand in the dataset. The average number of participant judgments per brand was 66.7. I do not include brand-specific means in the paper because I was not allowed to divulge brand names in reporting of these results.

Analysis, Results, and Discussion

Prior to merging the data for the main analysis, I calculated descriptive statistics by product category. They are shown below in table 3. For the main analysis I merged the data for the four categories into a single data set, first z-scoring the recommendation likelihood, simplicity, price, and age variables within category.

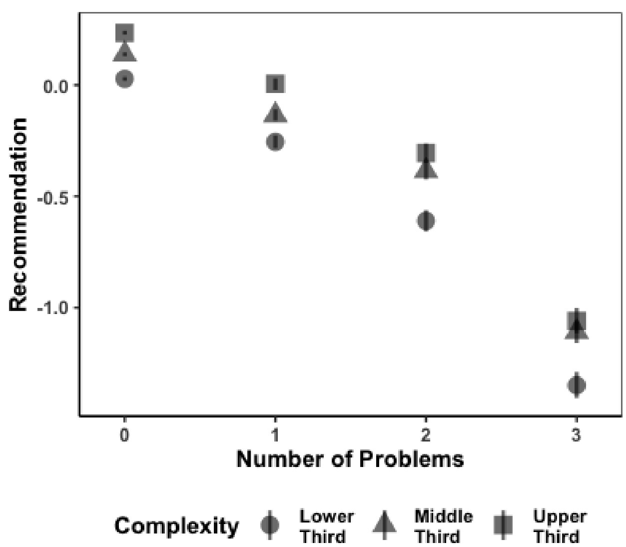
[5] The survey also included a predicted performance measure, "How well do you think [brand's] products perform?" However, this measure was not used in the analyses because every consumer in the Consumer Reports data chose to buy the product they reviewed, meaning their pre-purchase performance evaluations were necessarily high. Therefore, imputing the independent sample's performance scores would be inappropriate, since it would not be a good representation of performance expectations of the Consumer Reports respondents.

TABLE 3: STUDY 5 DESCRIPTIVE STATISTICS BY CATEGORY

Category	Blenders	Grills	Mowers	Vacuums	Total / Mean
Number of Brands	12	12	20	19	63
Number of Observations	26,727	33,360	35,742	51,631	147,460
Mean Recommendation Likelihood	3.50	3.57	3.57	3.47	3.52
Mean Complexity	4.14	3.91	4.06	3.85	3.97
0 Problems	88.6%	79.1%	70.6%	78.8%	78.6%
1 Problem	7.7%	11.0%	14.2%	10.8%	11.1%
2 Problems	2.4%	4.8%	7.5%	5.0%	5.1%
3 or More Problems	1.2%	5.2%	7.7%	5.5%	5.2%

Because of the way the problem variable was measured by *Consumer Reports*, I ran two versions of the main model: one with the problem variable operationalized by dummy codes, and one by a set of Helmert contrast codes (Judd et al. 2009). Both were linear mixed-effects models. They tested whether the effect of experiencing a problem on consumers' willingness to recommend a product depends on the perceived simplicity of the brand. The advantage of the dummy code version is that it allows me to test the effect of simplicity on recommendation when moving from zero problems to one problem. Its downside is that the model intercept is not meaningful for my predictions, and neither are the remaining dummy-coded interaction variables (zero versus two problems, zero versus three or more, etc.) The benefit of the Helmert code version of the model is that it allows me to test the effect of simplicity on recommendation when moving from zero problems to the remaining three problem levels. Its intercept is also more interpretable because it represents the mean of all problem level group means on the recommendation dependent variable. I am focused primarily on the interaction of simplicity and problems on the recommendation dependent variable, and each model included random intercepts and slopes by product category. I also ran these models both with and without control variables for the age of product and the price of the product. Note that the sample size for the models with controls is reduced to 126,475 observations because of incomplete price and age data. Complete results of all models are shown in table 4. Figure 4 shows average recommendation likelihood as a function of brand complexity tercile groups and number of problems experienced.

FIGURE 4: STUDY 5 RECOMMENDATION LIKELIHOOD MEANS AT THREE LEVELS OF SIMPLICITY AND INCREASING LEVELS OF PROBLEMS (WITH 95% CONFIDENCE INTERVALS)



Both versions of the model support this essay's main prediction: experiencing more problems with a product decreases consumers' subsequent willingness to recommend it, but this is more pronounced for simpler brands. In figure 4, this interaction is apparent by the larger distance between the upper and lower thirds of complexity as the number of problems increases. In the dummy code version of the model, the interaction of a none-versus-one problem dummy code and a brand simplicity variable (with higher values indicating more complexity) on recommendation likelihood was positive and significant ($\beta_{interaction}$ = .02, t(147400) = 3.01, p = .003, .50% of range). In the other version of the model, the interaction of a contrast-coded problem variable (representing one problem versus the average of the remaining three levels of problems) and brand simplicity (with higher values indicating more complexity) was also positive and significant ($\beta_{interaction}$ = .02, t(147100) = 3.72, p < .001, .50% of range). These positive interaction coefficients indicate that more brand simplicity exacerbates the downward effect of problems on consumer recommendation likelihood. This pattern of results replicates when I include control variables for age and price of the products (see table 4).

TABLE 4: REGRESSION COEFFICIENTS FOR ALL STUDY 5 INTERACTION MODELS

	Dependent variable: **Recommendation Likelihood**			
	(Dummy w/ controls)	**(Dummy)**	**(Contrast w/ Controls)**	**(Contrast)**
Dummy1	-0.29^{***}	-0.27^{***}		
Dummy2	-0.59^{***}	-0.57^{***}		
Dummy3	-1.35^{***}	-1.31^{***}		
Contrast.0v123			-0.75^{***}	-0.71^{***}
Contrast.1v23			-0.68^{***}	-0.67^{***}
Contrast2v3			-0.76^{***}	-0.74^{***}
Complexity	0.05	0.10^{***}	0.07^{*}	0.12^{***}
Product Age	0.00		0.00	
Product Price	0.10^{***}		0.10^{***}	
Dummy1:Complexity	0.03^{***}	0.02^{***}		
Dummy2:Complexity	0.04^{***}	0.04^{***}		
Dummy3:Complexity.	0.04^{***}	0.04^{***}		
Contrast0v123:Complexity			0.034^{***}	0.03^{***}
Intercept	0.16^{***}	0.13^{***}	-0.40^{***}	-0.40^{***}

Note: *p<.05, **p<.01, ***p<.001

Across all versions of the models in study 5, I find that consumers penalize brands perceived to be simpler more than complex brands when there is an unexpected problem. These analyses are correlational, so caveats apply, but they do provide evidence for the hypothesis that consumers punish simple brands for problems due to decreased risk perceptions. Notably, simpler brands also received poorer evaluations overall. A regression predicting recommendation likelihood with simplicity (again coded with higher values as more complexity) and random intercepts by category shows a positive and significant effect ($\beta_{complexity} = .09$, $t(147500) = 35.87$, $p < .001$, 2.25% of range). As can be seen in figure 4, recommendation likelihoods were lower for simpler brands at all levels of experienced problems. While I began the essay with the intuitive idea that brand simplicity may benefit liking, across studies the data provided only weak support for this. In study 2, evidence was mixed across product categories. Because participants evaluated real brands, these results could be due to specifics of the brands I chose. In studies 3a, 3b, and 4, with fictitious brands and a more minimal manipulation, I did find a benefit to liking from simplicity. Here in study 5, in a post-usage context, I found that simpler brands obtained lower recommendation likelihoods. One possible explanation is that simpler brands are held to a higher standard. In the case of this *Consumer Reports* data, pre-purchase liking was likely to be high because the consumer chose to purchase that option. The fact that evaluations for simpler brands were lower, even in the absence of reported problems, should be worrying to marketers of simple brands. It suggests that brand simplicity may be a good strategy for generating attention and trial, but could be less beneficial to post-purchase satisfaction and customer retention.

2.3.7. Study 6: Mediation through Perceived Simplicity

The purpose of study 6 is to conceptually replicate the correlational findings of study 5 after manipulating perceived simplicity and failure. Study 6 also examines each path of the essay's overall conceptual model, with continuous evaluations of simplicity mediating the relationship between manipulated simplicity and risk perceptions. Data from study 5 provide real-world support for consumers' more acute punishment of brands they believe to be simpler (relative to more complex ones) in the event of failures. Results from the other studies in this essay suggest that the phenomenon may be driven by consumers' inferences about the relationship between the perceived simplicity of a brand and the likelihood of its products or services failing. However, up to this point, I have not empirically demonstrated the full path from perceived simplicity to perceived risk to dissatisfaction in the event of a failure. In study 6 I attempt to do so by experimentally manipulating both simplicity and failure, and measuring perceived risk and subsequent star ratings, using the same four product categories from the Consumer Reports data in study 5. I replicate the essay's overall findings and provide evidence for the paths between these constructs using a moderated mediation analytical approach. However, I do not test the relationship between perceived simplicity and liking, as in previous studies.

Method

A combined sample 2053 participants from Mechanical Turk and Prolific Academic completed a short Qualtrics survey in exchange for $.50.[6] Fifty eight participants were excluded for either failing an attention check measure or receiving Recaptcha scores below .5 (indicating high likelihood of being bots), leaving a final sample of 1995 participants (525 from Mechanical Turk, 1750 from Prolific Academic; 47.3% female).

Study 5 used a two (simple vs. complex) by two (failure vs. no failure) between-subjects design. Participants were first randomly assigned to one of four product categories, which were identical to those in study 4: vacuums, mowers, grills, or blenders. They then viewed both a simple and complex brand's marketing image from their assigned category, representing the simplicity factor manipulation. Consistent with studies 1-3, simplicity was manipulated visually using primarily empty space, as well as a brief tagline that read, "Blend. Simple." or the equivalent from one of the other three product categories. In the complex condition manipulation, the image contained additional edges, words, and shapes. Each image also contained one of two images of the category product itself (i.e., a blender), which was counterbalanced to randomly appear in either the simple or complex condition. Across all categories, the same brand names accompanied the simple and complex brands: Simplicity and Xvolve. Therefore, while participants were assigned to answer question about only the simple or complex brand, they saw both the simple and complex brands' images. After viewing the stimuli, participants then answered the same 8-point simplicity and 6-point failure likelihood questions from the previous studies about either the simple or complex brand, in random order.

[6] I planned to collect the entire study 6 sample on MTurk, but because only participants with reliable worker statistics were allowed to take the survey, it was taking too long to complete. I therefore paused the survey after about 550 participants had completed it, and launched the survey to another 1500 participants on Prolific Academic. Other than this, all other plans and analyses associated with study 6 were pre-registered on AsPredicted.org (including the target sample size of ~2000 participants).

Participants then moved on to the failure manipulation and were given the following prompt: “Imagine that you have decided to buy the [brand name] [product]. Imagine that you use it, then decide to write an online review of it. On the next page you will see your written review of the product. Please read it carefully.” They then read “their” product review, the look of which mirrored the format of an Amazon or Yelp review. This review represented the main failure manipulation. Those participants in the “no failure” condition read the following review, which was changed slightly for each category: “Overall, this blender works very well. It blends frozen fruit and ice cubes quickly and smoothly, is fairly quiet, and the lid seals nicely to prevent splatters in my kitchen." The failure condition review included the same copy, plus the additional sentence (or its category-specific equivalent): “But every once in a while it turns off unexpectedly, and I have to unplug it, wait a minute, then plug it back in to get it working again.” Finally, participants were shown their category- and simplicity level-specific brand marketing stimulus again, before answering the following question: “Based on what you know about the company and the product, what is your star rating of the [brand name] [product]?” (9-point scale from 1 to 5 stars with half stars in between). Finally, they answered demographic measures of age, gender, and education before completing the survey and receiving payment.

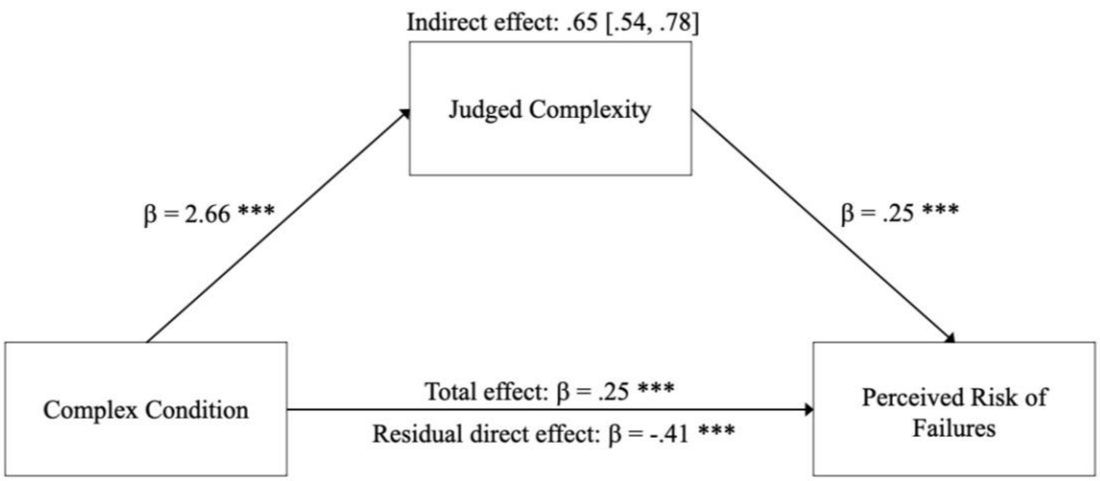
Results and Discussion

The main study 6 analyses test the paths between the essay’s constructs of interest in two ways. In the first, I test for the existence a significant mediation and a significant moderation. In the mediation model, I test whether the manipulated simplicity factor variable predicts perceptions of the risk of failures, mediated by continuous evaluations of brand simplicity. In the moderation portion, I test whether perceptions of failure risk predict participants' subsequent star ratings, moderated by a contrast-coded variable indicating whether or not participants were randomly assigned to the failure or no-failure condition. Together, these two models support the idea that consumers punish simpler brands more for failures because of lowered risk perceptions. In the second analytical approach, I test for the existence of a significant interaction between the two manipulated factors (simplicity and failure) on subsequent star ratings.

See figure 5 below. Testing the mediation model's component paths[7] in R with 200 bootstrapped iterations, the manipulated simplicity/complexity factor (coding: complex = .5, simple = -.5) positively predicts participants' perceptions of complexity ($\beta_{complex.contrast} = 2.66$, $t(1993) = 43.01$, $p < .001$, 33.25% of range), which positively predict perceptions of failure risk ($\beta_{complexity} = .25$, $t(1992) = 13.54$, $p < .001$, 4.17% of range. As a result, the indirect effect of manipulated complexity on failure risk perceptions is also positive (95% CI = [.56, .78], $p < .001$). For the moderation, perceptions of risk negatively predict star rating, but this negative effect is significantly and positively moderated by failure, indicating that failure is not as bad when participants have higher expectations of risk ($\beta_{interaction} = .17$, $t(1991) = 75.05$, $p < .001$). For the two-factor interaction model approach, a contrast-coded failure variable significantly and negatively predicts star rating, but the negative relationship is significantly worse for the simple brand condition in a linear mixed-effects model with random intercepts by product category ($\beta_{interaction} = .28$, $t(1991) = 2.44$, $p = .01$; positive interaction coefficient indicates an attenuation of the negative effect of failure on star rating for more complex brands, or a worsening of the effect for simpler brands).

[7] For an excellent discussion of the merits of this approach compared to one testing a mediational index, see Yzerbyt et al. 2018.

FIGURE 5: STUDY 6 MEDIATION MODEL



Note: *** $p < .001$

Study 6 results provide important and previously-missing evidence in support of the full conceptual argument that consumers punish simpler brands more for failures because they infer that they are lower risk. Whereas several of this essay's previous studies supported the idea that consumers infer lower risk for simpler brands, and separately, that consumers punish simpler brands more for failures, study 6 empirically connects these two ideas. It also replicates the results of the *Consumer Reports* data from study 5 using a cleaner, more internally valid paradigm.

2.3.8. Study 7: Perceptual versus Conceptual Simplicity

The goals of study 7 are to replicate the findings of study 4 (between subjects study) using the entire sixteen-item brand simplicity measure from study 1, and to test for potentially different effects on risk between the two main brand simplicity antecedent factors (perceptual versus conceptual simplicity). Study 7 also examines whether perceived brand simplicity is associated with consumer perceptions of ease, and uses a more established multi-item brand attitude measure instead of the one-item liking measure used previously.

Method

406 Mechanical Turk participants recruited via Cloud Research were paid $.50 to complete a short Qualtrics survey. Thirty one were removed from the data set for either failing an attention check measure or receiving Recaptcha scores indicating high likelihood of being bots, leaving 375 (49% female, M_{age} = 39.0 years) in the final data set.

Participants in study 7 were randomly assigned to one of two between-subjects conditions. In one condition, the focal brand, a fictional apparel company, was made to seem simple by comparison. In the other, the same focal brand will be made to seem complex by comparison. In each condition the same marketing image from the focal brand was presented next to either a very visually simple or complex fictional competitor brand's marketing image. This paradigm and manipulation were identical to those used in study 4. Participants then proceeded to the three main variables of interest in random order, reporting perceived simplicity using the full fifteen-item measure[8] developed in study 1, perceived risk of failures, and attitude

[8] Note that the full scale in study 1 used 16 items, whereas this study uses 15. This is because the original scale had separate questions asking participants to rate the perceived sparseness of advertising and websites (for real brands), and in this study the stimulus to which participants responded was one marketing image per (fictional) brand.

toward the brand (three items, Bad/Good, Unpleasant/Pleasant, Unattractive/Attractive, 7-point scales; Zarantonello and Schmitt 2010) for the focal brand in their assigned condition. As with the previous studies, participants finished the survey by answering age, education, and gender questions for completeness.

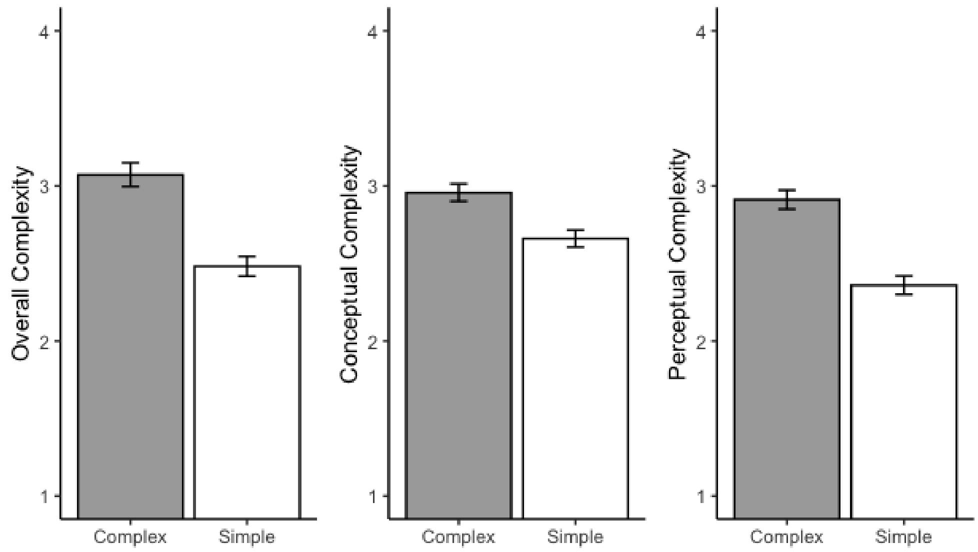
Results and Discussion

First, I conducted an exploratory factor analysis (EFA) on the fifteen-item brand simplicity scale (after removing the three "overall" simplicity dependent factor questions; see table 1 on p. 12). Replicating findings from the structural equation modeling approach in study 1, parallel analysis suggested two main factors (eigenvalues: 5.32 and .63). Importantly, the EFA naturally grouped items within those factors identically to the way they were grouped in study 1, forming a perceptual/visual factor (α = .83) and a conceptual/ease factor (α = .87; see appendix for all factor analysis output). Items within these factors and the three overall brand simplicity factor items (α = .88) were averaged within participants to form the three main simplicity variables in study 7. To check the effectiveness of the simplicity/complexity manipulation, I examined mean differences between the simple and complex conditions on all three of these simplicity variables separately. These tests also probe for potential differences in the strength of the manipulation, depending on the operationalization of simplicity, since it is possible that the manipulation successfully manipulated one type of simplicity more than others. See figure 6

Therefore, what was originally two items was combined into one: "Visually, [brand]'s marketing imagery is sparse/uncluttered."

below. For all three operationalizations of simplicity/complexity, there were significant differences in the predicted direction between conditions (all *p*s < .001), all of similar magnitude.

