Design for the Marketing Mix: The Past, Present, and Future of Market-Driven Engineering Design

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The four Ps of the marketing mix (Product, Price, Place, and Promotion) serve as a framework for characterizing the marketing decisions made during the product development process. In this paper, we describe how the last 40 years of engineering design research has increasingly incorporated representations of preference as a means of addressing the decisions that come with each "P." We argue that this incorporation began with problem formulations based on Product only, with surrogates of preference posed as objectives (such as minimizing weight, minimizing part count) representing a firm's desire for offering a mix of products while reducing cost and maximizing profit. As the complexity of problem formulations progressed, researchers began representing preferences of the designer (using decision theory techniques) and of the customer (often in the form of random utility models). The Design for Market Systems special session was created specifically in the Design Automation Conference for advancing our understanding of design in the content of a market, extending from the decision-based design framework introduced by Hazelrigg. Since then, researchers have explored the engineering design problem formulation challenges associated with the marketing decisions of Price, Place, and Promotion. This paper highlights the advancements of the design community in each of the Ps and shows how the marketing decisions of Place and Promotion extend from the central hub of considering Price in an engineering design problem. We also highlight the exciting research opportunities that exist as the community considers more complicated, and interconnected, problem formulations that encompass the entirety of the Marketing Mix.
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1 Introduction

The first *Design for Market Systems* special session was held in 2008 by the Design Automation Conference as part of the ASME International Design Engineering Technical Conferences and Computers and Information in Engineering (IDETC/CIE) Conference. As this community passes 10 years of concerted research effort in the area of market-driven engineering design, we observe how far the conducted research has advanced the state-of-the-art and identify compelling opportunities and avenues of future work. We review the progression of market-driven engineering design problem formulations and the resultant research from the perspective of the Marketing Mix [1], or the four Ps of Marketing as refined by McCarthy: Product, Price, Place, and Promotion.

We choose the Marketing Mix as the framework for our review because navigating the different marketing considerations yields problem formulations of increasing complexity and consideration of different design problem aspects. In Sec. 2, we show how engineering design research into product abstraction using form and function, and developments in multidisciplinary optimization, (often indirectly) address Marketing Mix decisions associated with *Product*. *Product* in the Marketing Mix describes decisions about product architecture, product line positioning, and product quality. These efforts are highlighted in this paper because they serve as a foundation for market-based engineering design research.

In Secs. 3 and 4, we show how the gradual integration of engineering and marketing disciplines facilitates the consideration of Marketing Mix decisions associated with *Price* (often through descriptors of purchase propensity that signify customer-perceived value). We argue that the inclusion of consumer behavioral models characterize and differentiate market-driven engineering design problems from other engineering design research. For example, some of the earliest academic studies, such as Shocker and Srinivasan [2] in 1974, describe how a single optimal (or improved) product solution can be generated using models of customer preference and demand. As repeated from Ref. [2], their approach has four steps:

(1) *Identify the relevant product-market.*
(2) *Represent these brands (products) abstractly.*
(3) *Provide a behavioral model consistent with user buying choices among existing products—to be used in predicting how potential purchases will react to nonexistent alternatives.*
(4) *Use the model (3) in implementing search to find or come close to finding that location or set of locations for new products which best achieve objectives specified by the firm.*

They also highlight the challenges of defining an appropriate set of objectives (step 4), stating that

> Ideally, search should be guided by a criterion such as net present value of incremental profits.… The viability of such a criterion depends upon the existence of means for predicting both incremental revenues and costs as functions both of time and of location within feasible regions of the attribute space. Such projections may be difficult to make validly.

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Green and Krieger [3] further expand on these objectives when multiple products are simultaneously designed by quantifying the welfare of the buyer [4] and the seller [5] in product line design problems.

We further argue in Secs. 3 and 4 that the decision-based design (DBD) framework [6] proposed by George Hazelrigg most comprehensively outlines a market-driven engineering problem by identifying the relationships between product architecture, sources of uncertainty, costs, product configuration, design automation, and the attainment of business objectives. Combined, these works have provided a springboard for four decades of research by incorporating the motivations of the customer and expanding the scope of research across all domains of the Marketing Mix.

In Secs. 5 and 6, we discuss research addressing Marketing Mix decisions of *Place* (channels of distribution) and *Promotion* (influencing customer perception through product image and/or offers). We show how decisions in these areas require unique problem formulation extensions that build on the concept of customer-perceived value established when considering *Price*. Most importantly, as shown in Fig. 1, research in market-driven engineering design has expanded the scope of problem formulation from the rather constrained decisions of *Product* in the Marketing Mix by considering the remaining marketing decisions. It is the complexities of these new problem formulations, and those problem formulations that will be associated with new Ps, that offer compelling avenues for future research activity.

2 Product in the Marketing Mix: Form, Function, and Product Modeling

We begin this section by acknowledging the inherent coupling of the Marketing Mix 4Ps and by acknowledging that each P is inherently important. In structuring our review, we use the different elements of the Marketing Mix as a theme for describing the major contributions of research efforts in the market-driven engineering design literature. This review starts with a focus on *Product* because the general nature of these decisions impact product mix through choices about product architecture, how a product architecture is used for creating product variants and assessing and managing the product's lifecycle.

We also posit that many of the fundamental *Product* decisions associated with the Marketing Mix are supported by research that has occurred outside of market-driven engineering design. Yet, this research establishes a foundation for addressing the other Ps by formalizing the interplay between system design parameters, system attributes, and costs. Of particular relevance are research efforts in product platform design [7], specifically those that have advanced our understanding of how modularity [8,9] and scalability provide opportunities for achieving product variety while controlling cost. Further, design tools like the House of Quality [10] provide an approach for relating customer and technical attributes on a qualitative basis, while design methods like functional modeling establish relationships between a product's abstraction in terms of function and the attainment of product variety [11].

In establishing analysis techniques for a proposed product architecture, designers must also choose whether monolithic or distributed system architectures are appropriate [12], or if hierarchical modeling approaches are needed [13,14]. Multidisciplinary design optimization (MDO) methods of various forms have been introduced in the literature, and a key assumption of these optimization problems is that designers act rationally when making product configuration decisions [15].

As the relationship between product mix and consumer response is not explicitly modeled, it is assumed that demand exists in a known quantity a priori—such as in a procurement contract awarded by the military or a set of satisficing specifications that have been established in a requirements document [16]. Often, problems are formulated in ways that navigate the tradeoffs occurring between system attributes, facilitating natural extensions of the design optimization problem that account for sources of uncertainty such as robust design [17–19] and reliability-based design optimization [20,21].

By using the satisfaction of requirements as a surrogate for demand, the focus was placed on modeling the designer's (engineer's) utility for different engineering options [22,23] and became the primary driver of decision-based design research. Tradespace exploration of product mix [24–27] has been proposed for establishing the construction of a value function [28,29] by allowing the real-time generation of designer preference [30–32]. However, this also means that consumer preferences are not explicitly modeled, limiting the role of price as a design variable and severely limiting simulations of consumer purchasing decisions among a set of available products.

