

A Methodology to Support Product Differentiation Decisions

Kamalini Ramdas, Oleksandr Zhylyevskyy, and William L. Moore

Abstract

Choosing the right set of new products to offer is a key driver of profitability. New products often share some design attributes with existing products, so firms need to decide which attributes to keep common, and which to differentiate. We propose and empirically implement a new methodology that can help managers navigate the complex decision of where to focus differentiation, using “looks like” prototypes that typically become available in the later stages of the product development process. Our methodology complements early stage product positioning methods such as conjoint analysis and perceptual mapping. It also offers a way to estimate the impact of context dependence on choice. Finally, our methodology provides a way to test empirically whether perceptual mapping based on pairwise similarity judgments is appropriate for a product category. Using data obtained from a major wristwatch manufacturer, we are able to suggest guidelines on how to differentiate the firm’s offerings, and estimate the magnitude of context dependent effects. We also find that for wristwatches, attributes that drive perceptions differ from those that drive choice. Overall, our approach can help avoid falling into the trap of focusing variety on attributes that are costly to differentiate and have little impact on choice.

Index Terms

Product differentiation, Product similarity, Consumer choice, “Looks like” prototype, Context dependence, Conjoint analysis, Perceptual mapping

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I. INTRODUCTION

For any firm, offering the right set of new products is a key driver of profitability. During the new product development process, ideas and verbal descriptions may first be converted into visual representations such as sketches, and computer representations such as virtual prototypes. In turn, these representations are converted into physical prototypes. The first physical prototypes may be rough models, which may be transformed into “looks like” prototypes¹ that have the look and feel of the final product. Even though they are typically non-functional, these prototypes are displayed at trade fairs and industry events. Finally, “looks like” prototypes are upgraded to working prototypes and products ready for sale. At each stage of the development process, prior ideas about the product’s design may be modified, combined, or dropped. Also, at each stage, different tools may be used to analyze new product ideas. For example, multidimensional scaling and conjoint analysis are employed primarily in the generation and testing of new ideas, before physical prototypes become available. However, product testing is possible only after a prototype has been developed.

Of course, most new products are not developed in isolation, but are part of an existing product line. Products can be viewed as bundles of attributes, where each attribute can take on multiple levels. For example, the horsepower of a car or the amount of memory in a PC are product attributes that take on different levels. Some attribute levels of a new product will typically be shared with other products in the product line, while others will be used to differentiate the new product from other products in the line.

Decisions about component sharing or common attribute levels impact both consumer reactions and product cost. For example, some automotive components, such as hinges, brackets, or hidden nuts and bolts are not usually noticed by the consumer, and also, whether or not they are shared has little impact on cost. On the other hand, components such as cup holders or vanity mirrors

¹In some industries, “looks like” prototypes are called “camera-ready” prototypes.

TABLE I
COST IMPACT AND MARKET IMPACT OF DIFFERENTIATION ALONG DIFFERENT PRODUCT ATTRIBUTES

	Low Cost Impact	High Cost Impact
Low Market Impact	Hinges Nuts and bolts Brackets	Braking systems Axles
High Market Impact	Cup holders Vanity mirrors	Outer body panels Engines Transmissions

are relatively easy to differentiate from a cost standpoint, yet they are quite visible and may impact preferences (see [1]). Other components, such as engines or transmissions, are both costly to differentiate and have a big impact on preferences. Finally, some components, such as braking systems, are costly to differentiate, but may not be noticed by the customer as long as they meet acceptable quality levels [2]. Table I summarizes this conceptualization of the cost impact and market impact of differentiation along different attributes. Since both the cost and market impact of differentiation can vary dramatically from one attribute to another, unwise decisions on which attributes to differentiate and which to keep common can be doubly costly for the firm.

The purpose of our paper is to develop and illustrate a methodology that complements early stage methods like conjoint analysis and multidimensional scaling, which rely primarily on verbal descriptions. Specifically, our methodology is used to evaluate prototypes in the context of an existing product line. We shed further light on the question of how to differentiate one's new product offerings, using the more tangible product prototypes that are available later in the development process.

First, we identify the impact of a prototype's common and unique attribute levels on choice and cannibalization by modeling the probability of a switch to the prototype from an existing product in an evaluated product set as a function of their *objective similarity*², using a random

²The objective similarity between two products is measured at the level of individual physical attributes and refers to the similarity of the two products along each of their attributes. For example, for wristwatches, objective similarity is captured by measures such as whether they have the same case shape or strap material, whether they both have a date indicator, or the price difference between them.

effects probit model. We then employ the same modeling framework to quantify the magnitude of the bias that can arise from ignoring the impact of competitive context on product choice. While context can include many dimensions, we focus specifically on the *choice set context* for a prototype, which we define as the presence or absence in the evaluated product set of a highly preferred product.

Next, we assess the impact of a prototype's objective similarity to other products in the product line, on its *perceived similarity*³ to these products. This assessment is important as it allows managers to identify which attributes, when differentiated, drive consumers' perceptions about whether a new product stands out and adds something to the overall line versus just increasing the clutter. Combining these two analyses, we learn whether the attributes that drive choice differ from those that drive perceptions about similarity for the product category in question.

We operationalize our methodology in the context of a major multinational wristwatch manufacturer. Wristwatches are characterized by numerous attributes, such as case shape, case plating and finishing, strap material, and dial color and layout, to name only a few, and each of these attributes can take on multiple levels. As with most complex products, the cost of differentiating along various attributes can differ significantly, making it important to pick the right ones to differentiate. For example, changing case shape requires the design and development of new stamping dies and may even require modification of stamping presses, an expensive and time consuming affair. On the other hand, changing the case finishing or dial color is much less expensive.

In our illustration, we find that the degree of objective similarity between a new product and existing products is important in explaining judgments about both choice and perceived similarity. We also find that choice set context affects choice, even after we control for objective watch similarity, observable respondent characteristics, and unobservable heterogeneity in individual responses. The magnitude of our estimates highlights the need for future research that incorporates context dependence into traditional choice models. Finally, we show that the product attributes that drive perceived similarity are quite distinct from those that drive choice. Obviously, the relationship between the attributes that drive similarity judgments and choices will differ by product category, but this is an empirical question that can be addressed with our

³Perceived similarity is a measure of the subjective judgments by respondents as to the overall similarity of two products.

methodology.