FIGURE 6: MEAN DIFFERENCES BETWEEN SIMPLE AND COMPLEX CONDITIONS ACROSS THREE OPERATIONALIZATIONS OF SIMPLICITY/COMPLEXITY IN STUDY 7



Note: Y axes here are labeled "Complexity" because higher values indicate more perceived complexity.

Next I tested the degree to which each operationalization of simplicity/complexity was associated with participants' judgments of risk and attitude toward the brand. Although it should be noted that there was no significant difference in perceived risk between conditions ($M_{risk.simple}$ = 4.35, $M_{risk.complex}$ = 4.41, $t(373) = .40$, $p = .69$), evaluations of the relationships between risk and the three continuous simplicity/complexity variables yielded more interesting results. In linear regression models both overall and perceptual complexity were positively associated with risk perceptions ($\beta_{overall.complexity} = .11$, $t(373) = 1.58$, $p = .11$, 1.38% of range; $\beta_{perceptual.complexity} = .16$, $t(373) = 1.90$, $p = .06$, 2% of range), whereas conceptual complexity was not ($\beta_{conceptual.complexity}$ =

.0005, $t(373) = .005$, $p = .97$, .06% of range). In terms of the three-item brand attitude measure ($\alpha = .93$), the simple condition's mean was significantly higher than the complex condition's ($M_{\text{attitude.simple}} = .88$, $M_{\text{attitude.complex}} = .54$, -3 to 3 scale, $t(373) = -2.62$, $p = .009$), consistent with marketing practitioners' assumption that simpler brands are better liked. Likewise, all three operationalizations of the simplicity/complexity variable had a negative relationships of similar magnitudes between perceived complexity and attitude toward the brand ($\beta_{\text{overall.complexity}} = -.61$, $\beta_{\text{perceptual.complexity}} = -.74$, $\beta_{\text{conceptual.complexity}} = -.72$, all ps < .001).

Finally, since the conceptual simplicity/complexity factor can be used as a proxy for consumers' perceptions of ease associated with a brand, I tested the degree to which this variable was associated with consumers' overall evaluations of brand simplicity/complexity, as well as how the perceptual factor relates to overall simplicity (as a reference point). Analyses demonstrated that consumers' overall perceptions of simplicity were indeed highly correlated with ease ($r = .68$), but the association between overall simplicity and perceptual simplicity was stronger ($r = .80$, both ps < .001). Importantly, in a model predicting risk perceptions with overall simplicity, controlling for the ease variable, the relationship between overall simplicity (coded with higher values indicating more complexity) remained positive and significant ($\beta_{\text{overall.simplicity}} = .21$, $t(372) = 2.14$, $p = .03$, 2.63% of range).

These results demonstrate that although the relationship between all three simplicity/complexity variables is strong, there is not a strong relationship between perceptions of ease and failure risk, except through perceptions of simplicity. However, perceptions of ease should also (separately) lead to dissatisfaction in the event of a failure (insofar as a failure is at least partially equated with lack of ease in consumers' minds), since the consumer still holds positive perceptions that are subsequently negatively disconfirmed.

2.4 Essay 1 Discussion

Across more than one hundred real and a dozen fictional brands from more than fifteen categories, several experiments, a pre-study, a practitioner survey, two pre-tests, structural equation models, and secondary data analysis revealed important antecedents and consequences of brand simplicity. Study 1 identified perceptual (e.g. sparse ads) and conceptual (e.g. easy-to-understand products) elements of marketing as antecedents of consumer perceptions of brand simplicity. By manipulating brand simplicity via stimulus selection and by varying the visual complexity of advertisements, findings from studies 2, 3a, 3b, and 4 demonstrated that consumers judge simpler brands as less risky. Analysis of a proprietary customer satisfaction dataset from *Consumer Reports* in study 5 found that consumers penalize simple brands more than complex ones when problems occur. Study 6 replicated the findings of study 5 and provided evidence that the pattern of effects is driven by simplicity causing lower perceptions of risk, which lead to dissatisfaction when disconfirmed by a failure. Results from study 7 showed correlational support for the positive relationship between overall perceptions of simplicity and ease, but not between ease and risk. Study 7 also provided support for the practitioner's simplicity-liking assumption using a more established multi-item brand attitude measure. Overall findings on the assumption across studies was mixed, although it should be noted that support for the assumption emerged only in studies where the brands were fictional. It is thus possible that there are too many additional (and unmeasured) inputs to consumers' liking / brand attitude judgments of real brands for the relationship to be uncovered, such as prior knowledge, experience, peer effects, social signaling, taste, etc. As a result, this essay's evidence on the relation between brand simplicity and liking are inconclusive.

Implications and Opportunities for Future Research

Among marketing practitioners, projecting simplicity in marketing is a popular strategy. Marketers have rightfully acknowledged that too much marketing can leave consumers with information overload. Simplicity of marketing, the thinking goes, allows marketers to reach overstimulated consumers in order to communicate benefits or a brand identity. There is some evidence that simplicity can be attention-grabbing in certain contexts. When the marketplace is cluttered with many options, each offering its own unique features, the simple option can stand out (Long 2019). Another possibility was raised by Pieters et al. (2010), who showed that one form of visual complexity encourages consumer attention, while another hurts it.

This work suggests that simple marketing has a previously undiscovered downside. If it is interpreted by consumers as a kind of promise of simplicity in general, they may develop unrealistic and inaccurate expectations of risk, which can cause real dissatisfaction in the event of a product or service failure. Data from study 5 also introduces the possibility that brands perceived to be simple may be held to a higher standard even in the absence of a failure. If this is true, marketers should be more careful about (or at least aware of) the simplicity messages they are sending to consumers. For marketers of objectively simple, high quality products with low frequency of failures, simplicity in marketing may be the right choice. However, for marketers of complex products with higher risk of failures, simplicity of marketing (and possibly customer acquisition efforts) may need to be traded off with sending more accurate signals of complexity and risk.

At their extremes, these ideas raise the possibility that high-risk companies could use excessively complex branding in order to insulate themselves against negative consumer sentiment in response to inevitable failures. Although satisfaction is a post-purchase measure, I see no reason why purchase would be a necessary condition for consumers to form simplicity judgments of brands they encounter.

In this essay I do not measure the implied tradeoff between the potential benefits of perceived brand simplicity and the dissatisfaction it may cause, compared to companies perceived to be more complex. Whether (or the degree to which) this is a tradeoff marketers should make is an empirical question that may itself depend on specific characteristics of companies. The existence of this tradeoff also depends in part on the simplicity-liking relationship. The mixed findings on liking suggest that the link between perceived simplicity and liking is at least more nuanced than I (or many marketing practitioners) expected. I speculate that any such calculation should weigh benefits to customer acquisition, lead generation, or choice, with additional resources potentially required to appropriately manage upset customers during service recovery (such as customer service staffing). This may be especially important given the fact that consumers are often more dissatisfied by an company's failure to adequately resolve a problem than by a given failure itself, and failed recoveries are a top contributor to consumer switching behaviors (Bitner, Booms, and Tetreault 1990; Keaveney 1995). Brand simplicity can thus be considered a moderator of the relationship between failure and recovery.

Finally, putting aside dissatisfaction in the event of failures, it is an open question whether brand simplicity is positive or negative for consumers themselves. On the one hand, if consumers do truly like simpler brands more than complex ones, they may also be willing to pay more for products from simpler brands, which is not ideal. The same can be said if consumers are taken in by low-quality simpler brands. On the other hand, I acknowledge that there is often a compromise between simplicity and functionality, and do not expect that consumers prefer simplicity at all costs. Rather, I speculate that marketing should be as simple as possible while still preserving the features that consumers are attracted to. If the true relationship between simplicity and liking does not translate to higher levels of choice for simpler brands because consumers are able to undertake a sort of risk-benefit analysis weighing simplicity and functionality, concerns about consumers being taken advantage of by marketers may be unfounded. All else equal, educating consumers about the judgments they are likely to make in response to simple marketing may be the most reasonable first step.

3) Essay 2: Consumer Perceptions of Product Complexity and Performance

Because essay 1 was motivated by a popular marketing strategy in which practitioners advocate simplicity of both branding and brands, it focuses on consumers' perceptions of the simplicity of brands themselves. However, a large portion of marketing attempts to communicate the benefits and value propositions of products, and under individual brands there can be many different products of varying sophistication, price, reliability, etc. For this reason it is also important to study consumers' simplicity and complexity perceptions at the *product* level.

There are several reasons to think consumers make judgments about the simplicity or complexity of products, and therefore that studying those judgments is important. Companies have traditionally attempted to differentiate themselves by adding or touting new features that their competitors do not possess, possibly creating more complexity in consumers' minds. Relatedly, since projecting simplicity in marketing is a popular strategy, this could potentially encourage consumers to consider the simplicity or complexity of other products in a consideration set, independent of whether they too are marketed as simple. Given essay 1's findings about the importance of consumers' simplicity and complexity judgments to downstream inferences about risk, in essay 2 I ask the following motivation questions:

i) If consumers think brand simplicity means less risk, does this belief extend to their judgments of products?
ii) If so, what do consumers think more product complexity buys them?
iii) What mental models of product complexity do consumers hold, and are those models appropriate?

In attempting to answer these questions, I discuss seven studies for essay 2 in this document.

3.1 Literatures on Complexity and New Products

Research from cognitive science suggests that humans prefer simpler things in general because simplicity encourages feelings of understanding without increasing cognitive effort (Chater 1999; Chater and Loewenstein 2016; Chater and Vitányi 2003; Hahn et al. 2003). In the marketing literature, higher complexity of a product has also usually been framed as a negative. Rogers (2003) suggested that it is a barrier to a product's adoption by consumers. The idea is that higher product complexity decreases the likelihood that consumers will understand a new product, which in turn decreases the likelihood that they will consume it (also see Alexander, Lynch, and Wang 2008; Jhang, Grant, and Margaret C. Campbell 2012; Moreau, Lehmann, and Markman 2001). Separate marketing research by Barwise and Meehan (2004) has argued that marketers are often too caught up with the idea of differentiation, since consumers care little for unique value propositions; instead they prefer products that consistently deliver the fundamentals of whatever they are supposed to deliver. Finally, in a test of whether or not the perceived association between simplicity and low risk in the domain of brands also extends to products, Holak and Lehmann (1990) found that consumers believe more complex-seeming products to be higher risk (in terms of both performance and psychosocial concerns).

As is the case for simplicity in branding, the truth about whether product complexity is good or bad for firms and consumers may be more nuanced. Individuals' information acquisition strategies depend on how many alternatives they are shown, as well as on the number and format of attributes for each alternative (Bettman et al. 1998; Swait and Adamowicz 2001). Increasing complexity often causes consumers to use simpler decision strategies, which can sometimes cause them to make suboptimal decisions (Bettman et al. 1998; Lussier and Olshavsky 1979; Payne 1976; Payne, Bettman, and Johnson 1990; Swait and Adamowicz 2001). There is some evidence that consumers may actually prefer more complexity in products when it is framed in terms of additional features. In evaluating products before purchase, consumers value capabilities more than usability, which results in choosing complex products that are hard to use, which makes consumers unhappy and causes "feature fatigue" (Thompson et al. 2005). Research on individuals' representations of others has shown that simpler cognitive representations leads to more extreme evaluations of people and products, and simplified mental models of complex political issues are associated with extreme views on those issues (Fernbach, Rogers, et al. 2013; Linville 1982). Applied to the current investigation, perceptions of more complexity could be good for encouraging less polarized responses to products, unless a product is universally well-liked, in which case extreme and positive evaluations may be preferred. Research on consumer perceptions of the similarity of items within sets has shown that greater complexity (measured in terms of Kolmogorov complexity, the shortest length of code that reproduces a set) leads to judgments of less similarity (Evers et al. 2014). Again, this could be good or bad depending on consumers' other evaluations of the set and its items, and this type of complexity is not product complexity *per se*.

Several papers exploring consumers' receptions and evaluations of new products are also relevant to the current essay. For example, studies have shown that consumers prefer products more congruent with their understanding of a product when the choice carries more social risk (Campbell and Goodstein 2001), that promotion-focused consumers are more open to really new products than prevention-focused consumers (Herzenstein, Posavac, and Joško Brakus 2007), and that consumers follow through on their purchase intentions for really new products less often compared to products that are incrementally new, an effect which grows with time (Alexander et al. 2008). Related research has shown that prior product or category knowledge and expertise effects expectations, emotions, and information search surrounding new product usage (Moreau et al. 2001; Moreau, Markman, and Lehman 2001; Wood and Lynch 2002; Wood and Moreau 2006). Although it is likely that consumer inferences about really new products occasionally align with those of complex products, it is not difficult to imagine scenarios or categories in which new products are not perceived to be more complex than the norm (consider the "X, Simplified" new product marketing trope), and testing the degree of alignment is beyond the scope of the current project. As a result, I believe there is value in exploring more specific consumer inferences about complex products, whether they are established, incrementally new, or really new.

3.2 Predictions

Although the term product complexity is fairly common in consumer research, definitions are rare and operationalizations inconsistent, making the formation of predictions difficult. An additional layer of difficulty is that this essay is primarily concerned with consumers' *perceptions* of simplicity and complexity, which may or may not be related to objective product complexity (for an excellent discussion of objective versus perceived product complexity, as well as definitions and operationalizations, see Mützel and Kilian 2016). One goal of this essay is to gain a better understanding of what consumers think product complexity means. Although studies 1 and 2 represent initial attempts to gain such an understanding, I also draw from prior research characterizing product complexity as higher numbers of features, characteristics, or functions, in conceptualizing the construct in this essay (e.g., Griffin 1997; Park 1976; Park, Ding, and Rao 2008; Scholz, Martin, and Reinhold 2010; Swaminathan 2004). This conceptualization is a useful starting point in the formation of predictions.

As mentioned above, this essay asks, if consumers think higher product complexity means higher risk of failures, what do they think higher complexity buys them? Although this is ultimately an empirical question, I propose that consumers think that more product complexity means a higher performance ceiling. Findings from prior research provide some support for this prediction. First, several groups of researchers have pointed out the existence of a more-is-better heuristic (Alba and Marmorstein 1987; Hasher and Chromiak 1977). Aaker (1991) argues that when quality or competence is difficult or impossible for consumers to judge, they tend to rely on "seemingly trivial but observable" characteristics. This results in inferences that larger stereo speakers produce better sound, or that more suds in detergent indicate better cleaning power, for example. Consumers also tend give better evaluations to products that have more attributes or more descriptors, and rate them higher in perceived capability, even if the additional attributes or descriptors are functionally meaningless (Carpenter, Glazer, and Nakamoto 1994; Sela and Berger 2012). Even if consumers are attracted to simpler products, they are unlikely to think that additional complexity is useless. Research on consumers' market efficiency judgments has shown that they make compensatory inferences about the performance of products in a choice set, believing that options are balanced such that advantages on one dimension are compensated for by disadvantages on another (Chernev 2007; Chernev and Carpenter 2001). If consumers believe simplicity confers benefits, and they also know that higher complexity products exist, they are likely to infer that both simplicity and complexity confer separate, more-or-less balancing benefits.

With these findings in mind, essay 2 considers a potential perceived benefit of higher product complexity. Specifically, it explores the relationship between consumers' perceptions of product complexity and a product's "performance ceiling." The primary prediction is that consumers believe products that they perceive to be more complex are capable of better maximum performance than products they perceive to be simple, ceteris paribus. I also explore the implication that consumers think a simplicity-complexity continuum means a tradeoff between reliability and peak performance. Since findings from essay 1 suggest that consumers believe complex products are more likely to experience failures, perceived quality or average performance are not appropriate dependent measures, since both failure likelihood and performance should be factored into these overall evaluations. Thus, I introduce here the idea of a product's "performance ceiling." In other words, ignoring failure risk (which should be factored in to quality judgments), what is the perceived likelihood that a product operating as intended by its creators outperforms other products?

If these inferences are always accurate judgments of product performance and risk (and thus adaptive, resource-conserving decision strategies), essay 2's contributions to scientific and practitioner knowledge would be limited. However, there are several ways in which consumers may be wrong to make inferences about the relationship between product complexity, risk, and performance. First, people tend to be poor judges of the true complexity of objects and phenomena in general, and often underestimate complexity (Alba and Hutchinson 2000; Fernbach et al. 2019; Rozenblit and Keil 2002; Thompson et al. 2005; Wood and Moreau 2006). Findings from essay 1 also suggest indirectly that inferences of complexity can be manipulated by different marketing strategies. In this essay I suggest that there is another important way these inferences can "go wrong." Even if consumers can accurately assess that one product is simpler or more complex than another in a relative sense, the degree to which their subsequent risk and performance inferences are accurate should depend on the correspondence between their mental models of product complexity and the *way* in which a product is complex.

Outside of marketing, researchers studying complex systems or information theory have defined complexity as a function of both dimensionality (i.e., more dimensions, features, or parts) and relatedness (how connected they are) (Jacobs 2007; Simon 1962). In Economics, Kremer's (1993) O-ring theory of economic development describes a production function in which there are "many tasks, all of which must be successfully completed in order for the product to have full value" (Kremer 1993, 551). As they relate to the current essay, these operationalizations / definitions suggest that the complexity of products can be rated on a scale measuring the degree to which their parts or features are independent or interdependent. Take, for example, online college courses. Each lecture or module could teach students independent facts or skills. However, in some courses the knowledge or skills could be more interdependent, with students' understanding of new concepts relying on or mutually reinforcing understanding gained from previous lectures. The same idea can be applied to physical products: additional features can individually provide different benefits or work together to support one or more benefits.

Whether consumers' mental models of product complexity account for the potential interdependence of features or attributes matters in assessing how right or wrong their subsequent inferences of risk and performance might be. In situations where complexity is characterized by additional independent features, the failure of one does not represent a failure of the whole, since one failure can still be compensated for by a weighted average of the benefits conferred by the other remaining features (i.e., the benefits of diversification). The same can be said for a product's performance ceiling. Although adding more independent features could add additional benefits, a higher performance ceiling (in terms of a product's core function or functions) depends in real life on the interdependence of its features or attributes. Scientists studying complex systems have argued that emergent properties, expected or unexpected phenomena that represent more than the sum of parts, only emerge through the interaction of parts in a complex whole (Pines 2014). Therefore, applying the same complexity-to-performance ceiling inference across products characterized by more independent complexity is either incorrect or less correct than doing so for products characterized by more interdependent complexity.