The absence of formal studies linking design decisions and consumer preference motivated researchers in both the marketing and engineering communities, as problem formulations that neglect consumer preference can result in solutions that forfeit significant value. Richer problem formulations were needed that capture customer purchase propensity. The inclusion of consumer preference established market-driven engineering design problem formulations simultaneously considering product mix and price and resulted in the creation of the Design for Market Systems special session.

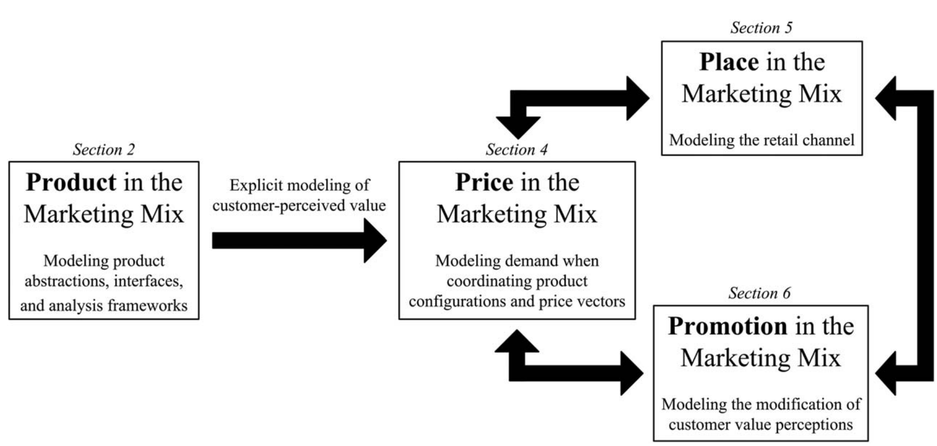

Fig. 1 We use the Marketing Mix as a means of discussing market-driven engineering design problem formulations. While all Ps are inherently interconnected, we argue that Price is a fundamental extension because of the explicit modeling of customer-perceived value. From this formulation, Place and Promotion decisions yield problem formulations with greater complexity.

3 The Decision-Based Design Framework Describes the Flow of Decisions in Market-Based Engineering Design When Considering the Remaining Marketing Mix

Explicitly including product price in the design problem formulation allows for the creation of market simulators that model consumer choice among available alternatives. This, in turn, supports the calculation of business objectives. Yet, this also requires an explicit mapping between engineering decisions and customer-perceived value. In defining the DBD framework, shown in Fig. 2, Hazelrigg states that potential customers perceive *System design* (x) and *Exogenous variables* (y) as having limited or no particular meaning. He acknowledges that these variables do influence manufacturing and life cycle costs, but argues that *System attributes* (a), *Product price* (P), and *Time* (t) are the key drivers of demand. This creates an iterative sub-optimization process where the *utility* (u) of an alternative is maximized by finding the optimal vector of product prices after establishing the vector of system attributes for each product. Value (utility) of an alternative is assigned using a von Neumann–Morgenstern utility [33], promoting rational engineering design decisions.

The DBD framework spawned at least two distinctly different avenues of research, each defined by the decision they consider [34]. The interest in describing the designer's decision-making process as a rational one resulted in exploratory studies of product development decision-making [35], exposition on the application of normative decision analysis in the engineering design process [36], and methods for elicitation and application of designer preferences in engineering decision-making [37,38].

We argue that our understanding of market-driven engineering design problems has benefited most from research where the customer's decision-making process is the focal point. Here, products' sales volumes and market-bearing prices are estimated by exercising customer purchase behavior models. These models, combined with cost estimate models, enabled the consideration of *Price* decisions in the Marketing Mix. The *Design for Market Systems* special session was created so that researchers could better distinguish their contribution from the research focused on modeling designer decision-making.

The earliest efforts integrating *Price* and product mix explore the use of conjoint analysis [39], linear demand models [40,41], and calculations of the net present value of profit when making product improvements [42]. Li and Azarm [43] expanded on these efforts by estimating utility functions for individuals using conjoint analysis and linear regression. They also considered net present values of share and profit. However, a limitation of conjoint analysis is that a ratings-based regression does not provide a probabilistic representation of consumer choice. Discrete choice experiments address this limitation using logistic regression and various forms of random utility models.

Wassenaar and Chen [44] introduced what could be considered the archetype for applying a random utility model in a market-based engineering design problem. Numerous extensions of this work have been created, including decomposing the optimization problem in the engineering domain [45–47] or in the marketing domain [48,49], designing entire product families rather than single products [50–53], and estimating a demand model using revealed preference data [52–54]. Since then, a wide variety of market demand models have been used, including models derived from traditional econometric methods [43,50–52,55,56] and random utility models spanning from multinomial logit [44,46,47,54] through generalized extreme value [49,53] and mixed logit [57,58].

These works further demonstrated that engineering design decisions can have a direct impact on business objectives and customer purchase propensity. Motivated by these efforts, researchers in the engineering design community began asking questions about the relationship between design decisions and problem formulation strategy. These works, which integrate the Marketing Mix decisions of *Product* and *Price* as the foundation of their problem formulation are discussed Sec. 4.

4 Price in the Marketing Mix: Coordinating Decisions of Product Mix and Pricing

This section presents the research progress made in understanding, formulating, and solving market-based engineering design problems that link configuration and product price decisions by accounting for customer-perceived value. The review in this section discusses papers published under the *Design for Market Systems* heading from 2008 to 2017 by mapping their research objectives and contributions areas onto elements of Hazelrigg's DBD framework. This is done so that the key assumptions being challenged about problem formulation can be discussed, and so that the aspects of the framework receiving greater amounts of

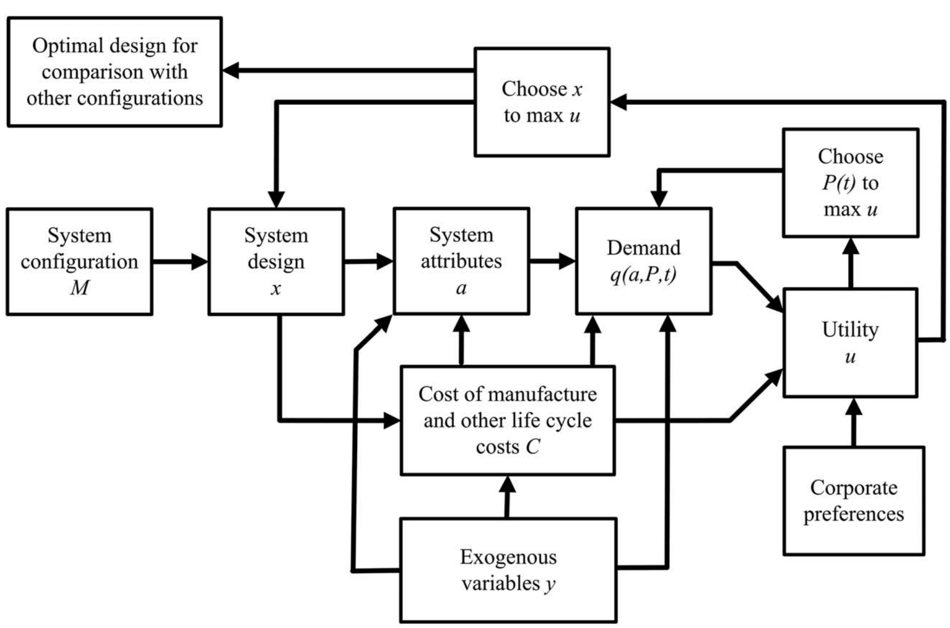

Fig. 2 A framework for decision-based engineering design (from Ref. [6])

research attention can be identified. In line with Fig. 2, the following categories will be discussed:

(1) Linking system design (x) and attributes (a) to the demand model (q)
(2) Cost of manufacture and other life cycle costs (C)
(3) Form of demand model (q)
(4) Optimizing the product concept
(5) Exogenous variables (y)

4.1 Linking System Design and System Attributes to the Demand Model. Our review of the literature found that only a small subset of papers directly addresses the link between system design variables, attributes, and the demand model. Much of the surveyed work assumes that the technical attributes defining the form and function of the design are well established, and place a more significant concern on the form of the demand model or the type of customer information captured when estimating the demand model. Two significant topics covered under this heading address (1) the challenge of visually representing product form so that a customer rating can be obtained and (2) understanding the relationship between different product attributes so that an appropriate demand model can be constructed.

