MARKETING A HORSE OF A DIFFERENT COLOR: THE ROLE OF UNIQUE FEATURES AND EXPLANATIONS IN PERCEIVED PRODUCT DIFFERENTIATION

By

ANDREW R. LONG

B.A., Vanguard University of Southern California, 2008

A thesis submitted to the

Faculty of the Leeds School of Business of the

University of Colorado in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy

Department of Marketing

2019

This thesis entitled:
Marketing a Horse of a Different Color:
The Role of Unique Features and Explanations in Perceived Product Differentiation
written by Andrew R. Long
has been approved for the Department of Marketing

Philip M. Fernbach

Bart de Langhe

Date______________

The final copy of this thesis has been examined by the signatories, and we find that both the content and the form meet acceptable presentation standards of scholarly work in the above mentioned discipline.

IRB protocol #: 18-0214

Long, Andrew R. (Ph.D., Marketing)

Marketing a Horse of a Different Color: The Role of Unique Features and Explanations in Perceived Product Differentiation

Thesis directed by Associate Professors Philip M. Fernbach and Bart de Langhe

Other committee members: John G. Lynch Jr., Nicholas Reinholtz, and Stephen A. Spiller

Product differentiation has been integral to the understanding of both competitive marketing strategy and consumer welfare. However, despites its ubiquity in theory and practice, product categories are often perceived by consumers to be homogenous and undifferentiated. Additionally, attempts by businesses to create differentiation often fail. I argue that understanding how differentiation is perceived by consumers is vital to understanding why these failures occur, why categories appear undifferentiated, and how to build successful differentiation strategies. In the first chapter, I provide an overview of product differentiation theories and research from both the economics and psychology traditions in marketing, describing the limitations and gaps within the various approaches. In the second chapter, I examine an apparent dilemma faced by marketers. Across a variety of products and categories, features that are more unique (i.e., less common) are also poorly understood by consumers. Thus, the features with the most potential to create differentiation are also the least likely to be perceived as such by consumers. Conversely, the features that are well-understood, and therefore allow a consumer to assess their value, are too common to create differentiation. However, this dilemma can be overcome with mechanistic explanations about how unique, poorly understood features work. In the third chapter, I examine how consumers' mental representation and comparison processes of products interact with differentiation attempts by multiple competitors. Specifically, I find that an undifferentiated product in a category can nevertheless appear to be highly distinct when multiple competitors are differentiated with poorly understood features. Again, mechanistic explanations help consumers see the true differentiation. Overall, the research highlights the importance of consumer cognition in product differentiation theory. Specifically, utilizing consumers' propensity to think about the causal connections between products and the benefits they provide allows for better outcomes for both businesses and consumers.

ACKNOWLEDGEMENTS

This accomplishment would not have been possible without the support of the people who inspired me, sacrificed time and energy to provide assistance, and, knowingly or not, helped carry me toward the finish.

To Phil Fernbach and Bart de Langhe, I want to thank you for always reminding me of both the potential you saw in me, and, perhaps more important, how far I'd already come. Your mentorship shaped not only my research but also the journey of my career and life.

To Holly, Snoopy, and Chloe, your love, patience, and understanding got me through the worst of times, multiplied the joy in the best of times, and are the reason I am where I am today.

I'd like to thank my mom, who taught me from a young age that I can aspire to do great things and, when I wasn't doing great things, that that's ok too but I'd probably be happier doing the great things. Also, thank you to my dad, who taught me to find wonder in everything, including how toothpaste worked, which, oddly enough, featured heavily in this dissertation. And, I'd like to thank my siblings, Josh, Meagan, Dave, Katie, and Zach. They were my first friends (and enemies, but that was temporary) and they all helped shape what family means to me. Every rare get-together, random text, beer, Facebook like, etc. helped me through.

Thank you to John Lynch, whose willingness to cut through the bad parts of a paper to find the nugget of gold was instrumental in developing this dissertation, improving my other research in grad school, and in inspiring me to always judge work by its best qualities. Thank you to Nick Reinholtz, whose willingness to help and to have discussions about esoteric statistical techniques in unparalleled. Thank you to Stephen Spiller, whose support goes back even further than he knows – providing thoughtful tips and opinions on this dissertation and teaching me 10 years ago how to use Qualtrics.

Thank you to Stefanie Ungphakorn, who made life easier and reminded me to be excited. Thank you to all the marketing department faculty. To Donnie Lichtenstein, who taught me, among other things, to have fun both in research and in life. To Lawrence Williams, who taught me to investigate from different perspectives. To Meg Campbell, who taught me to celebrate every accomplishment and to find inspiration not only from journals but also from everything else I enjoy. To Pete McGraw, who taught me to find the big picture. To Chuan He, whose class on economic marketing models unexpectedly introduced me to the fullness of marketing research and to the beginnings of the work behind this dissertation. To Laura Kornish, for always been willing to help and talk. And to Scott Shriver, who provided a great example and who appreciated my unique ability to judge other people's programming code.

Thank you to Lauren Min. Much of my memory with Lauren over the years of grad school surround the commiseration and shared struggle endemic to doctoral education. Yet, they are also some of my fondest memories, as I wouldn't have wanted anyone else to go through the process with. And thank you to Joe Harvey. Our frequent, short breaks and constant texting were the distraction I needed to keep myself anchored.

Thank you to the other students and scholars who passed through the Leeds School of Business. To Erin, Alison, Paul, Julie, Christina, Abby, Brigitte, Adrian, Jessica, and Francisco, they made the early days of school better and I still look forward to seeing them whenever I have the opportunity. To Sharaya, Justin, Nick, and Unseok, whose friendships I cherish. And thank you to Masha, Rachel, Jennie, Mike, Jared, Carolyn, Chris, Quentin, Evan, Liz, Tami, and all the other people who made me feel welcomed into the marketing community as a friend.

Thank you to those outside of the marketing world who took interest in me, became my friend, and helped me when I most needed it, especially George Karpoff and Helen Van Dam. And thank you to Zach Nichols of Cellar West Artisan Ales, not only for the beer but also for the friendship.

Finally, thank you to those who put me on the path toward this degree and provided assistance and guidance getting me into school. To Carl Renold and Noreen Dulin who inspired me to study psychology academically. To Vikram Peters, who introduced me to Paul Fillmore, who encouraged me to send out even more cold-call emails than I already had offering volunteer research assistance. Without their encouragement, I may never have found the first step on my path. To Craig Fox, the only person to respond to those cold-call emails, who gave me an enviable introduction into the world of academic research, and who steered me toward business school. To Kurt Carlson, who guided me into the marketing world and championed my talents early on. And to Simon Blanchard, Debora Thomson, Chris Long and the other faculty of the McDonough School of Business behavioral lab who all provided immense help, advice, and inspiration.

CONTENTS

TABLES

FIGURES

Chapter 1.
PERCEIVED PRODUCT DIFFERENTIATION

1.1 Introduction

"Always remember that you're unique, just like everyone else."

-Author Unknown

"You are not special. You're not a beautiful and unique snowflake. You're the same…as everything else."

-"Tyler Durden," *Fight Club*, Chuck Palahniuk

Product differentiation has long been a cornerstone element of marketing theory. By offering consumers something that competitors cannot, a business can realize a diverse set of rewards, including a price premium on its products and increased customer loyalty. However, while businesses may attempt to appear unique, each in their own way, those attempts typically fail, with the majority of product categories composed of products and brands that are viewed by consumers as essentially the same as everything else (Romaniuk, Sharp, and Ehrenberg 2007).

In my dissertation, I investigate how consumers perceive product differentiation. By learning about some of the cognitive processes that consumers use to analyze individual products, sets of competitors, and entire categories, the results of the studies offer mechanisms by which businesses can better differentiate their offerings. For instance, the research shows that explanations of how a product's unique features work and causally relate to potential benefits tend to make consumers perceive the product as more distinct, relative to competitors.

Additionally, the research has implications for topics beyond marketing tactics, including consumer welfare. If a business receives additional value from consumers in response to product differentiation, it should be because the business provided additional value to those consumers. While brands can differentiate themselves in meaningless ways that provide no value to customers (e.g., Carpenter, Glazer, and Nakamoto 1994), the processes investigated here allow consumers to perceive differentiation in a way that also helps them better assess the product's value. Thus, if a consumer is willing, for instance, to pay a higher price for the differentiated offering, it is likely because the consumer has reason to believe it is worth it.

Overall, I argue that understanding perceived product differentiation is a vital aspect of marketing theory and consumer psychology. The approach taken adds to a variety of topics within each area. To highlight these topics, the proceeding sections provide an overview of theories of product differentiation strategy and its perception by consumers. Then, in my first essay, I examine an apparent dilemma faced by marketers. Across a variety of products and categories, features that are more unique (i.e., less common) are also poorly understood by consumers. Thus, the features with the most potential to create differentiation are also the least likely to be perceived as such by consumers. Conversely, the features that are well-understood, and therefore allow a consumer to assess their value, are too common to create differentiation. However, this dilemma can be overcome with mechanistic explanations about how unique, poorly understood features work. In my second essay, I examine how consumers' mental representation and comparison processes of products interact with differentiation attempts by multiple competitors. Specifically, I find that an undifferentiated product in a category can nevertheless appear to be highly distinct when multiple competitors are differentiated with poorly understood features. Again, mechanistic explanations help consumers see the true differentiation.

1.2 Product Differentiation as a Theory of Value

Product differentiation was an early topic of interest within marketing theory. Indeed, early theorists discussed it extensively as a core function of marketing. Product differentiation was seen as an approach toward business that embraces consumer individualism by catering the production and distribution of product offerings, as well as advertising and communication, toward consumers' various needs and wants (Cherington 1920, Clark 1922, Shaw 1912). Such an approach results in product offerings that are perceived to differ from competitors along any attribute or feature of the product. The perceived product differentiation allows the seller to benefit by charging a higher price, increasing demand, or building customer loyalty, since it is rooted in an attempt to better satisfy the needs of some set of consumers. Indeed, this notion of providing marginal value to consumers was central to the importance of the strategy and it was described as a moral responsibility of the marketer (e.g., Cherington 1920, p. 139; Shaw 1912, p. 721; Smith 1776/1910, p. 155)

Economic formalizations of product differentiation, however, were more ambivalent. Product differentiation was the defining element Edward Chamberlin's theory of monopolistic competition, which was optimistic about differentiation's economic effects (1933/1949). Chamberlin's definition of differentiation pioneered the concepts that it is consumers' perceptions of products, rather than the products themselves, that determined demand and that consumers perceived and cared about non-physical attributes of products. These concepts, as well as other aspects of the theory, imply that consumers have heterogeneous preferences based on differing needs. Heterogeneous preferences imply that competitors' product offerings are not perfect substitutes, which violates the assumptions of the theory of perfect competition – neoclassical economics' theory of welfare-maximizing competition (Arrow 1972). Chief among his arguments was that heterogeneity of firms' products, prices, and profits in real-world markets, often attributed to imperfections and inefficiencies in the market, are actually the result of the degree to which the suppliers were successful in adapting their business to meet consumers' needs. Successful differentiation can thus be characterized, according to Chamberlin, as providing additional value to consumers.

Contemporaneously, Joan Robinson published the theory of imperfect competition, which made similar extensions to competition theory but from different perspectives and with different evaluations and interpretations (1933/1969).[1] As the

[1] Robinson (1933/1969) focused most of the original theorizing on how imperfect competition resulted in exploitation of labor markets by employers and did not mention product differentiation explicitly. Chamberlin (1936) identified the overlap of the two theories. Consequently, "monopolistic" and

name implies, Robinson interpreted imperfect competition as necessarily resulting in economic inefficiencies that result in lower general welfare compared to perfect competition (1953). For example, under perfect competition, the price of a product offering is equal to its marginal cost, while under imperfect competition, in the short-run, the equilibrium price is higher than the product's marginal cost. Paying higher prices than necessary would be interpreted as welfare decreasing for the consumer. Additionally, under imperfect competition, firms operate at suboptimal, higher-than-expected costs, interpreted as welfare decreasing for the firm. Successful differentiation can thus be characterized, according to proponents of perfect competition as a prescriptive theory, as resulting from imperfections in the market[2] and reducing the welfare of all involved, both in the short and long-run.

The pessimistic interpretation of product differentiation, and monopolistic competition more broadly, was typical for some time. Within economic research, product differentiation was viewed as a source of inefficiency. For instance, competitive advertising was viewed as a wasteful expense (Boulding 1966, Galbraith 1967), and product feature specifications were described as a contrived, valueless method of fragmenting markets (Samuelson 1948). This view was also prevalent within marketing thought. Wendall Smith's (1956) seminal discussion of

---

"imperfect" competition have since been used interchangeably, though imperfect competition is also sometimes used to refer to any non-perfect form of competition, e.g., monopoly/oligopoly.

[2] For example, differentiation may be achieved through a novel, patented feature, which is a form of market entry barrier. Under perfect competition, where there are no barriers to entry, competitors could add the feature to their product, and the consumer would not have to pay a premium price to have access to the feature.

the differences between product differentiation and segmentation characterized the former as "bending demand to the will of supply," implying that businesses benefit at the expense of consumers. Product heterogeneity was described as arising from imaginary differences instilled in consumers by advertising, product names, packaging, and other superficial or misleading tactics (Lancaster 1979). These critical views were rooted, in part, in the fact that marketers indeed commonly used such misleading tactics[3] and that monopolistic competition did not give a formal treatment to the utility gained by consumers through product differentiation.

Monopolistic competition and product differentiation have since risen in influence both in economic and marketing theory. Modern demand theory models products not as commodities, which fit the substitutability assumptions of perfect competition, but as goods which are produced from commodities (Bellante 2004). Products are seen as bundles of characteristics which yield utility, and there exists a distribution of consumer preferences over the different bundles (Becker 1965, Lancaster 1971, Rosen 1974). This distribution implies that there is a socially optimal degree of product differentiation (Lancaster 1975). Within marketing, the view of product differentiation shifted from an alternative to segmentation to a method of achieving segmentation (Dickson and Ginter 1987, Wedel and Kamakura 1998) and theorists have developed models to estimate the conditions of optimal differentiation (Hauser and Gaskin 1984, Hauser and Shugan 1983, Hauser and Simmie 1981). Product differentiation has become a core component of competitive

[3] For some examples, see Carpenter, Glazer, and Nakamoto (1994).

strategy (Drucker 1954, Levitt 1960, Porter 1980), branding and positioning theory (Keller 2009), and marketing research (Fader 2012).

Overall, product differentiation was the catalyst for a reconstruction of the theory of value, extending its formulation from market-defined prices to consumer-defined perceptions of product features that fulfill their needs. In order to maximize both the value provided to and received from consumers, firms must understand how these perceptions work. In the next section, I overview the varied approaches researcher have taken to investigate and model how consumers perceive product differentiation.

1.3 Quantitative and Behavioral Models of Perceived Product Differentiation

Product differentiation arises when consumers perceive valuable differences in product features between competitors. Achieving a competitive advantage and implementing a differentiation strategy, therefore, relies on an understanding of how consumers perceive products and their features. The marketing literature has examined perceived differentiation from a variety of perspectives. The economic and quantitative marketing traditions have focused on two, broad areas of research – how varying assumptions about the perception of differentiation affect market-level, competitive strategy (e.g., the optimal amount of differentiation in a market) and how the assumptions affect expected aggregate demand characteristics (e.g., the market share of a new product). The behavioral tradition has corroborated those findings, providing evidence for the psychological processes that bring about perceived differentiation, while also extending the theory of product differentiation into other meaningful outcomes, such as brand loyalty. The following discussion provides an overview of these perspectives and identifies areas where the research in the subsequent essays provides complementary insights.

1.3.1 Economic and Quantitative Marketing Models

Economic and quantitative marketing models of product differentiation fall into four broad categories – location models (also known as spatial competition or Hotelling models), perceptual mapping, conjoint analysis, and discrete choice models. While these classes, as well as their constituent models, differ in terms of their level of analysis and intended use, they all model consumer perception of differentiation by the consumers' utility function for the available products. If utility differs between products, then by definition there are valuable differences between the products that consumers must be aware of. Models can differ in terms of how they define utility, and differences in these assumed utility functions reflect differences in how consumers evaluate and, therefore, perceive the differentiation. These differences occur along three characteristics of the functions: utility constraints (e.g., a maximum willingness-to-pay), source of heterogeneous preferences (e.g., heterogeneous perception of attributes vs. heterogeneous attribute weights), and functional form (e.g., linear vs. power utility).

Location models were the earliest models of differentiation. These models describe the market of consumers as being distributed along some geometric shape, originally a line (Hotelling 1929, Lerner and Singer 1937), and later a circle (Salop 1979), a set of spokes emanating from a midpoint (Chen and Riordan 2007), and multidimensional spaces (Ansari, Economides, and Steckel 1998). Competitors differentiate otherwise identical products on price and location on the market shape. Location was originally interpreted literally (e.g., where along a street should two competing retailers place their stores), but it can also represent any characteristic where differences can be conceptualized by mathematical distance. Consumer utility for a product decreases as products are farther away from the consumer and as prices increase. The models are typically analyzed for competitive equilibrium strategies for product locations. [4] For example, Hotelling's (1929) original analysis concluded that the competitors' incentives are to relocate until they are as close to each other as possible. However, subsequent analysis showed that subtle changes, such as imposing a maximum willingness-to-pay, can lead to substantial differentiation between the competitors (Lerner and Singer 1937), and that, when competitors compete along multiple attributes, one attribute should be maximally differentiated and the others minimally differentiated (Ansari, Economides, and Steckel 1998). For a taxonomy of location models and a partial annotated bibliography, see Eiselt, Laporte, and Thisse (1993).

---

[4] These models would ideally have joint equilibria for locations and prices, in order to analyze both normative characteristics of products and the prices firms can charge for them. However, numerous problems often render such equilibria indeterminable (for a summary of problems and potential solutions, see MacLeod, Norman, and Thisse 1988). To avoid such problems, most models either assume market-wide price parity or that differences in price reflect only the cost differences in products.

Perceptual mapping and conjoint analysis, while distinct in assumptions, are unified in purpose. While location models are used to assess the differentiation characteristics of entire markets of competitors, the goal of these models is to allow a single firm to analyze how to optimally design their marketing plan around consumers' needs and desires (Shocker and Srinivasan 1979). Perceptual mapping is similar to location models in that products and consumers are represented by points in a multidimensional space, with the dimensions representing important product attributes (Shocker and Srinivasan 1974). The distance between a product's location (i.e., the attribute levels of the product) and a consumer's location (i.e., the consumer's ideal product configuration) is inversely proportional to the consumer's utility for the product. The major difference between location models and perceptual mapping is that the latter does not make assumptions about the distribution of consumers within the product attribute space. Instead, samples of consumers provide data that can identify their ideal points in the product attribute space, and clusters of ideal points can be interpreted as distinct consumer segments, as well as potentially fruitful product configurations.