3.3 Essay 2 Studies

3.3.1 Summary of Studies

In the following section I summarize the seven studies in essay 2. In study 1 participants record their open-ended responses to questions about examples of simple and complex products, as well as what they think about them. In studies 2a and 2b participants answer open-ended questions about what product complexity means, if there are tradeoffs between simplicity and complexity, and indicate their beliefs about whether simpler or more complex products have a higher performance ceiling. In study 3 participants use a distribution builder tool to record their evaluations of risk and performance over thirty product use experiences, and I analyze summary statistics of participants in simple versus complex conditions. Study 4 asks participants to list attributes of products that are either reliable or high performance, in a test of whether reversing the order of the conceptual model leads to participants listing fewer attributes (a simpler mental representation) for the reliable product. Study 5 uses a mathematical/computational operationalization of complexity that allows me to hold constant the number of listed attributes for simple and complex products, as a manipulation of product complexity, and tests for potential differences in risk and performance capability perceptions between conditions. Study 6 examines the possibility that consumers choose simpler products (which are less likely to fail, in theory) when the stakes for failure are higher. Finally, study 7 tests the degree to which participants' mental models of the relationships between product complexity, performance, and risk, account for differences in those relationships in the real world based on several different types of complexity. It also probes whether or not their inferences are appropriate for these different complexity types.

3.3.2 Study 1: Participants' Open-Ended Thoughts on Product Complexity

The primary goal of study 1 was to encourage participants to elaborate on the idea of simplicity or complexity of products, then record their thoughts, in order to inform subsequent conceptualization and study design with qualitative data.

Method

78 Amazon Mechanical Turk participants were recruited through Cloud Research (Litman et al. 2017) and paid $.40 for completing a Qualtrics survey. Participants were randomly assigned to one of two between-subjects conditions (simple or complex). They were first asked to list three products that they consider to be simple (complex), followed by a more specific open-ended question: "Now that you've listed a few, please write down your thoughts on products that you consider to be simple (complex). You may discuss what defines them or makes them unique, special, good or bad." Participants then recorded their age, education, and gender, before exiting the survey and receiving payment.

Results and Discussion

Since I was primarily interested in the second open-ended question (in which participants elaborated on what defines simple or complex products and what makes them unique, good, bad, etc.), I grouped responses together by common themes, and asked a hypothesis-blind undergraduate research assistant to do the same. We then met to discuss common themes, which are summarized in table 5, below.

TABLE 5: THEMES FROM PARTICIPANTS' OPEN-ENDED RESPONSES ON SIMPLE AND COMPLEX PRODUCTS

Theme	Verbatim Example
Simple Products	
Have fewer parts, attributes, ingredients	"do not have a lot of unique parts"
Are less likely to break/fail	"are less likely to break down…their simplicity is their strength"
Serve fewer purposes	"generally do one thing"
Are less differentiated	"pretty much all dishwashers are the same"
Complex Products	
Have more parts, attributes, ingredients	"there's a lot of components to them…many different and connected parts"
Are more difficult to make, use, understand	"work in ways that most of us will never understand… a crazy amount of time to develop"
Are more likely to break/fail	"need to be made with precision, or the entire product fails…risky and unpredictable"
Have the potential to perform better	"lots of capability and capacity…can do impressive things"

Providing initial support for essay 2's overall predictions, participants indicated that they think of product simplicity/complexity in terms of fewer or more features, parts, or attributes, that they believe simpler products are less likely to fail, and that complex products have the potential to perform better.

3.3.3 Studies 2a and 2b: Complex Products Have A Higher Performance Ceiling

There were two main goals of studies 2a and 2b. The first was to determine whether participants believe complex-seeming products have a higher performance ceiling in a simple proof-of-concept paradigm. The second was to obtain more participants' open-ended thoughts about what product complexity means to them, as well as whether simplicity and complexity engender any perceived tradeoffs. For this second goal, participants responded to more specific prompts than in study 1.

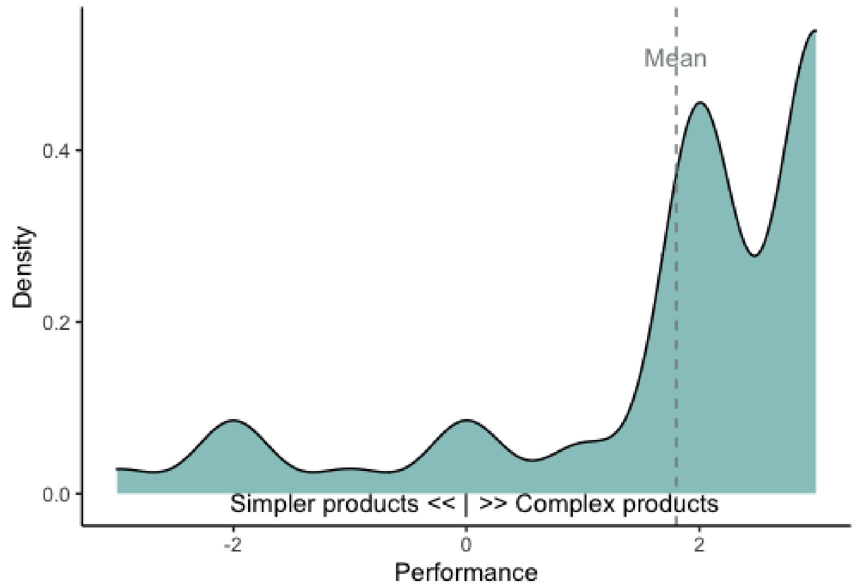
Method

In study 2a online participants recruited via Prolific Academic (N = 45) completed a short Qualtrics survey in exchange for $.55. They were first asked to imagine a simple product and a complex product from the same product category, then keep it in mind for the following questions. Participants then answered the proof-of-concept question: "In your opinion, which of the two products has a higher performance ceiling, the simple one or the complex one? Assume they cost the same amount. By 'performance ceiling,' I mean a product's maximum performance potential, ignoring its reliability or likelihood of breaking." The measure was a direct-comparison 7-point bipolar scale anchored by "the simple product definitely has a higher performance ceiling" and "the complex product definitely has a higher performance ceiling." To avoid any scale use effects, participants were randomly assigned to answer the question with the simple product or the complex product on the left side of the scale. Participants then answered the open-ended tradeoffs question by writing in a text box: "In comparing simple and complex products, what is the tradeoff, in your opinion? In other words, what do you gain or lose in terms of the benefits of products when you make a product more complex? Assume that the price doesn't change.” The final question was again open-ended, and was designed to provide further clarity on how participants conceptualize “complex” products: “In your opinion, what makes a complex product complex? What defines it as complex?” Participants then answered the same demographics questions from study 1 before exiting the survey and receiving payment.

Results and Discussion

Keeping in mind self-imagined examples of simple and complex products within the same product category, participants reported that they believed the complex products had a higher performance ceiling than simple ones (see figure 7 below). Because the bipolar direct-comparison dependent measure was centered at zero, a test of the intercept’s difference from zero indicates whether participants believed the simple product (negative values) or complex product (positive values) has a higher performance ceiling. The model’s intercept is positive and statistically significant ($\beta_0 = 1.80$ on a -3 to 3 scale, $t(44) = 7.53$, $p < .001$). Including a contrast-coded scale order variable (.5 for the simple product on the left of the dependent measure’s scale, -.5 for complex) as a covariate in the model indicated that order factor did not matter ($\beta_0 = 1.81$, $t(43) = 7.38$, $p < .001$; $\beta_{order.contrast} = -.07$, $t(43) = -.15$, $p = .88$). Relatedly, neither age, gender, nor education were meaningfully correlated with answers on the dependent measure.

FIGURE 7: DISTRIBUTION OF PARTICIPANT RESPONSES TO THE DIRECT-COMPARISON PERFORMANCE DEPENDENT MEASURE



Participants' open-ended responses to the prompt to define complexity was consistent with those from study 1. Higher product complexity to these participants meant additional features, uses, components, or attributes. For example, one wrote, "Having more features, a higher spec, more functions, settings etc.," and another wrote, "It is complex because it has more features and can go beyond basic tasks." These responses provide additional confidence in understanding consumers' conceptualization of product complexity, as well as possibilities for manipulating the construct in future studies.

In response to the open-ended complexity tradeoff question, participants gave similar answers to the less-focused responses in study 1. In addition to several mentions of complex products being harder to use and understand (on which I do not focus in this essay), participants again indicated their beliefs that more product complexity means a higher performance potential, couple with a higher likelihood of failures. This thinking is captured well by one participant's response: "When you make a product more complex there tends to be more things that can go wrong, such as breaking or system failures. When you make a product more complex however it often has more functions and things it can do making it a better consumer product." If perceptions of complex products having a higher performance potential is unsurprising, the pairing of higher performance potential with higher likelihood of failures, particularly within-participant, is notable. It suggests both that consumers separate their judgments of failure risk from judgments of performance potential, and that dependent measures failing to account for this separation could be inappropriate. Commonly used overall measures of quality, average performance, or even star rating may obscure the fact that they are a function of at least these two opposing consumer judgments.

Study 2b and Pretest

One limitation of study 2a is that it is possible that the paradigm created demand effects, since the same participants were asked to think of examples of—and evaluate—simple and complex products. In order to address this potential problem in study 2a, I re-ran a version of it in study 2b using a two-stage design with a pretest. First, one set of participants on Mechanical Turk (N = 144, 52.8% female) was asked to come up with both a simple and complex product in any product category, in exchange for $.25 (see pretest directions in figure 8 below). I recorded the five most commonly mentioned pairs of simple and complex products to use as stimuli in study 2b: a push mower and a riding lawnmower, a regular vacuum and a robotic vacuum, a traditional watch and a smart watch, earbuds and noise canceling headphones, and a manual toothbrush and an electric toothbrush.

FIGURE 8: DIRECTIONS FOR STUDY 2B PRETEST

We are interested in people's opinions of simple and complex products. Please write down one product (with the brand and product name) that is simple in your opinion, and one that is complex. Importantly, they should both be from the same product category.

- For example, a DeWalt Max Fit (manual) screwdriver and a Black & Decker LI2000 cordless rechargeable screwdriver are examples of a simple and complex product from the same product category.

Please choose the simple and complex product from a category that you are familiar with. If you need to look up specifics on websites, feel free to do so. Write the products in the text boxes below.

Simple product

Complex product

In the second stage of study 2b, a different group of Mechanical Turk participants (N = 132, 56.1% female, \$.45 payment) answered the same complexity and performance direct comparison questions from study 2a after being randomly assigned to one of the five product categories. Replicating results from study 2a, the within-subject perceived complexity of the complex product in each pair was significantly higher than that of the simple product ($M_{\text{complexity.simple}} = 3.35$, $M_{\text{complexity.complex}} = 5.73$, $t(136) = 15.88$, $p < .001$, all within-category ps < .001), and the complex product in each pair was perceived to have a higher performance ceiling (on the one-item direct comparison measure from -3 to 3 with midpoint at 0; $\beta_0 = .98$, $t(131) = 5.37$, $p < .001$).

3.3.4 Study 3: Distribution Builder

Studies 1, 2a, and 2b provide preliminary support for the prediction that consumers believe more complex products are simultaneously more likely to fail and have a higher performance ceiling. However, one potential weakness of studies 2a and 2b is that the main dependent measure forced participants to separate performance and failure risk (when they may not do so naturally). Therefore, the main goal of study 3 was to elicit these opposing judgments in a less heavy-handed procedure using a distribution builder tool.

Method

Participants from Prolific Academic (N = 435 after 16 attention check failure removals; 47.6% female; M_{age} = 34.1 years) were paid $.81 to complete a Qualtrics survey. Participants were asked to judge the frequency of different levels of performance on an 21-point X axis from 0 to 100 (in intervals of five), where zero indicates absolute failure and 100 indicates exceptional performance, across thirty hypothetical product experiences using a visual, "balls-in-bins" distribution builder tool (Andre, Reinholtz, and de Langhe 2017; Delavande and Rohwedder 2008; Goldstein, Johnson, and Sharpe 2008; Goldstein and Rothschild 2014; Long et al. 2018). See figure 9 below.

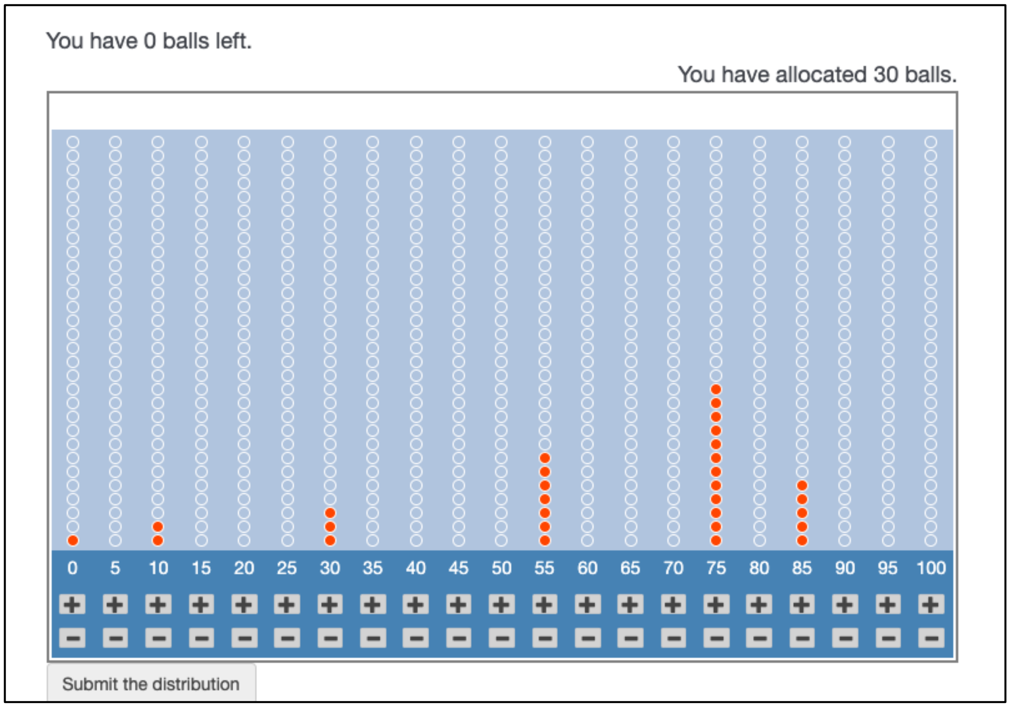
Each participant was randomly assigned to either a simple or complex product in one of the five product categories from the study 2b pretest (mowers, vacuums, watches, headphones, or toothbrushes). Like study 2b, product complexity was manipulated via stimulus selection, based on evaluations of product simplicity or complexity by an independent online sample of participants (two-stage design). Participants first viewed an image of an unbranded simple or complex product from their assigned category (push mower or riding mower, regular or robotic vacuum, etc.), before moving along to the distribution builder instructions and task. Participants used the plus and minus buttons on the distribution builder interface to add or remove thirty balls to different performance buckets, with each of the balls indicating one product use experience at a certain performance level. When they had added all thirty balls, they were permitted to proceed. After completing the task, participants recorded their evaluations of the simplicity/complexity of their assigned product on a 9-point scale anchored by “Extremely simple” and “Extremely complex,” with “Neither simple nor complex” at the midpoint. This complexity measure was deliberately placed after the distribution builder task in order to prevent the possibility of participants guessing the kinds of answers they perceived to be in line with experimental predictions. Participants finished the survey by providing their age, gender, and educational experience.

FIGURE 9: STUDY 3 INSTRUCTIONS AND DISTRIBUTION BUILDER TASK INTERFACE

Now you will rate how well this product performs over several usage experiences, using the tool below. Imagine that 30 different consumers use this product one time (30 total product use experiences). For each one of those experiences, the product's performance can be rated on a scale from 0 to 100 (where 0 means total failure to perform its core function, and 100 means the most amazing performance, compared to all other products in the vacuum category).

Please use the plus and minus buttons to add or remove balls (representing product use experiences) to the buckets (representing the product's performance score).

- For example, if you think that a product would totally fail to work 6 times out of the 30, you would add 6 balls to the "0" bucket. If you think it will perform at a level 50 ten times, add 10 balls to the "50" bucket, etc.



Results and Discussion

The complexity manipulation by stimulus selection was successful. The complex product was rated as significantly more complex than the simple product across categories ($M_{\text{complexity.simple}}$ = -1.84, $M_{\text{complexity.complex}}$ = -.24, $t(433) = -8.68$, $p < .001$; all *p*s < .05 within categories). I collected each participant's individual distribution means, maximums, minimums standard deviations, and frequency of zeroes. If it is true that consumers believe more complex products to be higher risk (or less reliable), but to be capable of higher performance, comparing the condition means of these summary statistics should reveal a higher average maximum, a lower average minimum, and a higher standard deviation for the complex product condition. I also compare means of the two conditions' distribution means in an exploratory way, since it is possible that mean performance is a function of both failure and performance expectations, and it is unclear whether to expect a complex product to have a higher distribution mean than a simple product on average.

All models testing these predictions used the same basic format: a contrast-coded condition variable (.5 for complex, -.5 for simple) predicting the summary statistic dependent variable, with random intercepts for product category. Results of these analyses were encouraging but mixed. On one hand, the complex product condition did have a higher average standard deviation ($M_{SD.complexcond}$ = 15.69, $M_{SD.simplecond}$ = 13.32, $t(403.99) = 2.39$, $p = .017$) and a lower average minimum ($M_{min.complexcond}$ = 31.58, $M_{min.simplecond}$ = 38.63, $t(404.06) = -2.10$, $p = .036$), indicating more perceived performance variability and lower low-performance expectations, respectively, for the complex product. On the other hand, the complex product condition only had a directionally higher average maximum than the simple product condition ($M_{max.complexcond}$ = 85.83, $M_{max.simplecond}$ = 84.93, $t(404.5) = .46$, $p = .65$), and a directionally *lower* average mean ($M_{mean.complexcond}$ = 66.14, $M_{mean.simplecond}$ = 68.23, $t(405.0) = -.86$, $p = .39$).

Using a more conservative paradigm, study 3 provides additional support for the idea that consumers believe complex products to be higher risk, but fails to provide support for the prediction that complex products also have a higher performance ceiling. Given the lack of differences in average maximums between the conditions, it is possible that the paradigm caused ceiling effects, such that participants randomly assigned to one of two between-subjects conditions lacked a reference point for performance on the high end, or mentally normalized the 0-100 scale to fit their expectations of each product. One potential follow-up would be to re-run the experiment using a within-subjects design to see if allowing participants to make direct comparisons (and thus elaborate on differences in complexity) would lead to more deliberate differences in the formation of their distributions.

3.3.5 Study 4: Within-Subject List Task

The purpose of study 4 is to test whether consumers make judgments of higher risk and higher performance potential for complex products, using a different procedure. Although results from study 3 suggest that consumers judge complex products to have higher performance variability, the study uses a between-subjects paradigm. Findings from essay 1 and prior research suggests that consumers' evaluations can change based on whether they evaluate objects jointly or individually (Fox and Tversky 1995; Hsee 1996). Making evaluations of multiple products at one time also more closely mimics how consumers consider products in the real world. Another difference between studies 3 and 4 is that study 4 reverses the order in this essay's conceptual model, examining whether more a complex product comes to mind when consumers think of a less reliable but high performance potential product, instead of the other way around.

Method

Online participants from Mechanical Turk (57.5% female, M_{age} = 36.2 years; N = 207 after data from 17 participants was removed for either failing an attention check or having Recaptcha scores indicating high likelihood of being bots) were recruited via Cloud Research. They completed a short Qualtrics survey in exchange for $.45. Participants were first randomly assigned to one of five products categories: cars, mattresses, phones, shirts, or watches. They were then given the main task's instructions. It read, "In the next part of this survey, we would like you to imagine two different [category products]: one that is very reliable but isn't very high performance, and one that can perform extremely well when working properly but isn't very reliable. Please take a moment to think about both of these [category products] in detail. We will ask you about them in the next part of the survey." After these instructions, the main dependent questions asked participants to "please list up to ten important attributes of the extremely reliable (high performance) [category product]." They were shown ten text boxes for each of the two types of products in which they could write up to ten attributes, and whether they were asked the reliable or performance product question first or second was counterbalanced. As with previous studies, participants finished the survey after answering questions about their age, gender, and educational experience.