Most market-driven product design studies are formed using text-based representations of a system. That is, respondents are presented with textual descriptions of product attributes and the qualitative/quantitative values that those attributes take on. Visual conjoint analysis [59–61] challenges this paradigm by representing a product using visual representations, inherently linking product form and customer preference. The major contribution of these works is that they explore how a shape should be parameterized and how this parameterization should be represented in a marketing research study. This is a significant departure from a bulk of the literature that lists product attributes in a text-based form and where the preference information being captured is about feature inclusion and/or qualitative/quantitative measures of system performance. An example of visual choice-based conjoint question used in Ref. [61] is shown in Fig. 3. Respondent perception of a vehicle's front-end is also considered in Refs. [62,63]. In these works, conjoint analysis is used rather than choice-based conjoint, and the preferences are estimated using scaled ratings and pairwise comparisons.

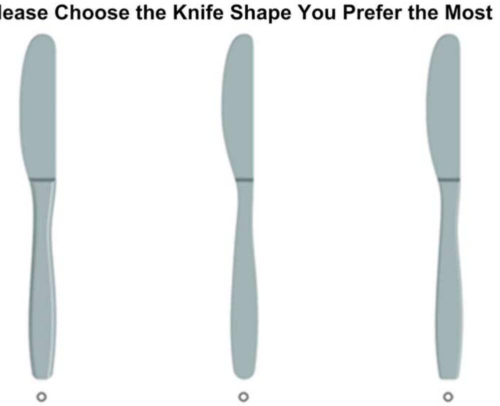

Fig. 3 Example visual choice-based conjoint question. The three attributes considered were the knife's slope, edge and end (from Ref. [61]).

We also include the hierarchical choice model approach from Refs. [64,65] in this section because of the larger ramifications implied by its hierarchical structure. As shown in Fig. 4, as taken from Ref. [65], respondent choices may be driven by their perception of various product attributes that exist multiple levels (M_1–M_3) above the engineering design decisions made in product definition and embodiment. A series of vehicle dimensions (denoted by x_1–x_8) were considered that represent engineering dimensions associated with the vehicle door opening (HEL_Z, GRD_Z and StoH), headroom (HR_X, HR_Y, HR_Z), and occupant package length (HNG_X) and width (ROK_Y). Further, these product attributes may be judged by a consumer on a quantitative or qualitative scale (often ratings based). By constructing a hierarchical choice model, a multi-level design space is navigated. This structure resembles the multi-level design space that is common in complex system design and multidisciplinary optimization approaches. Further, the hierarchical structure allows for detailed design decisions at the system level, or for a single sub-system.

Convergent product research [66] is also included in this section because it explores how functionality couplings can be addressed by integrating design solutions from existing product categories. We also include the work from Ref. [67] because it challenges assumptions about how many technical attributes actually drive demand. Five years' worth of data from residential solar photovoltaic installations in a California market were fed into three different machine learning methods so that critical technical attributes driving engineering design decisions could be identified. From a set of 34 technical attributes pulled from solar panel specification sheets, it was found that only three attributes critically influenced demand.

With the few exceptions listed above, market-driven engineering design literature often assumes that the system attributes: (1) which influence demand can be readily identified by the design team, (2) are well defined, and (3) focus on feature inclusion or quantitative performance. While the statistical significance of system attributes can be challenged in model fitting (as discussed in Sec. 4.3), there is usually minimal discussion about how system attributes are selected and whether they are the parameters actually driving respondent choice (it is assumed that, at a minimum, a subset of

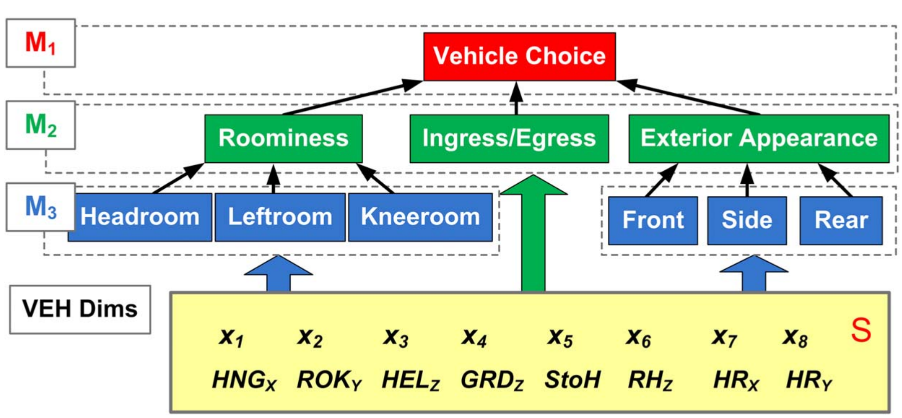

Fig. 4 All-at-Once Hierarchical Choice Model Estimation (from Ref. [65]). Engineering variables are the vehicle dimensions at the bottom of the figure.

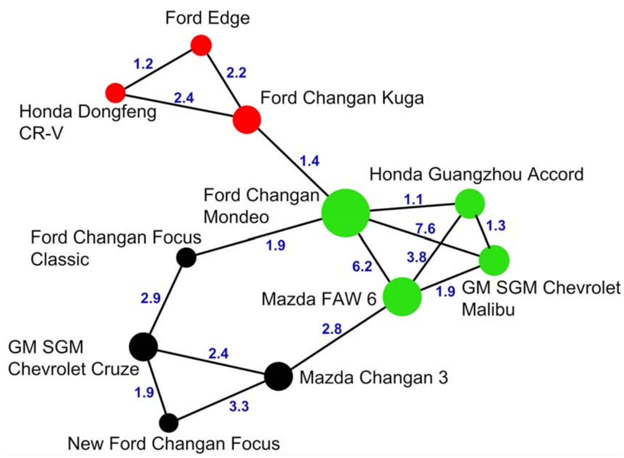

Fig. 5 An illustrative example of creating a network of vehicle associations to influence choice behavior (from Ref. [86])

the modeled system attributes influence choice in a meaningful way). This is also done without discussing the manner in which the system is purchased. We revisit and challenge this assumption when discussing decisions about *Promotion* and *Place* in the Marketing Mix in Secs. 6 and 7.