Conjoint analysis is a class of techniques that estimates consumers' preferences for products using overall evaluations of complete products, rather than product attributes as in perceptual mapping (Green and Rao 1971, Green and Srinivasan 1978, 1990). The researcher selects a finite number of attributes and attribute levels and constructs a set of product stimuli composed of various combinations of the levels for all attributes, using a specific combinatorial design, typically a fractional factorial. Samples of consumers then rate individual products, indicate preferences between subsets of products, or rank the entire set of products. The consumer responses, combined with the combinatorial design of product stimuli, allow the researcher to estimate the utility associated with each level of each attribute, called part-worths. The researcher can then use the part-worths to estimate consumer utility for different configurations of the product, and use those utility estimates for other important predictions, such as estimated market share and revenue.

Discrete choice models of product differentiation are the most ambitious of the four classes of models by combining the approaches of the previous three classes in a single model. Discrete choice models aim to describe markets of multiple competing firms by empirically estimating individual consumers' utilities for each product in the market, as well as potential new entrants and outside options (Berry 1994). The basis for the entire model is the utility function of individual consumers. The function describes utility using five parameters: observed product characteristics, unobserved product characteristics, price, unobserved consumer characteristics, and demand characteristics (e.g., the functional form of the utility function). A typical utility function predicts the utility of a product based on a linear-additive model of weighted product characteristics and price, with random error terms for individual products and consumers. These random error terms capture utility or disutility from products based on attributes unobserved by the researcher, as well as individual variation in the perceived importance of different product characteristics. While a comprehensive description of the rest of the model is beyond the scope of this review,[5] in short, the utility function is used to derive market shares for each product, and the market shares are combined with a market size estimate to determine overall demand. The demand model is jointly estimated with a supply-side model that determines product prices and firm costs. The resulting grand model can be used both for analyzing competitive equilibria between firms (Bresnahan 1987), as well as for informing marketing plans for an individual firm (Chintagunta and Nair 2011).

While the four classes of models vary across a host of characteristics, there are three sources of differences that reflect assumptions of how consumers perceive product differentiation. The sources of heterogeneous preferences consist of the aspects of the utility function that cause the function to predict different utilities for different consumers. The functional form of the utility function consists of assumptions about the shape of the function, and thus represents the nature of the relationship between attribute levels and perceived value. Finally, utility constraints consist of assumptions about utility that cannot be incorporated into the formal utility function, often because the assumptions require a discontinuity in utility.

Researchers typically identify two potential sources of heterogeneous preference – heterogeneous perceptions of product attributes and heterogeneous tastes. While research has shown that consumers have considerable heterogeneity

[5] For an exhaustive review, see Berry (1994).

across both potential sources, product differentiation models tend to only incorporate one source, likely because of the computational or analytical difficulty in incorporating other sources (Hauser and Gaskin 1984).[6] Heterogeneous perceptions are when consumers do not agree about what levels of an attribute a product has. Two common scenarios where this can occur are when an attribute is non-physical and, thus, based on a consumer's judgment (e.g., picture quality on a television) or when consumers do not evaluate complete products. Of the models reviewed, only traditional perceptual maps allow for heterogeneous perceptions (Shocker and Srinivasan 1974). A subclass of perceptual maps called per-dollar maps, which normalize product attribute levels to the price of the product (Hauser and Shugan 1983), as well as all location, conjoint analysis, and discrete choice models assume homogenous, perfect perception of product attributes (Ansari, Enonomides, and Steckel 1998; Hauser and Gaskin 1984; Berry 1994). Heterogeneous tastes are when consumers have different utility weights for the same attribute.[7] Location models, per-dollar perceptual maps, conjoint analysis, and discrete choice models assume heterogeneous tastes, while traditional perceptual maps assume homogenous tastes.

---

[6] Hauser and Gaskin (1984) also describe heterogeneous preferences arising from different choice rules among consumers; however, no model was found that incorporated such qualities.

[7] The term *taste* has two common usages with regard to product differentiation. In addition to the usage here, which is the most typical within the quantitative marketing literature, the other refers to horizontal differentiation – when consumers do not agree about the ranking of attribute levels. An example of the difference in definition is that models of vertical differentiation are typically described as having heterogeneous tastes – consumers agree on the ranking of the attribute levels but can still differ in terms of how important they view the attribute.

Functional forms of the utility functions also differ along two key dimensions – the shape of the utility function and the inclusion of horizontal vs. vertical differentiation. The modal utility model in product differentiation is linear. While this contradicts the well-accepted principle of diminishing marginal utility, researchers adopt this assumption for two reasons. First, nonlinearities in the hypothetical, true utility curve for a product attribute are often not substantial within the range of attribute levels investigated (Von Winterfeldt and Edwards 1986). Second, linear utility provides substantial computational and analytical ease. For example, Hauser and Shugan (1983) assume linear utility partially because it allows for easy-to-interpret, straight-line indifference curves within the product attribute space. However, concave functions, which exhibit diminishing marginal utility, are also common. In location and discrete choice models, concave utility functions are examples of separating pressures – factors that tend to increase the amount of differentiation seen in the market (Ansari, Economides, and Steckel 1996). For instance, quadratic utility leads to maximal differentiation between competitors, while logarithmic and power utility lead to intermediate differentiation. Finally, conjoint analysis utilizes a unique, piecewise-linear utility function, which allows the researcher to capture virtually any utility function shape, at the expense of having to estimate substantially more parameters in the model (Green and Srinivasan 1978).

Horizontal and vertical differentiation allow researchers to model utility differently based on a key difference in consumer beliefs about an attribute.

Typically, a product attribute is defined as horizontally differentiating when consumers disagree about the quality rankings of the attribute's levels (e.g., a car's color), while the attribute is defined as vertically differentiating when consumers agree about quality rankings (e.g., a car's gas mileage; Nevin and Thisse 1990). Both forms of differentiation are modeled using a variety of functional forms, as above. The difference is what value is supplied to the function. Horizontal differentiation is typically modeled as a function of the distance between a consumer's ideal attribute level and the attribute level of the product, and vertical differentiation is modeled as a function of the raw of attribute level. The primary exception is the part-worth model of conjoint analysis. Since it can directly estimate the utilities of individual attribute levels, horizontal and vertical differentiation do not need to be modeled differently.

Finally, while the source of heterogeneity and functional form of the utility function account for the primary differences in models of perceived product differentiation, researchers have also examined additional assumptions about utility by incorporating external constraints on the models. Most of these, such as examining when consumers purchase more than one of a product (Singh and Vives 1984) or incorporating variety seeking behavior (Sajeesh and Raju 2010), are tangential to the rest of the research here. However, the most common and relevant utility constraint in differentiation models is the specification of a maximum price that consumers are willing to pay for a product. Beyond the maximum price, the utility for the product is defined as zero. Maximum prices are common in location models (e.g., Lerner and Singer 1937, Sheth 1973) and perceptual mapping (e.g., Gwin and Gwin 2003), because these models conceptualize utility subtractively. Consumers are assumed to have an unknown, identical utility for their ideal product configuration and the disutility of price and distance from the ideal point are subtracted from that quantity. Maximum prices are another factor that promotes differentiation between competing products in location models (Ansari, Economides, and Steckel 1996). In perceptual mapping, maximum prices help define the limits of possible product configurations (Gwin and Gwin 2003, Schmalensee and Thisse 1988). While this assumption seems essential in isolation – consumers have budget constraints that limit the amount they can pay for products – it is unnecessary in other models. The maximum price assumption is a way of normalizing utility across consumers by setting the unknown, identical utility at each consumer's ideal point to the maximum price. Conjoint analysis (Green and Srinivasan 1978), discrete choice models (Berry 1994), and per-dollar perceptual maps (Hauser and Gaskin 1984) do not require such an assumption, since they can normalize consumer utility in other ways, such as estimating utility relative to a baseline product or empirically estimating threshold prices.

Overall, economic and quantitative marketing models of product differentiation attempt to explain the vast intricacies of consumer differentiation perceptions via a relatively small number of parameters. While the models differ substantially in terms of the kinds of data and statistical techniques needed to estimate the models and the intended uses for the model results, the different classes and examples of differentiation models are remarkably similar in terms of how they describe consumer perceptions of differentiation. Indeed, many of the differential assumptions between models are made based on tradeoffs between descriptive accuracy and computational simplicity, rather than differing theories of how consumers perceive differentiation. Further, other assumptions reflect circumstances of industries and marketplaces that differ in the real world (e.g., some product categories are dominated by horizontal differences between products while others are dominated by vertical differences).

The models have four primary limitations. First, the models only examine consumer preference. Consumer perception consists of a utility function that serves the purpose of determining which product a consumer would purchase within the stated environment. However, consumers often learn about products in non-choice and non-evaluative contexts. For instance, a consumer may view an advertisement and learn about a product without making an overall judgment about the value of the product. The aspects of the product the consumer learns about may factor into other processes and behaviors, such as how the consumer talks about particular brands with friends or how much further information search the consumer will engage in about the product or category. Second, the models primarily examine preferences in a one-time or snapshot context. The models cannot describe, for instance, how perceived differentiation can impact customer loyalty across multiple purchase occasions. Third, the models primarily examine preferences in stimulus-based contexts. Utility is determined based on descriptions of products or the models assume consumers have perfect knowledge of all attributes for all brands. However, consumers often have to make decisions by recalling both brands and attributes from memory (Lynch and Srull 1982). Finally, the models primarily assume a direct connection between product attributes and utility, without sufficiently incorporating the concept of perceived benefits. Marketers have long held that consumers value product benefits rather than product attributes (e.g., Haley 1968). Attributes are descriptive characteristics of a product, while product benefits are events valued by consumers that are caused by the product and its attributes. With the exception of perceptual mapping, which can utilize described benefits as a dimension in the perceptual space, these models, at best, incorporate the product benefit concept in a prohibitively simplified manner via the mathematical operations of the utility function. However, the process of perceiving benefits of, for instance, a car with a 35 miles per gallon fuel efficiency is likely more complicated than that which can be described by merely taking the logarithm of that numerical value (assuming a logarithmic utility function). Examining the complex processes by which consumers determine the value of products, including the contextual influences of those processes and how the processes affect consumers in different environments, will provide a deeper and more useful understanding of product differentiation.

1.3.2 Psychological and Behavioral Marketing Approaches

The behavioral marketing and consumer psychology approaches to perceived product differentiation have sought to provide a more comprehensive description of product differentiation, addressing many of the limitations of the quantitative models. In doing so, these approaches span a broad range of theories, topics, and findings but are more fragmented than the quantitative literature. This review structures the various approaches into four categories. First, researchers have investigated how consumers acquire differentiation-relevant information about products. The next two categories represent theories of how that information is structured and processed cognitively – theories of similarity and theories of categorization and schemas. Much of the research in these first three categories concerns how differentiation perceptions help shape preferences for products. In the final category, I summarize research into other important consequences of perceived differentiation for marketing and consumer behavior.

In order for product differentiation to occur, consumers both have to learn about attributes of competing products and process those attributes in a way that consumers can identify meaningful differences between brands. The most basic element of that process is how consumers learn relationships between products, attributes, and benefits. Research in this area has coalesced around two primary approaches – associative learning, derived from classical conditioning theories (e.g., Allen and Janiszewski 1989, Janiszewski and Van Osselaer 2000, Van Osselaer and Janiszewski 2001), and active learning, which investigates how learning is facilitated and mediated by a variety of cognitive processes, including categorization and causal reasoning (e.g., Alba and Hutchinson 1987, Fernbach et al. 2013, Hutchinson and Alba 1991, Meyer 1987). Broadly, both approaches show that consumers are often successful in learning about relationships between products, attributes, and benefits but that certain factors inhibit learning. For example, Allen and Janiszewski (1989) showed that participants learned brand associations (in this case, attitudes) through a classical-conditioning-style game that repeatedly associated the brand name with positive phrases. However, the ability to learn the association was mediated by a conscious recognition that an association could be learned. Thus, the study showed that consumers can learn through passive associations but that conscious, cognitive processing was also necessary. Noncognitive, subliminal learning was either unlikely or weak, if it occurred at all. In a study of active learning, Hutchinson and Alba (1991) showed that participants were able to accurately classify products based on perceptual features. Accuracy was improved when participants were instructed to learn about the two classification categories in advance (i.e., active as opposed to passive learning). Accuracy was also improved when the attributes that were most diagnostic of the categories were perceptually salient and when participants were not under memory load. Thus, learning product attribute associations was facilitated by having an active, intentional goal to learn the association, and that learning was mediated by attention and memory processes.

While research into modes of learning shows that consumer *can* learn information relevant to product differentiation, researchers have also investigated whether learning such information indeed results in the perception of differentiated products. Advertising has been one of the most common sources of differentiating information studied by marketing researchers. Mitra and Lynch (1995) investigated whether advertising by all competitors in a market was successful in achieving product differentiation. They presented participants with advertisements for a set of brands that contained information about the brands' unique attributes. They measured perceived differentiation as consumers' price sensitivity. Higher price sensitivity indicates that price is the primary determinant of purchase decisions, and thus attribute differences between products are perceived as less important. They found that category-wide advertising has multiple, competing influences on differentiation perceptions. First, advertising can decrease perceived differentiation because advertising increases the size of a consumer's consideration set when making a decision. Advertising makes consumers aware of more options and helps consumers recall brands better when making decisions from memory. This increased consideration set size allows consumers to easily identify acceptable substitutes. Second, advertising can increase perceived differentiation, because advertisements can provide information about how brands are different from each other, leading to differential preferences. These preferences decrease price sensitivity in two ways. First, if a consumer has a strong preference for a particular brand, they would be willing to purchase it even if a cheaper alternative is available. Second, strong preferences reduce the size of consideration sets, since only a small number of brands are preferred enough to compete for the consumer's choice. Thus, advertising can be a source of perceived differentiation when consumers can learn about unique features of brands. However, background factors help determine the net effect of the two competing influences. For example, in a category where consumers can easily determine their preferences from product attributes, advertising is likely to increase perceived differentiation. In a category where consideration sets tend to be drawn from memory rather than physical displays of alternatives, advertising is likely to decrease perceived differentiation. Other researchers have found support for advertising's ability to engender perceived differentiation across other product categories and using a wide variety of advertising content strategies (e.g., Chakravarti and Janiszewski 2004, Kalra and Goodstein 1998). Researchers have also found similar effects when consumers engage in information search outside of an advertising context. In a study of online wine retailers, Lynch and Ariely (2000) found that when consumers could more easily learn about product quality, price sensitivity decreased. Thus, when consumers learn about unique features that are relevant to the quality of a product, their perceived differentiation increases. However, search costs for quality information can also be lowered to the point where consumers can find a large number of similar alternatives (i.e., a larger consideration set), for instance by using a computer search algorithm to rank purchase options by their expected quality given product attributes (Diehl, Kornish, and Lynch 2003). Much like in the advertising context, this increase in consideration set size leads to an increase in price sensitivity, since consumers could more easily identify acceptable substitutes.

A notable exception to the findings that consumer preferences are based on learned product–attribute–benefit relationships is the controversial topic of meaningless differentiation. Carpenter, Glazer, and Nakamoto (1994) showed that adding features to products that offer no apparent benefit (e.g., adding silk fibers to a hair conditioner) attract consumer preferences. Importantly, the effect remained even when consumers were told that the feature was irrelevant and offered no benefit. They argue that, without revelation of the irrelevance, consumers will infer that the feature will have some relevant benefit, for example silk fibers in hair conditioner may improve the smoothness of hair. When the irrelevance is revealed, they argue that the meaningless feature's raw distinctiveness can still induce preference for the product. While the argument that consumers may infer benefits from product features in the absence of knowledge is not controversial, considerable debate has emerged over the importance of consumer-aware, meaningless differentiation. Many researchers failed to find significant effects of meaningless features on preferences in a variety of contexts or found that the revelation of a feature's meaningless hurt preferences rather than helped (e.g., Broniarczyk and Gershoff 1997, Kalra and Goodstein 1998, Meyvis and Janiszewski 2002). Other studies showed that irrelevant information and meaningless attributes only impact preferences when there is a minimal degree of meaningful differentiation between brands and consumers need to base decisions on a tie-breaker attribute (Brown and Carpenter 2000; Van Osselaer, Alba, and Manchanda 2004). Finally, Broniarczyk and Gershoff (2003) found that revelation of meaninglessness before a choice was beneficial to low prestige brands that shared the feature with high prestige brands. Thus, while some consumers indeed appear to find value in features that they know provide no benefit, the significant moderators and restrictive context limit the importance of the finding in consumers' lives and the applicability of the finding in marketing strategy.

In between the processes of learning information about products and using that information to indicate purchase preferences lies the cognitive processes consumers use to mentally organize and interact with the information. First, information about a product is organized in a mental representation. The mental representation consists of the information a consumer knows about the product, how the different pieces of information relate to each other (i.e., its structure), and how the structure is used for relevant judgments. Consumer researchers have generally relied on the mental representation models within similarity processing theories (Gentner 1983, Markman and Gentner 1993, Tversky 1977, Zhang and Markman 1998). Second, information about multiple products is organized into categories (groups of conceptually similar products; Cohen and Basu 1987) and schemas (the structure of and relationships between multiple categories; Myers-Levy and Tybout 1989).

Judgments of similarity are a common and essential aspect of consumers' lives. With regards to product differentiation, one relevant example is determining when a product is similar enough to be a substitute. To answer such questions, psychological theories of similarity processing suggest that consumers compare mental representations of the relevant products. While the two major theories, termed the contrast model (Tversky 1977) and structural alignment (Gentner 1983), differ in the precise organization of information in these representations, both suggest that consumers conceptualize products as sets of features. When making similarity judgments, the sets of features are broken down into commonalities – features that exactly match between the products being compared – and differences – features that do not exactly match. Differences can further be broken down into alignable and nonalignable differences (Markman and Gentner 1993). Alignable differences are features that are part of the common structure between the products under comparison but whose precise characteristics are not the same. In general, alignable differences are attributes that can be compared across the different products. For example, all computers have a processor speed. If two computers have different processor speeds, then that is an alignable difference. Nonalignable differences are features that are independent of any common structure between the products under comparison. In general, nonalignable differences are attributes that one product has and the other product does not. For example, one computer may have a built-in webcam while another does not.

Researchers have found that alignable and nonalignable differences play differential roles in judgments between products, as well as the subsequent processing of information. The typical finding shows that marketing strategies that emphasize alignable differences are superior to those that emphasize nonalignable differences, unless the consumers are high in involvement or expertise (Nam, Wang, and Lee 2012; Zhang and Markman 2001). Alignable differences are more likely to be stored in memory and used in subsequent judgments (Markman and Gentner

1997). Comparative advertising is more effective when it highlights alignable differences (Zhang, Kardes, and Cronley 2002). Consumers are more satisfied with decisions when they are made based on alignable differences (Griffin and Broniarczyk 2010, Zhang and Fitzsimons 1999). The finding most directly relevant to product differentiation shows how attribute alignability can help new entrants to a market overcome the pioneering advantage of established brands (Zhang and Markman 1998). The pioneering advantage describes how early entrants to a product category tend to outperform subsequent entrants even after controlling for traditional entry barriers, such as switching costs (Carpenter and Nakamoto 1989). Zhang and Markman (1998) showed that new entrants who are superior along alignable differences gain more market share than new entrants who are superior along nonalignable differences. Thus, brands that differentiate on alignable features are more likely to viewed as substitutes than brands that differentiate on nonalignable features.