The rest of this paper proceeds as follows. In Section II below, we discuss the relevant literature and how our research relates to it, and develop testable hypotheses. Section III describes the simulated test market experiment, collected data, and constructed variables. In Section IV, we discuss the empirical models and estimation methodology. Section V presents the main results of the analysis. Section VI provides a discussion of the results. Lastly, in Section VII, we outline limitations of our analysis and suggest directions for future research.

II. RELEVANT LITERATURE AND RESEARCH DESIGN

A. Background

A variety of methods have been developed in operations, accounting, engineering management, and marketing to help managers make product line decisions. For example, activity based costing enables better estimation of the cost of new product choices, and modular design can enable focused differentiation. The marketing methods of conjoint analysis and perceptual mapping (e.g., [3]–[10]) are used relatively early in the development process to identify new product concepts which embody attractive combinations of attribute levels.

Conjoint analysis estimates importance weights associated with product attribute levels, by asking respondents to either rate their likelihood of purchasing each of a set of hypothetical product descriptions – also referred to as product profiles – or to choose among different sets of hypothetical product profiles. These estimated importance weights can be combined with managerial judgments about the attribute levels of competitive products, in optimization models that determine the product or product line that maximizes sales or profits (see [11] for a review).

Multidimensional scaling (MDS) refers to a number of techniques that are used to study the perceptions of and preferences for products that are currently in the marketplace. Perceptual maps are low dimensional representations of people’s perceptions of products, where products that are perceived to be more similar are located closer to each other in the map. Perceptual maps can be estimated from either judgments of how various products rate on underlying product attributes (e.g., rate each of the following cars on their perceived safety) or on the perceived similarity of different pairs of products (e.g., rate the similarity of the following pairs of cars; see [7] for details). Joint spaces are created from perceptual maps by locating preference measures, either ideal points which denote points of maximum preference, or preference vectors which denote

directions of increasing preference, for each person or segment in the study. Perceptual maps and joint spaces can guide decision making on what new products to offer, based on identifying scarcely populated regions or “holes” in a perceptual map [12]. Product line optimization models can also be developed from joint spaces (e.g., [13], [14]).

Researchers in operations management and engineering have enhanced these marketing models by considering more realistic cost functions and operational constraints (e.g., [15]–[18]). Other models have examined the question of how much variety to offer for components that have relatively little impact on perceived differentiation (e.g., [2], [19], [20]). [21] provide an engineering perspective on the product line optimization literature and develop an approach that incorporates engineering constraints into a product line optimization model. [22] provides a review of the operations literature examining how to differentiate product offerings.

Despite their usefulness, these early stage approaches have certain drawbacks. In the case of conjoint analysis, one needs to assume that consumer and managerial perceptions of competitive products are similar. Second, one must assume that verbal product descriptions accurately communicate product characteristics to the customer. This assumption is likely to hold for functional products. For example, a laptop may be adequately described in terms of processor speed, hard drive capacity, memory, battery life, etc. However, it is much less likely in the case of more aesthetic products. For example, a consumer may have a hard time visualizing exactly what a watch would look like from its verbal description. [23] find that verbal product descriptions do not always do a good job of capturing many qualitative aspects of a product, such as aesthetics, usability and quality of manufacture.

A different set of problems can arise with MDS. First, it can be difficult to label the axes of a perceptual space as they typically represent a large number of underlying product attributes [24]. Second, it can be difficult to operationalize the perceptual locations in terms of attributes that the manager can actually control. Finally, when perceptual maps are based on pairwise similarity data, e.g., [25], a more subtle problem occurs. There is an implicit assumption that the underlying attributes that drive similarity are the same as those that drive choice. However, researchers have found that perceptual and preference dimensions can differ for some products. For example, [26] find that the color of a soda – or cola versus non cola flavor – emerges as the more important perceptual dimension, but in terms of preference and choice, the number of calories emerges as the more important dimension. In other words, people say that Coke and

Diet Coke are more similar than Coke and Seven Up, but they tend to prefer and drink either Coke and Seven Up or Diet Coke and Diet Seven Up rather than Coke and Diet Coke or Seven Up and Diet Seven Up. With a simple product like soft drinks, differences in the importance of the dimensions in determining similarity and preference can be accommodated by a differential stretching of the dimensions on a perceptual map.

With more complex products that are described in terms of a large number of attributes, this problem can be much greater. In these cases, attributes that are important in terms of preference may not even be represented in the perceptual space and will be entirely missed when looking for “holes” in which to position new products. Using joint spaces which incorporate both preference vectors and perceived product locations in a perceptual map, e.g., [27], does not alleviate this problem.

Because of the potential problems with early stage methods, [23] argue that several ideas generated from these methods should be developed into more customer-ready prototypes before making a final decision as to which products to introduce. Therefore, the purpose of our approach is to provide a way to evaluate customer-ready prototypes in the context of an existing product line. Thus, we develop an approach that can be used in later stages of the development process when product prototypes are available. Using prototypes enables us to identify the impact of differentiation in terms of physical characteristics rather than just verbal descriptions.

B. Our Research Design

We use a simulated test market experiment employing late stage “looks like” prototypes to assess the impact of differentiation in physical characteristics. In our experiment, management first chooses a group of existing products and, for each product in the set, it determines a subset of four to six products – both rival and “our” brand – that are close competitors, called the “family.” A prototype that will compete with each family is also selected. Next, each respondent is asked to choose his or her three most preferred products from the entire set of existing products. We refer to these as the respondent’s “top three” choices. This step ensures that future questions include the products that the respondent is most interested in, and is also useful in assessing the impact of choice set context on choice. Next, each respondent evaluates four product families, including the ones containing one of his or her top three choices. The respondent provides pairwise similarity judgments of the prototype with each of the existing products in each of his

or her assigned families. Then, the respondent allocates 100 points over all products in each family, excluding the prototype, so as to reflect his or her relative preference for each. Finally, the prototype is introduced and the respondent reallocates 100 points over each family.⁴

Our simulated test market experiment bears some similarity to choice based conjoint analysis (CBCA), in that respondents are shown a set of products and a measure of respondent preferences is recorded. The difference is that rather than estimate a part-worth utility function in attribute levels to determine the effect of a new product introduction as in CBCA, we directly analyze what part of the change in consumer evaluations after a new product becomes available may be attributed to objective similarity in product characteristics.