4.2 Cost of Manufacture and Other Life Cycle Costs (C). System design and system attribute definition align with the engineering space and influences manufacturing and lifecycle costs. All papers that consider the optimization of net present value for a product must define some cost structure. We found that of the relevant papers surveyed, research focused on extending problem formulations for product lines or product families. These efforts pursue the direct integration of decisions about *Price* and *Product* in the Marketing Mix, while opening avenues for research about *Promotion* and *Place* decisions in the Marketing Mix.

A product family deployment problem is introduced in Ref. [68] as a way of exploring decisions about required engineering resources, product lineup configuration, sequence of product rollout, and profit. Modules selected for the product line are determined by identifying commonality opportunities using a combinatorial optimization problem. Commonality is later treated as a surrogate for cost savings in Ref. [69] and used as a competing objective against market share. This formulation explores the relationship between cost, market share, and the number of product variants offered by the firm. A change in logit of preference share is used for determining the number of products that should be offered. Both bottom-up and top-down platforming approaches are investigated, and an activity-based costing method for top-down product family design is presented in Ref. [70].

Finally, product architecture and supply chain configuration decisions are integrated in Ref. [71]. Outcomes from this approach combine commonality strategy with manufacturing site selection for module production, assembly, and distribution. An important element of the Marketing Mix discussion is introduced by these papers. Random utility model application became more prevalent in market systems research as a means of representing the heterogeneity present in most product markets. Without an adequate consideration of cost, however, an optimization algorithm maximizing objectives of market share or revenue will increase the number of variants fielded without check. The incorporation of cost provides a stepping stone for the consideration of retail channel structure, as discussed when considering *Place* in the Marketing Mix.

4.3 Form of Demand Model. The third step of Shocker and Srinivasan's framework [2] requires creating a behavioral model consistent with how people make purchasing decisions. The research we surveyed address this challenge by considering data origin (where the data comes from and what survey instrument is used) and how the form of the market research model impacts optimization results (product configuration and prices).

Before selecting a model form, data are collected. Research into data collection techniques includes algorithm development for optimal experimental design that avoids respondent fatigue for human appraisal questions [72] and approaches resembling Efficient Global Optimization [73] that create questions using feedback from prior responses [67]. A query algorithm has also been introduced that updates the user preference model during data collection [68], allowing for survey length reductions by querying preferred designs from previous users with a similar preference structure. These efforts parallel adaptive choice-based conjoint techniques [74] introduced by the marketing research community that improve part-worth estimation when the number of questions per respondent is small.

Collection and fusion of survey data obtained directly from respondents are found in Refs. [75–77]. Modeling of customer interests and choice behavior at different stages of product design and development is studied in Ref. [75]. The results of this study indicate that a Decision Tree algorithm is more effective at predicting attribute relevance, while discrete choice analysis is more suited for estimating the share of an alternative. The unique nature of Customer Satisfaction Survey data is explored in Ref. [76]. This study found that an integrated mixed logit approach is most effective because of the lack of choice set information, the use of subjective ratings for product attributes, and collinearity amongst attributes. Further, they found that Customer Satisfaction Surveys often violate the first rule of Shocker and Srinivasan's framework [2] in that the products captured in the survey (real products on the market) did not represent a comprehensive enough range for each product attribute. The fusion of data from disparate data sets is explored in Ref. [77] by considering van Westendorp studies [78] and conjoint data. This allows for the use of multinomial logit analysis and a statistical test for measuring the fusibility of disparate data sets.

After collecting the data, the form of the demand model must be selected. This has resulted in two major research directions: (1) exploring the choice and functional form of demand model and (2) incorporating usage context. The ramifications of model form are explored in Ref. [79] by using automotive vehicle market data. Two different models forms are considered: horizontal differentiation and conventional model forms aligned for vertical differentiation. Horizontal differentiation occurs when consumers disagree about the relative ordering of products (or product attribute levels), while vertical differentiation occurs when agreement aligns with the relative ordering of products (or attribute levels) but there is disagreement on willingness to pay. Model evaluation methods used in this work include fit, interpretability, predictive validity, and plausibility. These measures, however, only allow for relative assessments of model quality. In stating their conclusions, the authors of Ref. [79] suggest a two-stage decision process modeled on a consider-then-choose formulation that is further explored in Ref. [80].

Vehicle data from 3 years of revealed preference data (2004–2006) is used in Ref. [81], and an exhaustive combinatorial set of utility covariates are used when estimating multinomial logit models. When simulating these models in the next year of data (2007), it was found that predictive capability is driven more by the presence of utility covariates and less by the form of the model. Finally, the work in Ref. [82] compares the relative performance (in terms of model fitness) and predictive ability of two heterogeneous market models (hierarchical Bayes mixed logit and latent class multinomial logit). Differences are observed both in preference structure and in the product line optimization result for a share of preference problem. It was found that better model fitness, predictive ability, and reduced design error are associated with the hierarchical Bayes mixed logit model because of its continuous representation of heterogeneity and larger degree of freedom.

The form of the choice model has also been manipulated by incorporating usage context [83,84]. The argument made in these works is that an overreliance on marketing and demographic attributes result in incorrect predictions of the attributes that actually drive choice for engineered systems. Product performance is modeled as a function of the design and usage context. By incorporating the usage context in a respondent's utility function, market segmentation opportunities can be considered. The impact of a social network on new product adoption rates is explored in Ref. [85], where peer effects are integrated with discrete choice responses in a three-stage process. Network analysis has also been used when studying the interactions between consideration behaviors. This is accomplished by creating associations between product attributes, customer demographics, and vehicle popularity [86,87] as shown in Fig. 5.

Finally, there is a subset of work exploring new forms and techniques for capturing customer information from surveys. This began with the use of User Generated Content available on the web [88]—such as blogs, social networking interactions, and online reviews. Various machine learning approaches have been explored that are capable of mining transactional data for hidden purchasing patterns. This use of data mining is used for:

- combining customer preference and technological obsolescence [89],
- creating new choice modeling scenarios [90],
- exploring the viability of Twitter as a source for product opinions [91],
- yielding high-accuracy predictions of preference by employing sparse coding and sparse restricted Boltzmann machines [92], and
- and creating market segments from online reviews focused on individual product attributes (such as zoom on a camera) and identifying attribute importance rankings [93].

It is this transition toward an online environment that we feel has the most significant opportunities. Customers can now access product data, reviews, and a selection of product offerings that is historically unmatched. Changing the manner by which consumers access and consume data, and where purchasing decisions are made, requires extensions of *Price* considerations in the Marketing Mix by including *Place*, as discussed later in the paper.

4.4 Optimizing the Product Concept. The iterative nature of Hazelrigg's DBD framework creates a direct relationship between corporate preferences, measures of goodness, and optimization of the product concept (configurations and prices). Optimization results are driven by the form of the demand model chosen and the market simulator constructed. Major modeling considerations in the market simulator include which set of competitor products should be represented and how the competition responds once new products are introduced. While profit or revenue is often used in single-objective optimization problem formulations, multiobjective formulations have also been introduced that trade market share with profit/revenue, for example. In our review of the literature, research efforts address three aspects of optimizing the product concept: formulating the objectives of the optimization, defining competitor response, and managing the computational cost/complexity of the design space.