While similarity processing theories explain how consumers mentally represent individual products and make comparisons between small sets of products, theories of categorization and schemas explain how consumers represent and make judgments relative to large groups of products and groupings of many categories. At the basic level, categorization theories are concerned with the structural characteristics of categories that determine the categories defining characteristics and how people judge an object’s fit with the category. Two of the most influential models presume categories are constructed by comparing potential members to an abstract, idealized representation of the category, called a prototype, or by comparing potential members to a small set of concrete, already-existing members of the category that are top-of-mind or typical, called exemplars (Cohen and Basu 1987; Loken, Barsalou, and Joiner 2008). Marketing research has found evidence that, rather than being competing theories, consumers engage in both types of categorization, prototype categorization when consumers are higher in involvement for the given scenario or when learning category-defining rules is important, and exemplar categorization when consumers are lower in involvement or when learning necessary and sufficient rules is especially difficult (Basu 1993). Research has also shown that people organize categories into hierarchical structures called schemas (Loken, Barsalou, and Joiner 2008, Meyers-Levy and Tybout 1989, Rosch 1973). For example, a consumer may have a mental category that contains all soda. However, the category may be divided into subordinate categories such as colas, lemon-lime sodas, root beers, etc., and the soda category is a constituent part of superordinate categories such as sweetened beverages, all beverages, consumables, etc.

Categorization and schema research has been influential in explaining a variety of consumer behaviors. Its most important contribution to perceived product differentiation is the notion that products can be viewed as too differentiated. While perceiving differences amongst products is an essential element to product differentiation, a product's unique features may be too different and hurt consumer evaluations of the product, despite objective benefits (Alexander, Lynch, and Wang

2008; Campbell and Goodstein 2001; Meyers-Levy and Tybout 1989; Perracchio and Tybout 1996). What defines a feature as too different is the degree to which the feature fits within a consumer's core conceptualization of the product category, also called its congruity (Sujan and Bettman 1989; Jhang, Grant, and Campbell 2012). Highly incongruous product features can result in consumers categorizing the product in a niche subcategory rather than as part of the broader, basic category, which further can result in a lower probability of brand recall (Sujan and Bettman 1989). More generally, consumers are thought to partially infer benefits of products from the categories that contain the product, as similar products generally serve similar functions in consumers' lives (Jhang, Grant, and Campbell 2012). Consumers have difficulty inferring the benefits of incongruous features because the feature is not commonly associated with the category or its typical benefits. However, factors that heighten a consumer's cognitive flexibility – the ability to hold multiple representations of a concept or multiple perspectives on a topic in mind (Spiro 1988) – help consumers to resolve the incongruity, improving evaluation of the product (Jhang, Grant, and Campbell 2012).

Both the quantitative and behavioral traditions have focused much of the research into perceived product differentiation on how it influences preferences between alternatives. This makes sense because preference is a primary determinant of demand for a product and, therefore, is of utmost importance to businesses and consumers alike. However, behavioral research has also examined several other important consequences of perceived product differentiation. First, perceived differentiation of products and categories leads to increased involvement with the product or category (Mittal and Lee 1988, Spiller and Belogolova 2016, Zaichkowsky 1986). Involvement is the degree to which a person feels a personal connection to some object or situation and is often measured as the number of personal connections a person makes during an experience (Krugman 1962, Zaichowsky 1986). High involvement, in turn, is related to a wide variety of consumer behaviors including the elicitation of supportive arguments and counterarguments in response to advertising, the amount of information search consumers engage in, and how long consumers deliberate before making a purchase (Zaichowsky 1986). Second, consumers are willing to pay a higher price when they perceive product differentiation, especially when the product is differentiated vertically rather than horizontally (Auh and Shih 2009, Kalra and Goodstein 1998, Spiller and Belogolova 2016). Finally, perceived differentiation is a key influence in the development of customer loyalty (Dick and Basu 1994, Iyer and Muncy 2005, Jensen 2011, Steenkamp and Gielens 2003). The variety of attributes in differentiated products are an attempt by the marketer to better meet the needs of consumers. Loyalty arises, in part, because consumers judge that other competing alternatives do not meet their needs as well.

1.3.3 Discussion

Product differentiation was originally conceived to be a business' attempt at implementing the marketing concept – that in order to achieve the objectives of the organization, the organization must discover the needs, wants, and desires of its potential customers and satisfy them better than competitors. Both the quantitative and behavioral approaches recognize that consumers' perception of differentiation results in them valuing product offerings more highly. That value can be expressed in preference and purchase decisions, as well as through the price paid, continued loyalty to the brand, and a variety of other judgments and behaviors important to both consumers and businesses. Further, the process that consumers go through to determine just how much they value some differentiated offering is complex and involves psychological processes ranging from low-level sensory perception and learning to high-level information processing and reasoning. The research in the proceeding essays builds on this area and sheds new light on various aspects of the perception of product differentiation.

In the first essay, I combine an analysis of the market in which consumers find themselves with an analysis of a psychological mechanism that can improve the perception of differentiation in that market. I show that, in actual categories of products, the actual features companies incorporate into their products tend to be poorly understood the more unique they are. In other words, the features that are the most objectively differentiating, in that only one or a small number of brands provide that feature and any benefits it conveys, are also the least subjectively differentiating, in that consumers do not have a basis for assessing the value the feature provides. I argue that mechanistic explanations of the features, which provide information on how the feature causally relates to product benefits, are an important mechanism that can improve the understanding on unique features and thereby improve the perceived differentiation of the products that contain them. In doing so, I build on recent research that investigates the role of causal understanding in consumers' perceptions of value (e.g., Fernbach at al. 2013; Long, Fernbach, and De Langhe 2018), showing that consumers can readily learn product–benefit relationships through explanations and that these relationships subsequently impact perceptions of the product. Second, I show how explanations benefit the recall of non-alignable differences. Whereas past research has shown that recall for such features is low, in general, but improved when background factors such as personal involvement are high, this research shows that the memorability of non-alignable differences can be directly manipulated and improved when consumers are provided a causal explanation of the feature.

In the second essay, I examine how the mental representation of products and the processes of similarity judgments impact differentiation perceptions when consumers encounter more than two options. When comparing three or more products, interesting effect emerge, such as the ability for a product that contains no unique feature to be viewed as the most distinctive by consumers. This research expands on similarity processing's role in perceived product differentiation by examining the similarity relationships within larger sets of products, rather than the traditional binary comparison. Additionally, it shows novel relationships between the similarity judgments and information search behaviors.

Chapter 2.
THE DIFFERENTIATOR'S DILEMMA

2.1 Introduction

The goal of differentiation is to occupy a unique position by providing benefits to consumers that other brands either do not provide at all or do not provide as well. When differentiating a product by adding a feature, the ideal case is for the feature to be both unique and easily understood. When a feature is easy to understand, consumers can readily ascertain the feature's benefit. When it is unique, consumers can recognize that competitors do not provide the benefit. However, I show that such features are rare. Instead, marketers are faced with the dilemma of choosing between unique but difficult to understand features and common but easy to understand features.

Multiple factors are involved in creating this dilemma. Competition between brands can result in competitors adopting each others' best features, causing well-understood features to be increasingly more common over time. The inverse of this is also plausible. As more competitors adopt a new innovation, consumers encounter it more and develop more knowledge and a better understanding of the feature (Alba and Hutchinson 1987). These processes predict that common features should be well-understood. However, the process of competition also causes businesses to add new features and develop innovations in an attempt to build differentiation from competitors. Ideally, these new features would be easy to understand, facilitating adoption and developing a unique product position for the brand. However, this likely not the case. Given that competition between brands suggests that features should become more common over time, the most likely reason for a feature to be unique is that it is new. Without exposure to the feature, consumers are not able to develop a base of knowledge that would indicate understanding. Recent research has shown that a lack of understanding of a product is associated with decreased purchase intentions and lower willingness to pay for the product (Fernbach et al. 2013). With a lack of understanding, consumers are unable to connect the features to any benefits they may provide, and thus the consumer is unlikely to perceive any meaningful differentiation with respect to that feature.

Research has also shown that unique features have little influence on brand and product evaluations (Gürhan-Canli 2003; Markman and Gentner 1997; Zhang and Markman 1998). This line of research categorizes differences between products as alignable, where the difference is comparable across products such as a car's horsepower, and nonalignable, where the difference I not comparable across products such as the presence of spoiler. Unique features of a product are thus nonalignable differences. The primary mechanism used to explain the lack of influence of unique features is that it is more difficult to process information about unique features. Processing information about a unique feature requires creating evaluation criteria for that feature, criteria that are not reusable when evaluating other products that do not have that feature. Thus, it is more cognitively efficient to focus on alignable differences, where one set of evaluation criteria can be used for many products (Hsee and Zhang 2010).

Mechanistic explanations should make it easier for consumers to process information about unique features, however. Mechanistic explanations provide detailed information about how some physical system works, providing the causal mechanisms necessary to predict some relevant outcome (Fernbach et al. 2013). A mechanistic explanation of a product feature would describe how the feature leads to some benefit. For instance, a toothpaste may contain iso-Active technology. This is a compound that increases the amount of foam produced when brushing. Foam can get in between teeth where bristles cannot reach, improving oral hygiene. By providing detailed information about how a feature works and the benefits it provides, consumers should be more able to create evaluation criteria for the features, making them easy to process and, thus, more likely to be used in evaluations. While all toothpaste brands provide the benefit of oral hygiene, connecting this benefit to a unique feature suggests the brand provides the benefit in a unique way.

In addition to affecting perceptions of differentiation and other stimulus-based judgments, previous research has also found that consumers tend to have poor recall of nonalignable differences, compared to alignable differences (Gürhan-Canli 2003; Markman and Gentner 1997). For instance, an attribute like a smart phone's processor speed has been found to be more common in memory. However, more basic-level memory research has shown that people tend to encode and recall novel information better than non-novel information (Friston 2005; Henson and Gagnepain 2010; Tulving and Kroll 1995). Novel information can be information that a person has not encountered before or information that deviates from a prediction. For instance, when learning about a new phone, a consumer may implicitly predict that its processor will have an average speed. If the phone's new processor is actually 200 MHz faster than comparable models, this would deviate from the prediction and be novel information.

Given these findings, consumers should be most likely to recall unique features of products due to their inherent novelty. Given their uniqueness, consumers are likely unfamiliar with the information, and given unfamiliarity, consumers likely would not predict the feature to be present at all. I propose that the reason this has not been found in the product attribute domain is due to the moderating role of information relevance. Several studies have found that people select only information relevant to some task to encode in and recall from memory and have better recall of brand names when they see advertisements that contain descriptions of benefits more relevant to the consumer (Dick, Chakravarti, and Biehal 1990; Feldman and Lynch 1988; Lynch, Marmorstein, and Weigold 1988; Mynatt, Doherty, and Dragan 1993; Sheinin, Varki, and Ashley 2011). If, as predicted, unique features tend to be poorly understood by consumers, then consumers will not be able to judge potential benefits, assess if the product will work specifically for their needs, or make other relevance-related judgments based on the presence of the feature. Such features will not be relevant to product evaluations, and thus those features are less likely to be encoded in and recalled from memory. However, improving subjective understanding of the features through mechanistic explanations should increase the probability of encoding and recalling unique product features.

2.2 Study 1: Dilemma in the Marketplace

Study 1 investigated whether product features that are unique in the marketplace are poorly understood. To examine this, the author collected product features from several categories and compared participants' subjective understanding of the features with the prevalence of the feature in the marketplace. Additionally, participants rated two attitude measures. The results show that the differentiator's dilemma exists in the marketplace and that it can have negative impacts on brands.

2.2.1 Method

The author collected a set of product features from all products reviewed by *Consumer Reports* in six product categories. For each product, the author recorded all features listed on the brand's product description webpage. Table 1 shows the number of features, products, and brands within the six categories.

Table 1.
BREAKDOWN OF PRODUCTS AND FEATURES

Category	**Number of Brands**	**Number of Products**	**Number of Features**
Computer Processors	2	487	11
Credit Cards	4	45	16
Facial Tissue	9	19	11
Hair Dryers	4	5	15
Hatchback Cars	9	27	40
Toothpaste	11	44	23
Total	39	627	116

The author then computed each features' uniqueness. The uniqueness scores took into account the imbalanced hierarchical structure of each category. For instance, the features within the computer processor category were attributes of products. Products were nested within product lines, which were nested within product line families, which were nested within brands (e.g., Brand: AMD, Family: Athlon, Line: X2, Product Version: 240). Uniqueness was computed by determining the percentage of products that did not contain the feature within the next highest level of the hierarchy (e.g., the number of products within the AMD Athlon X2 line that did not contain a particular feature). These percentages were then averaged at successive levels of the hierarchy until the category level.

To measure perceptions of features, participants from Amazon Mechanical Turk (N = 201, 92 females, M_{age} = 33.80, SD_{age} = 11.53) rated ten features randomly sampled from the 116 available. Participants read the product category the feature came from and the name of the feature. Participants then completed a three-item subjective understanding scale and rated their confidence in and perceived utility of the feature and its benefits. Table 2 provides item wordings, response scales, and summary statistics.

Prior to the primary analysis, I conducted exploratory factor analyses on the three understanding scale items using maximum likelihood factoring. To account for repeated measurements, I conducted ten separate analyses, separating each measurement by its order of presentation. The three items loaded highly on a single factor across all analyses (lowest loading = .85). Similarly, I computed separate Chronbach's alpha statistics for each of the ten measurements. The lowest alpha was .91. Given the results of the factor analysis, I averaged the three items for the following analyses.

2.2.2 Results

The primary hypothesis of study 1 was that more unique features will tend to be less well understood. Figure 1 shows the uniqueness and subjective understanding of each feature, averaged across all participants that rated the feature. Additionally, Figure 1 shows the regression line implied by the mixed model described below, as well as the model's parametric bootstrapped 95% confidence interval. Indeed, features that are common in their category tended to be well understood, while more unique features were less well understood.

Table 2.
SUMMARY STATISTICS AND CORRELATIONS FOR STUDY 1

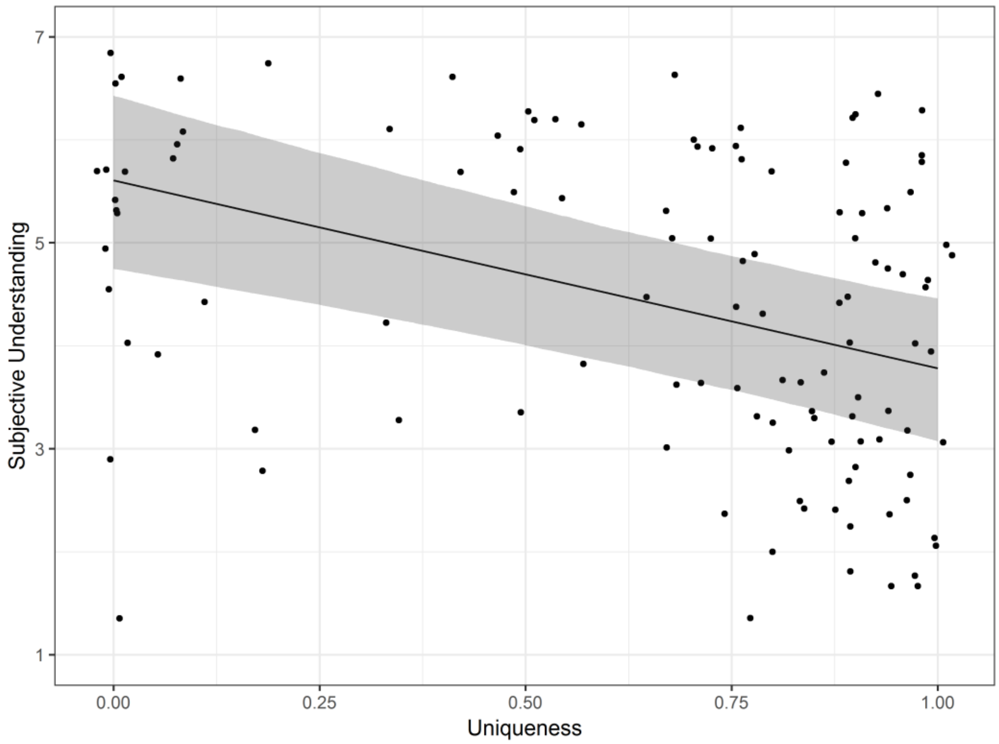
	M	SD	α
1. Uniqueness	.65	.34	
2. Subjective Understanding	4.36	2.15	.94
a) Do you know what the feature is?	4.60	2.26	
b) Do you know what benefit the feature provides?	4.45	2.25	
c) Do you know how the feature provides the benefit? (1: *Not at all*, 4: *Somewhat*, 7: *Completely*)	4.02	2.28	
3. Confidence in Benefits	4.45	2.06	
a) How confident are you the feature provides any benefit? (1: *Not at all*, 4: *Somewhat*, 7: *Completely*)			
4. Utility of Feature	4.54	1.89	
a) If you were using this product, how valuable would you expect this feature to be? (1: *Not at all valuable*, 4: *Somewhat valuable*, 7: *Extremely valuable*)			

	1	2	3
1. Uniqueness			
2. Subjective Understanding	-.25		
3. Confidence in Benefits	-.26	.83	
4. Utility of Feature	-.22	.66	.80

Notes: Descriptive statistics were calculated over all observations (N = 2010). Repeated measures correlations were calculated according to Bakdash and Marusich (2017). All correlations are significant at the $p < .001$ level.

To evaluate statistical significance, I conducted analyses using linear mixed effects models. The model regressed subjective understanding ratings on feature uniqueness. For this and all other models in this study, participants, product category, and product feature were all treated as random effects, in order to account for repeated measurement and stimulus sampling. The model estimated random intercepts by participant and by features nested within categories. As with all mixed models reported in this dissertation, models were estimated using the *lme4* package in R (Bates et al. 2015), and degrees of freedom were estimated using the Kenward-Roger approximation (Kenward and Roger 1997). The results of the model indicate that more unique features were associated with significantly lower ratings of subjective understanding (b = -1.82, t(114.30) = -4.57, $p < .001$).