To model the relationship between objective similarity in attributes and both choice perceived similarity, we draw on the marketing and psychology literature. Research in these fields suggests that consumers make attribute-by-attribute comparisons when making both choices and similarity judgments [28]. [29] and [30] suggest that subjects' decisions are more likely to involve attribute comparisons when the attributes of the objects are easily alignable and comparable, as is the case in our illustration.

The literature on choice has established that the choice set similarity affects choice [31]. By modeling choice as a function of underlying objective product attributes, we are able to validate this theory in a more realistic setting than those used in the existing literature. Hypothesis 1 below enables us to assess the impact of objective similarity in attributes on choice.

Hypothesis 1: The objective similarity between an existing product and a potential new product along individual product attributes is significantly related to the likelihood that a consumer will prefer a potential new product to the existing product.

The marketing and psychology literatures also provide a rich discussion of the influence of context on choice (e.g., [32]–[34]). These literatures suggest that when consumers choose from a set of product options, they do not simply compare the options along attributes and pick the option that maximizes consumer utility as a function of attribute levels, as is assumed in conjoint-based models for consumer choice. [35] suggest a method to incorporate context dependence post-hoc, after performing a standard conjoint-based estimation procedure. Using estimates from a standard conjoint model together with either a ranking of all available products or top choice

⁴See Section III for details on the simulated test experiment.

of each consumer, they modify the standard conjoint weights to produce new weights that are consistent with the ranking over all products. [36] urge that more research is needed in order to incorporate unobserved heterogeneity, including context dependence, into choice models.

Our experimental design provides one way to assess the impact of certain contextual variables on choice. In our experimental setup, a respondent's selection of a product as a top three choice among the entire set of offerings suggests positive values for unobservable contextual variables, all else equal. If context matters, then a respondent's choices should vary with the choice set context, i.e. whether or not the choice set (i.e., watch family) contains one or more of a respondent's top three watches. So, we would anticipate that after controlling for observable factors, the probability that a respondent switches from the most preferred product in a family to the later introduced prototype will be lower if this most preferred product is one of the respondent's top three choices overall, and higher, otherwise. This reasoning motivates our second hypothesis.

Hypothesis 2: After controlling for observable factors, the likelihood that a consumer will prefer a potential new product to an existing product is lower if the existing product is a top three choice for the consumer over all existing products.

Testing the above hypothesis in our experimental setup enables us to evaluate the impact of choice set context on choice. Since consumers are likely to have assigned positive values to unobservable contextual variables related to their top three choices, we are able to tease out the effect of some of the unobserved heterogeneity referred to by [36].

Our approach also enables us to examine the validity of the upstream product positioning technique of perceptual mapping based on similarity judgments. A key assumption in this approach is that the dimensions of the perceptual space are the same as those that influence preference. To test the validity of this assumption in our experimental context, we draw additionally on contrast theory [37], which posits that the perceived similarity between two products is increasing in objective similarity in individual attributes. We first test this prediction from contrast theory in Hypothesis 3 below.

Hypothesis 3: The degree of perceived similarity between products in a pair is increasing in the extent of objective similarity along individual product attributes.

Since we also model choice as a function of objective similarity in attributes, we can examine the extent to which the attributes that drive similarity differ from those that drive choice.

Hypothesis 4 below, taken together with Hypotheses 1 and 3, enables us to test the usefulness of perceptual mapping as a tool to guide the question of which product attributes to differentiate and which to keep relatively common across products.

Hypothesis 4: The set of product attributes that drive the degree of perceived similarity between an existing product and a potential new product differs from the set of product attributes that drive changes in consumer preference for the existing product if the potential new product is introduced in the marketplace.

III. DATA AND VARIABLES

A. Simulated Test Market Experiment

In this research, we use data collected in a simulated wristwatch store experiment. Since watches are typically offered in a variety of styles and makes, the experiment is an excellent setting for the empirical application. The experiment was sponsored by Titan Industries, Ltd., a large multinational manufacturer of analog quartz wristwatches based in India. At the time of the experiment, Titan offered over 1,000 models and refreshed up to 15 percent of the product line every year, after evaluating hundreds of line extensions annually. A part of this dataset was used by [18].

The experiment was conducted in 1996 by a professional market research firm in two large Indian cities, Mumbai and Hyderabad. To choose participants in the experiment, interviewers visited a random sample of households in each city, collecting information on household income and employment of household members. Low-income households (monthly income of less than Rs. 2000) and households with any member employed by an advertising agency, market research company, or wristwatch manufacturer were excluded from further consideration. In the remaining households, a randomly chosen adult member was administered a brief questionnaire as to his or her interest in purchasing jewelry, electronics, and wristwatches over the following six months. A total of 300 individuals who indicated an interest in buying a watch were then invited to participate in the experiment on the research firm's site.

For this experiment, Titan managers selected 13 prototype watch models that were potential extensions of Titan's product line for the year 1997. Then, the managers identified 35 existing watch models, including 23 watches of Titan brand and 12 competitor watches, which they believed to be close substitutes to the 13 prototypes. The 35 existing watches were grouped



Fig. 1. Sample Family of Ladies' Watches

into 13 choice sets, which we refer to as “families,” with one family per prototype. Including the prototype model, each family consists of four to six watches, with several existing watch models belonging to more than one family. Of the 13 families, eight were marketed as watches for gentlemen and five as watches for ladies. Figure 1 provides a photo of one actual ladies’ watch family.

The setting of the experiment closely mimicked what a consumer would experience in a store. All models, existing and prototype, were actual watches that could be touched and tried out, unlike in the case of many conjoint analysis studies in which respondents are given photos, pictures, or cards with product descriptions rather than actual products. Price tags were visible and attached to each watch.

On site, the experiment participants, whom we refer to as “respondents”, were initially asked to choose their three most preferred watches out of the entire set of existing models. From the total of 300 respondents, 298 individuals successfully completed this task.⁵ For further detailed evaluation, each of these 298 respondents was assigned four different watch families: all the

⁵The two remaining respondents, who failed to identify their three most preferred models, subsequently provided subjective similarity assessments for four randomly assigned prototype models (see a discussion below on the wording of similarity questions), reported their own socio-demographic characteristics, and left the experiment site.

watch families – i.e. up to three – containing any of the respondent’s top three choices, and the remaining families drawn at random from the pool of all families. Men were assigned families of models marketed as gentlemen’s watches and women were assigned families of ladies’ watches. If, for example, the top three choices belonged to the same family, additional families were assigned at random, so that the total number of distinct families evaluated by a respondent was always four. The restriction of four families per respondent was introduced to minimize respondent fatigue, whereas random assignment of at least one family was intended to ensure that every family was covered in the experiment.