We argue that the problem formulations introduced in the literature are often driven by supplemental research interests that integrate with market-driven engineering design. For example, a multiobjective formulation is introduced in Ref. [94] that explores the trade between maximizing profit (a business objective) and a product's environmental impact (a social objective). This trade is explored by modeling the interplay between technology changes, competition, preference, and regulation. A policy-driven optimization problem is constructed in Ref. [95] that identifies the most profitable product development efforts in a given policy environment. This work uses technology-adoption indifference curves and discusses how government organizations could use the formulation when defining policies that maximize technology adoption within a market. A customization environment is considered in Ref. [96] that minimizes a measure of customer sacrifice by considering the increased costs of product customization. This formulation is constructed so that firms can identify which components should be made available in a build-to-order environment. Finally, a satisficing optimization problem is constructed in Ref. [97] as a means of exploring whether a computer can generate designs that satisfy style-based design goals.

There have also been significant advancements that explore how the dynamics within the market simulator impact the optimized product configurations. The marketability of a vehicle concept subject to design constraints is explored in Ref. [98] by considering technology advancements, vehicle style, and market fluctuations that change customer preference. A responsive competitor is considered in Ref. [99] by allowing for pricing reactions. Three product design case studies are introduced, and it is shown that a Stackelberg leader strategy outperforms a Nash strategy when the objective is profit. However, it is also shown that both strategies outperform one that ignores competitor reactions. The numerical stability of an optimization in such "design-then-pricing" problems is explored in Ref. [100] by comparing the outcomes when equilibrium prices are treated as an intermediate quantity, and when prices are treated as variables that must satisfy a constraint describing equilibrium.

Finally, there are a number of works that consider the computational cost associated with optimization in market-driven engineering problems [101–103]. These works explore more effective optimization starting locations using the demand model. The starting population of a genetic algorithm is seeded using a targeted population strategy for both single and multiobjective problem formulations. Respondent-level preference estimates from a hierarchical Bayes mixed logit model provide the information needed when creating the initial designs. The notion of algorithm tailoring is extended in Ref. [103] by exploring crossover operators modifications in ways unique to market-driven engineering problems. Combined, these studies demonstrate that using information from the market model can reduce computational cost and improve solution quality when optimizing product line design problems.

The role of design prohibitions as constraints is explored in Ref. [104]. Design prohibitions exist when two product attributes cannot mutually exist together on a defined configuration. This paper explores the effectiveness of two strategies: (1) incorporating design prohibitions when estimating the design model versus (2) enforcing design prohibitions as constraints during the optimization. The recommendation made by the authors is that constraints should be included in the optimization problem formulation rather than enforcing the prohibitions in model estimation.

4.5 Exogenous Variables. We view the exogenous variable block from the DBD diagram as encompassing focused efforts that address the presence of uncertainty. While specifying the form of the demand model was covered in Sec. 4.3, the papers in that section do not explicitly focus on the relationship between uncertainty and product (line) optimization. As discussed in Ref. [105], at least two forms of uncertainty can be associated with the choice model: structural and parameter. Structural uncertainty can be thought of as demand model misspecification [106–108]. Parameter uncertainty is associated with the model parameter estimates—including, but not only, part-worth values and segment probabilities. Additionally, uncertainty exists when considering the representation of competitor products (configurations and prices), the manufacturer's product attributes (such as fuel economy, acceleration time), and the manufacturer's component costs.

Outside of the *Design for Market Systems* session, researchers have explored parameter uncertainty using draws from a posterior distribution, interval variables, or moment estimation techniques. Camm et al. [109] and Wang et al. [110] use samples from the posterior distribution and introduce post-optimality robustness tests that assess the negative impact of part-worth uncertainty. In Ref. [109], individual draws are used so that the deterministic optimization problem can be repeatedly solved. The optimal product configuration is also found using part-worth coefficient point estimates. Resultant solutions are then compared, and the product configuration that maximized first choice share when using point estimates aligned with only 23.5% of the random draw solutions. Wang et al. [110] implement a sample average approximation method using stochastic discrete optimization [111]. Parameter uncertainty is modeled by pulling multiple draws from a respondent's posterior distribution. Each draw is then treated as a separate respondent, and the product line is optimized. Results from this study showed that as the sampling of the posterior distribution increased, the number of optimal products reduced.

Wang and Curry [112] studied robustness in the share-of-choice problem by assuming that individual preferences are bounded, independent, and symmetric. Also, the covariance matrix for individual-level part-worths is assumed to have a diagonal form, preventing correlation among product features. Luo et al. [113] and Besharati et al. [114] use segment-level part-worth confidence intervals and calculate the lower and upper bounds of product utility. Both studies only consider the design of a single product (rather than a line) but consider multiple design objectives, namely, maximizing the share of preference using the nominal model, minimizing variation in share of preference, and minimizing the worst-case performance.

Within the engineering design community, a Bayesian approach from the econometrics literature has been applied so that the variance of predicted profit can be decomposed into two components [115]. These components represent the intrinsic uncertainty that cannot be avoided and the extrinsic uncertainty arising from a lack of precision in the model calibration parameters. Adopting a simulation-based approach avoids the limitations of analytical treatments when non-normal distributions are encountered. Resende et al. [116] explore the uncertainty in a profit maximization problem by considering firm-defined risk tolerance. An α-profit metric is introduced so that the optimal solution has a $(1-\alpha)$ chance of exceeding the found value of profit given the distribution of possible outcomes in an uncertain market. Here, it is assumed that uncertainty exists in the model parameter estimates but the demand model's form is correctly specified.

The work in Ref. [117] introduces a multiobjective confidence-based product line optimization problem that considers parameter uncertainty when calculating First Choice Share (FCS), confidence-level of the FCS, and choice inconsistency. A utility-theory based approach for handling multi-attribute decision-making is used [37], motivated by research on the engineer's decision-making process that also spawned from Hazelrigg's DBD framework. This approach was later updated using the robust product line optimization formulation presented by Bertsimas and Mišić [105] that optimizes worst-case revenue over an uncertainty set. A three objective problem formulation is used that maximizes revenue under a nominal model, maximizes the worst-case revenue from an uncertainty set, and minimizes the variation of First Choice Share within the product line [118].

Finally, the work in Ref. [119] addresses the challenge of launching new product models when market requirements change over time using a real options-based approach. Both price and design modifications are considered, but a redesign decision must be made in advance since it requires greater engineering effort. A hybrid electric vehicle design problem is discussed where gas price is uncertain over time. Profit maximization using a reliability-based optimization framework is presented in Ref. [120] by modeling the uncertainties associated with battery life and driving patterns of electric vehicles. These papers represent the few efforts—compared against the number of papers exploring the form of demand model—that optimize product configuration while considering outside factors that are beyond the designer's control.