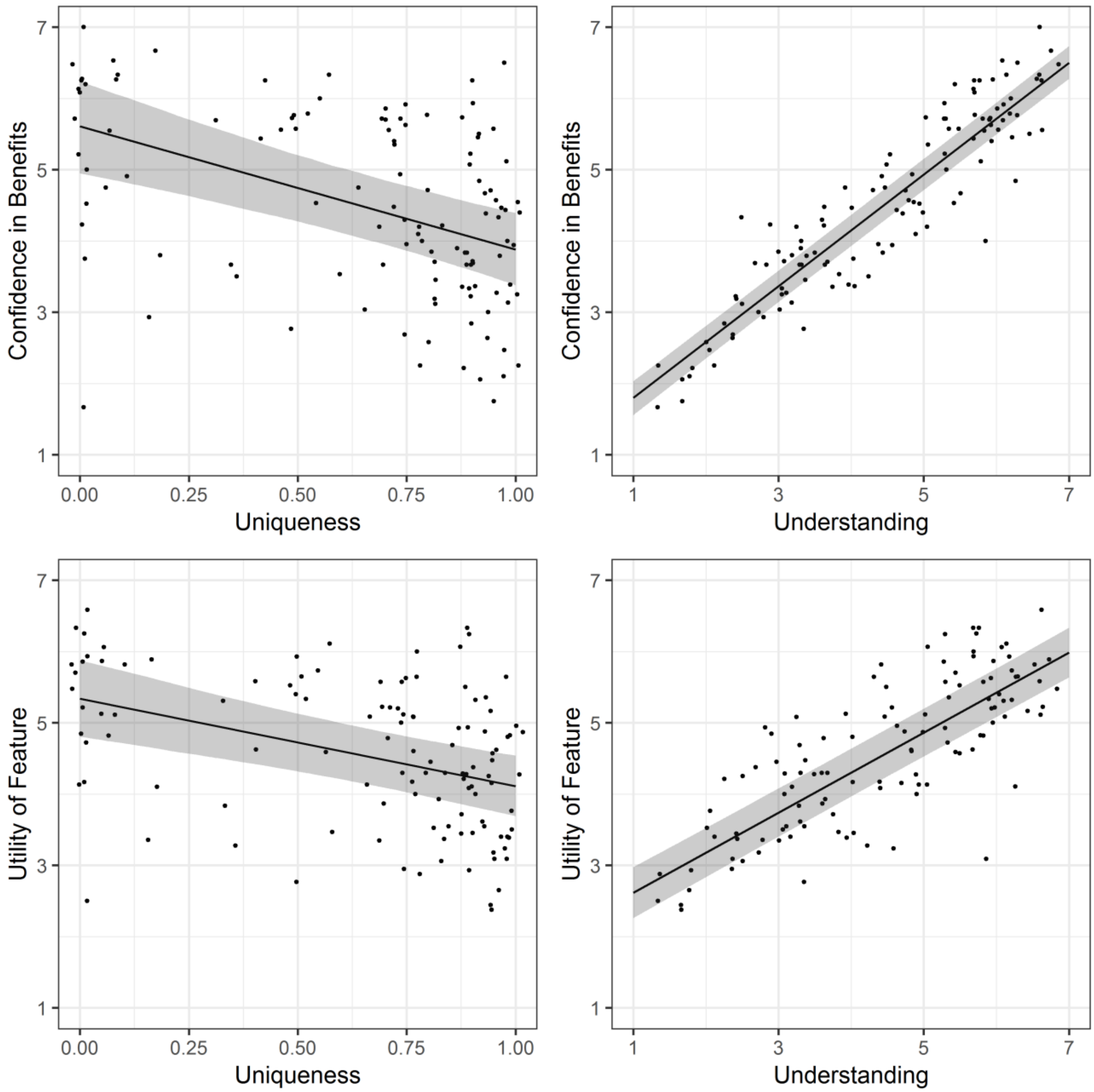
Figure 1.
UNIQUE PRODUCT FEATURES TEND TO BE POORLY UNDERSTOOD



Participants also made two evaluative judgments for each feature – confidence in the benefits the feature provides and the perceived utility of the feature. These judgments were analyzed in an exploratory manner to evaluate the potential effects feature uniqueness and subjective understanding may have on them. Each chart in Figure 2 displays the values for each product feature, averaged across all participants that rated the feature. Charts in Figure 2 also display the regression line and 95% confidence interval for the single-predictor, mixed model implied by each chart (as opposed to the multiple regression models discussed below). For instance, for the chart depicting the relationship between confidence in benefits and uniqueness, the regression line is for a model predicting confidence in benefits by uniqueness, with random intercepts by participant and by features nested within categories. These models are also equivalent to the respective correlations in Table 2. The charts indicate that more unique features are associated with lower confidence in the feature's benefits, as well as lower perceived utility in the feature. Higher levels of feature understanding are associated with more confidence and more utility.

Finally, confidence and utility judgments were separately modeled in two, multiple-predictor, linear, mixed models. Initially, each judgment variable was predicted by feature uniqueness, subjective understanding, and their interaction. However, neither model had a significant interaction (smallest $p > .35$), so that term was removed. For the model predicting confidence in benefits, the results indicate that, controlling for the other predictor variable, more unique features were associated with significantly lower confidence in the feature's benefits (b = -.33, t(123.38) = -2.59, $p < .02$), and higher subjective understanding of a feature was associated with significantly higher confidence in its benefits (b = .78, t(1226.05) = 54.09, $p < .001$). For the model predicting perceived feature utility, there was not a significant relationship between uniqueness and perceived utility of the feature after controlling for understanding (b = -.21, t(121.62) = -1.28, $p > .20$). However, controlling for uniqueness, subjective understanding of the features was associated with significantly higher perceived utility (b = .56, t(1403.63) = 32.17, $p < .001$).

Figure 2.
RELATIONSHIPS BETWEEN UNIQUENESS, UNDERSTANDING, AND FEATURE EVALUATIONS



2.2.3 Discussion

The results highlight the dilemma that marketers face when differentiating products using features. Features that are unique in the marketplace, and thus are more likely to give a product a unique positioning, tended to be poorly understood by participants. Participants also had negative attitudes toward unique features, as measured by their confidence that the feature causes a benefit for them, as well as the perceived utility of the feature.

Additionally, the final models provide evidence that the relationship between understanding and each attitudinal measure is robust to a feature's uniqueness. However, the relationship between feature uniqueness and the attitudinal measures shows less robustness. When predicting a participant's confidence in the feature's benefits, controlling for subjective understanding of the feature, the reliability of the relationship is still statistically significant but substantially reduced. When predicting the perceived utility of the feature, the relationship is no longer statistically significant. While these final analyses were exploratory in nature, they imply the possibility that understanding mediates the relationship between feature uniqueness and attitudes toward those features. However, further research is needed to support this relationship.

Together, these results suggest marketers are left with the unfortunate options of either adding common features, which consumers have better attitudes toward but make the product appear more similar to other offerings, or adding unique features which make the product objectively different from other offerings but in ways that consumers often cannot perceive. Of course, marketers are not helpless in this situation. In the proceeding studies, I show how fostering a causal understanding of how features work improves consumer perceptions.

2.3 Study 2: Explanations Help Resolve the Dilemma

Study 1 showed the differentiator's dilemma exists in the marketplace. In study 2, the author investigated how attribute uniqueness and subjective understanding affect consumers' perceptions of product differentiation. This provides several important insights. First, it generalizes the findings of study 1 to show that the traits and perceptions of individual attributes affect perceptions of overall products. Second, it establishes a positive effect of unique attributes on product perceptions. Previous research has shown that unique features have little influence on brand and product evaluations, because it is difficult to integrate information about unique features with information about common or shared features (Gürhan-Canli 2003; Markman and Gentner 1997; Zhang and Markman 1998). Study 2 shows that unique features have a strong influence on perceptions when consumers also have a high subjective understanding of the feature and its benefits. Finally, study 2 provides an additional way by which mechanistic explanations can influence consumers' product perceptions and downstream decision behavior. Fernbach et al. (2013) showed that mechanistic explanations, in general, improve attitudes toward the product by improving the consumer's understanding of the feature and its benefits. Study 2 will show that subjective understanding can also aid in perceptions of product differentiation through similarity judgments.

To investigate these ideas, the author adapted a category learning task from Basu (1993). Consumers learn information about a product category and then are presented with a new product. Participants then assess the product's dissimilarity to the category. The new product is described with either a unique feature or a feature that is shared with category members and the feature is either given no explanation or a mechanistic explanation describing how the feature works.

2.3.1 Method

Participants from Amazon Mechanical Turk were randomly assigned to one condition in a factorial design. The focal portion of the design had a 2 (Explanation: no vs. yes) x 2 (Uniqueness: low vs. high) structure. In addition, several other factors were included in order to bolster external validity. The focal 2 x 2 design was crossed with a product category factor, using the same six categories as study 1. Nested within product categories were between three and six target brands, depending on the category. In total, there were twenty-six category-brand groups. Finally, each product category contained two unique features used to differentiation target products. These features were selected from the features used in study 1. In total, there were 208 conditions (2 explanation levels x 2 uniqueness levels x 52 category-brand-feature groupings). Five participants were nested within each condition for a total N = 1,040 participants (491 females, $M_{age} = 34.26$, $SD_{age} = 10.76$).

After basic instructions, participants were shown a screen containing two to five brands, depending on the category. The brands were described using three attributes and features, as well as product packaging, brand name, and logo. After examining the category, participants were shown another brand, with the original brands still on the screen. They were asked to imagine that the brand was a new offering and that they would be judging it relative to the brands already available in the category. The target brand was described with one of two target features for the category, as well as two additional attributes and features, similar to the other products. For participants in the explanation conditions, the target feature was accompanied by a mechanistic explanation of how the feature worked. Below are two examples.

- *Iso-Active Technology is a compound that increases the amount of foam formed when brushing, which can get in between teeth, cleaning areas that bristles can't reach.*
- *CVT transmissions don't use gears like regular transmissions. Instead, they work by using a continuously adjustable system leading to more optimal and efficient power transfer; a smoother, safer ride; less upkeep; and improved fuel efficiency.*

The other category members were also accompanied by a similar amount of text; however, the text did not provide informative details about product features. Those not in an explanation condition received no additional text.

For those in high uniqueness conditions, the target feature was unique to the target brand. In low uniqueness conditions, all of the target brand's features were shared with at least two competitors. Similarly, across all conditions, the features of competitor brands were arranged such that some features were shared between some of the brands. Table 3 shows one way that features were distributed within the toothpaste category. Feature A, the target feature, was either unique or possessed by three brands, depending on the uniqueness condition. When Feature A was unique to the target brand, the other two brands that could contain Feature A contained the features in parentheses instead. Additionally, Table 3 shows the packaging, brand names, and logos used for the toothpaste category.

Finally, to measure how differentiated the target brand is perceived to be within the category, participants indicated dissimilarity on an item adapted from Tversky and Gati (1979). Participants answered, “How distinct is [brand]’s toothpaste from other members of the toothpaste category?” on a 1 (Minimally distinct) to 20 (Maximally distinct) scale.

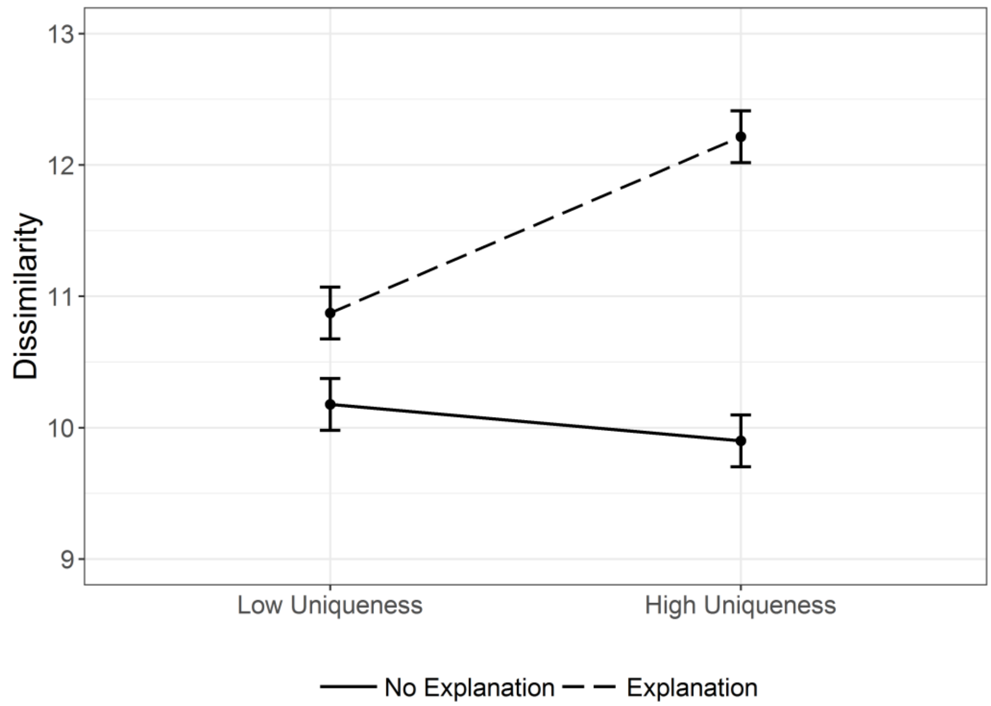
Table 3.
FEATURE DISTRIBUTION WITHIN THE TOOTHPASTE CATEGORY

		
Radiant (current target) A) Iso-Active Technology B) Contains peroxide C) 4 oz. size	Mosaic D) Formulated with Fluoride E) WhiteSeal Technology C) 4 oz. size	DentaFresh F) Micropolishers B) Contains peroxide C) 4 oz. size
		
Oralogic E) WhiteSeal Technology A) (Iso-Active Technology) F) (Micropolishers) C) 4 oz. size	Beam D) Formulated with Fluoride B) Contains peroxide C) 4 oz. size	Iris B) Contains peroxide A) (Iso-Active Technology) E) (WhiteSeal Technology) C) 4 oz. size

2.3.2 Results

The primary prediction for study 2 was that the effect of a feature's uniqueness on differentiation perceptions will depend on whether the person received an explanation, since explanations tend to increase subjective understanding. Figure 3 shows the means of the perceived differentiation item collapsed across the category, brand, and feature factors. As predicted, simply having a product feature that is unique among competitors does not necessarily impact differentiation perceptions in a particular direction. Only after receiving an informative explanation of how the feature works does feature uniqueness have a substantial impact on differentiation ratings. Similarly, the influence of explanations on differentiation perceptions appears drastically diminished when the feature is common.

Figure 3.
THE EFFECT OF FEATURE UNIQUENESS ON PERCEIVED DIFFERENTIATION DEPENDS ON FEATURE UNDERSTANDING



Note: The error bars represent the standard errors computed during the linear mixed model analysis.

Again, to improve generalizability and to account for stimulus sampling, dissimilarity ratings were analyzed using linear mixed effects models. Participants' dissimilarity ratings were used as the dependent variable and explanation, uniqueness, and their interaction were the fixed effects. The model estimated random slopes for all three fixed effects and random intercepts, influenced by three random factors – product category, brands nested in categories, and product features nested within categories and crossed with brands.

The results of the model indicate that there were two main effects qualified by a significant interaction. On average across levels of uniqueness, explanations increased perceived differentiation by 1.51 units (M_{no} = 10.03, M_{yes} = 11.54; t(51) = 7.12; p < .001; d = .44). Across levels of explanations, feature uniqueness increased perceived differentiation by .53 units (M_{low} = 10.52, M_{high} = 11.05; t(51) = 2.44; p < .02; d = .15). However, the interaction term shows that there was a significant difference in the effect of feature uniqueness when explanations were present compared to when they were not (t(51) = 4.03; p < .001; d = .23).

Decomposing the interaction, the simple effect of feature uniqueness on perceived differentiation when explanations were not provided was negative but not significant ($M_{low,no}$ = 10.18, $M_{high, no}$ = 9.90; t(51) = -.98, p > .32, d = -.08) and the simple effect was positive and significant when explanations were provided ($M_{low,yes}$ = 10.87, $M_{high, yes}$ = 12.22; t(51) = 4.31, p < .001, d = .39).

In addition to the design discussed and analyzed above, other factors of the stimuli were analyzed as well. Note that these treatments were not randomly assigned to stimuli, so they were analyzed in a non-causal, exploratory fashion, using standard regression and ANOVA models. In all models, dissimilarity ratings were predicted by the focal variable (described separately for each model), explanation condition, uniqueness condition, category-brand-feature group, and all possible interactions. Factors were Helmert coded and continuous variables were mean-centered.

First, product categories differed in how many brands were presented to the participants – ranging from three to six. This was done partially because some categories had few brands with available data during study 1's collection. Results indicated that as more competitor brands are present, the effect of uniqueness on perceived differentiation is stronger ($b_{\text{Num x Unique}} = .81$, $t(832) = 2.05$, $p < .05$). There was no main effect of the number of competitors, and no other interactions.

Second, categories differed in whether the stimuli contained real or fake brand names. Real brand names were used for computer processors, cars, and credit cards, while fake brand names were used for hair dryers, facial tissue, and toothpaste. Results indicated that the effect of uniqueness on perceived differentiation was stronger when real brands names were used compared to when fake brand names were used ($b_{\text{unique|fake}} = .48$, $b_{\text{unique|real}} = .60$, $t(832) = 2.05$, $p < .05$). There was no main effect of real vs. fake brand names and no other interactions.

Finally, the two target features used within each category differed in terms of their average subjective understanding ratings from study 1. Within each category, the feature with the higher average rating from study 1 was coded as feature 1 and the feature with the lower average rating was coded as feature 2. The results indicated that features with higher mean understanding ratings were associated with higher dissimilarity ratings ($M_{\text{low}} = 10.45$, $M_{\text{high}} = 11.13$, $t(832) = 3.47$, $p < .001$). Feature type did not interact significantly with any other variable.

2.3.3 Discussion

Study 2 investigated how feature uniqueness and subjective understanding impacted participants' subjective perceptions of product differentiation through similarity judgments. While features that are unique among competitors should make a product appear highly differentiated, the results indicate that unique features only affect perceptions of differentiation when the person feels they understand what the feature does.

Second, study 2 provided some initial evidence of potential boundary conditions and moderators that can be explored in future research. For practical purposes, experimental consumer research often involves small sets of potential decision options. However, consumers often are faced with dozens of alternatives to process and choose between. Study 2 showed that in such common situations, the effect of a feature's uniqueness on differentiation perceptions appears to get stronger.

Similarly, experimental consumer research often uses fake brand names to control for beliefs about brands, among other purposes. The results of study 2 showed that when real brand names were used, the predicted effects were stronger. However, the categories that contained real brand names may also have stronger brand identities and more brand equity. Future research may look into what aspects of branding, outside of product characteristics, influence perceived differentiation.

2.4 Study 3: The Memory Component of the Dilemma

Study 3 investigated a downstream consequence of increasing perceived differentiation by adding novel product features. As described in the introduction, previous research has shown that unique features (labeled nonalignable features in this study to juxtapose with alignable features) are often not recalled from memory when considering a product at a later time, while alignable features are readily recalled (Gürhan-Canli 2003; Markman and Gentner 1997). This improved recall for alignable features is attributed to their ease of evaluation. One cause for this is that consumers see several levels of an alignable feature when comparing products versus only one level of a nonalignable feature. These additional levels provide reference values that consumers can use to make more informed judgments of utility (Hsee and Zhang 2010). Without proper evaluation, nonalignable features become less relevant to judgments, which makes them less likely to be encoded in and recalled from memory. Mechanistic explanations should aid people in evaluating attributes, which should improve their recall. Additionally, I predict that mechanistic explanations should have a stronger influence on nonalignable differences compared to alignable differences. Consumers tend to have more prior knowledge about alignable differences compared to nonalignable differences, in part because more products contain an alignable difference's underlying attribute (Zhang and Markman 1998). This can create a differential effect of explanations in two ways. First, the explanation may not provide as much additional information above that which the person already knows. Second, research has shown that higher prior knowledge can inhibit the learning of new information about innovative products (Wood and Lynch 2002).