Results and Discussion

Study 4 analyses began by counting the number of attributes recorded by each participant for each type of product, and assigning them a sum score. The study's main analysis tested whether consumers listed more attributes (higher complexity) on average for the higher performance product and fewer (simplicity) for the more reliable product (see Linville 1982 for a similar operationalization of product complexity). A paired t-test revealed a directional but insignificant difference, with participants listing slightly more attributes for the performance product than the reliable product on average ($M_{\text{attributes.complex}} = 5.99$, $M_{\text{attributes.simple}} = 5.83$, $t(206) = 1.27$, $p = .21$). A model predicting a within-subject attribute difference score variable (number of listed performance attributes minus reliable) with a contrast-coded order variable (.5 if participants were tasked with listing the reliable product's attributes first, -.5 if the performance product's attributes first) revealed large and significant order effects, such that those completing the reliable task first listed 1.61 fewer relative attributes for the performance product compared to those who completed the performance task first ($t(205) = 6.83$, $p < .001$, 7.67% of range).

These results suggest that motivation to complete the survey was a stronger driver of number of listed attributes in the task than inferences about product simplicity or complexity. There is also the possibility that the equal number of text boxes for each product type led to participants inferring that the survey designer wanted them to list the same number of attributes (more or less) for each product type. A future re-run of this study could include a filler task in between participants' attribute listing tasks for the two different product types, one large text box for each product type, or could use a more heavy-handed test of the prediction by swapping out the list task altogether for a direct complexity evaluation measure.

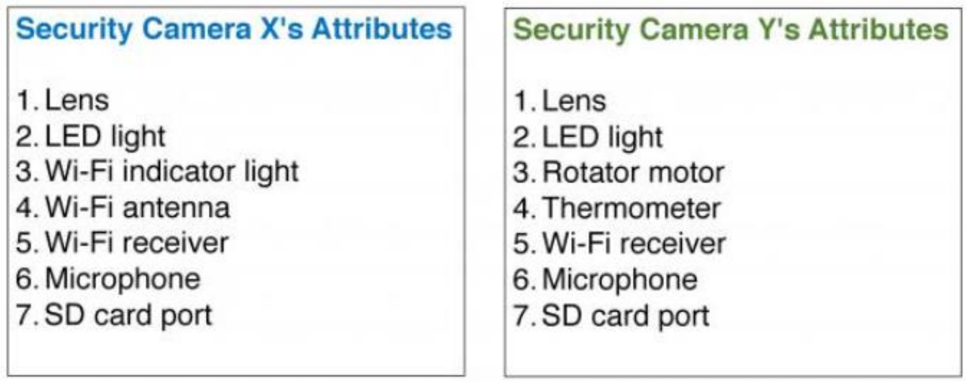
3.3.6 Study 5: Manipulating Product Complexity with Feature Similarity

In a series of experiments on consumer perceptions of the fit of items within sets, Evers et al. (2014) demonstrated that participants think the similarity of items (and thus their perceived fit in a set) depends on the regularity in their differences. For example, a string of numbers, 2, 4, 6, 8, 10 would be judged as more similar than 2, 4, 8, 8, 10, even though the second string actually contains a duplicate number (and thus fewer unique numbers), because the first string can be reduced to a clear pattern: two to ten, by twos. In turn, 2, 4, 8, 8, 10 would be seen as more similar than 2, 4, 8, 12, 10, because neither string can be intuitively simplified beyond its current form, but the latter has more non-redundant numbers. This "regularity in differences" measure can thus be used as an alternative operationalization of product complexity by presenting products as bundles of features or attributes with more or less similarity. Study 5 examines whether consumers judge as simpler a product with more similarity in its composing features, and tests if products perceived to be more complex are also seen as more likely to fail, and to be capable of higher performance.

Method

Study 5 participants (N = 375 after 33 removals for attention check failures or bot likelihood; 56.3% female, M_{age} = 35.8 years) completed a Qualtrics survey in exchange for $.48 via Mechanical Turk/Cloud Research. They first viewed the descriptions of two hypothetical security cameras with lists of each product's features (see figure 10 below). Although the numbers of listed features was the same for each product, the simpler product had more redundancy (with three of the seven features starting with the word "Wi-Fi"). Participants then continued on to the three main measures in random order: complexity, which read, "In your opinion, based on the information you know, how simple or complex are the two security cameras?" (8-point matrix scale, "Extremely simple" to "Extremely complex"); failure likelihood, which read "In your opinion, based on the information you know, how likely are each of the two security cameras to stop working correctly?" (8-point matrix scale, "Extremely unlikely" to "Extremely likely"); and performance ceiling, which read, "All products can be rated on their performance ceiling, meaning the best they are likely to perform when operating exactly as their designers intended, on a scale from 1 to 10. In your opinion, what is the performance ceiling of each of the two security cameras?" (10-point matrix scale, "Terrible performance (1)" to "Incredible performance (10)"). They ended the survey after answering age, gender, and education questions.

FIGURE 10: SIMPLE (LEFT) AND COMPLEX (RIGHT) PRODUCT MANIPULATIONS IN STUDY 5

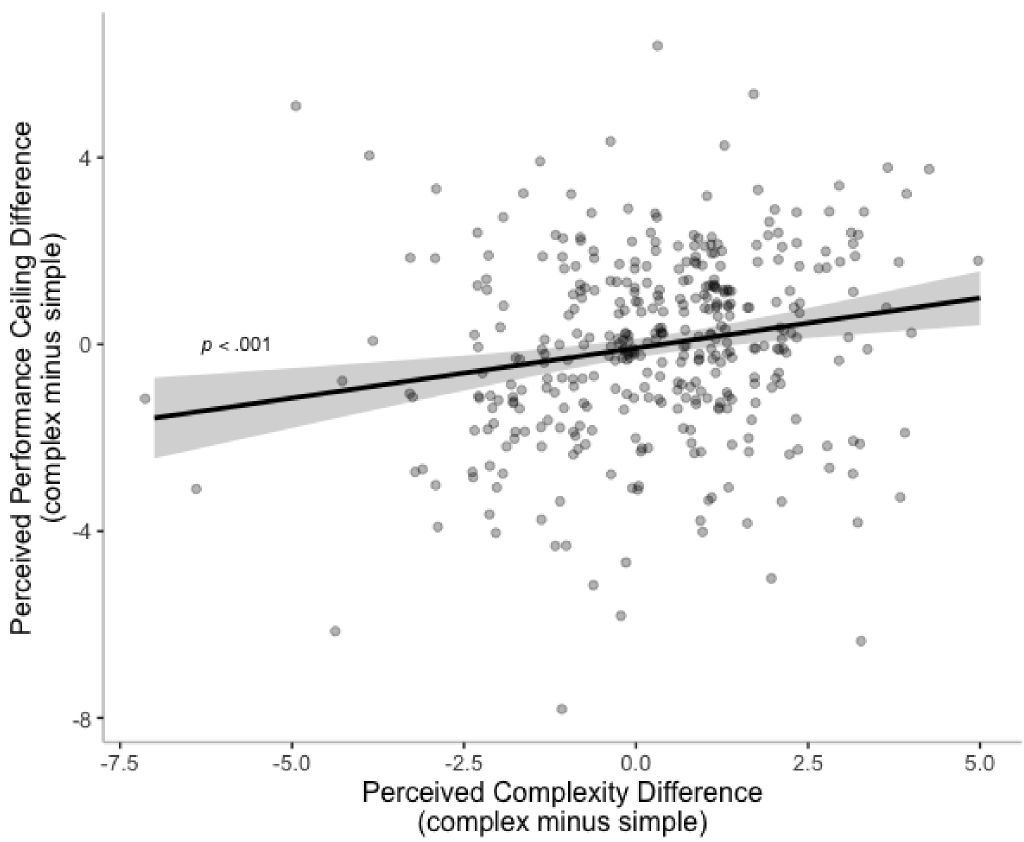


Results and Discussion

The within-subject manipulation of simplicity/complexity via regularity in differences was successful. The average perceived complexity of the complex product (Camera Y) was higher than that of the simple product (Camera X) ($M_{complexity.complex}$ = 5.22, $M_{complexity.simple}$ = 4.94, $t(374) = 3.15$, $p = .002$). Study 5's main predictions are that the simpler product's mean failure likelihood will be lower than the complex product's, but the complex product's mean maximum performance capability will be higher. The failure likelihood prediction was supported by the data, with higher perceived failure likelihood for the complex product ($M_{fail.complex}$ = 4.69, $M_{fail.simple}$ = 4.46, $t(374) = -2.56$, $p = .01$). There was no significant difference, however, in participants' judgments of performance ceiling between the two products ($M_{perform.complex}$ = 7.44, $M_{perform.simple}$ = 7.46, $t(374) = -.21$, $p = .83$). However, additional (exploratory) models predicting a within-participant performance difference score variable (complex performance minus simple) with complexity variables of both the simple and complex products (in the first model) and a within-participant complexity difference score variable (in the second model) were encouraging.

In the first model, more complexity of the complex product positively and significantly increased the perceived performance ceiling of complex product relative to the simple one, as did additional simplicity of the simple product ($\beta_{complexity.complex}$ = .21, $t(372) = 2.87$, $p = .004$, 1.23% of range; $\beta_{simplicity.simple}$ = .22, $t(372) = 3.15$, $p = .002$, 1.29% of range). Put slightly differently in the second model, the more the complex product is perceived to be higher in complexity relative to the simple product, the more it is also seen to have a higher relative performance ceiling ($\beta_{complexity.diff}$ = .21, $t(373) = 3.64$, $p < .001$, 1.23% of range, see figure 11 below).

FIGURE 11: RELATIONSHIP BETWEEN PERCEIVED DIFFERENCE IN COMPLEXITY AND PERCEIVED DIFFERENCE IN PERFORMANCE CEILING IN STUDY 5



Whereas the test of mean differences that did not support this study's performance ceiling prediction represents an average treatment effect (ATE), these exploratory analyses demonstrate something more akin to a treatment on treated (TOT) effect, suggesting that the effect of perceived complexity on perceived performance ceiling was stronger for those participants who were more sensitive to the manipulation. And since study 5's manipulation was fairly subtle, these results also hint that strengthening the manipulation or likely perceived difference in complexity between the two products (perhaps by increasing the number of similar features in the simple condition or the number of unique features in the complex condition) could potentially lead to more meaningful differences between the two condition means in the predicted direction.

3.3.7 Study 6: Moderating Consumer Inferences

If it is true that consumers believe complex products are simultaneously more likely to fail and have a higher performance ceiling, they should choose simpler products when the stakes for a choice are much higher (more risk). The opposite should be true when the consumption goal necessitates higher performance with less risk (see earlier discussion in the essay 2 introduction about Campbell and Goodstein 2001, which is relevant here). I test this moderating factor in study 6. Scenarios related to this type of decision are also described in research on the preference for potential over a track record of success, such as the preference for a job candidate with the potential to win an award versus one who has already won one, for example (Tormala, Jia, and Norton 2012). Although Tormala et al. do not explicitly mention risk in their discussion of potential moderators, one has to imagine that the "preference for potential" diminishes when the consequences of failure are too great to take a chance on the risky upside.

Method

In study 6, Mechanical Turk participants recruited via Cloud Research (N = 379 after 24 attention check and/or bot likelihood removals, 42.7% female, M_{age} = 35.0 years) were randomly assigned to one of two between-subjects conditions: (stakes: high versus low). In the high stakes condition, they were asked to imagine a smartwatch-buying scenario in which the watch would be used "to communicate with an elderly relative, who sends messages to you through the watch when her life-saving prescription medication needs to be refilled." In the low stakes condition, participants were told that the watch would be used "to communicate with an elderly relative, who sends messages to you through the watch at irregular times when she wants to chat." The dependent variable was a 7-point continuous direct comparison measure between the two smartwatches: a simple one and a complex one (manipulated via descriptions of more or fewer attributes; see figure 12 below). It read, "Given that your smart watch will be used to communicate with an elderly relative, who [condition-specific piped text – identical to wording in the stakes manipulation], which watch would you prefer? In making this decision, please consider how likely each watch is to stop working correctly or perform well." ("Much prefer watch X" to "Much prefer Watch Y," with a "No preference" midpoint). Participants then evaluated the simplicity/complexity of both watches on an 8-point matrix table from "Extremely simple" to "Extremely complex," and finished the survey by answering age, education, and gender questions.

FIGURE 12: STUDY 6 DESCRIPTIONS OF SIMPLE AND COMPLEX SMARTWATCH OPTIONS

Given what you know about what you will use the watch for, you have two watches to choose from: Watch X and Watch Y.

The attributes of each watch are listed below. Please read them carefully.

Smart Watch X's Attributes
1. Wi-Fi
2. Email
3. Messaging
4. Time and date

Smart Watch Y's Attributes
1. Wi-Fi
2. Email
3. Messaging
4. Time and date
5. GPS run/bike tracker
6. Sync with Spotify or iTunes

Results and Discussion

The within-subject mean complexity evaluation of the complex smart watch was higher than the simple smart watch ($M_{\text{complexity.compwatch}} = 5.43$, $M_{\text{complexity.simpwatch}} = 3.34$, $t(378) = 26.56$, $p < .001$). The main analysis examined whether being in the higher stakes condition led to differentially higher preference for the simpler smart watch. I ran a model predicting the direct-comparison watch preference measure with a contrast-coded condition variable (-.5 for lower stakes, .5 for higher stakes). A negative coefficient for the effect of the contrast-coded condition would indicate preference toward the simpler product in the higher stakes condition. Model output indeed revealed a negative coefficient, but the result was not statistically significant ($\beta_{\text{higherstakes.cc}} = -.17$, $t(377) = -.76$, $p = .45$, 2.43% of range). The mean preference across conditions indicated a slight preference for the complex watch on average (M_{pref} = 4.45 out of 7, where 4 indicates no preference between the two products). Given this, it is possible that the two additional features of the complex watch (GPS run/bike tracker and Sync with Spotify or iTunes) were either too desirable in general or did not present enough additional complexity to meaningfully increase perceptions of failure risk over the additional benefits of the features.

3.3.8 Study 7: Different Mental Models of Complexity

Results from essay 2's studies have provided strong evidence that consumers think more complex products are more likely to fail. They have also provided mixed evidence that they think they have a higher performance ceiling. These results were obtained in both within- and between-subjects experiments, in an open-ended qualitative study, and in correlational analyses, using different paradigms across numerous product categories. However, so far essay 2 has not discussed the degree to which these specific consumer complexity, risk, and performance inferences may be correct or appropriate. Therefore, the goals of study 7 are to examine consumers' mental models of complexity, whether they depend on the type of complexity (either independent or interdependent and the specific type of interdependence), and the degree to which consumers make the same complexity-to-risk and complexity-to-performance inferences across complexity types.

As stated in the introduction to essay 2, researchers outside of marketing have defined complexity as a function of both component dimensionality and relatedness. These definitions suggest that the complexity of products can be measured on the degree to which their parts or features are independent or interdependent. Furthermore, within these two categories of complexity there can also be finer distinctions based on the specific structure of component inter- or independence. The literature on group performance provides a useful framework for considering these finer distinctions, as well as the degree to which these different complexity types may relate to risk of failures and performance in the real world (see Forsyth 2018; Steiner 1972). In study 7 I focus on three types of complexity described in the group performance literature:

1. **Additive** (independent) – In an additively complex task or object, overall performance is defined by the sum of each individual component's performance, similar to how the combined force of a tug-of-war team's pull is equal the sum of each individual's force.
2. **Conjunctive** (interdependent) – In a conjunctively complex task or object, overall performance depends on all components performing equally well, similar to how a chain is strong when each link is strong, and is only as strong as its weakest link.
3. **Disjunctive** (interdependent) – In a disjunctively complex task or object, overall performance depends on one component performing well, similar to how a trivia team gets the right answer if one team member knows it.

Whether consumers' mental models of product complexity consider the potential existence and type of interdependence of components matters in assessing the correctness of their subsequent inferences about risk and performance in the real world (see table 6 below). In terms of risk, it should be true that a simple product without component interdependence has a lower probability of failing than any more complex product, but also a higher likelihood that any failure will be detrimental to the operation of the product's core function (due to the likely high importance of any given component). However, among more complex products of equal complexity, the likelihood of any one component failing should be equal (all else equal except complexity type). Additive complexity (characterized by component independence) should hold relatively lower risk of any one failure affecting the core function dramatically (because the failure of one component does not affect the performance of another, by definition), whereas the failure of one component in a conjunctively complex product is, by definition, detrimental. This is what happened with the Space Shuttle Challenger, which exploded because one rocket booster O-ring failed. For disjunctively complex products, the failure of one component should not meaningfully affect the overall performance either, since any of the other components could step up in its place.

In terms of performance ceilings in the real world, simpler products should have lower performance ceilings than more complex ones, simply because complex products can have more features or components performing additional functions. Among complex products of different complexity types, however, performance ceiling predictions are less clear. It seems likely that the possibility of component interactions (or “emergent” properties, to use the language of complex systems researchers) in interdependently complex products should lead to higher performance ceilings than for products characterized by independent (additive) complexity. Performance interactions (or “emergent properties”) exist in many products with computers, or in chemical products with chemical interactions, since they are defined as properties arising from a system, but not from any one of its parts (Pines 2014). However, the degree to which products characterized by conjunctive or disjunctive interdependent complexity have higher or lower performance ceilings (relative to each other) should depend on factors outside of degree and type of complexity, since both types have components that interact with each other.

TABLE 6: RELATIVE RISK AND PERFORMANCE BY DEGREE AND TYPE OF PRODUCT COMPLEXITY

Note: Simple compared to Complex, and three sub-types compared to each other

	Simple	Complex	Additive	Conjunctive	Disjunctive
Risk of any one component failing	Lower	Higher	Same	Same	Same
Risk of any failure being detrimental to overall functioning	Higher	Lower	Lower	Higher	Lower
Performance Ceiling	Lower	Higher	Lower	Higher	Higher

Method

Study 7 used a non-factorial between-subjects design. Participants from Prolific Academic (N = 859 after 43 attention check and bot likelihood removals; 50.4% female, M_{age} = 35.2 years) were paid $.49 to complete a Qualtrics survey. They were first randomly assigned to one of three product categories: laptops, color printers, or kitchen stand mixers. They were then randomly assigned to one of five complexity conditions: simple, complex control, additive, conjunctive, or disjunctive. Participants viewed an unbranded image of a product from their assigned product category (identical across all complexity conditions; see appendix for images) before reading a short condition-specific description of the product. These descriptions constituted the main manipulations in study 7:

- **Simple** – "This [category product] has 2 main components involved in the operation of its core function."
- **Control** (complex) – "This [category product] has eight main components involved in the operation of its core function."

- **Additive** – “This [category product] has eight main components involved in the operation of its core function. The [category product]’s overall performance depends on adding up each individual component’s performance, like how the strength of a tug-of-war team pulling on a rope is the sum of each individual team member’s efforts.”
- **Conjunctive** – “This [category product] has eight main components involved in the operation of its core function. The [category product]’s overall performance depends on every individual component performing equally well, like a metal chain that will break if one link isn’t strong.”
- **Disjunctive** – “This [category product] has eight main components involved in the operation of its core function. The [category product]’s overall performance depends on at least one individual component performing well, like when a trivia team gets the right answer if one person on the team knows the right answer.”