4.6 Lessons Learned From the Design for Market Systems Review.

Our review of the literature found that, over the last 10 years, the engineering design community has spent significant effort exploring the impact of demand model choice/form by considering various sources of consumer inputs and different implementations of the random utility model. This application of economic theory in the context of the DBD framework complemented the original motivation for the framework itself. In introducing the DBD framework, Hazelrigg was more concerned with the decision-making challenges faced by the designer and how utility theory could ensure that rational choices were being made during alternative selection. The richer understanding of preference modeling (a representation of product demand) has been driven by an interest in achieving higher fidelity estimates of the relationship between product attributes and customer choice. Collectively, these research efforts have approached market-driven engineering problems by assuming that purchase choice is driven by a combination of technical product attributes, consumer-specific attributes, and the social network of the customer. As a summary of this review, we introduce Fig. 6 as highlighting the major themes of research advancements in each area of Hazelrigg's DBD framework.

A missing element across almost all research in this section is validating model form by demonstrating true predictive capabilities and understanding the context (or heuristics [29]) under which a model form remains valid. Further, Hazelrigg did describe demand as a function of time, suggesting that additional work is needed exploring how we model temporal changes in consumer preference and diffusion rates. It is also unclear whether the system attributes that drive choice when considering *Price* in the Marketing Mix are the same attributes as those when considering formulations that consider *Place* and *Promotion*.

A pivotal transition in market-driven engineering design research is the work of Shiau and Michalek [58] that formally structures the concept of market systems. Beyond presenting a proof that clearly demonstrates the need for using random coefficient and mixture models of customer choice (because optimal design frameworks employing multinomial logit models converge to a single optimum), they also introduce the challenge of modeling market structure in engineering design problems. This effectively initiated work within the engineering design community of considering *Place* in the Marketing Mix.

5 Place in the Marketing Mix: Considering Retail Channel When Coordinating Decisions of Price and Product Mix

The importance of *Place* in the Marketing Mix is the concept that a manufacturer should consider producing and selling different product variants in different retail channels. This also includes the process of transporting the product, requiring formulations that consider both where and how a product is purchased. In 2008, Shiau and Michalek [58] introduce a *market systems* problem formulation where the action of competitors and the structure of the manufacturer-retailer interaction influences demand. This work aligned with the concurrent efforts by Williams et al. [121] who consider retail channel acceptance as an influential parameter when making engineering design decisions. These efforts highlight the community's beginning efforts at integrating *Place* in market-driven engineering design problems. Specifically, Shiau and Michalek introduce three classes of competitor response and four different manufacturer-retailer formulations (as shown in Fig. 7):

- Class I—competitor products remain fixed in terms of configuration and price.
- Class II—competitor products remain fixed in configuration but can respond with price changes.
- Class III—competitor products can respond with both configuration and price changes.

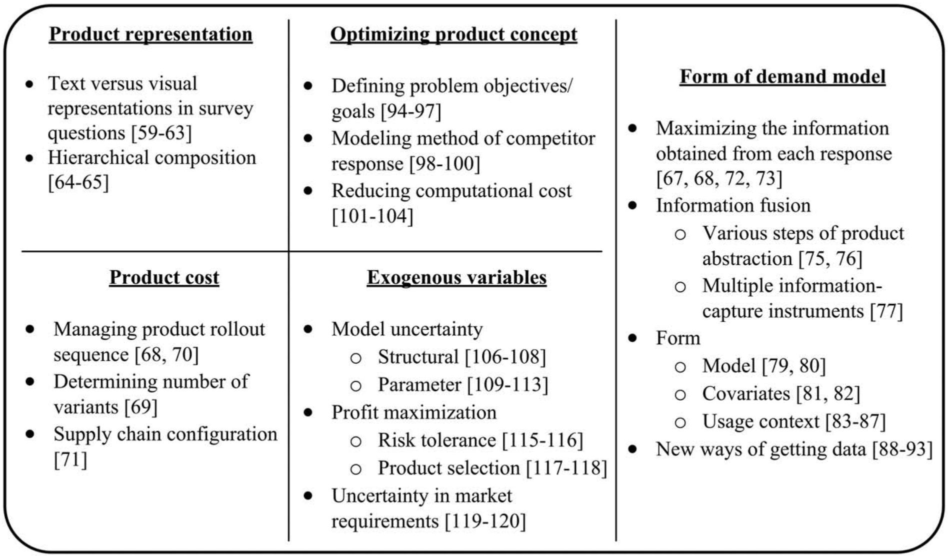

Fig. 6 A brief summary of the research directions and contributions when considering Price in the Marketing Mix

Acknowledging the interaction between manufacturer and retailer, a nested multinomial logit approach is presented in Ref. [122] that considers correlations between product bundles and individual product categories. A nested optimization approach is used so that the retail price can be defined by a retailer's relative clout. This work is significant in that it demonstrates how engineering design decisions coupled with neglecting the retailer's pricing decision can create unfavorable wholesale prices and poorly positioned products. The uncertainty associated with other market players is modeled using an agent-based approach with learning behavior in Ref. [123]. Agents in this formulation represent both competing manufacturers (capable of changing product price and product configuration) and retailers (capable of changing pricing), as shown in Fig. 8. A no-regret learning algorithm is used so that equilibrium is analytically guaranteed. Agent-based simulations are also presented in Ref. [124] by modeling consumer purchasing behavior and how producers navigate a competitive space by investing in different technology improvements.

Place decisions also include the manufacturing supply chain. A network structure supply chain between suppliers, manufacturers, and retailers is created using stochastic and robust models in Ref. [125]. Disruption probabilities in the procurement process are introduced, and the demand is modeled by a random variable with a normal distribution. Uncertainty analysis is also considered in Ref. [126] by exploring the challenge of interoperating sourced parts and services. The relationship between manufacturer and independent repair service providers is demonstrated in Ref. [127], and subgame perfect Nash equilibrium is identified that describes repair services and pricing strategies offered by the independent providers.

We propose a future vision for problem frameworks that include *Place* decisions that extend from the random utility model traditionally used when considering product mix and *Price*. In a random utility model, the customer's stated choices are regressed on product attributes (typically brand, price, and features of the product). Revealed preference models can also be estimated using real purchase data. This model implicitly relates product choice and product features, which is a reasonable assumption under the following conditions [128,129]:

- Customers recognize the product features used as independent variables in the choice model.
- Product attribute information is available equally for all alternatives (this is commonly known as a Complete Information assumption).
- The respondent has unrestricted access to all alternatives (this is commonly known as a Complete Availability assumption).

These assumptions seem plausible for transactions in traditional retail outlets where products are available for direct comparison, the purchase is an interactive process between the customer and the merchant, and the numbers of available product alternatives is limited by shelf space constraints. Our vision for future work when considering *Place* in the Marketing Mix is challenging the validity of these assumptions as a function of the marketing channel. Today's market dynamics are shifting increased volumes of transactions from traditional retail outlets to online merchants

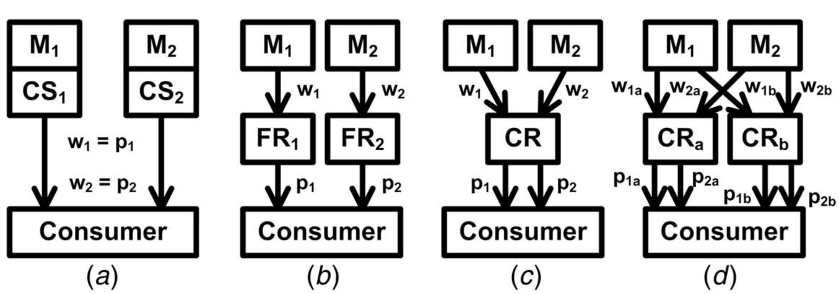

Fig. 7 Channel structure scenarios: (*a*) company store, (*b*) franchised retailer, (c) single common retailer, and (*d*) multiple common retailers (from Ref. [58]). In these scenarios, M is the manufacturer, w is the wholesale price, and p is the retail price.