To investigate this, participants examined products and, later, attempted to recall the products' attributes. One attribute was cast as either an alignable or nonalignable feature. Since alignability is a function of the features perceived in other products, by manipulating the composition of features in competitors' products, the effect of feature alignability on memory were tested while holding the actual feature constant.

2.4.1 Method

Participants from Amazon Mechanical Turk were randomly assigned to one condition in a factorial design. The focal portion of the design had a 2 (Explanation: no vs. yes) x 2 (Feature Type: alignable vs. nonalignable) structure. As with study 2, the design also involved additional random factors – six product categories and two feature replicates nested within categories. In total, there were 96 conditions (2 explanation levels x 2 feature types x 6 categories x 2 feature replicates). Twenty participants were nested within each condition for a total N = 960 participants (452 females, $M_{\text{age}} = 35.07$, $SD_{\text{age}} = 10.94$).

After basic instructions, participants were shown two products, each described with four attributes. Participants were instructed that they will have to later make judgments about the products without any additional information and, thus, should learn and memorize the products' features. One of the features was the target feature and was subject to the feature type and explanation manipulations.

To manipulate feature type, the comparison product either contained the same feature but with a different level (alignable; e.g., 0.09% fluoride content vs. 0.15% fluoride content in toothpaste) or did not contain the same feature (nonalignable). Regardless of the condition, the products contained two alignable and two nonalignable features. To manipulate explanations, the target attribute was either accompanied by a mechanistic explanation of what the feature does or by a non-explanatory description. Figure 4 shows an example from the computer processor category in the nonalignable and no-explanation conditions.

Figure 4.
TARGET AND COMPARISON PRODUCT FROM STUDY 2

Option A: Intel Core Processor | Option B: AMD FX Processor

Option A: Intel Core Processor	Option B: AMD FX Processor
Speed: 2.8 GHz	Speed: 2.6 GHz
Memory Cache: 4 MB	Memory Cache: 8 MB
PowerNow	QuickTransport
Hyperthreading: 8 total threads	Smart caching

Hyperthreading was first introduced in 2002. Intel has updated the technology significantly to implement it in the Core series of processors. It is also available in the Xeon and Atom processor lines.

After examining the two products, participants completed a short filler task. The task consisted of pretesting stimuli for an unrelated study. There was an average of 5.23 minutes between examining the products and returning for the remainder of the study. Upon return, participants were shown brand names and images of the products with four empty text boxes underneath. Participants were asked to recall the four product features for each option. After, participants were shown the original stimuli (as in Figure 4) and asked to rate their subjective understanding of the target attribute on the same three-item understanding scale used in study 1 (items labeled *what*, *benefit*, and *how*).

Recall results were coded by the author. Condition assignments were hidden from view and the data was sorted base on a random identifier. In order to measure the overall memorability of the target feature, if the participant mentioned the target feature in any of the available text boxes the response was scored as a 1 and otherwise 0. Participants correctly remembered the target feature 44% of the time.

Finally, prior to analysis, the understanding scale underwent exploratory factor analysis using maximum likelihood factoring. The three items loaded highly on a single factor (loadings: what = .91, benefit = .91, how = .95). The single factor model accounted for 85% of the observed variance. The three measures had a Chronbach's $\alpha = .96$. Given the results of the factor analysis, I averaged the three items for the analyses below.

2.4.2 Results

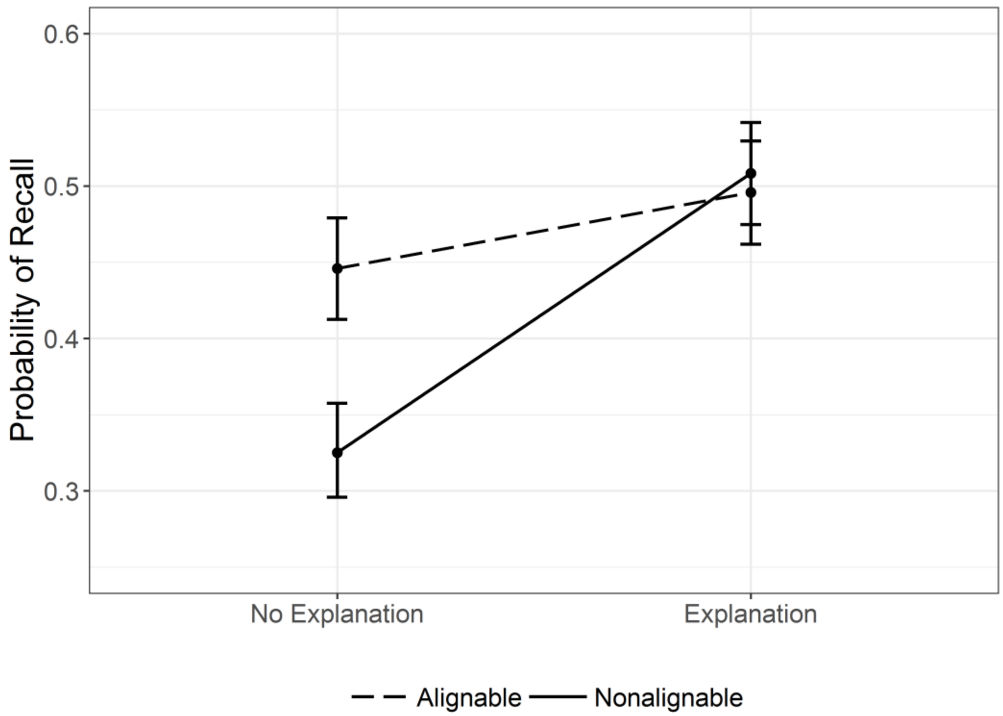
Study 3 had several hypotheses. For target feature recall, first, explanations of a feature should increase the likelihood of a person recalling the feature. Second, explanations should improve recall better for nonalignable features compared to alignable features. For the subjective understanding of features, there should be a similar pattern. Explanations should increase subjective understanding of features overall; however, they should have a stronger influence on nonalignable features. Finally, the effect of explanations on feature recall, moderated by feature types, should be mediated by subjective understanding. That is, explanations should increase subjective understanding, which in turn improves recall. However, the indirect effect should be larger for nonalignable features.

Figure 5 displays the group means for feature recall (5A) and subjective understanding (5B), collapsed across product categories and feature replicates. Supporting the hypotheses, explanations improved both recall and subjective understanding of the target features. Additionally, explanations have a steeper slope when the target feature was nonalignable.

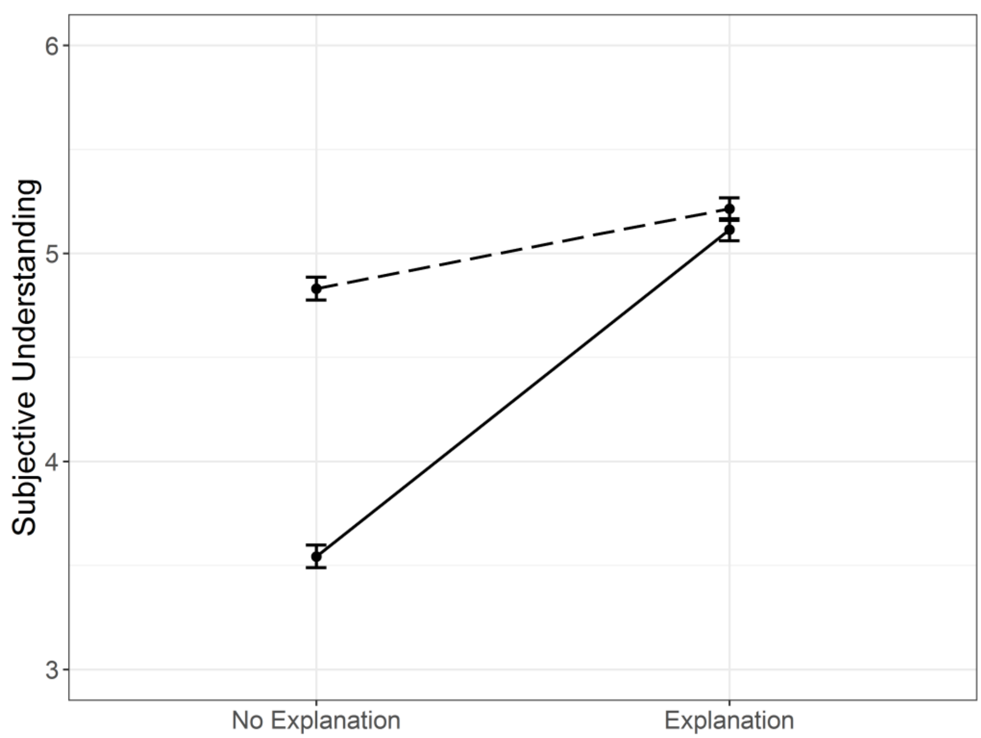
To assess the statistical significance of these findings, two models were created, one for feature recall and one for feature understanding. Feature recall was modelled using a logistic mixed model. Explanation (no exp. = -1, exp. = 1), feature type (align. = -1, nonalign. = 1), and their interaction were the fixed effects. The model estimated random intercepts by product category and feature replicate nested within categories. The model results indicated that there was a main effect of explanation, such that explanations, on average, improved feature recall (P(recall | no exp.) = .38, P(recall | exp.) = .50, z = 3.68, $p < .001$). Recall was marginally greater when the target feature was alignable compared to nonalignable (P(recall | align.) = .47, P(recall | nonalign.) = .42, z = -1.77, $p < .08$). However, the significant interaction indicates that the effect to explanations was stronger for nonalignable features (ΔP(recall | align.) = .05, ΔP(recall | nonalign.) = .18, z = 2.15, $p < .04$). Explanations did not significantly improve feature recall for alignable features (P(recall | no exp., align.) = .45, P(recall | exp., align.) = .50, z = 1.10, $p > .27$). Explanations did significantly improve feature recall for nonalignable features (P(recall | no exp., nonalign.) = .33, P(recall | exp., nonalign.) = .51, z = 4.06, $p < .001$).

Figure 5.
EFFECTS OF MECHANISTIC EXPLANATIONS AND FEATURE ALIGNABILITY ON RECALL AND SUBJECTIVE UNDERSTANDING

A.



B.



Subjective understanding was modelled in the same manner, except using a linear mixed model, rather than a logistic model. The results indicate two main effects qualified by a significant interaction. On average across feature alignability, explanations increased subjective understanding ($M_{\text{no exp.}}$ = 4.19, $M_{\text{exp.}}$ = 5.16, t(945) = 18.03, p < .001, d = .46). Additionally, the features were rated higher in understanding when they were alignable compared to nonalignable (M_{align} = 5.02, M_{nonalign} = 4.33, t(945) = -12.80, p < .001, d = -.32). However, again, a significant interaction indicated that the effect of explanations was stronger for nonalignable features (t(945) = 10.96, p < .001). Explanations improved subjective understanding of nonalignable features by 1.57 units ($M_{\text{no, nonalign}}$ = 3.54, $M_{\text{yes, nonalign}}$ = 5.11, t(945) = -20.50, p < .001, d = .73). Explanations also significantly improved subjective understanding of alignable features, but to a smaller extent ($M_{\text{no, align}}$ = 4.83, $M_{\text{yes, align}}$ = 5.21, t(945) = 5.00, p < .001, d = .18).

Finally, to test whether the effect of explanations on feature recall, moderated by feature type, was mediated with subjective understanding, I followed the procedure described by Muller, Judd, and Yzerbyt (2005). Mediated moderation is indicated when three effects are significant. First, there must be overall moderation of the effect of explanations on recall. This is shown in the first model described above. Second, there must be a moderated effect of explanations on the mediator (subjective understanding). This is shown in the second model described above. Finally, the mediator’s effect on recall must be significant, on average across explanations and feature types. To test this third condition, I estimated a third model. Recall was the dependent variable, and the random effects were the same as previous models. Explanation, feature type, their interaction, subjective understanding, and the understanding by feature type interaction were the fixed effects. In this model, subjective understanding was associated with higher recall, on average across explanations and feature types ($b = .08$, $z = 3.32$, $p < .001$). As a result, the moderation of the effect of explanations on recall (the explanation x feature type interaction) was substantially reduced when controlling for subjective understanding and the understanding by feature type interaction. While the coefficient was significant previously, the coefficient was no longer statistically significant in the current model ($z = 1.14$, $p > .25$).[8]

2.4.3 Discussion

Study 3 extended the findings in several ways. First, it showed that consumers indeed pay attention to and learn about nonalignable product features. Previous research found that nonalignable features tend to not influence decisions and that consumers tend to recall only alignable product features from memory. However, study 3 showed that these findings may have been rooted in the fact that nonalignable product features tend to be more poorly understood by consumers, and thus are deemed less relevant. When poor understanding is improved through explanations, the results of study 3 suggest that nonalignable features are at least

[8] MacKinnon, Fairchild, and Fritz (2007) show that the procedure used above can misestimate the indirect effects of an independent variable on a dichotomous dependent variable. To correct for this possibility, I also assessed the hypothesized mediated moderation using structural equation modeling (SEM). See the appendix for this analysis.

as important in differentiation perceptions as alignable features. Second, study 3 connected the influence of explanations on perceived differentiation to an important downstream behavior – the ability to store and retrieve product feature information from memory. Finally, as highlighted earlier, several different streams of research have highlighted the importance of subjective understanding and subjective knowledge in consumers' product perceptions. A common way to improve a person's subjective understanding of a product is to provide causal explanations of how it works. However, the results of study 3 indicate that explanations do not uniformly improve understanding. While explanations significantly increased understanding in the alignable feature conditions, its impact was substantially diminished compared to nonalignable features.

2.5 General Discussion

The studies in this essay showed several important findings relevant to product differentiation strategy and consumer behavior. In study 1, I found that the more unique a product feature tends to be, the more poorly it is understood. This is important not only because it exposes a deficiency in the ability of brands to differentiate their product offerings, but also because it offers a path to improve differentiation – by facilitating better understanding of unique product features. In studies 2 and 3, I showed how relatively short, simple explanations of poorly understood features can improve understanding and recall of the feature, as well as increase perceived differentiation of products that contain the feature.

The research has several limitations that offer opportunities for future research. First, the audit of features in study 1 came from a relatively small set of categories that may not be representative of typical or important decisions consumers make. Future research can examine a wider range of categories and look for systemic differences in effects across categories that may provide additional theoretical insights into the role of feature uniqueness and understanding on perceived product differentiation.

Second, in order to have a manageable set of product information, the studies only examined product features that fit the definition of nonalignable differences. While alignable differences were examined in study 3, future research can examine the role of subjective understanding of alignable differences in similarity judgments and perceived differentiation. Additionally, future research can look at abstract features of a brand. For instance, previous research in judicial decision making has shown that people arrive at judgments by constructing an explanatory, narrative story (Pennington and Hastie 1988). Applied to a consumer setting, narrative aspects of a brand, such as the company history or a company's traditional manufacturing process, may aid in perceived differentiation by assisting in incorporating other facts about the brand into judgments and evaluations.

Finally, the studies examined important cognitive processes related to perceived product differentiation – similarity judgments and memory. However, the hallmark of perceived product differentiation is reduced price elasticity or sensitivity. While the research here connected explanations to cognitive aspects of perceived differentiation and Fernbach and colleagues (2013) connected explanation to preference, future research can more directly study the impact of explanations on perceived product differentiation by measuring the degree to which explanations focus preference judgments on product attributes compared to price.

Chapter 3.
THE PLAIN VANILLA EFFECT

3.1 Introduction

Increasingly, consumers have been displaying preferences for simpler products (Flatters and Willmott 2009). While, on an abstract level, a product loaded with features seems like it should provide a myriad of benefits, when consumers use such products they are often disappointed and prefer to have purchased something simpler (Thompson, Hamilton, and Rust 2005). Additionally, brands that are positioned as being a master-of-one-trade rather than jack-of-all-trades are viewed as superior along the dimension they specialize in, even if the jack-of-all-trades brand has the same attributes and features (Chernev 2007). In this essay, I will investigate another consequence of product simplicity by examining how consumers perceive similarity between competing brands. Brands often differentiate themselves with novel features. However, if consumers do not understand what the features do, I show that these features make products look more similar, rather than more differentiated. Instead, in these environments, plain, “vanilla” products stand out to consumers.

To model perceived differentiation, I use Tversky’s (1977) contrast model of similarity processing. The contrast model represents objects as a set of features, and similarity is assessed as a function of the shared features between two targets, the unique features of one target, and the unique features of the other target. Thus, judged similarity is determined by both commonalities and differences between products. The specific function that represents the similarity judgment is

$$S(a,b) = \theta f(A \cap B) - \alpha f(A - B) - \beta f(B - A)$$

A and B represent the sets of features of products a and b, respectively. $A \cap B$ represents the set of shared features, A – B represents the set of features of A that B does not have, and B – A represents the set of features of B that A does not have. The function f maps sets to an interval scale. In this investigation, products will be simple enough that the specific functional form of f does not change predictions, and I will use the cardinality function (i.e., the number of elements in the set). Finally, θ, α, and β are weighting parameters. For instance, if α and β were zero, then only common attributes would factor into similarity judgments. Equal weighting for the three parameters is common in studies (Tennenbaum and Griffiths 2001). While studies have found variables that impact the weightings, these variables typically involve dramatic differences in knowledge between the objects or differences in the number of features provided – variables that will not be relevant in this investigation (Tversky and Gati 1978). For simplicity, I will assume equal weighting. Thus, the equation above simplifies to the following process. To compute the expected perceived similarity between two products, count the number of shared attributes, subtract the number of distinct attributes for product A, and subtract the number of distinct attributes for product B. Table 4 shows a simple example.

The contrast model does not specify rules that determine when features correspond. Correspondence is whether two attributes or features are directly comparable. Features do not need to be identical to correspond. For instance, one brand of toothpaste may be peppermint flavored and another spearmint flavored.

Since they are both flavorings, the attributes will likely correspond. If the person does not have a preference between two, they would judge these as a common feature. However, if the person does have a preference, this would be perceived as a difference – often called an alignable difference. Finally, when a feature in one product does not have a comparable feature in the other, the feature does not correspond – often called a nonalignable difference. For example, in Table 4, MicroActives in Brand B does not correspond with any feature in Brand A.

Table 4.
SIMILARITY COMPUTATION

Toothpaste Brand A	**Toothpaste Brand B**
Baking Soda	Baking Soda
Peroxide	Peroxide
	MicroActives
Common features	2
Unique features of A	0
Unique features of B	1
Expected Similarity = Common – $Unique_A$ - $Unique_B$	1

While determining correspondence is trivially easy for examples like in Table 4, in other cases it is uncertain. For instance, if Brand A had an additional feature called Micropolishers, would that correspond with Brand B's MicroActives? The answer determines whether a consumer perceives the two brands as essentially identical or significantly differentiated.