After reading the manipulation, participants responded to the three main measures in random order: complexity – “In your opinion, based on what you know about the [category product], how simple or complex is it?” (9-point scale, “Extremely simple” to “Extremely complex” with “Neither simple nor complex” at the midpoint); performance ceiling – “All products can be rated on their performance ceiling, meaning the best they are able to perform when operating exactly as their designers intended, on a scale from 1 to 10. In your opinion, what is the performance ceiling of the [category product]?” (10-point scale, “Terrible performance (1)” to “Incredible performance (10)”); and failure risk – “In your opinion, based on the information you know, how likely is the [category product] to stop working correctly?” (9-point scale, “Extremely unlikely” to “Extremely likely” with “Neither unlikely nor likely” at the midpoint. Participants finished the survey by answering the same three demographic questions used in previous studies.

It is important to note that both the complexity manipulations and perceived failure risk measure were careful to relate both complexity and risk to the operation or failure of a product’s core function. This was done to avoid having to subsequently interpret what failure means to different consumers, and to be able to compare participants' mental models of risk to risk of core function failure between complexity degree and types in the real world.

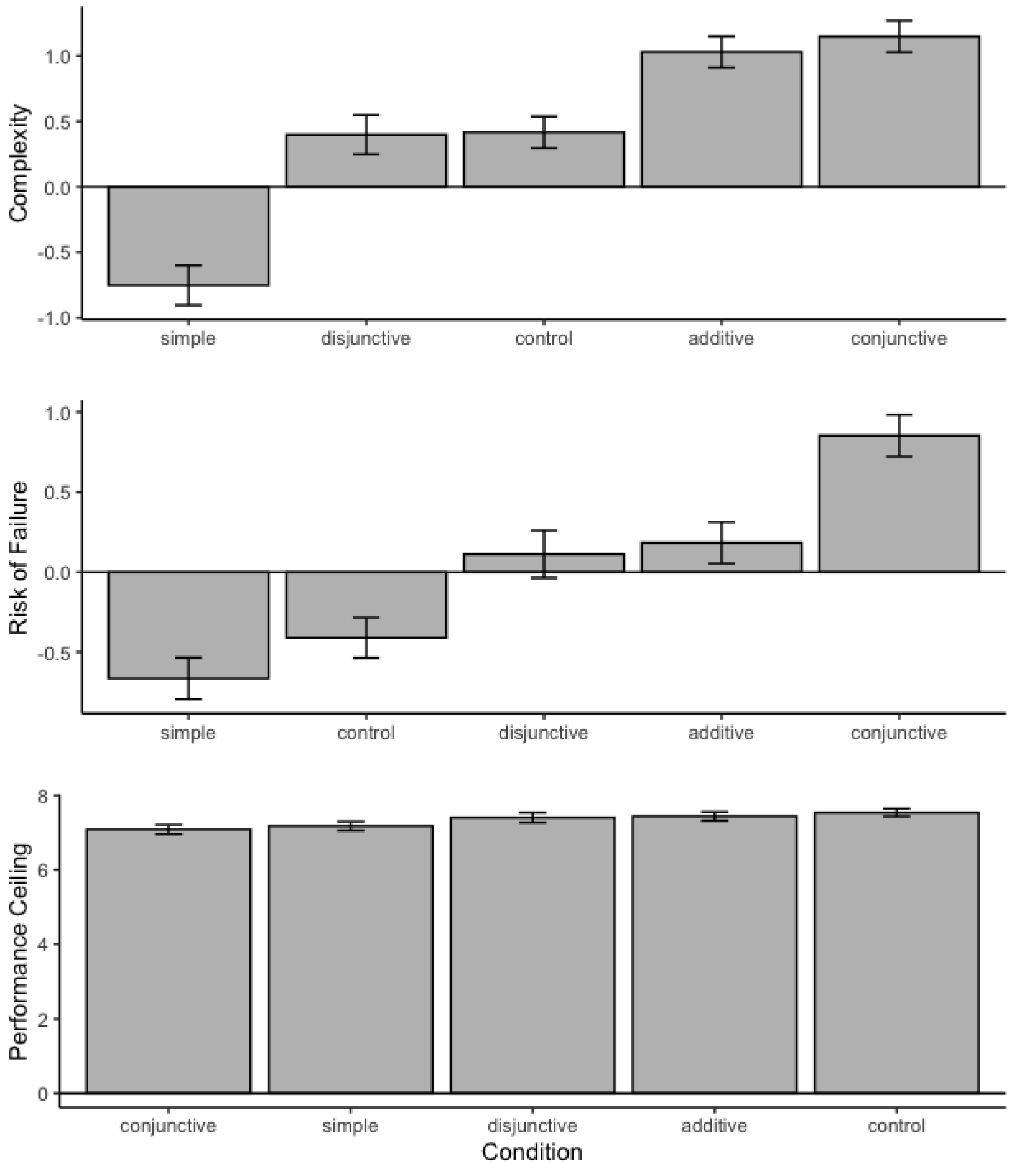
Results and Discussion

The primary analyses in study 7 compared the conditions' means on the three main measures: complexity, failure risk, and performance ceiling (see figure 13 below, with conditions in each panel ordered from smallest to largest). I tested differences between conditions by creating several sets of orthogonal Helmert contrast-coded predictor variables (Judd et al. 2009), which allow different planned contrasts without having to subset the data set to just the conditions being compared (which would reduce statistical power). The first main measure was complexity. As expected, the simple condition had the lowest mean complexity, which was significantly lower than the average of the other four conditions ($M_{\text{complexity.simple}} = -.75$ on a 9-point scale from -4 to 4, simple vs. all others contrast $t(852) = -10.17$, $p < .001$). Putting aside the control condition for the time being, the additive condition should be the next highest complexity in the real world, since there is no interdependence between components. Instead, the results show that the disjunctive condition had the next highest perceived complexity (alongside the control condition), with both additive and conjunctive conditions another level higher. Interestingly, the control condition's mean complexity was essentially equal to the disjunctive condition's, but significantly lower than either the additive's or conjunctive's condition means ($M_{\text{complexity.control}} = .42$, $M_{\text{complexity.disjunctive}} = .40$, $M_{\text{complexity.additive}} = 1.03$, $M_{\text{complexity.conjunctive}} = 1.15$; control vs. additive contrast $t(852.3) = 3.58$, $p < .001$; control vs. disjunctive contrast $t(852.1) = -.28$, $p = .78$; conjunctive vs. additive contrast $t(852.1) = -.80$, $p = .42$).

Participants correctly rated the simpler condition as less complex than the complex conditions, and incorrectly rated the additive condition as high as the conjunctive condition and higher than the disjunctive condition. The fact that disjunctive complexity was rated as less complex than either additive or conjunctive complexity is interesting. It may suggest that consumers interpret the redundant interdependence of disjunctive complexity not as additional complexity, but as some simpler "backup" model. It is also important to note that the condition most closely resembling the control (complex) condition was the disjunctive condition, which is to say the type of complexity that has an upside in terms of mitigating detrimental risk (or at least increasing it at a decreasing rate compared to other types of complexity) through redundancy. If consumers' natural mental models of product complexity when they are not specifically cued to consider other types are most similar to the lower-risk, higher-performance kind, this could lead to meaningful anger or dissatisfaction when the true complexity they encounter is additive or conjunctive.

FIGURE 13: STUDY 7 COMPLEXITY, FAILURE RISK, AND PERFORMANCE CEILING CONDITION MEANS

Note: conditions ordered smallest to largest in each panel

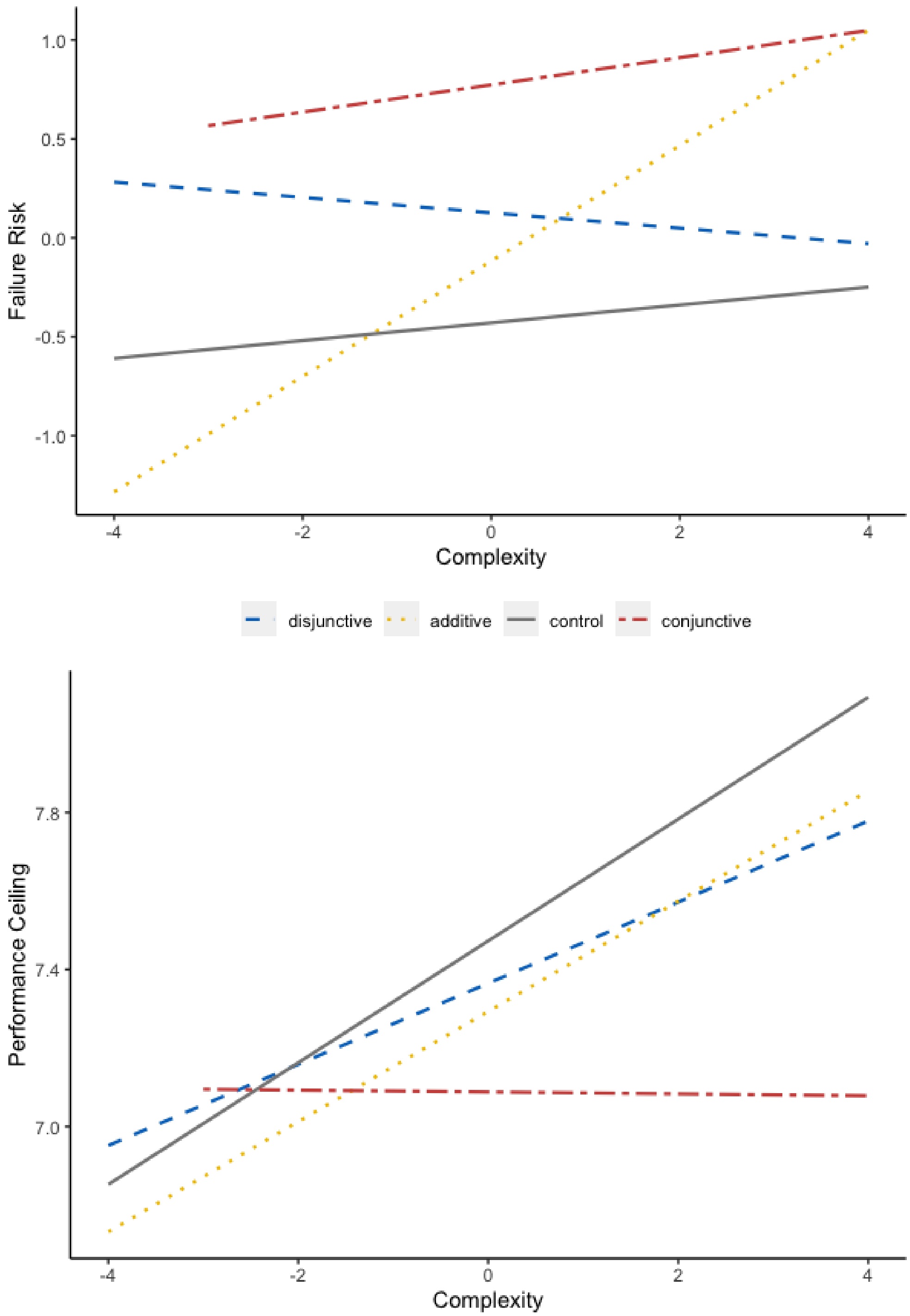


In terms of failure likelihood, the order from lowest to highest in the real world (all else equal) would be simple, then additive or disjunctive, then conjunctive. Interestingly, that is the exact pattern in participants' perceptions here ($M_{\text{risk.simple}}$ = -.66, $M_{\text{risk.control}}$ = -.41, $M_{\text{risk.disjunctive}}$= .11, $M_{\text{risk.additive}}$ = .18, $M_{\text{risk.conjunctive}}$ = .85). The simple condition's risk mean was again significantly lower than the average of the other conditions (as well as lower than the condition closest in magnitude, the control condition), while the conjunctive condition was significantly higher than all conditions, and the disjunctive and additive conditions were essentially equal (simple vs. all others contrast $t(852.2) = -5.67$, $p < .001$; control vs. simple contrast $t(852.1) = -6.14$, $p < .001$; conjunctive vs. additive contrast $t(852.9) = -3.59$, $p < .001$). These patterns provide additional support for the previous study's findings that consumers are fairly good at judging how relative complexity is associated with relative risk of failures. It should be noted, however, that the conjunctive condition's manipulation text was the only one where failure was specifically mentioned (in the chain metaphor), a mistake which could have artificially raised the condition's risk mean compared to the others.

For performance ceiling, the order of increasing performance ceiling in the real world would be simple, additive, then conjunctive or disjunctive. In this study, the means on performance ceiling appear almost equal across all conditions, but there are several small differences ($M_{perform.conjunctive} = 7.08$, $M_{perform.simple} = 7.18$, $M_{perform.disjunctive} = 7.41$, $M_{perform.additive} = 7.44$, $M_{perform.control} = 7.54$). Although the conjunctive and simple conditions' means are not different (contrast $t(852) = 2.05$, $p = .53$), conjunctive is significantly lower than the remaining three conditions on performance ceiling: disjunctive, additive, and control (conjunctive vs. disjunctive contrast $t(852) = 2.05$, $p = .04$). The simple condition also has a significantly lower performance ceiling than the control condition, but is not different from any other condition's mean (simple vs. control contrast $t(850.3) = 2.16$, $p = .03$; simple vs. additive contrast $t(850.2) = 1.47$, $p = .14$). These results provide support for the overall prediction that consumers distinguish performance ceiling based on complexity at a basic level, since they rated the control condition product, with 8 main components, as higher than the simple condition's, which had 2 main components. However, they also appear to (incorrectly) neglect differences in performance capabilities between more specific types of complexity, and may also wrongly equate the performance ceilings of simple products with products characterized by conjunctive complexity.

To dig deeper on consumers' perceptions of the relationships between complexity and performance and risk, I conducted several exploratory analyses on this study 7 data. I ran two linear mixed effects models with rated (continuous) complexity as the independent variable and random intercepts by category. In the model predicting risk, there was a significant positive relationship, such that more perceived complexity was associated with more perceived risk of failures ($\beta_{complexity}$ = .12, $t(829.4) = 3.66$, $p < .001$, 1.33% of range). There was also a significant positive relationship in the model predicting consumers' perceptions of performance ceiling ($\beta_{complexity}$ = .12, $t(854.3) = 4.05$, $p < .001$, 1.20% of range). Although both of these relationships are consistent with this essay's overall predictions, there were also slope differences by complexity sub-type (see figure 14 below). Of particular interest is the inaccurate perceived flat relationship between conjunctive complexity and performance ceiling, as well as the remarkably accurate negative relationship between more disjunctive complexity and failure risk.

FIGURE 14: STUDY 7 LINEAR RELATIONSHIPS BETWEEN COMPLEXITY AND FAILURE RISK (TOP) AND PERFORMANCE CEILING (BOTTOM) BY COMPLEXITY TYPE



Overall, findings from study 7 suggest that consumers are fairly well calibrated in their complexity and risk assessments when specifically cued to consider complexity type. But if they are left to their own devices their default mental models may lead to a trap of assuming a specific type of complexity (and thus lower risk) that may not apply. These findings also support the essay's overall predictions about consumers assuming higher performance and higher risk with higher product complexity, but the strength of a consumer' complexity-performance perceptions again depended significantly on their sensitivity to the complexity manipulation.

3.4 Essay 2 Discussion

Considered together, results from across essay 2's studies provide initial evidence that consumers believe complex products are more likely to experience failures and have the potential to perform at a higher level than simpler products. The details underlying this evidence are much more nuanced, of course, and come with several caveats. While evidence in support of consumers' complexity-risk inferences was fairly consistent, evidence for their complexity-performance inferences was mixed-to-weak. If the performance ceiling predictions are true in reality (and the mixed results were not simply a function of my choices of stimuli, categories, paradigms, or experimental designs), one possible interpretation of this data is that consumers are much more sensitive to potential differences in risk than differences in performance, as a function of complexity. Perhaps this should not be too surprising. Additional failures should be more salient and less abstract to consumers than increased performance. Imagining the failure of a core function is much easier than imagining what performance above the core function looks like. Prior research has also shown that losses loom larger than gains, so even if consumers were equally sensitive to changes in the two outcomes as a function of product complexity, a one unit increase in the probability of additional failures should feel worse to consumers than a one unit increase in the probability of higher performance. Another possibility is that perceived performance is much more a function of taste (versus quality) for the types of products in this essay than I had originally thought. All of the product categories in this essay were chosen for their perceived likelihood of being vertically differentiable, but even within product categories differentiated by quality there can be individual differences in consumers' preferred ordering and weighting of attributes. Additional studies exploring the complexity-to-performance relationship, particularly in categories where performance is more subjective, are clearly warranted.

4) Dissertation Contributions and General Discussion

This dissertation has important implications for consumers and marketers, representing contributions to both theory and practice. First and foremost, it suggests that consumers' simplicity and complexity judgments of brands and products can, in fact, be affected by the decisions of marketing practitioners. Although this may seem obvious to many, up to this point it was only a strongly held assumption, and had never been formally tested. In essay 1 a structural equation modeling approach revealed several marketing-influenced antecedents of consumer perceptions of brand simplicity, representing a first-of-its-kind attempt in the marketing literature. Second, this dissertation demonstrates that simplicity and complexity judgments matter in terms of their potential to change inferences about risk, performance, and liking. Although these inferences may be associated with positive outcomes for marketers and consumers, they also come with previously unconsidered pitfalls. This dissertation contributes the literatures on risk, brand associations, and satisfaction by showing that a simplicity marketing strategy can give consumers artificially low expectations of the risk of product or service failures, which causes significant and unexpected consumer dissatisfaction. Low expectations could be caused by the popular marketing strategy of suggesting a brand or product is simpler than it is, by consumers' own notoriously miscalibrated evaluations of how complex things truly are, or if consumers assume one type of lower-risk complexity and the reality is a different type with higher inherent risk (as in essay 2, study 7). A survey of marketing practitioners also revealed that this potential downside of simple marketing is not remotely on their radars, which shows that these results are novel and surprising to many marketers.

Consumers' lowered risk and performance inferences can also present problems for marketers. If marketing practitioners convince consumers that something is simpler than it really is, consumers will be very upset in the event of a failure, which forces marketers to engage consumers in an attempt to right the perceived wrong. This could come at temporal and monetary cost, for example by adding additional customer service employees, or by paying for more sophisticated customer relationship management (CRM) or marketing automation systems, etc. Essay 2 suggests that cueing consumers to consider simplicity and complexity could heighten their risk sensitivity relative to performance desires, which could make positioning or differentiation based on innovation or the addition of new features much more difficult.

On a theoretical level, this dissertation also contributes more subtly to the literature on brands and brand perceptions by offering a novel perspective from which to study how consumers think about and interact with brands and their products. Whereas much of the well-cited research on brand perceptions has focused on consumers' relationships with brands using metaphors of human-to-human relationships, or drawn heavily on personality psychology to classify brands in terms of their "personalities," this dissertation borrows ideas from research in cognitive science, information theory, and complex systems to show that consumers can and do hold associations between the simplicity or complexity of products and brands, and make inferences based on those associations. Because simplicity or complexity are not traditionally used in descriptions of human personalities, relying on personality-based brand perception frameworks comes up short in examinations of consumer perceptions of failure risk and performance capabilities.

In conclusion, this work uses a multimethod approach to build new knowledge on how consumers react to increasingly common cues to the simplicity or complexity of brands and products, how their inferences about brand and product simplicity/complexity inform downstream inferences, and on what the potential consequences of those inferences might be. In doing so, it moves our field closer to a more comprehensive understanding of the haphazardly defined construct of simplicity/complexity as it relates to consumer decision making, which is an increasingly important goal in a quickly complexifying market environment.