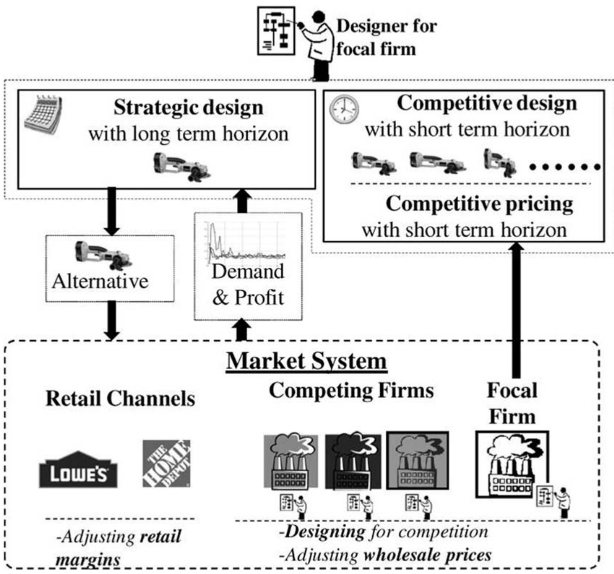

Fig. 8 Considering Place in problem formulation. Competition from competing manufacturers influences both short term design and long term design for a retail channel (from Ref. [123]).

and the assumptions underlying the conventional random utility model grow weaker. In the online environment, products are not available for direct comparison and shoppers rely on incomplete and/or imperfect information from published product specifications, photos, or videos [130,131]. Further, the purchase decision is typically much less interactive [132]; a customer's communication with merchants may be asynchronous and even indirect if sales support functions have been outsourced. In this environment, user-generated product reviews become a primary source of information. However, these data are highly unstructured and often contradictory [133]. The relationships of product attributes derived from user-generated product reviews could relate indirectly (at best) with those included in a highly structured discrete choice model. Finally, the number of product alternatives available from online merchants is exceedingly large compared against the offerings available in traditional retail outlets. Under these conditions, customers will likely limit their choice sets by applying heuristics. Customer choice models used for engineering design problems must accurately account for differences in choice behavior exhibited when purchasing through different retail channels.

As the community continues the development of approaches tailored toward considering *Place*, the following techniques and considerations might apply for online channels:

- Modeling customer heuristics for limiting choice using lexicographic choice models [134,135] or non-compensatory models [80,136].
- Automatically annotating unstructured online reviews using natural language processing and machine learning [137,138] such that the review structures afford estimation of traditional discrete choice models.
- Deployment of agent-based choice models that account for the more complicated dynamics of online purchasing. Consumers often lack the data and/or do not apply traditional "rational" decision-making methods in online spaces (often characterized by a daunting number of alternatives and limited access to necessary information). Instead, customers may rely on the judgments of opinion leaders (professional reviewers or those with elevated status in social networks). Such opinion leaders must be incorporated in agent-based models as acting between the buyers, retailers, and designers/manufacturers/producers. This may change corporate strategy where the designer optimizes around the value of the opinion leaders, who in turn influence customer purchases.
- Understanding the core causes of a product getting a minimal (1 or 2) star review in an online environment. Specific negative feedback in such reviews may be a failure of meeting either basic needs or performance needs as defined by the Kano model [139,140]. A fundamental assumption of the Kano model is that customers will not have a negative reaction when a "surprise and delight" feature is missing, but will have a significant negative reaction when basic and performance needs are missing or poorly implemented. Delivering on basic and performance needs may require formulating the need as an inequality constraint in the optimization problem statement so that penalties are applied when basic needs are not met. Further, we must understand the relationship between delighting a customer and a positive review. One hypothesis is that a fundamentally new solution can delight a customer group, resulting in a 5-star review as long as all basic and performance needs are satisfied [141–143]. A second hypothesis is that products which lack "surprise and delight" features, but still satisfy all basic and performance needs, may be given a sub-5 star review without reason for penalty.

Recalling the DBD framework, addressing *Place* in the Marketing Mix challenges existing problem formulation assumptions about the blocks associated with system attributes, demand, and exogenous variables. It may not be true that the attributes influencing demand are the demographic and technical attributes often used when considering *Product* and *Price* alone. Rather, online reviews may have a greater influence on purchase behavior. Further, more complex optimization problem formulations may require improved computational efficiency and the use of MDO frameworks. Problem formulation extensions may also be needed for retail environments that consider a system-of-systems model [144–146] where a retail channel has customers shopping multiple sellers for a variety of different products.

We view problem formulations that directly consider *Place* as an extension of the formulations discussed in Sec. 4. *Place* and *Price*-driven market-based engineering design formulations are inherently linked because they both assume that customer motivation is given and that we as engineers are designing products with the goal of best meeting their mental model of what the product should be. In Sec. 6, we introduce how considering *Promotion* in the Marketing Mix can be viewed as a separate extension of a *Price* formulation—as the product-price strategy can be described in a way that reshapes the customer's motivational pattern.

6 Promotion in the Marketing Mix: Reshaping Value Perceptions While Coordinating Decisions of Price and Product Mix

The five major promotional tools used in marketing are advertising, sales promotions, direct marketing, personal selling, and public relations [147]. Using promotional tools as a means of strategically influencing customer behavior is also highlighted by Shocker and Srinivasan [2]. They state that product bundles should be targeted at individual market segments and that promotion can

> potentially affect perceptions concerning the location of the promoted product or competitive products as well as the saliences of attributes and locations of ideal points… Indeed the framework could some day provide the basis for comparing product, promotion, and other elements of the marketing mix in terms of their effectiveness (over time) in achieving desired marketing objectives.

Overall, there has been a limited effort in the *Design for Market Systems* session directly addressing *Promotion* decisions. Of the papers we surveyed, those that qualify coordinate products and services. For example, the similarity between customer requirements, or functions, that could support the acquisition of new services is investigated in Ref. [148]. More recently, the work by Sinha et al. use canonical affinity curves when exploring the relationship between member acquisition and value when simulating the relationship between users and developers [149].

We also see alignment between results published from market research studies on product aesthetics and the design community's exploration of sustainable products. When considering the impact of aesthetics on market positioning, Liu et al. found that consumers prefer products that look "neither too typical nor too different from the average look of products in the category" [150]. The rise of social media as promotional platforms is studied in Ref. [151], where the authors found that user response is more positive when products are pictured in average situations rather than studio representations. Tangentially, the design community's exploration of sustainable product design is closely linked with these two papers, in that sustainability can become a promotional tool for product positioning. Having a product's environmental impact information serve a promotional role (instead of simply conveying technical information) has been called for in the marketing literature [152,153]. Research linking product configuration decisions with consumer sustainability triggers [154,155] provides avenues for aligning decisions about form and function with the promotional strategy pursued by the seller.