Research has shown that people select and differentiate between pieces of information based on how diagnostic the information is for some judgment of interest (e.g., Feldman and Lynch 1988). When consumers have a low sense of understanding, they make more variable predictions, indicating they do not perceive much diagnosticity in the information they have (Long, Fernbach, and de Langhe 2018). Thus, when making judgments of similarity, consumers are less likely to differentiate features they do not feel they understand, meaning those features are more likely to correspond, or appear as if they are the same. It follows that improving understanding of a feature will cause consumers to represent the features as distinct (assuming the features' objective qualities are sufficiently different). Table 5 displays three brands of toothpaste. Below, I compute expected similarity judgments under different assumptions.

Table 5.
THREE BRAND SIMILARITY COMPUTATION

Toothpaste Brand A	Toothpaste Brand B	Toothpaste Brand C
Baking Soda	Baking Soda	Baking Soda
Peroxide	Peroxide	Peroxide
	MicroActives	Iso-Active Technology

Comparing Brand A to Brand B or C yields the same value as before (2 – 0 – 1 = 1). When comparing Brand B to Brand C, however, the value depends on whether the features in the bottom row (MicroActives and Iso-Active Technology) correspond. Assuming a low understanding of the two features, I predict that they will correspond. Brands B and C would, thus, have three common features and no unique features and their expected similarity value would be 3 – 0 – 0 = 3. However, assuming high understanding, such that MicroActives and Iso-Active Technology are understood to be distinct features, Brands B and C would have two common features, and each would have one unique feature. Thus, their expected similarity value would be $2 - 1 - 1 = 0$.

These values indicate that when people have a high sense of understanding of the unique features among products, those features increase perceived differentiation (i.e., lower similarity scores). However, when people have a low sense of understanding of unique features, the products that contain the features look more similar to each other, and the plain, undifferentiated alternative (e.g., Brand A) appears to be different and stands out.

To extend these predictions beyond mere similarity judgments, consider how similarity judgments impact the orienting of attention. People tend to orient attention toward information that is novel, unexpected, and distinctive (Roediger and McDermott 1995; Wallace 1965). In the context of learning about product alternatives, the most dissimilar product would be the most distinctive and would receive the most attention. Further, research has shown that people tend to prefer an option more after attending to it more (Krajbich and Rangel 2011). The additional attention allows the person to process more information about the alternative which, assuming the information is positive, improves evaluations. Thus, when additional information is available, attending to the most dissimilar option should increase preference for that option.

I will investigate these predictions in four studies. In studies 1 and 2, I will show that a product with no distinctive features can nonetheless be perceived as distinctive when competitors differentiate with poorly understood features. In study 3, I will show that improving understanding of the poorly understood features reverses this effect. Finally, in study 4, I will show how the increased distinctiveness of being the plain, vanilla option leads to increased attention and preference.

3.2 Study 1: The Plain Vanilla Effect

Study 1 investigated how the product features of competitors can influence perceptions of differentiation in a target brand. A product that shares all of its features with competitors should be seen as relatively undifferentiated. However, in study 1, I will show that an undifferentiated product can be seen as highly distinct what competitors are differentiated with poorly understood features. To investigate this, participants were presented with information similar to Table 5, where two products are differentiated with unique features, but features that are poorly understood. Participants then rated the three pairwise dissimilarities between brands. I predicted that the plain option will be rated as dissimilar to both comparison options, while the two comparison options will be rated similar to each other.

3.2.1 Method

Participants from Amazon Mechanical Turk (N = 300, M_{age} = 34.82, SD_{age} = 11.10) were randomly assigned to one of six product categories, borrowed from essay 1 (hatchback cars, hair dryers, computer processors, toothpaste, credit cards, and facial tissue). Participants examined a table containing three products, accompanied by an image, brand name, and information about product features. The brand name and packaging was counterbalanced between subjects.

One product was the plain vanilla option – that is, it had only two features. The two comparison options had the same two product features that the vanilla option had, and each had an additional unique feature taken from those recorded in study 1 from essay 1. Participants rated three pairwise dissimilarities, comparing the plain vanilla option to each of the comparison options, and comparing the comparison options to each other. Participants rated dissimilarity on the same 20 point scale used in study 2 of essay 1. Figure 6 shows example stimuli for the toothpaste category.

Figure 6.
TOOTHPASTE STIMULI FOR STUDY 1

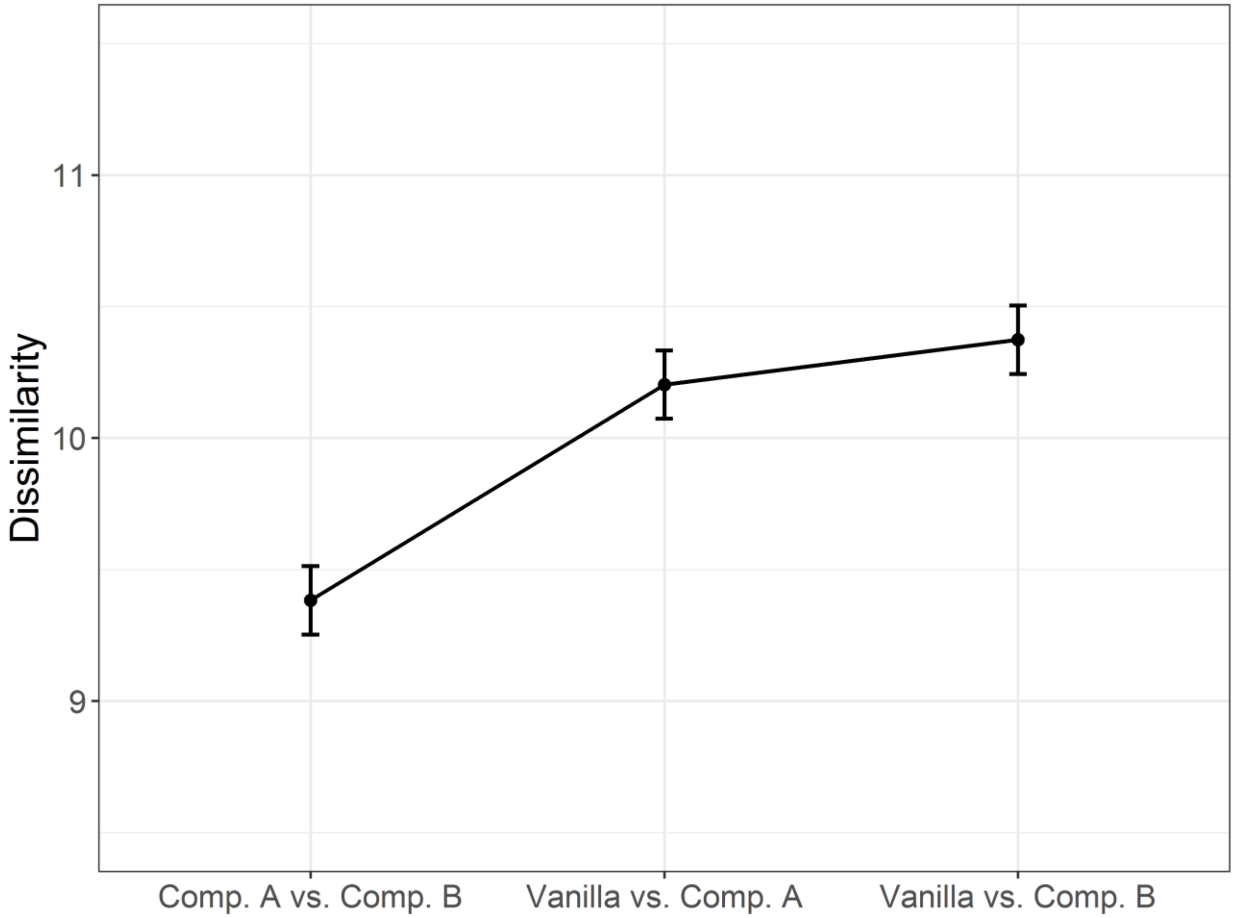
3.2.2 Results and Discussion

The primary prediction of study 1 was that the two dissimilarity ratings between the plain vanilla option and the comparison options will be significantly higher than ratings between the two comparison options. The data were analyzed using a linear mixed model. Dissimilarity ratings were the dependent variable. Product comparison pair was the independent variable. In order to assess the difference in means across all three comparisons, two sets of contrasts were used. First, comparisons were dummy coded with Comparison Product A vs. Comparison Product B as the comparison group. Second, comparisons were dummy coded with Plain Vanilla vs. Comparison Product A as the comparison group. Finally, the model estimated random intercepts by product category and by participants nested within categories.

Figure 7 displays the mean dissimilarity ratings for each comparison. The dissimilarity ratings for both the Vanilla vs. Comp. A and Vanilla vs. Comp. B conditions were significantly higher compared to the Comp. A vs. Comp. B ratings ($M_{VA} = 10.20$, $M_{VB} = 10.37$, $M_{AB} = 9.38$; $t_{VA,AB}(598) = 6.31$, $p < .001$, $d = .26$; $t_{VB,AB}(598) = 7.61$, $p < .001$, $d = .31$). The Vanilla vs. Comp. A ratings were not significantly different from the Vanilla vs. Comp. B ratings ($t_{VB,AB}(598) = 1.31$, $p > .19$, $d = .05$).

Study 1 provided initial evidence of the plain vanilla effect. Participants encountered a plain, undifferentiated offering in conjunction with multiple products that are differentiated with poorly understood attributes. Rather than perceiving the plain offering as non-distinct, participants rated the product as significantly more distinct than the differentiated offerings.

Figure 7.
DISSIMILARITY BETWEEN PLAIN VANILLA AND COMPARISON OPTIONS



Note: Error bars represent bootstrapped standard errors.

3.3 Study 2: A Conceptual Replication

Study 2 investigated the same phenomenon as study 1, but using a different procedure. Rather than measuring and comparing pairwise similarities, I varied the number of alternatives that had differentiating features and measured perceived differentiation for just the target brand. When only one alternative brand had a differentiating product feature, the target brand was seen as not very unique.

However, when all the competitors had low-understanding features, the target brand, which had no unique features was judged a highly unique.

3.3.1 Method

Participants from Amazon Mechanical Turk (N = 326) were randomly assigned to one of three competitor context conditions. In the first condition, participants saw two brands. The target brand was described using five attributes. The other brand had the same attributes and attribute levels, but also had a differentiating product feature. The features were rated lowest on subjective understanding within their category from study 1 of essay 1. In a second condition (the differentiated condition), the target brand and comparison brand were the same as the first condition, but four additional comparison brands were included. These additional brands were essentially identical to the target brand in that they had the same features and attribute levels. In the third condition (the plain vanilla condition), all comparison brands had low-understanding, differentiating product features. After examining the products, participants rated how unique the target brand was among its competitors on a seven-point scale ranging from 1: Not at all unique to 7: Very unique. Figure 8 shows the condition stimuli for the hatchback car category. Participants completed the task for five different product categories (hatchback cars, hair dryers, computer processors, toothpaste, credit cards). Participants were randomly assigned to condition for each category. The order of categories and the horizontal order of brands in the tables was randomized.

Figure 8.
HATCHBACK CAR FEATURES AND ATTRIBUTES

	Brand A	Brand B
Engine Cylinders	4	4
Horsepower	185 hp	185 hp
Fuel Economy	37 mpg	37 mpg
Transmission Type	Automatic	Automatic
Transmission Speeds	6	6
Added Features		StabiliTrak™ Stability System

	Brand A	Brand B	Brand C	Brand D	Brand E	Brand F
Engine Cylinders	4	4	4	4	4	4
Horsepower	185 hp	185 hp	185 hp	185 hp	185 hp	185 hp
Fuel Economy	37 mpg	37 mpg	37 mpg	37 mpg	37 mpg	37 mpg
Transmission Type	Automatic	Automatic	Automatic	Automatic	Automatic	Automatic
Transmission Speeds	6	6	6	6	6	6
Added Features				EcoLogic™ Fuel System		

	Brand A	Brand B	Brand C	Brand D	Brand E	Brand F
Engine Cylinders	4	4	4	4	4	4
Horsepower	185 hp	185 hp	185 hp	185 hp	185 hp	185 hp
Fuel Economy	37 mpg	37 mpg	37 mpg	37 mpg	37 mpg	37 mpg
Transmission Type	Automatic	Automatic	Automatic	Automatic	Automatic	Automatic
Transmission Speeds	6	6	6	6	6	6
Added Features		Sensing™ Control Sytem	Xtronic CVT™ Transmission	EcoLogic™ Fuel System	StabiliTrak™ Stability System	SYNC™ Entertainment System

3.3.2 Results and Discussion

Because participants were randomly assigned to condition at the beginning of each trial, the data is highly unbalanced. This would lead a standard mixed ANOVA to drop participants that were always in the same condition, and would estimate both a within-subject effect of condition on uniqueness scores and a between-subjects effect. Linear mixed models can handle such unbalanced data without removing any participants and can compute a single effect of condition on uniqueness scores. However, unlike in other studies, product category was not treated as a random variable, because the data did not allow such models to converge. Instead, uniqueness was the independent variable, competitor context, category, and their interaction were the independent variables, and the model estimated random intercepts by participant. There were no significant main effects of category nor interactions, so I will not discuss them further. As predicted, uniqueness ratings for target brand were significantly higher in the plain vanilla condition compared to both the differentiated condition and the two-brands condition ($M_{\text{vanilla}} = 4.56$, $M_{\text{diff}} = 2.94$, $M_{\text{2-brands}} = 3.08$; $t_{\text{v-d}}(312.23) = 3.15$; $p < .001$, $t_{\text{v-2}}(312.23) = 2.87$; $p < .003$).

Study 2 shows that consumers' perceptions of differentiation for a product are affected by the context the product is in. Without changing any aspect of a product, the perception of differentiation can be influenced by whether comparison brands are differentiated with low-understanding product features. While it is not uncommon for brands to be concerned with competitors adding similar features and benefits to their products, brands are probably not aware of the potential benefits when competitors add poorly understood but unique features. In study 3, I extend the findings of studies 1 and 2 by showing how subjective understanding influences the plain vanilla effect. Specifically, providing causal explanations for the poorly understood, differentiating product features can reverse the results and highlight the distinctiveness of the differentiated products.

3.4 Study 3: Explanations Reverse the Plain Vanilla Effect

Studies 1 and 2 showed that products with poorly understood features were perceived as similar to each other, despite being objectively different, or, equivalently, that plain, undifferentiated options were seen as highly distinct from products with poorly understood product features. This suggests that participants were processing the two, unique features of the differentiated options as if they were actually the same thing (i.e., the features corresponded). In study 3, I examined whether subjective understanding plays a role in the correspondence process. Features in studies 1 and 2 were selected such that they were poorly understood in previous studies. In study 3, participants read mechanistic explanations for the unique features, similar to those used in essay 1. I predicted that explanations would increase participants' subjective understanding of the benefits a feature provides and how the feature works. This understanding should make participants more likely to identify the previously poorly understood features across two options as separate, non-corresponding entities. The participant would, thus, perceive two points of difference where they otherwise would have perceived a point of similarity, increasing dissimilarity ratings.

3.4.1 Method

Study 3 (N = 480, 228 females, M_{age} = 35.27, SD_{age} = 10.81) employed a similar design and method as study 1, except for an additional between-subjects factor – explanations. Again, participants were randomly assigned to one of six product categories. The no-explanation condition was identical to study 1.

Participants saw three brands – a vanilla brand with two features and two comparison brands that shared the same features as the vanilla brand plus had one differentiating feature. In the explanation condition, participants read mechanistic explanations for the differentiating features in the comparison options. The plain, vanilla option was accompanied by equal-length, non-explanatory text. Figure 9 shows example stimuli for the toothpaste category. Participants rated dissimilarity for the three pairwise comparisons among brands. Dissimilarity was measured using the same 20-point scale as in previous studies.

Figure 9.
EXPLANATIONS FOR DIFFERENTIATING FEATURES

Mosaic

Contains:
Flouride
Baking Soda

Mosiac toothpaste is a division of the OraCare family. It was first introduced in 1967 and now is sold in dozens of countries. Mosaic also markets lines of toothbrushes, floss, and mouthwash.

DentaFresh

Contains:
Flouride
Baking Soda
WhiteLock Technology

WhiteLock Technology is a compound that forms a temporary seal around your teeth. This seal holds cleaning and whitening compounds close to your teeth longer, improving their effectiveness.

Radiant

Contains:
Flouride
Baking Soda
Dual Silica Technology

Silica is the primary part of toothpaste that cleans your teeth. It is a mild abrasive that scrubs plaque off. Dual silica technology also contains an extra fine silica that polishes teeth better than standard silica.

3.4.2 Results and Discussion

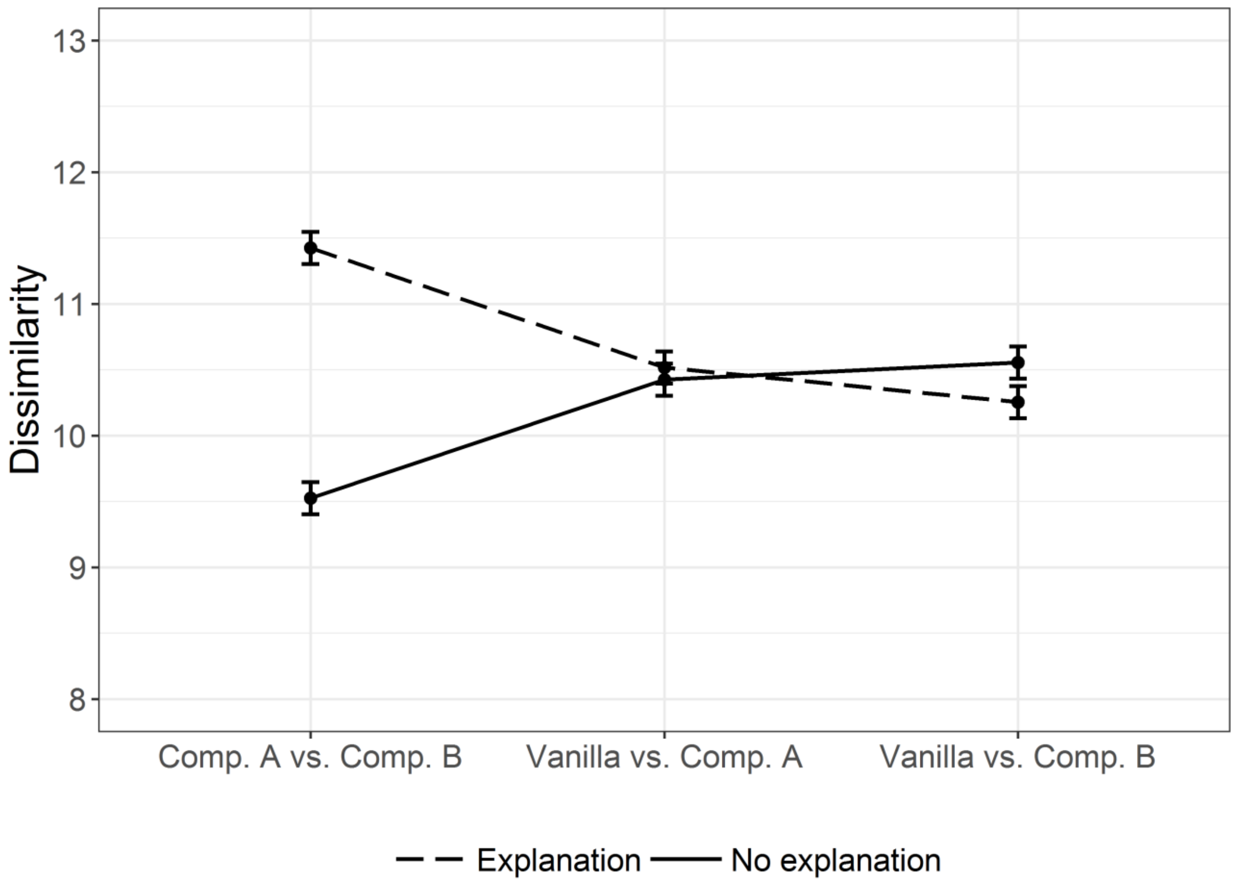
Dissimilarity ratings were analyzed using a linear mixed model with dissimilarity as the independent variable and explanation, comparison pair, and their interaction as the independent variables. Random intercepts were estimated by product category and participant nested within categories. I first assessed whether the no-explanation condition replicated the findings of study 1. Figure 10 displays the mean dissimilarity ratings for the six conditions. Examining the solid line, which is the three dissimilarity ratings for the no-explanation condition, the results appear to replicate study 1. Dissimilarity ratings were higher for the two comparison's that included the plain vanilla option. The results of the mixed model confirm that these differences were statistically significant ($M_{VA} = 10.42$, $M_{VB} = 10.55$, $M_{AB} = 9.53$; $t_{VA,AB}(956) = 5.48$, $p < .001$, d = .21; $t_{VB,AB}(956) = 6.26$, $p < .001$, d = .24). However, the dissimilarity ratings for the two vanilla comparisons were not significantly different from each other ($t_{VA,VB}(956) = .79$, $p > .43$).