Next, for every combination pair of his or her assigned watch families, the respondent assessed similarity between the two corresponding prototypes. Questions on similarity were phrased as “How similar are these 2 products to one another?” as opposed to “How similar is product X to product Y?”, eliminating the possibility of asymmetry induced by directionality of the task [37]. These perceived similarity comparisons were recorded on an integer scale from 0 (very dissimilar) to 10 (very similar). In addition, within every assigned family, the respondent evaluated similarity between the prototype and every other watch. On average, the respondents compared approximately 23 watch pairs each. Overall, perceived pairwise similarity judgments were obtained for 91 distinct pairs and, pooling across the respondents, there are 6,797 comparisons in total. At this stage of the experiment, watch families and pairs within families were sequenced in predetermined order, according to identification numbers assigned by Titan managers before the experiment. The respondents were not rushed to judgment and, as during all other stages of the experiment, were given enough time to try out watches if they wanted to do so.

Next, to elicit individual preferences and to evaluate the effect of the prototype and of choice set context on choice, the respondent was requested to perform two exercises. In the first exercise, the respondent was presented with the assigned watch families *without* the prototype models. One family was presented at a time, with families sequenced in the same order as in the stage of the experiment during which perceived similarity judgments were collected. The respondents were asked to allocate 100 points across the watches. They were instructed to assign points according to their preferences, with the largest fraction of points going to the most preferred watch in the family. In the second exercise, the prototypes were added to the previously evaluated watches in each family and the respondent was requested to *reallocate* the 100 points recorded earlier, again in line with his or her preferences.

TABLE II
STAGES OF DATA COLLECTION

Stage	Description
Pre-experimental stage	Survey of a random sample of households and selection of experiment participants
Stage 1	Collection of responses about three most preferred watch models
Stage 2	Collection of perceived similarity judgments
Stage 3	<i>Exercise 1</i> : elicitation of preferences over watch models within each family, prototype models excluded <i>Exercise 2</i> : elicitation of preferences over watch models within each family, prototype models included
Post-experimental stage	Collection of socio-demographic characteristics

Once the latter exercise was completed, the respondent filled out a short survey with questions about his or her socio-demographic characteristics. Respondents left the experiment site after the survey. Table II provides a concise summary of the data collection stages described above.

B. Explanatory Variables

As noted above, we observe some socio-demographic characteristics of the respondents. Collected data allow us to create the following respondent-specific variables: *age* represents the age of a respondent in years, *male* dummy is 1 if a respondent is male, *many adults* dummy is 1 if a respondent's household contains more than two adults, *low income* dummy is 1 if the monthly household income per adult is at most Rs. 2,000, *high income* dummy is 1 if the monthly household income per adult is at least Rs. 6,500,⁶ *no high school* dummy is 1 if a

⁶The income range between Rs. 2,000 and Rs. 6,500 comprises the base category. The income cutoffs are chosen so that respondents below the low cutoff of Rs. 2,000 and above the high cutoff of Rs. 6,500 represent – as closely as possible – the bottom and top ten percent of the sample, respectively (since the actual income distribution is “lumpy,” it is not possible to split the sample into deciles evenly). Since our choice of the cutoffs may seem arbitrary, we performed an additional analysis of robustness of the results to income categorization. First, we considered splitting the sample into high and low income ranges using the mean income as the boundary. Second, we replaced categorical income variables by actual numerical income values. In both cases, the coefficients on income variables remain statistically insignificant, and all other results turn out to be numerically very close to the ones we report in the paper. Details on the robustness analysis are available from the authors on request.

TABLE III
RESPONDENT CHARACTERISTICS

Variable	Mean	Std. Dev.	Min	Max
age	28.09	10.95	18	75
male	0.5033	0.5008	0	1
many adults	0.7766	0.4172	0	1
low income	0.1133	0.3175	0	1
high income	0.0800	0.2717	0	1
no high school	0.1066	0.3092	0	1
college degree	0.2166	0.4127	0	1
urban occupation	0.4233	0.4949	0	1

TABLE IV
WRISTWATCH MODEL ATTRIBUTES

Characteristic	Possible Values	Characteristic	Possible Values
product type	Titan brand, competitor, prototype	dial color	white, champagne, gold, black, brown, mother of pearl
case shape	round, shaped, oval, diamond	dial layout	roman prints, inserts, 12 inserts, 4 inserts, dots, plain, arabic digits
case finishing	buffed, dual finished	third hand	present, not present
case plating	gold, ion plating	date exhibit	present, not present
strap material	brass, steel, leather	day exhibit	present, not present
strap finishing	buffed, dual finished, plain, padded	price in Rs.	mean: 2134, std. dev.: 749.46, min: 1025, max: 4725

respondent did not complete secondary schooling, *college degree* dummy is 1 if a respondent has a college degree, and *urban occupation* dummy is 1 if a respondent's primary occupation is not in agriculture. Summary statistics for the individual-specific variables are given in Table III.

Titan managers provided us with a list of watch model characteristics and details on actual characteristic levels, as shown in Table IV. On the basis of this information, we created a set of variables that reflect objective similarity between watches in a given pair. Specifically, we

TABLE V
OBJECTIVE SIMILARITY VARIABLES

Variable	Mean	Std. Dev.	Min	Max
<i>objective similarity dummy variables:</i>				
case shape	0.6154	0.4892	0	1
case finishing	0.6593	0.4766	0	1
case plating	0.8681	0.3402	0	1
strap material	0.5604	0.4991	0	1
strap finishing	0.4066	0.4939	0	1
dial color	0.3736	0.4864	0	1
dial layout	0.2088	0.4087	0	1
third hand	0.7363	0.4431	0	1
date exhibit	0.8462	0.3628	0	1
day exhibit	0.8352	0.3731	0	1
titan brand	0.7253	0.4488	0	1
family	0.5824	0.4959	0	1
<i>objective similarity continuous variable</i>				
absolute price difference	648.68	555.61	0	2445

created dummy variables to denote whether or not both watches in a pair have the same case shape, same case finishing, same case plating, etc., as well as whether or not they are both of Titan brand, indicated by *titan brand*, and whether or not they both belong to the same family, indicated by *family*. We also computed a variable called absolute price difference, to capture objective similarity in price. Summary statistics for the created objective similarity variables are given in Table V.