References:

Aaker, David A. (1991), *Managing Brand Equity: Capitalizing on the Value of a Brand Name*, New York: The Free Press.

Aaker, Jennifer (1997), "Dimensions of Brand Personality," *Journal of Marketing Research*, 34(3), 347–56.

Aaker, Jennifer, Susan Fournier, and S. Adam Brasel (2004), "When Good Brands Do Bad," *Journal of Consumer Research*, 31(1), 1–16.

Ahto, Ossi (Google) (2015), "Why Simplicity and Creativity Are Vital for Marketing Efficiency," *Google*, https://www.thinkwithgoogle.com/nordics/article/wh, https://www.thinkwithgoogle.com/nordics/article/why-simplicity-and-creativity-are-vital-for-marketing-efficiency/.

Alba, Joseph W. and J. Wesley Hutchinson (2000), "Knowledge Calibration: What Consumers Know and What They Think They Know," *Journal of Consumer Research*, 27(2), 123–56.

Alba, Joseph W. and Howard Marmorstein (1987), "The Effects of Frequency Knowledge on Consumer Decision Making," *Journal of Consumer Research*, 14(1), 14–25.

Alexander, David L., John G. Lynch, and Qing Wang (2008), "As Time Goes by: Do Cold Feet Follow Warm Intentions for Really New versus Incrementally New Products?," *Journal of Marketing Research*, 45(3), 307–19.

Andre, Quentin, Nicholas Reinholtz, and Bart de Langhe (2017), "Variance Spillover in Intuitive Statistical Judgments," *ACR North American Advances*.

Bar-Yam, Y (2002), "General Features of Complex Systems," *Encyclopedia of Life Support Systems (EOLSS)*.

Barwise, Patrick and Sean Meehan (2004), *Simply Better: Winning and Keeping Customers by Delivering What Matters Most*, Boston: Harvard Business Press.

Belk, Howard and Brian Rafferty (2012), "Simple Is Smart and Other Lessons from the Global Brand Simplicity Index," *Journal of Brand Strategy*, 1(3), 254–61.

Berlyne, Daniel E. (1958), "The Influence of Complexity and Novelty in Visual Figures on Orienting Responses," *Journal of Experimental Psychology*, 55(3), 289.

Bettman, James R., Mary F. Luce, and John W. Payne (1998), "Constructive Consumer Choice Processes," *Journal of Consumer Research*, 25(3), 187–217.

Biswas, Dipayan, Robin L. Keller, and Bidisha Burman (2012), "Making Probability Judgments of Future Product Failures: The Role of Mental Unpacking," *Journal of Consumer Psychology*, 22(2), 237–48.

Bitner, Mary Jo, Bernard H. Booms, and Mary Stanfield Tetreault (1990), "The Service Encounter: Diagnosing Favorable and Unfavorable Incidents," *Journal of Marketing*, 54(1), 71–84.

Brighton, Henry and Gerd Gigerenzer (2015), "The Bias Bias," *Journal of Business Research*, 68(8), 1772–84.

Briscoe, Erica and Jacob Feldman (2011), "Conceptual Complexity and the Bias/Variance Tradeoff," *Cognition*, 118(1), 2–16.

Brown, Timothy A. (2015), *Confirmatory Factor Analysis for Applied Research*, 2nd ed., Guilford Publications.

Carpenter, Gregory S., Rashi Glazer, and Kent Nakamoto (1994), "Meaningful Brands from Meaningless Differentiation: The Dependence on Irrelevant Attributes," *Journal of Marketing Research*, 31(3), 339–50.

Chater, Nick (1999), "The Search for Simplicity: A Fundamental Cognitive Principle?," *Quarterly Journal of Experimental Psychology Section A: Human Experimental Psychology*, 52A(2), 273–302.

Chater, Nick and George Loewenstein (2016), "The Under-Appreciated Drive for Sense-Making," *Journal of Economic Behavior and Organization*, 126, 137–54.

Chater, Nick and Paul Vitányi (2003), "Simplicity: A Unifying Principle in Cognitive Science?," *Trends in Cognitive Sciences*, 7(1), 19–22.

Chernev, Alexander (2007), "Jack of All Trades or Master of One? Product Differentiation and Compensatory Reasoning in Consumer Choice," *Journal of Consumer Research*, 33(4), 430–44.

——— (2003), "When More Is Less and Less Is More: The Role of Ideal Point Availability and Assortment in Consumer Choice," *Journal of Consumer Research*, 30(2), 170–83.

Chernev, Alexander and Gregory S. Carpenter (2001), "The Role of Market Efficiency Intuitions in Consumer Choice: A Case of Compensatory Inferences," *Journal of Marketing Research*, 38(3), 349–61.

Conway, Lucian Gideon, Felix Thoemmes, Amy M. Allison, Kirsten Hands Towgood, Michael J. Wagner, Kathleen Davey, Amanda Salcido, Amanda N. Stovall, Daniel P. Dodds, Kate Bongard, and Kathrene R. Conway (2008), "Two Ways to Be Complex and Why They Matter: Implications for Attitude Strength and Lying," *Journal of Personality and Social Psychology*, 95(5), 1029–44.

Cox, Dena S. and Anthony D Cox (1988), "What Does Familiarity Breed? Complexity as a Moderator of Repetition Effects in Advertisement Evaluation," *Journal of Consumer Research*, 15(1), 111.

Delavande, Adeline and Susann Rohwedder (2008), “Eliciting Subjective Probabilities in Internet Surveys,” *Public Opinion Quarterly*, 72(5), 866–91.

Dellaert, Benedict G.C. and Stefan Stremersch (2005), “Marketing Mass-Customized Products: Striking a Balance between Utility and Complexity,” *Journal of Marketing Research*, 42(2), 219–27.

Diehl, Kristin and Cait Poynor (2010), “Great Expectations?! Assortment Size, Expectations, and Satisfaction,” *Journal of Marketing Research*, 47(2), 312–22.

Dolan, Robert J. (2017), “Casper Sleep Inc.: Marketing the ‘One Perfect Mattress for Everyone,’” 1–22.

Evers, Ellen R.K., Yoel Inbar, and Marcel Zeelenberg (2014), “Set-Fit Effects in Choice,” *Journal of Experimental Psychology: General*, 143, 504–9.

Eytam, Eleanor, Noam Tractinsky, and Oded Lowengart (2017), “The Paradox of Simplicity: Effects of Role on the Preference and Choice of Product Visual Simplicity Level,” *International Journal of Human Computer Studies*, 105, 43–55.

Fernbach, Philip M., Nicholas Light, Sydney E. Scott, Yoel Inbar, and Paul Rozin (2019), “Extreme Opponents of Genetically Modified Foods Know the Least but Think They Know the Most,” *Nature Human Behaviour*, 3(3), 251–56.

Fernbach, Philip M., Todd Rogers, Craig R. Fox, and Steven A. Sloman (2013), “Political Extremism Is Supported by an Illusion of Understanding,” *Psychological Science*, 24(6), 939–46.

Fernbach, Philip M., Steven A. Sloman, Robert St. Louis, and Julia N. Shube (2013), “Explanation Fiends and Foes: How Mechanistic Detail Determines Understanding and Preference,” *Journal of Consumer Research*, 39(5), 1115–31.

Fischhoff, Baruch, Paul Slovic, Sarah Lichtenstein, Stephen Read, and Barbara Combs (1978), “How Safe Is Safe Enough? A Psychometric Study of Attitudes Towards Technological Risks and Benefits,” *Policy Sciences*, 9(2), 127–52.

Forsyth, Donelson R. (2018), *Group Dynamics*, 7th editio, New York: Cengage Learning.

Fournier, Susan (1998), “Consumers and Their Brands: Developing Relationship Theory in Consumer Research,” *Journal of Consumer Research*, 24(4), 343–73.

Fox, Craig R. and Amos Tversky (1995), “Ambiguity Aversion and Comparative Ignorance,” *The Quarterly Journal of Economics*, 110(3), 585–603.

Goldstein, Daniel G., Eric J. Johnson, and William F. Sharpe (2008), “Choosing Outcomes versus Choosing Products: Consumer-Focused Retirement Investment Advice,” *Journal of Consumer Research*, 35(3), 440–56.

Goldstein, Daniel G. and David Rothschild (2014), "Lay Understanding of Probability Distributions," *Judgment and Decision Making*, 9(1), 1–14.

Grandjean, Martin (2019), "New England Complex Systems Institute - Emergence," *necsi.edu*.

Griffin, Abbie (1997), "The Effect of Project and Process Characteristics on Product Development Cycle Time," *Journal of Marketing Research*, 34(1), 24–35.

Griffith, Erin (2017), "How Casper Flipped the Mattress Industry," *Fortune*.

Hahn, Ulrike, Nick Chater, and Lucy B. Richardson (2003), "Similarity as Transformation," *Cognition*, 87, 1–32.

Hasher, Lynn and Walter Chromiak (1977), "The Processing of Frequency Information: An Automatic Mechanism?," *Journal of Verbal Learning and Verbal Behavior*, 16(2), 173–84.

Herzenstein, Michal, Steven S. Posavac, and J. Joško Brakus (2007), "Adoption of New and Really New Products: The Effects of Self-Regulation Systems and Risk Salience," *Journal of Marketing Research*, 44(2), 251–60.

Holak, Susan L. and Donald R. Lehmann (1990), "Purchase Intentions and the Dimensions of Innovation: An Exploratory Model," *The Journal of Product Innovation Management*, 7(1), 59–73.

Horst, Peter (2018), "The Power Of Simplicity; What You Can Learn From Netflix And The Top 10 Simplest Brands," *Forbes*, November.

Hsee, Christopher K. (1996), "The Evaluability Hypothesis: An Explanation for Preference Reversals between Joint and Separate Evaluations of Alternatives," *Organizational Behavior and Human Decision Processes*, 67(3), 247–57.

Jacobs, Mark A. (2007), "Product Complexity: A Definition and Impacts on Operations," *MIS/OM/DS Faculty Publications*, 94, 6–21.

Janiszewski, Chris and Tom Meyvis (2001), "Effects of Brand Logo Complexity, Repetition, and Spacing on Processing Fluency and Judgment," *Journal of Consumer Research*, 28(1), 18–32.

Jhang, Ji Hoon, Susan Jung Grant, and Margaret C. Campbell (2012), "Get It? Got It. Good! Enhancing New Product Acceptance by Facilitating Resolution of Extreme Incongruity," *Journal of Marketing Research*, 49(2), 247–59.

Jhang, Ji Hoon, Susan Jung Grant, and Margaret C Campbell (2012), "Get It? Got It. Good! Enhancing New Product Acceptance by Facilitating Resolution of Extreme Incongruity," *Journal of Marketing Research*, 49(2), 247–59.

Judd, Charles M, Gary H McClelland, Carey S Ryan, and C. S. Judd, C. M., McClelland, G. H., & Ryan (2009), *Data Analysis - A Model Comparison Approach*, 2nd ed., Taylor and

Francis.

Keaveney, Susan M. (1995), “Customer Switching Behavior in Service Industries: An Exploratory Study,” *Journal of Marketing*, 59(2), 71–82.

Keller, Kevin Lane (1993), “Conceptualizing, Measuring, and Managing Customer-Based Brand Equity,” *Journal of Marketing*, 57(1), 1–22.

——— (2012), *Strategic Brand Management: Building, Measuring, and Managing Brand Equity*, Pearson, 4th ed., Upper Saddle River: Pearson.

Kelley, Tom and Jonathan Littman (2001), *The Art of Innovation*, Art of Innovation - Business Book Summaries, HarperCollinsBusiness.

Kenny, David A. (2015), “Measuring Model Fit,” *Davidakenny.Net*, http://davidakenny.net/cm/fit.htm.

Kremer, Michael (1993), “The O-Ring Theory of Economic Development,” *Quarterly Journal of Economics*, 108(3), 551–75.

Linville, Patricia W. (1982), “The Complexity-Extremity Effect and Age-Based Stereotyping,” *Journal of Personality and Social Psychology*, 42(2), 193–211.

Litman, Leib, Jonathan Robinson, and Tzvi Abberbock (2017), “TurkPrime.Com: A Versatile Crowdsourcing Data Acquisition Platform for the Behavioral Sciences,” *Behavior Research Methods*, 49(2), 433–42.

Long, Andrew R. (2019), *Marketing a Horse of a Different Color: The Role of Unique Features and Explanations in Perceived Product Differentiation*.

Long, Andrew R., Philip M. Fernbach, and Bart de Langhe (2018), “Circle of Incompetence: Sense of Understanding as an Improper Guide to Investment Risk,” *Journal of Marketing Research*, 55(4), 474–88.

Lussier, Denis A. and Richard W. Olshavsky (1979), “Task Complexity and Contingent Processing in Decision Making: A Replication and Extension,” *Organizational Behavior and Human Performance*, 24(December), 300–316.

March, James G. and Zur Shapira (1987), “Managerial Perspectives on Risk and Risk Taking,” *Management Science*, 33(11), 1404–18.

Meyer, Russ (2012), “Simplicity, The Most Powerful Branding Principle,” *Fast Company*, October.

Mizerski, Richard W. (1978), “Causal Complexity: A Measure of Consumer Causal Attribution,” *Journal of Marketing Research*, 15(2), 220–28.

Molloy, Margaret (2015), “Why Simple Brands Win,” *Harvard Business Review*.

Moreau, C. Page, Donald R. Lehmann, and Arthur B. Markman (2001), “Entrenched Knowledge Structures and Consumer Response to New Products,” *Journal of Marketing Research*, 38(1), 14–29.

Moreau, Page C, Arthur B Markman, and Donald R Lehman (2001), “‘What Is It?’ Categorization Flexibility and Customers’ Responses to Really New Products,” *Journal of Consumer Research*, 27(March), 489–98.

Muthén, Linda and Bengt O. Muthén (2017), *Mplus User’s Guide*, Los Angeles, 8th Editio.

Mützel, Lisa Monika Anna and Thomas Kilian (2016), “Product Complexity in Consumer Research: Literature Review and Implications for Future Research,” in *Rediscovering the Essentiality of Marketing*, ed. Luca Petruzzellis and Russell S. Winer, Springer, 645–61.

Oliver, Richard L. (1980), “A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions,” *Journal of Marketing Research*, 17(4), 460–69.

——— (1993), “Cognitive, Affective, and Attribute Bases of the Satisfaction Response,” *Journal of Consumer Research*, 20(3), 418–30.

Pacer, M. and Tania Lombrozo (2017), “Ockham’s Razor Cuts to the Root: Simplicity in Causal Explanation,” *Journal of Experimental Psychology: General*, 146(12), 1761–80.

Park, C. Whan (1976), “The Effect of Individual and Situation-Related Factors on Consumer Selection of Judgmental Models,” *Journal of Marketing Research*, 13(2), 144–51.

Park, Young Hoon, Min Ding, and Vithala R. Rao (2008), “Eliciting Preference for Complex Products: A Web-Based Upgrading Method,” *Journal of Marketing Research*, 45(5), 562–74.

Payne, John W. (1976), “Task Complexity and Contingent Processing in Decision Making: An Information Search and Protocol Analysis,” *Organizational Behavior and Human Performance*, 16(August), 366–87.

Payne, John W., James R. Bettman, and Eric J. Johnson (1990), “The Adaptive Decision Maker: Effort and Accuracy in Choice,” *Insights in Decision Making: A Tribute to Hillel J. Einhorn*, 129–53.

Pieters, Rik, Michel Wedel, and Rajeev Batra (2010), “The Stopping Power of Advertising: Measures and Effects of Visual Complexity,” *Journal of Marketing*, 74(5), 48–60.

Pines, David (2014), “Emergence: A Unifying Theme for 21st Century Science,” *Santa Fe Institute Bulletin*, 28(2).

Rogers, Everett M. (2003a), *Diffusion of Innovations*, Simon and Schuster, 5th ed., New York.

——— (2003b), *The Diffusion of Innovations*, Diffusion of Innovations.

Rozenblit, Leonid and Frank Keil (2002), "The Misunderstood Limits of Folk Science: An Illusion of Explanatory Depth," *Cognitive Science*, 26(5), 521–62.

Scholz, Sören W., Meissner Martin, and Decker Reinhold (2010), "Measuring Consumer Preferences for Complex Products: A Compositional Approach Based on Paired Comparisons," *Journal of Marketing Research*, 47(4), 685–98.

Sela, Aner and Jonah Berger (2012), "How Attribute Quantity Influences Option Choice," *Journal of Marketing Research*, 49(6), 942–53.

Siegel+Gale (2018), "Siegel+Gale 2018 Brand Simplicity Index," http://simplicityindex.com/.

Simon, Herbert A. (1962), "The Architecture of Complexity," *Proceedings of the American Philosophical Society,* 106(6), 467–82.

Slovic, Paul (1987), "Perception of Risk," *Science*, 236(4799), 280–85.

Song, Hyunjin and Norbert Schwarz (2009), "If It 's Difficult to Pronounce, It Must Be Risky," *Psychological science*, 20(2), 135–38.

Spenner, Patrick and Karen Freeman (2012), "To Keep Your Customers, Keep It Simple," *Harvard Business Review*.

Spreng, Richard A., Scott B. MacKenzie, and Richard W. Olshavsky (1996), "A Reexamination of the Determinants of Consumer Satisfaction," *Journal of Marketing*, 60(3), 15–32.

Steiner, Ivan Dale (1972), *Group Process and Productivity*, New York: Academic Press.

Swait, Joffre and Wiktor Adamowicz (2001), "The Influence of Task Complexity on Consumer Choice: A Latent Class Model of Decision Strategy Switching," *Journal of Consumer Research*, 28(1), 135–48.

Swaminathan, Vanitha (2004), "The Impact of Recommendation Agents on Consumer Evaluation and Choice: The Moderating Role of Category Risk, Product Complexity, and Consumer Knowledge," *Journal of Consumer Psychology*, 13(1–2), 93–101.

Swan, John E. and I. Frederick Trawick (1981), "Disconfirmation of Expectations and Satisfaction with a Retail Service," *Journal of Retailing*, 57(3), 49–67.

Thompson, Debora Viana, Rebecca W. Hamilton, and Roland T. Rust (2005), "Feature Fatigue: When Product Capabilities Become Too Much of a Good Thing," *Journal of Marketing Research*, 42(4), 431–42.

Tormala, Zakary L., Jayson S. Jia, and Michael I. Norton (2012), "The Preference for Potential," *Journal of Personality and Social Psychology*, 103(4), 567–83.

Weber, Elke U., Sharoni Shafir, and Ann-Renée Blais (2004), "Predicting Risk Sensitivity in Humans and Lower Animals: Risk as Variance or Coefficient of Variation," *Psychological*

Review, 111(2), 430–35.

Wood, Stacy L. and John G. Lynch (2002), "Prior Knowledge and Complacency in New Product Learning," *Journal of Consumer Research*, 29(3), 416–26.

Wood, Stacy L. and C. Page Moreau (2006), "From Fear to Loathing? How Emotion Influences the Evaluation and Early Use of Innovations," *Journal of Marketing*, 70(3), 44–57.

Zarantonello, Lia and Bernd H. Schmitt (2010), "Using the Brand Experience Scale to Profile Consumers and Predict Consumer Behaviour," *Journal of Brand Management*, 17(7), 532–40.

Appendix

ESSAY 1 STUDY 1

Structural Equation Model Output

Here I report the output for three structural equation models. The first two are the two models discussed in the main body of the document, and the third is a robustness check on the second model without participant exclusions based on time spent on the survey.