The dashed line in Figure 10 shows the dissimilarity ratings when explanations were present. While the means for plain vanilla comparisons were similar after adding explanations, the dissimilarity between the two comparison products dramatically increased. Indeed, the dissimilarity between the two comparison products was significantly larger than the dissimilarities between either pair that included the plain, vanilla option ($M_{VA} = 10.52$, $M_{VB} = 10.25$, $M_{AB} = 11.43$; $t_{VA,AB}(956) = -5.53$, $p < .001$, d = -.21; $t_{VB,AB}(956) = -7.12$, $p < .001$, d = .27).

The difference between the two comparisons involving the plain, vanilla option was not significant ($t_{VA, VB}(956) = -1.60$, $p > .11$).

The primary hypothesis for study 3 was that explanations would significantly increase dissimilarity ratings between the two comparison options, relative to the plain vanilla option. Statistically, this is evidenced by a significant interaction between explanations and comparison pair ($t(956) = -9.96$, $p < .001$). Specifically, the Comp. A vs. Comp. B pair was coded -2 and both pairs involving the plain, vanilla option were code +1. This contrast compares the comparison brand dissimilarity to the average of the two, plain, vanilla brand dissimilarities. When interacted with explanations, the term asks whether there is a significant difference in slopes between the comparison brand pair and plain, vanilla pairs when explanations are present. In the no-explanation condition, the simple effect of the comparison pair contrast was positive and significant, that is, the average plain, vanilla dissimilarity was greater than the comparison brands dissimilarity ($t(956) = 6.78$, $p < .001$). However, in the explanation condition, the contrast was negative and significant, that is, the dissimilarity between comparison brands was significantly greater than the average dissimilarity between the plain, vanilla brand and the comparison brands ($t(956) = -7.30$, $p < .001$).

Figure 10.
EFFECTS OF EXPLANATIONS AND PRODUCT FEATURES ON PERCEIVED DIFFERENTIATION



Study 3 showed that subjective understanding of a product feature helps determine how correspondence between features is determined in similarity processing. While in many situations it is obvious whether two features correspond for the purpose of assessing similarity, there are also many cases where it is not obvious. When consumers do not understand a set of features, they are treated as, essentially, the same thing. For instance, one toothpaste brand may advertise WhiteLock technology as a new feature, and another brand may advertise that they recently added White Seal technology to their toothpaste. Consumers assessing the two brands would need to determine if they are corresponding features (for instance, different trademark names for the same compound). Study 3 illustrated that explanations which gave differentiating information about the distinctive features led to increased perceptions of product differentiation.

3.5 Study 4: Plain Vanilla Effect, Attention, and Choice

In study 4, I investigated downstream consequences of the plain vanilla effect on attention and choice. Participants saw stimuli similar to those from study 1; however, participants could also choose to read additional, general information about the brands. People tend to orient their attention toward distinctive objects – those that are different from their surrounding context (Roediger and McDermott 1995; Wallace 1965). Since the plain, vanilla option tends to be seen as more dissimilar compared to other products in its context, I predicted that participants will orient attention toward it by choosing to read additional information more than for other options. Additionally, since attention and elaboration toward an option tend to increase preference for that option (Krajbich and Rangel 2011), I predict that when asked to choose between the options, participants will select the vanilla option.

3.5.1 Method

Participants from Amazon Mechanical Turk (N = 300, 164 females, M_{age} = 35.79, SD_{age} = 12.31) were randomly assigned to one of six product categories. Participants viewed a set of three decision options similar to those used in studies 1 and 3. The plain, vanilla option had two product features described and each of the comparison options had the same two features plus a unique feature not shared with any other option. The primary difference in stimuli in study 4 was that below each option, was a button the participants could click to read more information about the brand. The additional information was adapted from Wikipedia entries for real brands and is meant to provide mildly positive information about the brand. Figure 11 shows example stimuli for the toothpaste category.

Figure 11.
PLAIN VANILLA EFFECT STIMULI WITH OPTIONAL ADDITIONAL INFORMATION

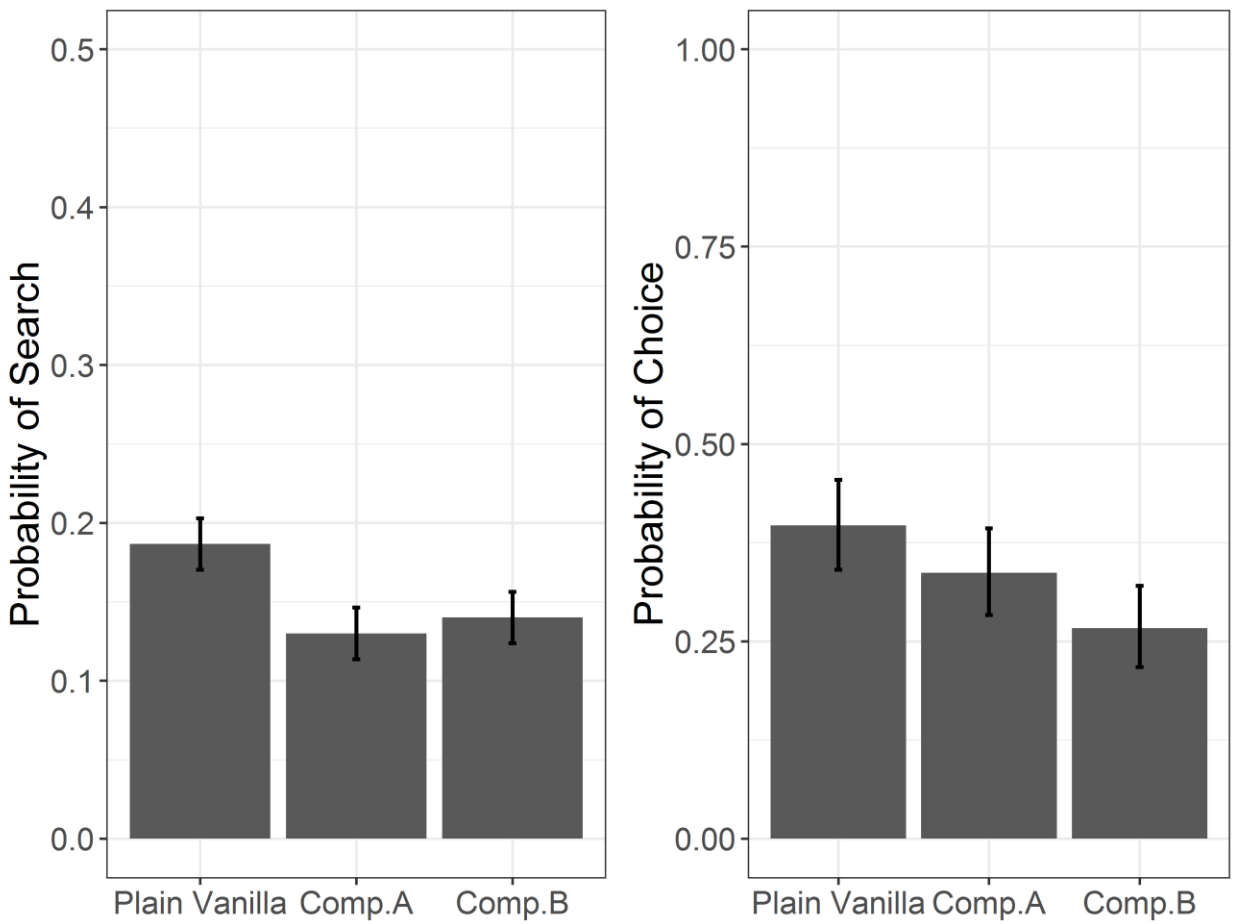
Mosaic	DentaFresh	Radiant
Contains: Flouride Baking Soda	Contains: Flouride Baking Soda WhiteLock Technology	Contains: Flouride Baking Soda Dual Silica Technology
Click to read more...	Click to read more...	Click to read more...
Mosaic toothpaste was first introduced in 1967 and has always been an approved brand of American Dental Association. Mosaic toothpastes come in mint and citrus mint flavors. Mosaic also markets toothbrushes under the Oracare brand.		

Participants were asked to examine the products as if they were going to purchase one and were told that if they would like more information about the brand, they can click on the button below each option. After the participant was ready to make a decision, they could click a button taking them to a new page. The new page had the same stimuli except the option to read more information was no longer available. Participants were asked to indicate which option they would choose to purchase, if they had to purchase one of the three brands, assuming the three brands had equal prices.

3.5.2 Results and Discussion

The first prediction of study 4 was that more people would engage in information search with the plain vanilla option than with the other two options. Figure 12 depicts the proportion of people who engaged in information search for each option, averaged across product categories. Nineteen percent of participants chose to read more information about the plain vanilla option, compared to 13% and 14% for comparison options A and B. Information search choices were analyzed statistically using a generalized logistic mixed model. The dependent variable was the three search choices each participant made (whether or not to examine information about the plain vanilla option, comparison option A, and comparison option B). The target option of the information search choice was the independent variable, with two orthogonal contrasts: Plain Vanilla = +2, Comp. A, Comp. B = -1; Plain Vanilla = 0, Comp. A = +1, Comp. B = -1. Finally, the model estimated random intercepts by product category and participants nested within categories. The results of the model indicated that participants were significantly more likely to engage in information search for the plain vanilla option ($z = 2.07$, $p < .04$). The difference in search likelihood between the two comparison options was not significant (z = 0.37, $p > .71$).

Figure 12.
INFORMATION SEARCH AND CHOICE FOR PLAIN AND DIFFERENTIATED OPTIONS



Note: error bars in the search chart represent the bootstrapped standard errors computed from the logistic model. Error bars in the choice chart represent the 95% confidence interval computed from the binomial test.

Second, I predicted that the plain vanilla option would receive more choice share than the comparison options. Figure 12 also displays these results. The plain vanilla option was chosen by 40% of participants, compared to 34% and 24%, respectively, for comparison option A and comparison option B. Separate binomial tests were used to assess statistical significance, with 1/3 as the expected probability. The plain vanilla option was chosen significantly more than chance ($p <$ .03), comparison option A was not chosen significantly differently from chance ($p >$ .90), and comparison option B was chosen significantly less than chance ($p <$.02).

Finally, I predicted that demand for the plain vanilla option would be stronger after people choose to view information about the plain vanilla option. To analyze this question, first, the choice variable was recoded as: plain vanilla = 1, comparison A, comparison B = 0. Second, this choice variable was used as the outcome variable of a generalized logistic mixed model. The two independent variables were an indicator variable for whether the participant engaged in information search for plain vanilla brand and a variable that measured whether the participant engaged in search with zero, one, or both of the comparison options. Finally, the model estimated random intercepts by product category and participants nested within categories. As predicted, those who chose to view information for the plain vanilla option were significantly more likely to choose the plain vanilla option ($P(choice_{vanilla} | search_{vanilla}) = .54$, $P(choice_{vanilla} | nosearch_{vanilla}) = .36$, z = 2.38, $p < .02$).

Study 4 showed an important consequence of the plain vanilla effect. Whereas previous studies examined how providing information changed participants' differentiation perceptions, in this study, participants were able to choose options to receive more information about. Supporting the hypothesis that people orient attention toward distinctive stimuli, participants chose to examine more information about the plain vanilla option, which previous studies showed is viewed as more distinctive, compared to other options. Additionally, the act of viewing more information about the plain vanilla option led to an overall increase in choice share. Thus, while merely being different may not directly cause consumers to view a brand as superior, study 4 highlighted an indirect path to preference that increased perceived differentiation can put a brand on.

3.6 General Discussion

The studies in this essay that the processes by which consumers make similarity judgments can influence the perceived differentiation of products in counterintuitive ways. Typically, a brand might try to differentiate itself by adding a novel feature. However, this research suggests that doing so can backfire. If the feature is poorly understood by consumers, which studies in essay 1 suggest is common, it can make the product seem more similar to other products that also have poorly understood features. Instead, a product that is otherwise undifferentiated appears highly distinct.

The research has several limitations that offer opportunities for future research. First, three of the four studies only examined products that contained two commonalities and one unique feature. This restrictive format may mask more complex relationships between the attribute structure of products and their perceived similarity and differentiation. Future research can vary the structures to see if relationships are different as the numbers of commonalities and differences change both within and across competing options. Additionally, the format of the studies bears a resemblance to context effect paradigms, such the decoy effect (Huber, Payne, and Puto 1982), in that consideration of more than two alternatives changes how individual alternatives are processed. Future research can examine how common context effect paradigms affect dependent variables other than choice, such as similarity.

Second, as with essay 1, essay 2 did not assess the direct impact the plain vanilla effect has on preference (study 4 measured preference as an effect of added attention paid toward the plain vanilla option). One reason for this is that several, unreported, exploratory studies found mixed results with regards to the effects of the paradigm used here on preference. Future research can determine conditions under which the plain, vanilla effect is more likely to increase preference for the plain, vanilla option directly, rather than as an indirect effect of other cognitive processes. Subsequently, future research can then investigate the plain, vanilla effect's role in price sensitivity.

Finally, all explanations given in study 3 differentiated the features used in the comparison products. The results indicate that such explanations decreased the perceived similarity between those products. However, explanations could also be phrased so that two features seem similar to each other. For instance, two features could provide the same general benefit or operate along a similar causal process. While the models discussed here suggest that such explanations should increase the similarity between the two products, other relationships are possible. For instance, despite having the same benefit, different causal routes to that benefit may reduce similarity.

REFERENCES

Alba, Joseph W., and J. Wesley Hutchinson (1987), "Dimensions of consumer expertise." *Journal of Consumer Research*, 13(4), 411-454.

Allen, Chris T., and Chris A. Janiszewski (1989), "Assessing the role of contingency awareness in attitudinal conditioning with implications for advertising research." *Journal of Marketing Research*, 26(1), 30-43.

Ansari, Asim, Nicholas Economides, and Joel Steckel (1998), "The Max-Min-Min Principle of Product Differentiation." *Journal of Regional Science*, 38(2), 207-230.

Arrow, Kenneth Joseph (1972), "Economic welfare and the allocation of resources for invention." In C. K. Rowley (Ed.) *Readings in Industrial Economics* (pp. 219-236), London: Palgrave.

Auh, Seigyoung, and Eric Shih (2009), "Brand name and consumer inference making in multigenerational product introduction context." *Journal of Brand Management*, 16(7): 439-454.

Bakdash, Jonathan Z., and Laura R. Marusich (2017), "Repeated measures correlation." *Frontiers in Psychology*, 8(456).

Basu, Kunal (1993), "Consumers' categorization processes: An examination with two alternative methodological paradigms." *Journal of Consumer Psychology,* 2(2), 97-121.

Bates, Douglas, Martin Maechler, Ben Bolker, and Steve Walker (2015), “Fitting Linear Mixed-Effects Models Using lme4.” *Journal of Statistical Software*, 67(1), 1-48. <doi:10.18637/jss.v067.i01>.

Becker, Gary S. (1965), "A Theory of the Allocation of Time." *The Economic Journal*, 75(299), 493-517.

Bellante, Don (2004), "Edward Chamberlin: monopolistic competition and pareto optimality." *Journal of Business and Economics Research*, 2(4), 17-26.

Berry, Steven T. (1994), "Estimating discrete-choice models of product differentiation." *The RAND Journal of Economics*, 25(2), 242-262.

Boulding, Kenneth E. (1966), *Economic Analysis*. London: Harper and brothers Publishers.

Bresnahan, Timothy F. (1987), "Competition and collusion in the American automobile industry: The 1955 price war." *The Journal of Industrial Economics*, 35(4), 457-482.

Broniarczyk, Susan M., and Andrew D. Gershoff (1997), "Meaningless differentiation revisited." *ACR North American Advances*.

Broniarczyk, Susan M., and Andrew D. Gershoff (2003), "The reciprocal effects of brand equity and trivial attributes." *Journal of Marketing Research*, 40(2), 161-175.

Brown, Christina L., and Gregory S. Carpenter (2000), "Why is the trivial important? A reasons-based account for the effects of trivial attributes on choice." *Journal of Consumer Research*, 26(4), 372-385.

Campbell, Margaret C., and Ronald C. Goodstein (2001), "The moderating effect of perceived risk on consumers' evaluations of product incongruity: Preference for the norm." *Journal of Consumer Research*, 28(3), 439-449.

Carpenter, Gregory S., and Kent Nakamoto (1989), "Consumer preference formation and pioneering advantage." *Journal of Marketing Research*, 26(3), 285-298.

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), 339-350.

Chakravarti, Amitav, and Chris Janiszewski (2004), "The influence of generic advertising on brand preferences." *Journal of Consumer Research*, 30(4), 487-502.

Chamberlin, Edward Hastings (1936), “Monopolistic Competition and the Productivity Theory of Distribution.” In Frank W.Taussig (Ed.) *Explorations in Economics* (pp. 237-249). New York: McGraw-Hill.

Chamberlin, Edward Hastings (1949), *Theory of monopolistic competition: A re-orientation of the theory of value*. London: Oxford University Press. (Originally published in 1933.)

Chen, Yongmin, and Michael H. Riordan (2007), "Price and variety in the spokes model." *The Economic Journal*, 117(522), 897-921.