Finally, we define a dummy variable *avored watch* that is coded as 1 if a respondent’s most preferred watch among the watches in a product family, excluding the prototype model, was one of the respondent’s top three choices over all existing watches, as recorded at stage 1 of the experiment (see Table II).

When defining the *avored watch* dummy to represent one of the top three choices over all existing offerings, we are constrained by the design of the experiment. A legitimate question to ask is whether our method is robust to this “top three” criterion, i.e., whether results would substantially change if we instead considered, for example, the “top two” or “top four” choices.

While we cannot rigorously address the latter modification of the criterion, because we do not observe the fourth most preferred watch over all offerings, we are able to analyze the impact of redefining the *favored watch* dummy to represent the top two criterion, i.e., the first and second best watches overall, ignoring the collected information about the third best alternative. We find that the reestimation results, which are available on request, are qualitatively the same and numerically very close to the ones we present in the paper, in which *favored watch* stands for a top three choice. Thus, our method is not sensitive to a small change in the criterion.

IV. EMPIRICAL MODELS AND ESTIMATION METHODOLOGY

A. Choice and Context Dependence

We observe respondent preference rankings in each product family both without and with the prototype watch model. These rankings allow us to answer the question to what extent the *change* in a respondent's evaluation of a baseline watch when a prototype is introduced is affected by objective similarity of the baseline watch to the prototype. To the best of our knowledge, we are the first to analyze this issue using experimental micro-level data.

Accurately predicting consumer choice is critical for product managers, who frequently consider many alternatives for a product line extension, each with a different market and cost impact. Ideally, managers want to pick a new model that is likely to attain a reasonable market share, without cannibalizing the firm's older models, and at the same time with a reasonable cost. In practice, surveys that collect all necessary inputs for perceptual mapping are time consuming and costly to administer, whereas data on manipulable objective attributes, physical or otherwise,⁷ of existing models and those of proposed line extensions are easily accessible. In our approach, we decompose the effect of model similarity by objective watch attribute. Once we have estimated the impact of objective similarity in each watch attribute on choice, we can evaluate the market impact of any potential new product.

In what follows, we index respondents by i and denote the vector of socio-demographic characteristics (see Table III) of respondent i by \mathbf{R}_i . Watch pairs are indexed by j and the vector of objective similarities across watch features in pair j (Table V) is denoted by \mathbf{Z}_j .

⁷The extent of after-sales service provided is an example of a non-physical but manipulable attribute.

Let dummy variable π_{ij} be 1 if a baseline watch from pair j is no longer the top choice of respondent i , after the prototype is included among watches in the family and let π_{ij} be 0, otherwise. We use a random effects probit model, in which the probability of a switch from the baseline watch to the prototype, i.e., the probability that $\pi_{ij} = 1$, is a function of objective similarities \mathbf{Z}_j , the respondent's socio-demographic characteristics \mathbf{R}_i , and an unobservable respondent effect u_i . Specifically, the probability of $\pi_{ij} = 1$ given u_i is:

$$\Pr(\pi_{ij} = 1|u_i) = \Phi(\mathbf{Z}'_j\boldsymbol{\varphi} + \mathbf{R}'_i\boldsymbol{\kappa} + u_i),$$

where $\boldsymbol{\varphi}$ and $\boldsymbol{\kappa}$ are parameter vectors to be estimated and Φ is the standard normal cumulative distribution function.

In turn, $\Pr(\pi_{ij} = 0|u_i)$, i.e., the probability of no switch from the baseline watch to the prototype, is the complement of $\Pr(\pi_{ij} = 1|u_i)$, namely:

$$\begin{aligned} \Pr(\pi_{ij} = 0|u_i) &= 1 - \Pr(\pi_{ij} = 1|u_i) = 1 - \Phi(\mathbf{Z}'_j\boldsymbol{\varphi} + \mathbf{R}'_i\boldsymbol{\kappa} + u_i) = \\ &= \Phi(-[\mathbf{Z}'_j\boldsymbol{\varphi} + \mathbf{R}'_i\boldsymbol{\kappa} + u_i]), \end{aligned}$$

where the last equality follows from the symmetry of the standard normal distribution.

As is common in the econometrics literature (see p. 778 in [38]), the above cases of $\pi_{ij} = 1$ (switch) and $\pi_{ij} = 0$ (non-switch) can be concisely combined as:

$$\Pr(\pi_{ij}|u_i) = \Phi([2\pi_{ij} - 1][\mathbf{Z}'_j\boldsymbol{\varphi} + \mathbf{R}'_i\boldsymbol{\kappa} + u_i]).$$

Then, assuming that $u_i \sim i.i.d.N(0, \sigma_u^2)$, the likelihood contribution of respondent i is obtained by integrating out u_i (see pp. 552, 798-799 in [38]):

$$L_i = \frac{1}{\sigma_u} \int_{-\infty}^{\infty} \left(\prod_j \Phi([2\pi_{ij} - 1][\mathbf{Z}'_j\boldsymbol{\varphi} + \mathbf{R}'_i\boldsymbol{\kappa} + u_i]) \right) \phi\left(\frac{u_i}{\sigma_u}\right) du_i,$$

where $\sigma_u > 0$ is an additional parameter to estimate and $\phi(\cdot)$ is the standard normal density function.⁸

In words, the likelihood contribution L_i is the probability of observing the set of decisions made by respondent i when he or she evaluated watch families, with some of these decisions

⁸ [39] discuss how to estimate the random effects probit model numerically.

representing a switch from a baseline watch to a prototype and the rest corresponding to a non-switch.⁹ The advantage of using a random effects probit model is that we allow for potential dependence across decisions made by the same respondent, even after all observable factors have been taken into account. It is crucial to do so, because the experimental design only guarantees independence of observations across different respondents rather than independence across observations for the same respondent and we can never observe all factors that determine an individual's decisions.