Initial Model

```
MODEL:


F2 by decideproduct@1;
F2 by purchproducts*;
F2 by makeproducts*;
F2 by accessafterpurch*;
F2 by setup*;
F2 by understandhowwork*;
F2 by learntimeuse*;

F3 by websparse@1;
F3 by adsparse*;
F3 by proddesign*;
F3 by packaging*;
F3 by adwords*;
F3 by name*;

F1 by simple@1;
F1 by aura*;
F1 by compare*;

F1 on F2;
F1 on F3;



Estimator                                                   WLSMV
Maximum number of iterations                                 1000
Convergence criterion                                   0.500D-04
Maximum number of steepest descent iterations                  20
Maximum number of iterations for H1                          2000
Convergence criterion for H1                            0.100D-03
Parameterization                                            DELTA
Link                                                       PROBIT



MODEL FIT INFORMATION

Number of Free Parameters                        99

Chi-Square Test of Model Fit

Value                            438.347*
Degrees of Freedom                    101
P-Value                            0.0000
```

RMSEA (Root Mean Square Error Of Approximation)

Estimate	0.081	
90 Percent C.I.	0.073	0.089
Probability RMSEA <= .05	0.000	

CFI/TLI

CFI	0.953
TLI	0.944

Chi-Square Test of Model Fit for the Baseline Model

Value	7310.826
Degrees of Freedom	120
P-Value	0.0000

WRMR (Weighted Root Mean Square Residual)

Value	1.334

STANDARDIZED MODEL RESULTS

STDYX Standardization

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
F2 BY				
DECIDEPROD	0.569	0.033	17.159	0.000
PURCHPRODU	0.744	0.025	30.290	0.000
MAKEPRODUC	0.226	0.045	4.960	0.000
ACCESSAFTE	0.603	0.032	18.684	0.000
SETUP	0.710	0.027	26.456	0.000
UNDERSTAND	0.561	0.033	16.921	0.000
LEARNTIMEU	0.636	0.031	20.242	0.000
F3 BY				
WEBSPARSE	0.429	0.037	11.496	0.000
ADSPARSE	0.499	0.034	14.504	0.000
PRODDESIGN	0.728	0.025	28.962	0.000
PACKAGING	0.703	0.027	26.193	0.000
ADWORDS	0.597	0.035	16.848	0.000
NAME	0.524	0.038	13.942	0.000
F1 BY				
SIMPLE	0.905	0.011	78.982	0.000
AURA	0.937	0.010	94.426	0.000
COMPARE	0.819	0.016	52.242	0.000
F1 ON				
F2	0.258	0.053	4.830	0.000
F3	0.503	0.050	10.078	0.000
F3 WITH				
F2	0.644	0.033	19.622	0.000
Variances				
F2	1.000	0.000	999.000	999.000
F3	1.000	0.000	999.000	999.000
Residual Variances				
F1	0.514	0.035	14.501	0.000

Final Reported Model

```
MODEL:


F2 by decideproduct@1;
F2 by purchproducts*;
F2 by makeproducts*;
F2 by accessafterpurch*;
F2 by setup*;
F2 by understandhowwork*;
F2 by learntimeuse*;

F3 by websparse@1;
F3 by adsparse*;
F3 by proddesign*;
F3 by packaging*;
F3 by adwords*;
F3 by name*;

F1 by simple@1;
F1 by aura*;
F1 by compare*;

adwords with adsparse*;
packaging with proddesign*;
learntimeuse with understandhowwork*;

F1 on F2;
F1 on F3;



SUMMARY OF ANALYSIS

Number of groups                                                 1
Number of observations                                         512

Number of dependent variables                                   16
Number of independent variables                                  0
Number of continuous latent variables                            3


Estimator                                                    WLSMV
Maximum number of iterations                                  1000
Convergence criterion                                    0.500D-04
Maximum number of steepest descent iterations                   20
Maximum number of iterations for H1                           2000
Convergence criterion for H1                             0.100D-03
Parameterization                                             DELTA
Link                                                        PROBIT


MODEL FIT INFORMATION

Number of Free Parameters                        102

Chi-Square Test of Model Fit

Value                              363.393*
Degrees of Freedom                      98
P-Value                             0.0000


RMSEA (Root Mean Square Error Of Approximation)
```

```
Estimate                          0.073
90 Percent C.I.                   0.065  0.081
Probability RMSEA <= .05          0.000

CFI/TLI

CFI                               0.963
TLI                               0.955

Chi-Square Test of Model Fit for the Baseline Model

Value                          7310.826
Degrees of Freedom                  120
P-Value                          0.0000

WRMR (Weighted Root Mean Square Residual)

Value                             1.175



STANDARDIZED MODEL RESULTS


STDYX Standardization

Two-Tailed
Estimate       S.E.  Est./S.E.    P-Value

F2       BY
DECIDEPROD         0.573      0.033     17.183      0.000
PURCHPRODU         0.748      0.025     30.292      0.000
MAKEPRODUC         0.227      0.046      4.954      0.000
ACCESSAFTE         0.607      0.032     18.732      0.000
SETUP              0.714      0.027     26.243      0.000
UNDERSTAND         0.522      0.037     14.052      0.000
LEARNTIMEU         0.607      0.033     18.173      0.000

F3       BY
WEBSPARSE          0.421      0.038     11.124      0.000
ADSPARSE           0.454      0.038     12.031      0.000
PRODDESIGN         0.665      0.032     20.743      0.000
PACKAGING          0.639      0.034     18.976      0.000
ADWORDS            0.556      0.039     14.142      0.000
NAME               0.524      0.038     13.859      0.000

F1       BY
SIMPLE             0.905      0.011     78.885      0.000
AURA               0.937      0.010     94.327      0.000
COMPARE            0.819      0.016     52.302      0.000

F1       ON
F2                 0.166      0.070      2.370      0.018
F3                 0.605      0.066      9.184      0.000

F3       WITH
F2                 0.699      0.036     19.548      0.000

ADWORDS  WITH
ADSPARSE           0.293      0.044      6.662      0.000

PACKAGIN WITH
PRODDESIGN         0.312      0.047      6.644      0.000

LEARNTIM WITH
UNDERSTAND         0.249      0.045      5.523      0.000



Variances
F2                 1.000      0.000    999.000    999.000
```

```
F3                1.000      0.000    999.000    999.000

Residual Variances
F1                0.466      0.039     12.059      0.000
```

Final Model Robustness Check (no data exclusions based on time spent taking the survey)

```
MODEL:

F2 by decideproduct@1;
F2 by purchproducts*;
F2 by makeproducts*;
F2 by accessafterpurch*;
F2 by setup*;
F2 by understandhowwork*;
F2 by learntimeuse*;

F3 by websparse@1;
F3 by adsparse*;
F3 by proddesign*;
F3 by packaging*;
F3 by adwords*;
F3 by name*;

F1 by simple@1;
F1 by aura*;
F1 by compare*;

adwords with adsparse*;
packaging with proddesign*;
learntimeuse with understandhowwork*;

F1 on F2;
F1 on F3;


Estimator                                                    WLSMV
Maximum number of iterations                                  1000
Convergence criterion                                    0.500D-04
Maximum number of steepest descent iterations                   20
Maximum number of iterations for H1                           2000
Convergence criterion for H1                             0.100D-03
Parameterization                                             DELTA
Link                                                        PROBIT



MODEL FIT INFORMATION

Number of Free Parameters                        102

Chi-Square Test of Model Fit

Value                             390.797*
Degrees of Freedom                     98
P-Value                            0.0000


RMSEA (Root Mean Square Error Of Approximation)

Estimate                            0.075
90 Percent C.I.                     0.067  0.083
Probability RMSEA <= .05            0.000

CFI/TLI
```

```
CFI                                0.961
TLI                                0.952

Chi-Square Test of Model Fit for the Baseline Model

Value                           7536.748
Degrees of Freedom                   120
P-Value                           0.0000

WRMR (Weighted Root Mean Square Residual)

Value                              1.219



STANDARDIZED MODEL RESULTS


STDYX Standardization

Two-Tailed
Estimate       S.E.  Est./S.E.    P-Value

F2       BY
DECIDEPROD         0.567      0.033     17.184      0.000
PURCHPRODU         0.738      0.025     29.481      0.000
MAKEPRODUC         0.224      0.045      5.016      0.000
ACCESSAFTE         0.617      0.032     19.487      0.000
SETUP              0.708      0.027     26.284      0.000
UNDERSTAND         0.542      0.036     15.126      0.000
LEARNTIMEU         0.614      0.033     18.878      0.000

F3       BY
WEBSPARSE          0.404      0.038     10.629      0.000
ADSPARSE           0.447      0.037     11.963      0.000
PRODDESIGN         0.660      0.032     20.879      0.000
PACKAGING          0.646      0.033     19.698      0.000
ADWORDS            0.533      0.040     13.368      0.000
NAME               0.529      0.036     14.487      0.000

F1       BY
SIMPLE             0.904      0.011     80.178      0.000
AURA               0.938      0.010     96.274      0.000
COMPARE            0.818      0.016     52.129      0.000

F1       ON
F2                 0.148      0.074      2.007      0.045
F3                 0.615      0.069      8.864      0.000

F3       WITH
F2                 0.716      0.035     20.687      0.000

ADWORDS  WITH
ADSPARSE           0.321      0.042      7.725      0.000

PACKAGIN WITH
PRODDESIGN         0.298      0.046      6.437      0.000

LEARNTIM WITH
UNDERSTAND         0.248      0.045      5.512      0.000



Variances
F2                 1.000      0.000    999.000    999.000
F3                 1.000      0.000    999.000    999.000

Residual Variances
F1                 0.470      0.038     12.236      0.000
```

ESSAY 1 STUDY 2

Construct Correlations

	risk.diff	liking.diff	complexity.diff	premium.diff	age	income
risk.diff	1.00	-0.27	0.19	-0.25	0.01	0.05
liking.diff	-0.27	1.00	-0.10	0.29	0.02	0.04
complexity.diff	0.19	-0.10	1.00	0.08	-0.09	0.04
premium.diff	-0.25	0.29	0.08	1.00	0.03	0.09
age	0.01	0.02	-0.09	0.03	1.00	0.00
income	0.05	0.04	0.04	0.09	0.00	1.00

Robustness Checks

In testing the effect of simplicity on the risk difference score in study 2, I also ran the following robustness check model. It tested whether participants' randomly assigned presentation order condition (ads or websites first) meaningfully affected their risk perceptions. A model identical to that reported in the paper, but with a contrast-coded order variable added revealed a significant difference in risk perceptions such that participants in the ads-first condition reported higher risk for the complex companies compared to participants in the web-first condition ($\beta_{adsfirst.cc}$ = .23, $t(187.33) = 2.00$, $p = .05$, 1.77% of range). In order to test if this difference affected my interpretation of the data, I ran two models. The first was identical to the main model reported in the study except it contained a dummy-coded predictor variable for order with 0 as ads first and 1 as web first. The second was identical except the dummy-coded order variable was coded as 1 for ads first and 0 for web first. These two models allow me to test the magnitude and significance of the intercept for both order conditions separately. In both models (as in the main paper) the intercept was positive and significant, indicating more risk for companies perceived to be more complex ($\text{intercept}_{adsfirst}$ = .47, $t(15.15) = 5.66$, $p < .001$; $\text{intercept}_{webfirst}$ = .24, $t(19.18) = 2.72$, $p = .01$).

ESSAY 1 STUDIES 3A & 3B

Study 3A Construct Correlations

	like.diff	lux.diff	prof.diff	size.diff	complex.diff	risk	age	income	edu
like.diff	1.00	0.34	0.55	0.27	-0.06	-0.41	0.03	-0.02	-0.09
lux.diff	0.34	1.00	0.52	0.25	0.09	-0.26	0.04	0.00	-0.05
prof.diff	0.55	0.52	1.00	0.38	-0.02	-0.41	0.00	0.01	0.02
size.diff	0.27	0.25	0.38	1.00	0.22	-0.25	0.06	0.01	0.07
complex.diff	-0.06	0.09	-0.02	0.22	1.00	0.06	-0.09	-0.05	-0.13
risk	-0.41	-0.26	-0.41	-0.25	0.06	1.00	0.04	0.03	0.02
S.age	0.03	0.04	0.00	0.06	-0.09	0.04	1.00	0.15	0.19
S.income	-0.02	0.00	0.01	0.01	-0.05	0.03	0.15	1.00	0.29
S.edu	-0.09	-0.05	0.02	0.07	-0.13	0.02	0.19	0.29	1.00

Study 3B Construct Correlations

	like.diff	lux.diff	prof.diff	size.diff	complex.diff	risk	age	income	edu
like.diff	1.00	0.43	0.55	0.29	-0.09	-0.43	0.14	0.00	0.04
lux.diff	0.43	1.00	0.57	0.42	0.16	-0.33	0.11	-0.06	-0.01
prof.diff	0.55	0.57	1.00	0.40	0.04	-0.40	0.13	-0.03	0.03
size.diff	0.29	0.42	0.40	1.00	0.12	-0.24	0.02	0.03	0.01
complex.diff	-0.09	0.16	0.04	0.12	1.00	0.06	-0.06	-0.02	-0.10
risk	-0.43	-0.33	-0.40	-0.24	0.06	1.00	-0.01	-0.01	-0.04
age	0.14	0.11	0.13	0.02	-0.06	-0.01	1.00	0.11	0.25
income	0.00	-0.06	-0.03	0.03	-0.02	-0.01	0.11	1.00	0.24
edu	0.04	-0.01	0.03	0.01	-0.10	-0.04	0.25	0.24	1.00

ESSAY 1 STUDY 4

Construct Correlations

	complexity	risk	liking	age	edu
complexity	1.00	0.23	-0.01	-0.08	0.04
risk	0.23	1.00	-0.10	-0.15	-0.02
liking	-0.01	-0.10	1.00	0.07	-0.04
age	-0.08	-0.15	0.07	1.00	0.08
edu	0.04	-0.02	-0.04	0.08	1.00

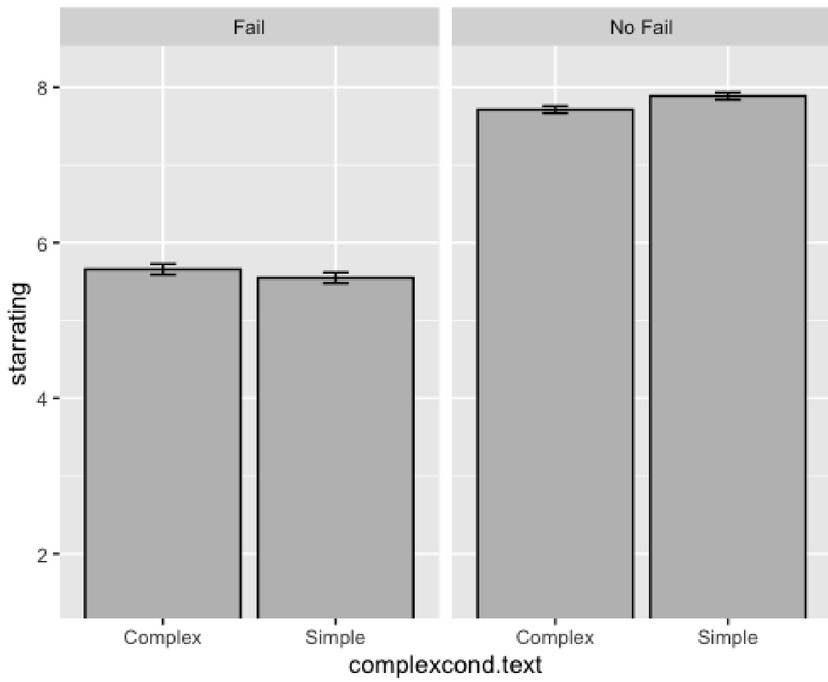
ESSAY 1 STUDY 5

Construct Correlations

	complexity	Problems	recommend	price.num	product.age
complexity	1.00	-0.01	0.09	0.43	-0.03
Problems	-0.01	1.00	-0.30	0.04	0.21
recommend	0.09	-0.30	1.00	0.10	-0.07
price.num	0.43	0.04	0.10	1.00	0.06
product.age	-0.03	0.21	-0.07	0.06	1.00

ESSAY 1 STUDY 6

Main interaction figure (failure hurts simpler brands' star rating more than complex brands')



Main Mediation Analysis Full Output

```
model=' complexity ~ a*complexcond.cc
risk ~ c*complexcond.cc+b*complexity
indirect :=(a)*(b)
direct :=c
total := direct + indirect
prop.mediated := indirect / total
 '
fit=sem(model=model,data=uploaded,se='bootstrap',bootstrap=200,missing='pairwise')
summary(fit,fit.measures = FALSE,standardize = TRUE, rsquare = TRUE)

lavaan 0.6-3 ended normally after 22 iterations

  Optimization method                           NLMINB
  Number of free parameters                          5

  Number of observations                          1995
  Number of missing patterns                         1

  Estimator                                         ML
  Model Fit Test Statistic                       0.000
  Degrees of freedom                                 0

Parameter Estimates:

  Standard Errors                            Bootstrap
  Number of requested bootstrap draws              200
  Number of successful bootstrap draws             182

Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  complexity ~
```

```
    cmplxcnd.c (a)    2.662    0.064   41.628    0.000    2.662    0.694
  risk ~
    cmplxcnd.c (c)   -0.408    0.066   -6.219    0.000   -0.408   -0.174
    complexity (b)    0.245    0.020   12.298    0.000    0.245    0.401

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .complexity        1.908    0.073   26.054    0.000    1.908    0.519
   .risk              1.247    0.030   41.658    0.000    1.247    0.906

R-Square:
                   Estimate
    complexity        0.481
    risk              0.094

Defined Parameters:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
    indirect          0.653    0.056   11.673    0.000    0.653    0.278
    direct           -0.408    0.066   -6.202    0.000   -0.408   -0.174
    total             0.245    0.050    4.911    0.000    0.245    0.104
    prop.mediated     2.665    0.778    3.424    0.001    2.665    2.665

parameterEstimates(fit,boot.ci.type = 'bca.simple',level = .95,
ci = TRUE,standardized = FALSE)

              lhs op             rhs         label    est    se      z pvalue
1      complexity  ~  complexcond.cc             a  2.662 0.064 41.628  0.000
2            risk  ~  complexcond.cc             c -0.408 0.066 -6.219  0.000
3            risk  ~      complexity             b  0.245 0.020 12.298  0.000
4      complexity ~~      complexity                1.908 0.073 26.054  0.000
5            risk ~~            risk                1.247 0.030 41.658  0.000
6  complexcond.cc ~~  complexcond.cc                0.250 0.000     NA     NA
7        indirect :=         (a)*(b)      indirect  0.653 0.056 11.673  0.000
8          direct :=               c        direct -0.408 0.066 -6.202  0.000
9           total := direct+indirect         total  0.245 0.050  4.911  0.000
10  prop.mediated :=  indirect/total prop.mediated  2.665 0.778  3.424  0.001
   ci.lower ci.upper
1     2.536    2.811
2    -0.561   -0.292
3     0.209    0.283
4     1.797    2.100
5     1.186    1.316
6     0.250    0.250
7     0.561    0.779
8    -0.561   -0.292
9     0.146    0.356
10    1.915    4.834

Regression Analysis for Equation 1

fit[[1]]= lm(complexity ~ complexcond.cc,data=uploaded)

Call:
lm(formula = complexity ~ complexcond.cc, data = data1)

Residuals:
    Min      1Q  Median      3Q     Max
-4.6166 -0.9548  0.0452  1.0452  5.0452

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
```

```
(Intercept)     4.28572    0.03094  138.50   <2e-16 ***
complexcond.cc  2.66180    0.06189   43.01   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.382 on 1993 degrees of freedom
Multiple R-squared:  0.4814, Adjusted R-squared:  0.4811
F-statistic:  1850 on 1 and 1993 DF,  p-value: < 2.2e-16
```