Cherington, Paul Terry (1920), *The Elements of Marketing*. New York: The Macmillan Co.

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), 430-444.

Chintagunta, Pradeep K., and Harikesh S. Nair (2011), "Structural workshop paper—Discrete-choice models of consumer demand in marketing." *Marketing Science*, 30(6), 977-996.

Clark, Fred Emerson (1922), *Principles of Marketing*. New York: The Macmillan Co.

Cohen, Joel B., and Kunal Basu (1987), "Alternative models of categorization: Toward a contingent processing framework." *Journal of Consumer Research*, 13(4), 455-472.

Dick, Alan, Dipankar Chakravarti, and Gabriel Biehal (1990), "Memory-based inferences during consumer choice." *Journal of Consumer Research*, 17(1), 82-93.

Dick, Alan S., and Kunal Basu (1994), "Customer loyalty: toward an integrated conceptual framework." *Journal of the Academy of Marketing Science*, 22(2): 99-113.

Dickson, Peter R. and James L. Ginter (1987), "Market segmentation, product differentiation, and marketing strategy." *Journal of Marketing*, 51(2), 1-10.

Diehl, Kristin, Laura J. Kornish, and John G. Lynch Jr. (2003), "Smart agents: When lower search costs for quality information increase price sensitivity." *Journal of Consumer Research*, 30(1), 56-71.

Drucker, Peter (1954), "The Principles of Management." New York: HarperCollins.

Eiselt, Horst A., Gilbert Laporte, and Jacques-Francois Thisse (1993), "Competitive location models: A framework and bibliography." *Transportation Science*, 27(1), 44-54.

Fader, Peter (2012), *Customer Centricity: Focus on the right customers for strategic advantage*. Philadelphia: Wharton Digital Press.

Feldman, Jack M., and John G. Lynch (1988), "Self-generated validity and other effects of measurement on belief, attitude, intention, and behavior." *Journal of Applied Psychology,* 73(3), 421-435.

Fernbach, Philip M., Steven A. Sloman, Robert St Louis, and Julia N. Shube (2012), "Explanation fiends and foes: How mechanistic detail determines understanding and preference." *Journal of Consumer Research,* 39(5), 1115-1131.

Flatters, Paul, and Michael Willmott (2009), "Understanding the post-recession consumer." *Harvard Business Review*, 87(7-8), 106-12.

Friston, Karl (2005), "A theory of cortical responses." *Philosophical transactions of the Royal Society B: Biological sciences*, 360(1456), 815-836.

Galbraith, John Kenneth (1967), *The New Industrial State*. Boston: Houghton Mifflin Company.

Gentner, Dedre (1983), "Structure-mapping: A theoretical framework for analogy." *Cognitive Science*, 7(2), 155-170.

Green, Paul E., and Venkatachary Srinivasan (1978), "Conjoint analysis in consumer research: issues and outlook." *Journal of Consumer Research*, 5(2), 103-123.

Green, Paul E., and Venkat Srinivasan (1990), "Conjoint analysis in marketing: new developments with implications for research and practice." *Journal of Marketing*, 54(4), 3-19.

Green, Paul E., and Vithala R. Rao (1971), "Conjoint measurement-for quantifying judgmental data." *Journal of Marketing Research*, 8(3), 355-363.

Griffin, Jill G., and Susan M. Broniarczyk (2010), "The slippery slope: The impact of feature alignability on search and satisfaction." *Journal of Marketing Research*, 47(2), 323-334.

Gürhan-Canli, Zeynep (2003), "The effect of expected variability of product quality and attribute uniqueness on family brand evaluations." *Journal of Consumer Research*, 30(1), 105-114.

Gwin, Carol F., and Carl R. Gwin (2003), "Product attributes model: A tool for evaluating brand positioning." *Journal of Marketing Theory and Practice*, 11(2), 30-42.

Haley, Russell I. (1968), "Benefit segmentation: A decision-oriented research tool." *Journal of Marketing*, 32(3), 30-35.

Hauser, John R., and Steven P. Gaskin (1984), "Application of the 'Defender' consumer model." *Marketing Science*, 3(4), 327-351.

Hauser, John R., and Steven M. Shugan (1983), "Defensive marketing strategies." *Marketing Science*, 2(3), 319-360.

Hauser, John R., and Patricia Simmie (1981), "Profit maximizing perceptual positions: An integrated theory for the selection of product features and price." *Management Science*, 27(1), 33-56.

Henson, Richard N., and Pierre Gagnepain (2010), "Predictive, interactive multiple memory systems." *Hippocampus,* 20(11), 1315-1326.

Hotelling, Harold (1929), "Stability in Competition." *Economic Journal*, 39 (153): 41–57.

Hsee, Christopher K., and Jiao Zhang (2010), "General evaluability theory." *Perspectives on Psychological Science*, 5(4): 343-355.

Huber, Joel, John W. Payne, and Christopher Puto (1982), "Adding asymmetrically dominated alternatives: Violations of regularity and the similarity hypothesis." *Journal of Consumer Research*, 9(1), 90-98.

Hutchinson, J. Wesley, and Joseph W. Alba (1991), "Ignoring irrelevant information: Situational determinants of consumer learning." *Journal of Consumer Research*, 18(3), 325-345.

Iyer, Rajesh, and James A. Muncy (2005), "The role of brand parity in developing loyal customers." *Journal of Advertising Research*, 45(2), 222-228.

Janiszewski, Chris, and Stijn MJ Van Osselaer (2000), "A connectionist model of brand–quality associations." *Journal of Marketing Research*, 37(3), 331-350.

Jensen, Jan (2011), "Consumer loyalty on the grocery product market: an empirical application of Dick and Basu's framework." *Journal of Consumer Marketing*, 28(5), 333-343.

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), 247-259.

Kalra, Ajay, and Ronald C. Goodstein (1998), "The impact of advertising positioning strategies on consumer price sensitivity." *Journal of Marketing Research*, 35(2), 210-224.

Keller, Kevin Lane (2009), "Building strong brands in a modern marketing communications environment." *Journal of Marketing Communications*, 15(2-3), 139-155.

Kenward, Michael G., and James H. Roger (1997), "Small sample inference for fixed effects from restricted maximum likelihood." *Biometrics*, 53(3), 983-997.

Krajbich, Ian, and Antonio Rangel (2011), "Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based decisions." *Proceedings of the National Academy of Sciences,* 108(33), 13852-13857.

Lancaster, Kelvin (1971), *Consumer demand: A new approach*. New York: Columbia University Press.

Lancaster, Kelvin (1975), “Socially Optimal Product Differentiation.” *American Economic Review*, 65(4), 567-586.

Lancaster, Kelvin (1979), *Variety, Equity, And Efficiency: Product Variety in an Industrial Society*. New York: Columbia University Press.

Lerner, Abba P., and Hans Werner Singer (1937), "Some notes on duopoly and spatial competition." *Journal of Political Economy*, 45(2), 145-186.

Levitt, Theodore (1960), "Growth and Profits Through Planned Marketing Innovation." *Journal of Marketing*, 24(4), 1-8.

Loken, Barbara, Lawrence W. Barsalou, and Christopher Joiner (2008), “Categorization Theory and Research in Consumer Psychology,” in C. Haugtvedt, P. Herr, and F. Kardes (eds.), Handbook of Consumer Psychology. New York: Psychology Press, 133-163.

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), 474-488.

Lynch Jr, John G., and Dan Ariely (2000), "Wine online: Search costs affect competition on price, quality, and distribution." *Marketing Science*, 19(1) 83-103.

Lynch Jr, John G., Howard Marmorstein, and Michael F. Weigold (1988), "Choices from sets including remembered brands: Use of recalled attributes and prior overall evaluations." *Journal of Consumer Research,* 15(2), 169-184.

Lynch Jr, John G., and Thomas K. Srull (1982), "Memory and attentional factors in consumer choice: Concepts and research methods." *Journal of Consumer Research*, 9(1), 18-37.

MacLeod, William Bentley, George Norman, and J-F. Thisse (1988), "Price discrimination and equilibrium in monopolistic competition." *International Journal of Industrial Organization*, 6(4), 429-446.

Markman, Arthur B., and Dedre Gentner (1993), "Splitting the differences: A structural alignment view of similarity." *Journal of Memory and Language*, 32(4), 517-535.

Markman, Arthur B., and Dedre Gentner (1997), "The effects of alignability on memory." *Psychological Science,* 8(5), 363-367.

Meyer, Robert J. (1987), "The learning of multiattribute judgment policies." *Journal of Consumer Research*, 14(2), 155-173.

Meyvis, Tom, and Chris Janiszewski (2002), "Consumers' beliefs about product benefits: The effect of obviously irrelevant product information." *Journal of Consumer Research*, 28(4), 618-635.

Mitra, Anusree, and John G. Lynch Jr. (1995), "Toward a reconciliation of market power and information theories of advertising effects on price elasticity." *Journal of Consumer Research*, 21(4), 644-659.

Mittal, Banwari, and Myung-Soo Lee (1989), "A causal model of consumer involvement." *Journal of Economic Psychology*, 10(3), 363-389.

Muller, Dominique, Charles M. Judd, and Vincent Y. Yzerbyt (2005), "When moderation is mediated and mediation is moderated." *Journal of Personality and Social Psychology*, 89(6), 852-863.

Meyers-Levy, Joan, and Alice M. Tybout (1989), "Schema congruity as a basis for product evaluation." *Journal of Consumer Research*, 16(1), 39-54.

Mynatt, Clifford R., Michael E. Doherty, and William Dragan (1993), "Information relevance, working memory, and the consideration of alternatives." *The Quarterly Journal of Experimental Psychology*, 46(4), 759-778.

Nam, Myungwoo, Jing Wang, and Angela Y. Lee (2012), "The difference between differences: How expertise affects diagnosticity of attribute alignability." *Journal of Consumer Research*, 39(4), 736-750.

Neven, Damien, and Jacques-Francois Thisse (1990), "On Quality and Variety Competition." In J.J. Gabszewicz, J. F. Richard, and L.A. Wolsey (Eds.) *Economic Decision-Making: Games, Econometrics and Optimization*, Amsterdam: North-Holland, 175-199.

Pennington, Nancy, and Reid Hastie (1988), "Explanation-based decision making: Effects of memory structure on judgment." *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 14(3), 521.

Peracchio, Laura A., and Alice M. Tybout (1996), "The moderating role of prior knowledge in schema-based product evaluation." *Journal of Consumer Research*, 23(3), 177-192.

Porter, Michael E. (1980), *Competitive Strategy: Techniques for Analyzing Industries and Competitors*. New York: Free Press.

Robinson, Joan (1953), "Imperfect competition revisited." *The Economic Journal*, 63(251), 579-593.

Robinson, Joan (1969), *The Economics of Imperfect Competition*. New York: Springer. (Originally published in 1933.)

Roediger, Henry L., and Kathleen B. McDermott (1995), "Creating false memories: Remembering words not presented in lists." *Journal of experimental psychology: Learning, Memory, and Cognition,* 21(4), 803-814.

Romaniuk, Jenni, Byron Sharp, and Andrew Ehrenberg (2007), "Evidence concerning the importance of perceived brand differentiation." *Australasian Marketing Journal*, 15(2), 42-54.

Rosch, Eleanor H. (1973), "Natural categories." *Cognitive Psychology*, 4(3): 328-350.

Rosen, Sherwin (1974), "Hedonic prices and implicit markets: product differentiation in pure competition." *Journal of Political Economy*, 82(1), 34-55.

Rosseel, Yves (2012), “lavaan: An R Package for Structural Equation Modeling.” *Journal of Statistical Software*, 48(2), 1-36.

Sajeesh, S., and Jagmohan S. Raju (2010), "Positioning and pricing in a variety seeking market." *Management Science*, 56(6), 949-961.

Salop, Steven C. (1979), “Monopolistic Competition with Outside Goods.” *The Bell Journal of Economics*, 10(1), 141-156.

Samuelson, Paul Anthony (1948), *Economics*. New York: McGraw-Hill.

Schmalensee, Richard, and Jacques-Frangois Thisse (1988), "Perceptual maps and the optimal location of new products: An integrative essay." *International Journal of Research in Marketing*, 5(4), 225-249.

Shaw, Arch Wilkinson (1912), "Some problems in market distribution." *The Quarterly Journal of Economics*, 26(4), 703-765.

Sheinin, Daniel A., Sajeev Varki, and Christy Ashley (2011), "The differential effect of ad novelty and message usefulness on brand judgments." *Journal of Advertising,* 40(3), 5-18.

Sheth, Jagdish N. (1973), "A model of industrial buyer behavior." *Journal of Marketing*, 37(4), 50-56.

Shocker, Allan D., and Venkataraman Srinivasan (1974), "A consumer-based methodology for the identification of new product ideas." *Management Science*, 20(6), 921-937.

Shocker, Allan D., and Venkataraman Srinivasan (1979), "Multiattribute approaches for product concept evaluation and generation: A critical review." *Journal of Marketing Research*, 16(2), 159-180.

Singh, Nirvikar, and Xavier Vives (1984), "Price and quantity competition in a differentiated duopoly." *The RAND Journal of Economics*, 15(4), 546-554.

Smith, Adam (1910), *The Wealth of Nations*, vol. 2. New York : E.P. Dutton. (Originally published in 1776.)

Smith, Wendell R. (1956) "Product differentiation and market segmentation as alternative marketing strategies." *Journal of Marketing*. 21(1), 3-8.

Spiller, Stephen A., and Lena Belogolova (2016), "On consumer beliefs about quality and taste." *Journal of Consumer Research,* 43(6), 970-991.

Spiro, Rand J. (1988), "Cognitive flexibility theory: Advanced knowledge acquisition in ill-structured domains." *Center for the Study of Reading Technical Report*, 441.

Steenkamp, Jan-Benedict EM, and Katrijn Gielens (2003), "Consumer and market drivers of the trial probability of new consumer packaged goods." *Journal of Consumer Research*, 30(3): 368-384.

Tenenbaum, Joshua B., and Thomas L. Griffiths (2001), "Generalization, similarity, and Bayesian inference." *Behavioral and Brain Sciences,* 24(4), 629-640.

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), 431-442.

Tulving, Endel, and Neal Kroll (1995), "Novelty assessment in the brain and long-term memory encoding." *Psychonomic Bulletin & Review*, 2(3), 387-390.

Tversky, Amos (1977), "Features of similarity." *Psychological Review*, 84(4), 327-352.

Tversky, Amos, and Itamar Gati (1978), "Studies of similarity." *Cognition and categorization,* 1, 79-98.

Van Osselaer, Stijn MJ, and Chris Janiszewski (2001), "Two ways of learning brand associations." *Journal of Consumer Research*, 28(2), 202-223.

Van Osselaer, Stijn MJ, Joseph W. Alba, and Puneet Manchanda (2004), "Irrelevant information and mediated intertemporal choice." *Journal of Consumer Psychology*, 14(3), 257-270.

Von Winterfeldt, D. and W. Edwards (1986), *Decision Analysis for Management Judgment*. Cambridge: Cambridge University Press.

Wallace, William P. (1965), "Review of the historical, empirical, and theoretical status of the Von Restorff phenomenon." *Psychological Bulletin,* 63(6), 410-424.

Wedel, Michel, and Wagner A. Kamakura (1998), *Market segmentation: Conceptual and methodological foundations*. Berlin: Springer Science & Business Media.

Wood, Stacy L., and John G. Lynch Jr. (2002), "Prior knowledge and complacency in new product learning." *Journal of Consumer Research*, 29(3), 416-426.

Zaichkowsky, Judith L. (1986), "Conceptualizing involvement." *Journal of Advertising*, 15(2): 4-34.

Zhang, Shi, and Arthur B. Markman (1998), "Overcoming the early entrant advantage: The role of alignable and nonalignable differences." *Journal of Marketing Research,* 35(4), 413-426.

Zhang, Shi, Frank R. Kardes, and Maria L. Cronley (2002), "Comparative advertising: Effects of structural alignability on target brand evaluations." *Journal of Consumer Psychology*, 12(4), 303-311.

Zhang, Shi, and Gavan J. Fitzsimons (1999), "Choice-process satisfaction: The influence of attribute alignability and option limitation." *Organizational behavior and human decision processes*, 77(3), 192-214.

APPENDIX

To further assess the mediated moderation relationship hypothesized in Essay 1, Study 3, I conducted structural equation modeling analysis. The *lavaan* package in R was used to estimate the models (Rosseel 2012). The estimated models correspond to the three models discussed in the original analysis. In the first model, recall was predicted by explanations, feature type, and their interaction. Software limitations prevented the model from having additional random effects. To control for product category and feature replicate, these factors were collapsed into a single variable. That variable was Helmert coded and included in the model as fixed effects. The focal test of this model is whether there is overall moderation of the effect of the explanations on recall (i.e., the interaction between explanations and feature type), which was indeed significant (standardized estimate = .12, z = 2.15, $p < .03$).

The second SEM jointly estimated two regressions, as well as estimated two latent variables. Rather than using the averaged values of the three understanding scale items, this model estimated the latent subjective understanding factor through confirmatory factor analysis. The interaction between subjective understanding and feature type was also estimated using confirmatory factor analysis. To do so, each understanding item was mean centered then multiplied by the feature type contrast code (align. = -1, nonalign. = 1). These products were the indicators for the understanding by feature-type interaction.

The two regression equations, again, correspond to the second two mixed models described in the original analysis. The first predicted subjective understanding by explanation, feature type, and their interaction. The second predicted feature recall by explanation, feature type, their interaction, subjective understanding, and the understanding by feature type interaction. Finally, the model estimated intercepts for the latent variables.

The overall fit of the second model was good ($\chi^2(83) = 42.82$, $p > .05$; RMSEA = .005; GFI = .99). The three understanding items loaded highly on the latent variable (standardized loadings > .90). Additionally, the three product indicators for the understanding by feature type interaction loaded highly on their latent variable (standardized loadings > .88).

This model also corroborated the prior evidence of mediated moderation. Feature type significantly moderated the effect of explanations on the mediator, subjective understanding (standardized estimate = .40, z = 10.86, $p < .001$), and subjective understanding was significantly related to recall on average across explanation and feature types (standardized estimate = .18, z = 3.46, $p < .002$). Additionally, when controlling for understanding, the moderated effect of explanations on recall (i.e., the explanation x feature type interaction) was no longer significant (standardized estimate = .08, z = 1.25, $p > .21$).

Finally, this second model allowed for the direct estimation of the indirect effect of explanations on recall, mediated by subjective understanding. The indirect effect was significant in both the alignable and nonalignable feature conditions;

however, as predicted, it was substantially reduced in the alignable feature conditions. The SEM estimated that explanations increase the probability of recall by .28 in the nonalignable conditions (standardized estimate = .16, $z = 3.42$, $p < .002$), while the model predicted only a .07 increase in the alignable conditions (standardized estimate = .01, $z = 2.85$, $p < .005$). Thus, explanations have a positive effect on feature recall; however, this effect is stronger for nonalignable features, compared to alignable features. Finally, the moderated effect of explanations on feature recall is mediated by subjective understanding.