Importantly, using this model we can estimate the impact of the objective similarity variables (vector \mathbf{Z}_j) on the switching decision. Moreover, we can examine the effect of context dependence on choice by including the dummy variable *favored watch* as an additional explanatory variable in the model specification.¹⁰

B. Perceived Similarity

Let y_{ij} stand for the perception of respondent i about similarity of watches in pair j , in other words, his or her perceived similarity between watches in the pair. We hypothesize that y_{ij} is a respondent-specific function of the objective similarities \mathbf{Z}_j :

$$y_{ij} = f_i(\mathbf{Z}_j).$$

Further, in line with [37], perceived similarity is linearly additive in \mathbf{Z}_j :

$$y_{ij} = \mathbf{Z}_j' \boldsymbol{\alpha} + \eta_{ij},$$

where $\boldsymbol{\alpha}$ is parameter vector to be estimated and η_{ij} is an error term.

The error term η_{ij} encompasses the impact of factors other than \mathbf{Z}_j . For instance, there may be systematic differences across socio-demographic groups in rating watch similarities, as well as differences across individuals within the same group. Using specification tests to select the most efficient decomposition of the error term, we choose to decompose η_{ij} as $\eta_{ij} = \mathbf{R}_i' \boldsymbol{\gamma} + \lambda_i + \epsilon_{ij}$, where vector $\boldsymbol{\gamma}$ captures the effect of observable socio-demographic characteristics, λ_i is the unobservable respondent-specific impact, and ϵ_{ij} is residual noise.

⁹Recall that a respondent evaluated four watch families in the experiment.

¹⁰The additional explanatory dummy variable *favored watch* should not be confused with the dummy variable π_{ij} .

Thus, our model for perceived similarity becomes:

$$y_{ij} = \mathbf{Z}'_j \boldsymbol{\alpha} + \mathbf{R}'_i \boldsymbol{\gamma} + \lambda_i + \epsilon_{ij},$$

and it can be estimated with a conventional random effects estimator (see pp. 200-205 in [38]).

It should be noted that the role of the random effect λ_i in the perceived similarity model is similar to that of the random effect u_i in the choice change model. Specifically, λ_i allows us to capture potential dependence across similarity judgments of respondent i , after all observable factors have been taken into account. Still, λ_i is, in general, different from u_i , since mental processes used to make judgments about perceived similarity and choice, despite sharing many common features [28], are distinct processes. In other words, unobservable factors affecting λ_i need not be identical to the ones impacting u_i .

V. RESULTS

A. Choice and Context Dependence

The estimated choice change model is presented in Table VI. To help with the interpretation of the results, we additionally report marginal effects, which represent the change in the probability of a baseline watch losing its status as the most preferred alternative in a watch family after a prototype with the same physical attribute (case shape, dial color, etc.) is introduced.

Overall, our findings reveal that many variables of interest have sizeable effects, which are often precisely estimated. Thus, we see strong support for Hypothesis 1. Also, we find that individual gender and education matter for choice. For instance, men are less likely than women to switch to the prototype watch, which could reflect a fundamental difference in behavior between the gender groups, but may also simply indicate that prototypes evaluated by men were less appealing than the ones evaluated by women.

For the objective similarity variables, we find that the strongest effect is associated with same *dial layout*. If the initially selected watch and the prototype share this attribute, the probability that the a respondent would give up his or her baseline preference increases by 22 percentage points. This probability also increases by 9 percentage points if the watch and the prototype have the same *case shape*, by 19 percentage points if they have the same *strap material*, and by 11 percentage points if they share Titan's brand.

TABLE VI
ESTIMATED MODEL OF CHOICE CHANGE

Variable	Random Effects Probit		
<i>objective similarity dummy variables:</i>			
case shape	0.2347*	(0.1109)	[0.0882]
case finishing	-0.3488**	(0.1234)	[-0.1356]
case plating	-0.0465	(0.1950)	[-0.0179]
strap material	0.5290**	(0.1377)	[0.1919]
strap finishing	0.0673	(0.1122)	[0.0257]
dial color	0.0312	(0.0987)	[0.0120]
dial layout	0.5497**	(0.1566)	[0.2158]
third hand	-0.0102	(0.1289)	[-0.0039]
date exhibit	-0.1004	(0.1616)	[-0.0388]
day exhibit	-0.2892*	(0.1458)	[-0.1130]
titan brand	0.2756*	(0.1269)	[0.1056]
<i>objective similarity continuous variable:</i>			
abs. price difference ^a	0.0141	(0.1003)	[0.0054]
constant	-0.2336	(0.4253)	—
respondent variables		included ^b	
# of observations		1375	

Notes:

Standard errors are in parentheses. Marginal effects computed at variable means are in brackets.

* and ** denote significance at 5 and 1 percent level, respectively. $\sigma_u > 0$ at 1 percent significance level.

^aAbsolute price difference is expressed in Rs. 1,000's.

^bMale gender dummy and no secondary schooling dummy coefficient (standard error) [marginal effect] are -0.4763** (0.1559) [-0.1803] and 0.3713* (0.1764) [0.1457], correspondingly. All other respondent variables are jointly insignificant.

On the contrary, if the watch and prototype have the same *case finishing*, the probability that the respondent's initial selection is driven out drops by about 14 percentage points. This probability also drops by 11 percentage points if the watch and prototype are similar with respect to the *day exhibit* availability. Thus, the model suggests that respondents are less inclined to switch levels for some attributes, than for others.

We examine the effect of context dependence by including the dummy variable *favoured watch* in the choice change model, as shown in Table VII. The coefficient on *favoured watch* is negative and highly significant, providing strong support for Hypothesis 2. Moreover, the coefficient itself

TABLE VII
ESTIMATED MODEL OF CHOICE CHANGE WITH CHOICE CONTEXT

Variable	Random Effects Probit		
<i>objective similarity dummy variables:</i>			
case shape	0.2167	(0.1108)	[0.0816]
case finishing	-0.3302**	(0.1237)	[-0.1284]
case plating	0.0109	(0.1951)	[0.0041]
strap material	0.5941**	(0.1391)	[0.2138]
strap finishing	0.0740	(0.1127)	[0.0283]
dial color	0.0219	(0.0988)	[0.0084]
dial layout	0.5343**	(0.1566)	[0.2098]
third hand	-0.0498	(0.1291)	[-0.0190]
date exhibit	-0.0556	(0.1621)	[-0.0214]
day exhibit	-0.3115*	(0.1465)	[-0.1218]
titan brand	0.2718*	(0.1270)	[0.1042]
<i>objective similarity continuous variable:</i>			
abs. price difference ^a	0.0180	(0.1004)	[0.0069]
<i>choice context variable:</i>			
favored watch	-0.3481**	(0.0850)	[-0.1306]
constant	-0.2073	(0.4244)	—
respondent variables	included ^b		
# of observations	1375		

Notes:

Standard errors are in parentheses. Marginal effects computed at variable means are in brackets.