Regression Analysis for Equation 2

```
fit[[2]]= lm(risk ~ complexcond.cc+complexity,data=uploaded)

Call:
lm(formula = risk ~ complexcond.cc + complexity, data = data1)

Residuals:
    Min      1Q  Median      3Q     Max
-3.2293 -0.7387  0.0160  0.8346  3.4878

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)     2.47084    0.08157  30.291  < 2e-16 ***
complexcond.cc -0.40789    0.06950  -5.869 5.12e-09 ***
complexity      0.24530    0.01812  13.541  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.118 on 1992 degrees of freedom
Multiple R-squared:  0.09427,Adjusted R-squared:  0.09336
F-statistic: 103.7 on 2 and 1992 DF,  p-value: < 2.2e-16
```

Table Summarizing Model Coefficients

	Consequent									
	complexity(Mi)					risk(Y)				
Antecedent		Coef	SE	t	p		Coef	SE	t	p
complexcond.cc(X)	b	2.662	0.062	43.010	<.001	c	-0.408	0.069	-5.869	<.001
complexity(Mi)						b	0.245	0.018	13.541	<.001
Constant	iy	4.286	0.031	138.500	<.001	iy	2.471	0.082	30.291	<.001
Observations		1995					1995			
R2		0.481					0.094			
Adjusted R2		0.481					0.093			
Residual SE		1.382 (df = 1993)					1.118 (df = 1992)			

```
      F statistic          F(1,1993) = 1849.871, p < .001       F(2,1992) = 103.664, p <
.001
```

Order factor interaction model (order factor not significant)

```
Formula: starrating ~ complexcond.cc * fail.cc * counterbalance.cc + (1 | cat) + male.binary +
edu.c + age.c
   Data: df

REML criterion at convergence: 6635.2

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.7638 -0.5872  0.1520  0.8355  2.9346

Random effects:
 Groups   Name        Variance Std.Dev.
 cat      (Intercept) 0.000    0.000
 Residual             1.671    1.292
Number of obs: 1970, groups:  cat, 4

Fixed effects:
                                           Estimate Std. Error        df t value Pr(>|t|)
(Intercept)                               6.706e+00  2.917e-02  1.959e+03 229.901  < 2e-16 ***
complexcond.cc                           -3.142e-02  5.829e-02  1.959e+03  -0.539    0.590
fail.cc                                  -2.196e+00  5.831e-02  1.959e+03 -37.671  < 2e-16 ***
counterbalance.cc                         6.291e-02  5.830e-02  1.959e+03   1.079    0.281
male.binary                              -6.838e-02  5.850e-02  1.959e+03  -1.169    0.243
edu.c                                     2.510e-02  2.740e-02  1.959e+03   0.916    0.360
age.c                                    -1.149e-02  2.382e-03  1.959e+03  -4.824 1.52e-06 ***
complexcond.cc:fail.cc                    2.969e-01  1.166e-01  1.959e+03   2.547    0.011 *
complexcond.cc:counterbalance.cc          4.813e-02  1.166e-01  1.959e+03   0.413    0.680
fail.cc:counterbalance.cc                 1.245e-01  1.166e-01  1.959e+03   1.067    0.286
complexcond.cc:fail.cc:counterbalance.cc -1.744e-02  2.337e-01  1.959e+03  -0.075    0.941
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Platform (Prolific vs. Mturk) Interaction Model (significant differences in the outcome by platform, but controlling for these, the main interaction was still significant and not meaningfully changed)

```
Formula: starrating ~ complexcond.cc * fail.cc * prolific.cc + (1 | cat) + male.binary + edu.c
+ age.c
   Data: df

REML criterion at convergence: 6611.3

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.9993 -0.5940  0.1302  0.8010  2.8102

Random effects:
 Groups   Name        Variance Std.Dev.
 cat      (Intercept) 0.000    0.000
 Residual             1.651    1.285
Number of obs: 1970, groups:  cat, 4
```

```
Fixed effects:
                                    Estimate Std. Error        df t value Pr(>|t|)    
(Intercept)                        6.755e+00  3.281e-02  1.959e+03 205.884  < 2e-16 ***
complexcond.cc                    -6.645e-03  6.557e-02  1.959e+03  -0.101   0.9193    
fail.cc                           -2.076e+00  6.558e-02  1.959e+03 -31.651  < 2e-16 ***
prolific.cc                       -2.028e-01  6.586e-02  1.959e+03  -3.080   0.0021 ** 
male.binary                       -5.489e-02  5.823e-02  1.959e+03  -0.943   0.3460    
edu.c                              1.773e-02  2.726e-02  1.959e+03   0.650   0.5157    
age.c                             -1.164e-02  2.369e-03  1.959e+03  -4.911 9.81e-07 ***
complexcond.cc:fail.cc             2.879e-01  1.312e-01  1.959e+03   2.194   0.0283 *  
complexcond.cc:prolific.cc        -1.102e-01  1.311e-01  1.959e+03  -0.841   0.4007    
fail.cc:prolific.cc               -5.167e-01  1.312e-01  1.959e+03  -3.938 8.49e-05 ***
complexcond.cc:fail.cc:prolific.cc  2.996e-02  2.626e-01  1.959e+03   0.114   0.9092    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

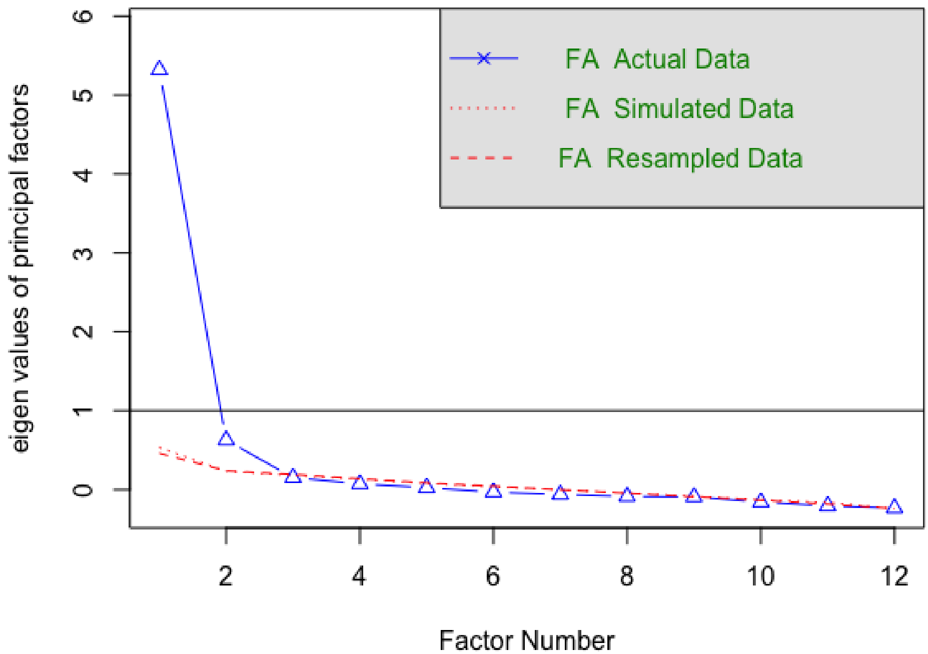
Construct Correlations

```
           complexity  risk starrating   age  edu
complexity       1.00  0.28       0.00  0.06 0.10
risk             0.28  1.00      -0.07 -0.03 0.06
starrating       0.00 -0.07       1.00 -0.06 0.01
age              0.06 -0.03      -0.06  1.00 0.21
edu              0.10  0.06       0.01  0.21 1.00
```

ESSAY 1 STUDY 7

Factor Analysis Output

The following factor analysis output includes a scree plot with parallel analysis, factor eigenvalues, and output for a two-factor model using oblimin rotation.



Parallel analysis suggests that the number of factors = 2

Factor eigenvalues: 5.32, 0.63, 0.15, 0.07, 0.02, -0.03, -0.06, -0.09, -0.09, -0.16, -0.21, -0.23

```
Factor Analysis using method =  minres
Call: fa(r = dfscale, nfactors = 2, rotate = "oblimin", fm = "minres")
Standardized loadings (pattern matrix) based upon correlation matrix
                  MR1   MR2   h2   u2 com
imagerysparse   -0.11  0.80 0.54 0.46 1.0
proddesign       0.25  0.62 0.64 0.36 1.3
packagaing       0.25  0.61 0.62 0.38 1.3
productswork     0.81 -0.20 0.49 0.51 1.1
useprods         0.72  0.03 0.54 0.46 1.0
easymake         0.61  0.09 0.44 0.56 1.0
purchase         0.58  0.26 0.59 0.41 1.4
decide           0.57  0.16 0.47 0.53 1.2
access           0.56  0.13 0.42 0.58 1.1
setup            0.70  0.10 0.59 0.41 1.0
name            -0.04  0.63 0.36 0.64 1.0
wordsunderstand  0.19  0.51 0.42 0.58 1.3

Factor loadings with cutoff at .4
Loadings:
                MR1    MR2
imagerysparse           0.799
proddesign              0.621
packagaing              0.605
productswork     0.807
useprods         0.720
easymake         0.606
purchase         0.577
decide           0.571
```

```
access           0.557
setup            0.702
name                    0.627
wordsunderstand         0.512

                       MR1  MR2
SS loadings           3.54 2.58
Proportion Var        0.29 0.22
Cumulative Var        0.29 0.51
Proportion Explained  0.58 0.42
Cumulative Proportion 0.58 1.00

 With factor correlations of
     MR1  MR2
MR1 1.00 0.63
MR2 0.63 1.00

Mean item complexity =  1.1
Test of the hypothesis that 2 factors are sufficient.

The degrees of freedom for the null model are  66  and the objective function was
5.5 with Chi Square of  2030.07
The degrees of freedom for the model are 43  and the objective function was  0.22

The root mean square of the residuals (RMSR) is  0.03
The df corrected root mean square of the residuals is  0.03

The harmonic number of observations is  375 with the empirical chi square  39.19
with prob <  0.64
The total number of observations was  375  with Likelihood Chi Square =  81.19  with
prob <  0.00039

Tucker Lewis Index of factoring reliability =  0.97
RMSEA index =  0.049  and the 90 % confidence intervals are  0.032 0.065
BIC =  -173.67
Fit based upon off diagonal values = 1
Measures of factor score adequacy
                                                   MR1  MR2
Correlation of (regression) scores with factors   0.94 0.92
Multiple R square of scores with factors          0.88 0.85
Minimum correlation of possible factor scores     0.76 0.69
```

Construct Correlations

```
           brand.att perceptual conceptual OVsimp  risk   age   edu
brand.att       1.00      -0.50      -0.43  -0.47 -0.16  0.06 -0.10
perceptual     -0.50       1.00       0.65   0.80  0.10 -0.09  0.05
conceptual     -0.43       0.65       1.00   0.68  0.00 -0.03  0.03
OVsimp         -0.47       0.80       0.68   1.00  0.08 -0.07  0.07
risk           -0.16       0.10       0.00   0.08  1.00 -0.03  0.14
age             0.06      -0.09      -0.03  -0.07 -0.03  1.00  0.10
edu            -0.10       0.05       0.03   0.07  0.14  0.10  1.00
```

ESSAY 2 STUDY 2A

Construct Correlations

	edu	age	simpfirstCEILING	compfirstCEILING	performance
edu	1.00	0.11	-0.12	0.28	0.08
age	0.11	1.00	0.04	0.19	0.12
simpfirstCEILING	-0.12	0.04	1.00	NA	1.00
compfirstCEILING	0.28	0.19	NA	1.00	1.00
performance	0.08	0.12	1.00	1.00	1.00

ESSAY 2 STUDY 2B

Construct Correlations

	edu	age	complexity.simpprod	complexity.compprod	perform
edu	1.00	0.06	0.09	0.02	-0.21
age	0.06	1.00	0.02	-0.03	-0.16
complexity.simpprod	0.09	0.02	1.00	0.30	-0.10
complexity.compprod	0.02	-0.03	0.30	1.00	0.17
perform	-0.21	-0.16	-0.10	0.17	1.00

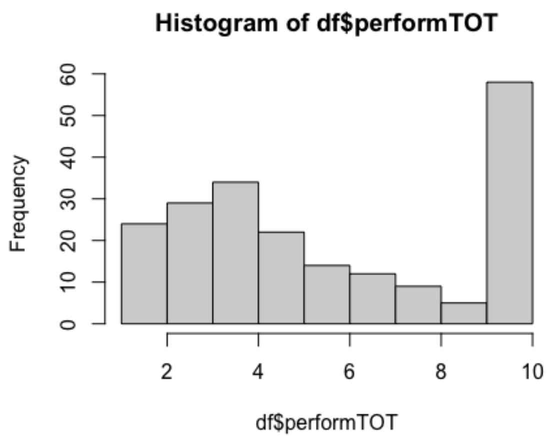
ESSAY 2 STUDY 3

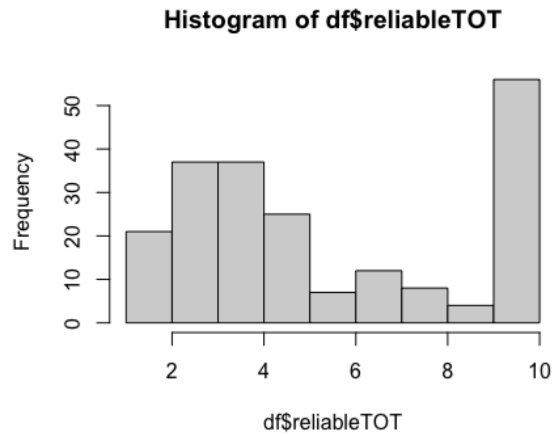
Construct Correlations

	SDDist	MeanDist	complexity	minim	maxim	Count0s	edu	age
SDDist	1.00	-0.14	0.13	-0.76	0.31	0.02	-0.07	-0.13
MeanDist	-0.14	1.00	-0.04	0.64	0.82	-0.48	0.01	-0.05
complexity	0.13	-0.04	1.00	-0.12	0.03	0.07	0.03	-0.06
minim	-0.76	0.64	-0.12	1.00	0.28	-0.31	0.06	0.07
maxim	0.31	0.82	0.03	0.28	1.00	-0.51	-0.02	-0.11
Count0s	0.02	-0.48	0.07	-0.31	-0.51	1.00	-0.02	0.07
edu	-0.07	0.01	0.03	0.06	-0.02	-0.02	1.00	0.24
age	-0.13	-0.05	-0.06	0.07	-0.11	0.07	0.24	1.00

ESSAY 2 STUDY 4

Distributions of sum scores for number of attributes listed for the reliable and performance products:





Construct Correlations

	performTOT	reliableTOT	performminusrely	age	edu
performTOT	1.00	0.81	0.31	0.02	0.01
reliableTOT	0.81	1.00	-0.30	0.08	0.05
performminusrely	0.31	-0.30	1.00	-0.10	-0.07
age	0.02	0.08	-0.10	1.00	-0.04
edu	0.01	0.05	-0.07	-0.04	1.00

ESSAY 2 STUDY 5

Construct Correlations

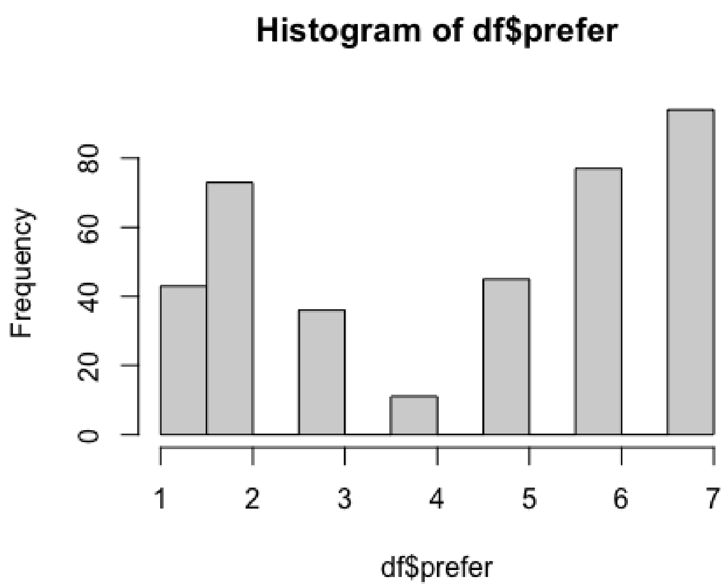
	complexdiff	performdiff	age	perform.compcam	perform.simpcam	fail.compcam
complexdiff	1.00	0.19	0.06	0.08	-0.15	0.03
performdiff	0.19	1.00	-0.05	0.64	-0.61	-0.04
age	0.06	-0.05	1.00	-0.11	-0.05	0.15
perform.compcam	0.08	0.64	-0.11	1.00	0.22	-0.06
perform.simpcam	-0.15	-0.61	-0.05	0.22	1.00	0.00
fail.compcam	0.03	-0.04	0.15	-0.06	0.00	1.00
fail.simpcam	-0.16	0.05	-0.02	0.00	-0.05	0.44
complexity.compcam	0.52	0.09	-0.10	0.25	0.14	0.03
complexity.simpcam	-0.60	-0.11	-0.16	0.14	0.29	0.00
age.1	0.06	-0.05	1.00	-0.11	-0.05	0.15
edu	0.01	0.06	0.11	0.03	-0.04	0.15

	fail.simpcam	complexity.compcam	complexity.simpcam	age.1	edu
complexdiff	-0.16	0.52	-0.60	0.06	0.01
performdiff	0.05	0.09	-0.11	-0.05	0.06
age	-0.02	-0.10	-0.16	1.00	0.11
perform.compcam	0.00	0.25	0.14	-0.11	0.03
perform.simpcam	-0.05	0.14	0.29	-0.05	-0.04
fail.compcam	0.44	0.03	0.00	0.15	0.15
fail.simpcam	1.00	-0.06	0.11	-0.02	0.15
complexity.compcam	-0.06	1.00	0.37	-0.10	0.12

```
complexity.simpcam         0.11               0.37                1.00 -0.16  0.10
age.1                     -0.02              -0.10               -0.16  1.00  0.11
edu                        0.15               0.12                0.10  0.11  1.00
```

ESSAY 2 STUDY 6

Distribution of the dependent variable: a direct comparison measure from 1 (“Much prefer Watch X)” to 7 (“Much prefer Watch Y”), where Watch X is simple and Watch Y is more complex.



Construct Correlations

```
                     complexity.simpwatch complexity.compwatch   age   edu complexdiff prefer
complexity.simpwatch                 1.00                 0.44  0.02  0.06       -0.55   0.12
complexity.compwatch                 0.44                 1.00 -0.13 -0.07        0.51   0.03
age                                  0.02                -0.13  1.00  0.28       -0.13  -0.10
edu                                  0.06                -0.07  0.28  1.00       -0.12   0.07
complexdiff                         -0.55                 0.51 -0.13 -0.12        1.00  -0.09
prefer                               0.12                 0.03 -0.10  0.07       -0.09   1.00
```

ESSAY 2 STUDY 7

Category-specific product images (used across all complexity conditions within category):


KIM'S
OPEN DAILY 7 AM - 4 PM
EAST END OF THE LIBRARY

Construct Correlations

	age	edu	risk	perform	complexity
age	1.00	0.22	-0.06	0.11	0.03
edu	0.22	1.00	0.11	0.11	0.09
risk	-0.06	0.11	1.00	-0.25	0.12
perform	0.11	0.11	-0.25	1.00	0.13
complexity	0.03	0.09	0.12	0.13	1.00