* and ** denote significance at 5 and 1 percent level, respectively. $\sigma_u > 0$ at 1 percent significance level.

^aAbsolute price difference is expressed in Rs. 1,000's.

^bMale gender dummy coefficient (standard error) [marginal effect] is -0.4542** (0.1547) [-0.1722]. All other respondent variables are jointly insignificant.

is quite large. Specifically, it indicates that an “unfavorable” choice context for new models may reduce the likelihood of their adoption by consumers by as much as 13 percentage points.

Conceptually, the result shows that context dependence, in the form of whether or not the choice set includes watches that are favorites based on a respondent's private information, contributes significantly to unobserved choice change heterogeneity in our random effects probit model. Moreover, our approach of identifying a respondent's most preferred watches over all

offerings highlights a path to reducing the magnitude of this unobserved heterogeneity, and provides an estimate of the potential error from failing to do so. [36] have noted that it is essential to find ways to reduce unobserved heterogeneity due to contextual variables in choice models.

B. Perceived Similarity

The estimated perceived similarity model is presented in Table VIII.¹¹ Overall, the results for the objective similarity variables provide strong support for Hypothesis 3. We find that eight out of twelve objective similarity dummies have positive and statistically significant coefficients, whereas the coefficient on absolute price difference is negative and significant, in line with intuition. Moreover, nearly all significantly estimated coefficients are significant at the one percent level.¹²

Interestingly, the *case shape* dummy has the strongest effect on perceived similarity. Respondents would rate a pair of watches with the same case shape 1.7 categories higher on the 11-point similarity scale, than when the watches had different case shapes. Objective similarity in *strap material*, *dial color*, *dial layout*, *date exhibit* and *day exhibit* availability, whether the watches share the *Titan brand* and *family* matter, as well, but to a lesser degree.

Table IX qualitatively summarizes the effect of the watch attributes on choice change and perceived similarity. Instances in which a characteristic has a statistically significant positive (negative) effect are denoted as “positive” (“negative”), with asterisks representing the significance level. The dash (“–”) indicates instances of no significant effect.

Comparing drivers of choice change with drivers of perceived similarity, we find that 5 variables – *case shape*, *strap material*, *dial layout*, *day exhibit*, and *Titan brand* – affect both perceived similarity and choice change. Thus, for the product category of wristwatches, the set of characteristics that affect perceived similarity judgments overlaps with the set of characteristics that influence choice change. However, the two sets do not coincide. In particular, three of the most significant variables that affect perceived similarity, *dial color*, *date exhibit*, and *absolute price difference*, are not even significant in explaining choice change. Also, *case finishing* is

¹¹The socio-demographic characteristics are jointly insignificant, and we do not report their coefficients to save space.

¹²The only exception is the coefficient on *titan brand*, which is significant at the five percent level.

TABLE VIII
ESTIMATED MODEL OF PERCEIVED SIMILARITY

Variable	Random Effects	
<i>objective similarity dummy variables:</i>		
case shape	1.6993**	(0.0788)
case finishing	-0.0087	(0.0859)
case plating	-0.1364	(0.1128)
strap material	0.4611**	(0.0833)
strap finishing	0.0550	(0.0724)
dial color	0.4724**	(0.0668)
dial layout	0.4688**	(0.0902)
third hand	0.0045	(0.0893)
date exhibit	0.3257**	(0.1136)
day exhibit	0.3027**	(0.1098)
titan brand	0.2132*	(0.0912)
family	0.3644**	(0.1043)
<i>objective similarity continuous variable:</i>		
abs. price difference ^a	-0.5536**	(0.0698)
constant	1.6570**	(0.4363)
respondent variables	included ^b	
# of observations	6797	

Notes:

Standard errors are in parentheses.

* and ** denote significance at 5 and 1 percent level, respectively.

^aAbsolute price difference is expressed in Rs. 1,000's.

^bAll respondent variables are jointly insignificant.

highly significant in explaining choice, but insignificant in explaining perceived similarity. In MDS, this attribute, which is relatively easy to differentiate from an operational perspective, may not even show up as a perceptual dimension. Thus, we find support for Hypothesis 4.

Also, note that although same case shape and same dial layout are important in explaining both perceived similarity and choice change, case shape is more important in explaining perceived similarity, whereas dial layout is more important in explaining choice. Therefore, case shape will likely emerge as the most important feature for product similarity and if the firm wants to create a highly differentiated new product, it will differentiate along case shape, which is an

TABLE IX
QUALITATIVE SUMMARY OF RESULTS

Variable	Choice Change	Perceived Similarity
<i>objective similarity dummy variables:</i>		
case shape	positive*	positive**
case finishing	negative**	–
case plating	–	–
strap material	positive**	positive**
strap finishing	–	–
dial color	–	positive**
dial layout	positive**	positive**
third hand	–	–
date exhibit	–	positive**
day exhibit	negative*	positive**
titan brand	positive*	positive*
<i>objective similarity continuous variable:</i>		
abs. price difference	–	negative**

Note:

* and ** denote significance at 5 and 1 percent level, respectively.

expensive proposition. However, our choice change model shows that keeping dial layout the same is the biggest reason for cannibalization of an existing Titan watch by a new Titan model. Thus, changing case shape, while very expensive to implement, may not actually protect against cannibalization if dial layout is kept the same.

C. Robustness Checks

We estimate several additional versions of the random effects probit model for choice change, to check the robustness of our results. We find that the results from these models are qualitatively similar to the ones reported in Section V.¹³

First, in a number of instances, the respondents violated a logically plausible rationality restriction proposed by [40], which in our case states that a baseline watch chosen when the prototype is available should still be selected when the prototype is excluded. Violations of

¹³Detailed estimation results for all models described in this section are available from the authors on request.

this restriction in the data (4.29 percent of responses) may be due to respondent fatigue. We check whether our previous conclusions are robust to the exclusion of observations with these violations and find that dropping such observations has practically no impact on results that support Hypotheses 1-4.

Second, the specification of the choice change model presumes that objective similarity variables enter into it additively through a linear index $Z'_j\varphi$. It may be that this specification is overly restrictive, since it omits interactions across these variables. While checking for all possible interaction effects is not feasible, we did try to assess the impact of one particular interaction that makes logical sense. Specifically, respondents may care not about objective similarity in terms of presence of *date exhibit*, *day exhibit*, and *third hand* per se, but about similarity in terms of the watch *functionality*, which represents a combination of these three features. Namely, watches are functionally similar if they have exactly the same combination of the features (say, both watches have date and day exhibits, but no third hand). Reestimating the model, we find that the coefficient of *functionality* is positive and marginally significant, but all other results are qualitatively the same as before.

Third, our model may also be misspecified if we included irrelevant variables in place of the relevant ones. In particular, we are surprised by the finding that objective similarity in watch prices has no impact on the change in choice. It may be that respondents are less likely to switch to a prototype the more expensive the prototype is relative to the baseline watch. Therefore, we created an objective dissimilarity variable called *price difference* (the difference between the price of the prototype watch and the price of the baseline watch) and substituted it for *absolute price difference*. As expected, the coefficient on *price difference* is negative, but not statistically significant, whereas all other results remain virtually the same as before.

In a separate analysis (not reported here), we used hierarchical Bayesian techniques [41] to estimate respondent-specific regressions relating objective product characteristics to perceived similarity and logit models relating product characteristics to choice. Then, using the method of conjoint analysis, we calculated the importance of each attribute for perceived similarity and for choice and computed respondent-specific correlation coefficients across the attributes. The average correlation coefficient in the sample is .07, and this low value provides additional, although, indirect, support for Hypothesis 4.

VI. DISCUSSION

As most new products are not developed in isolation, but are part of an existing product line, determining which product attributes to differentiate and which to keep in common is an important driver of profitability as it impacts both revenues and costs. Furthermore, many existing tools to help design optimal new products and product lines use verbal product descriptions early in the new product development process. However, as noted by [23] verbal product descriptions do not always capture aspects such as aesthetics and usability. They suggest that several verbal models be further developed into more customer ready prototypes before making decisions about which new products to introduce. Our methodology complements these early stage tools as it provides a way to incorporate information from product prototypes into decisions about how to differentiate a firm's offerings.

Our methodology, allows one to make recommendations regarding the selection of product line extensions. To do so, we focus on the qualitative results of the model for choice change, contained in Table IX. For example, if a line extension has the same *case shape*, *strap material*, and *dial layout* as successful watches currently on the market, the line extension will tend to take market share from these products. Objective similarity in *case finishing* and presence of *day exhibit* will mitigate this effect.

This information can be used either to introduce line extensions that will cause minimal disruption in the other products in the firm's own product line or it can be used to cause maximum disruption in the products in another firm's product line. These market effects must be traded off against the costs of differentiating along different attributes. Therefore, a firm may choose to cannibalize one of its currently successful products if it can do so with a higher margin product by offering an extension with the same *case shape*, *strap material*, and *dial layout* as the successful product. Alternatively, it can focus on a different segment by differentiating the extension from the successful product on these same attributes. Similarly, a firm can either choose to attack a competitive product directly by offering an extension with the same *case shape*, *strap material*, and *dial layout* as it has. Alternatively, it can choose to focus on a different segment from the competition by differentiating on these same attributes. Therefore, while our illustration has focused on cannibalizing a firm's own products, the basic findings can be used in a number of ways.

Certainly, in each specific instance, the choice of a new model may be more a matter of art than science. However, our methodology provides a new lens on this difficult problem of deciding which products to market, by capitalizing on the downstream availability of physical product prototypes.

Our results also provide a way to assess the impact of context on choice, or in other words, to reduce some of the unobserved heterogeneity associated with choice models. While [35] developed an approach to adjust conjoint weights post factum in order to factor in information about a respondent's most favored choices that is not captured in the conjoint experiment, we demonstrate that there is a need to reduce the magnitude of unobserved heterogeneity in the choice task itself.

Finally, a key finding from our study is that the underlying product attributes that drive perceived similarity are not identical to those that drive changes in relative preferences when a product line extension is introduced. Taken together with the well known fact that the cost of differentiation varies by attribute, this finding has important implications for practitioners designing line extensions. Essentially, it suggests that the widely used approach of analyzing perceptual maps derived from perceived similarity data may in some cases result in new product choices that both reduce revenues *and* increase costs. Thus, practitioners need to use discretion in applying this technique. Our approach provides a way to check whether or not perceptual mapping based on similarity data should be used as an aid in product positioning, for a particular product category.

VII. LIMITATIONS AND FURTHER DIRECTIONS

The methodology we have developed in this paper is appropriate for aiding in differentiation decisions for product line extensions, as opposed to radically new products. Also, our methodology is not directly generalizable to products that have very many attributes, like automobiles. In these cases, the number of attributes is too large for a comparison across all attributes and the analysis must focus on a subset of the attributes that have been determined to be important by some other method.

While this study used physical prototypes, advances in ways to construct virtual prototypes mean that this kind of research can be conducted at a slightly earlier stage in the process [42]. The ability to make these decisions earlier in the development process may open up a number

of opportunities for new research.

This research has looked at the impact of perceptual similarity on the probability of cannibalizing. Another interesting approach is looking at the impact of similarity of utility on the probability of cannibalization [43].

The focus of this paper has been primarily on determining the impact of a new product on products in an existing product line of the same firm. As suggested in Section VI, another interesting extension is to look at the impact of a new product on existing competitive products. While one might want to minimize cannibalization within a firm's product line, one may want to maximally disrupt competitive product lines, even if it does not add that much to one's own bottom line.

Finally, our methodology contributes to better assessing the market impact of line extensions using late stage prototypes. However, as mentioned in the introduction, when making decisions on which product attributes to keep common and which to differentiate, managers must analyze both the market impact as well as the cost impact of attribute level decisions. This is important because the market and cost impact of differentiation can be quite different for any particular attribute. Thus, developing models that incorporate cost issues into more sophisticated methods for assessing market impact is a fruitful direction for future research.

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