Modeling promotion activities align with the decision-based design framework by actively modifying customer purchasing behavior using engineering design decisions and marketing tools in maximizing corporate utility. The resultant problem formulations necessitate a multidisciplinary (or systems) modeling approach, thereby requiring research advancements developed when addressing the other Ps of the Marketing Mix. We propose a vision where research opportunities include:

6.1 Leveraging Advancements Associated With Product Decisions in the Marketing Mix. Promotional strategies should be created that provide marketing staff maneuvering ability. This can be accomplished by developing optimization problems that assign excess attribute performance or feature inclusion over-achievement. Such excess is especially useful when combating uncertain competitor behavior or other exogenous factors. The inclusion of slack variables used in classical optimization techniques [156] could provide an initial starting point for such a formulation. Additional extensions could include multidisciplinary approaches, such as analytical target cascading [46], by framing the effective allocation of business and engineering resources toward promotional tools.

The use of tradespace visualization tools [25] can be explored as a means of guiding discussions with marketing staff when developing messaging campaigns. Engineers and marketing staff could identify dimensions in system attribute space where the company's offerings are non-dominated because of existing product features or the inclusion of new product features. Strategies could then be formed that (1) actively shift a customer's attention toward attributes reflective of the product line's strength and/or (2) influence public opinion so that attributes a manufacturer is specifically interested in highlighting receives a higher perceived value.

6.2 Leveraging Advancements Associated With Price Decisions in the Marketing Mix. In Sec. 4, the price vector is driven by the demand model. When considering *Promotion* in the Marketing Mix, price can be strategically balanced by customer demand and promotional considerations. This allows for defining specific targeted price points and exploring commonality as a means of achieving the needed cost efficiencies [157]. Once a product has been placed in the market, managing the variations in product sales may be possible using control strategies—such as proportional and derivative control—by changing price discounts and promotions [158].

Additional extensions require a more comprehensive understanding of the relationship between promotion and product customization [159]. Identifying product attributes that provide delight [160,161] and the subsequent engagement of a heterogeneous market in ways that encourage adoption using promotional strategies can be explored. This work will build on existing mathematical models of product adoption [85,162] by linking engineering design decisions with social media presence for a product [138] in ways that identify lead users and the promotional strategies capable of accelerating adoption rates.

6.3 Leveraging Advancements Associated With Place Decisions in the Marketing Mix. A product's retail channel can be aligned with promotional strategies that include warranties and the creation of specialized products. For example, existing design studies have explored the relationship between design decisions, reliability, maintenance, and the warranty package offered [163]. These considerations are then extended toward the creation of service contracts [164]. Principles associated with systems-of-systems [165] engineering may be one avenue for understanding how promotional strategies can be tailored that bundle products and product-service combinations.

Online shopping is not the only purchasing avenue that can benefit from increased data analytics and technological advancements. Physical retail locations can engage consumers by leveraging technology [166], allowing for the real-time generation of promotions tailored for the specific shopper. Further, promotional strategies can result in tailored products offered only at specific vendors. Promotion can also be aligned with larger social aspects, such as the RED™ product campaign [167] that has partnered with brands for creating products and experiences. Funds from this collaboration are then allocated toward the Global Support Fund in support of HIV/AIDS programs.[2] Successfully navigating such design problems requires a combination of all Ps of the Marketing Mix.

7 Conclusions

This paper reviews the current state-of-the-art in market-driven engineering design research and discusses how far we have come as a community in addressing the Four Ps of Marketing (Product, Price, Place, and Promotion). We argue that design research addressing *Product* decisions in the Marketing Mix focused on abstractions of the product itself, providing ways of establishing requirements, managing variety from a component perspective, and coordinating communication across multiple players/disciplines. Exploring *Price* in the Marketing Mix required modeling the explicit link between preference and demand. The decision-based design framework provided a comprehensive scope for market-driven engineering design problems and facilitated two different research developments. The first direction focused on the engineer's decision-making process by applying normative decision analysis and methods for eliciting engineer preference toward alternatives. Simultaneously, this framework sparked a significant exploration of the impact of demand model choice/form and how customer preferences for product attributes could be captured. By focusing on this second research direction, research in the *Design for Market Systems* special session has generated a richer understanding of how consumer preference modeling should be executed and incorporated when formulating market-driven engineering problems. We now have advanced capabilities for posing problem formulations that relate purchase choice metrics and a combination of technical product attributes, consumer-specific attributes, and the social network of the customer. This has been done in the interest of achieving higher fidelity estimates of how engineering design decisions actually influence market behavior, though future research must demonstrate the true predictive capabilities of random utility models for engineering design problems and explain the context under which model forms remain valid.

The more complicated problem formulations associated with the Marketing Mix decisions of *Place* and *Promotion* have received

[2]https://www.red.org/how-red-works

less attention. However, creating effective problem formulations was likely not possible until we better understood the coordination of *Product* and *Price*. We strongly encourage greater exploration of these problems, as they represent the changing dynamics of today's market and challenge some of the modeling assumptions made by our community. The importance of *Place* in the Marketing Mix is the suggestion that a manufacturer should produce different product variants when selling in multiple retail channels. As market dynamics shift transactions increasingly toward online merchants the assumptions behind the conventional random utility model grow weaker. Online environments change the way that people compare products, information is not always available or can be conflicting, and the number of alternatives that consumers must sort through can be substantially large. Research opportunities include modeling customer heuristics for limiting choice across various retail channels, understanding how natural language processing and machine learning can automatically structure reviews in a way that informs consumer choice model estimation, developing of richer agent-based models, exploring which product attributes actually drive purchasing decisions, and exploring how existing design tools (such as the Kano model) can provide insights into the relationship between product attributes and online review scores.

Finally, *Promotion* in the Marketing Mix challenges the assumption that product-price strategies can be designed that actively reshape a customer's motivational pattern driving purchasing decisions. We argue that clearer communication between engineers and marketing staffs is needed when developing effective messaging campaigns that (i) actively shift a customer's attention toward attributes reflective of the product line's strength and/or (ii) influence public opinion for an attribute the manufacturer specifically is interested in highlighting so that it is perceived as having a higher value. Research opportunities include exploring optimization problem formulations that integrate slack variables as a means of providing maneuverability when faced with uncertain competitor behavior or other uncontrollable market factors, relating costs and strategic product placement especially in the context of price points, leveraging current optimization problem formulations by considering how resources for promotional tools can be most effectively allocated, and integrating product adoption models, social media and engineering design decisions as a way of driving market success especially for new technologies or customized products.

Most importantly, considering *Promotion* fully demonstrates the interplay between all elements of the Marketing Mix: requirements generation and optimization approaches when considering *Product* decisions, understanding how demand is influenced by system attributes, price and time (*Price*), and understanding the distribution channels and purchasing environments modeled when considering *Place* in the Marketing Mix. Further, the cornerstone of having 4Ps in the Marketing Mix has been challenged by others [168,169]. They suggest that additional Ps—People, Process, etc.—should be considered as part of the Marketing Mix. We must better understand how these additional elements impact problem formulation and the key assumptions behind the methods we propose as a community.

Over the last 10 years, the engineering design community has made significant advancements formulating problems that address decisions associated with the Marketing Mix. There remains a significant opportunity for community collaboration—and for collaboration with colleagues in other disciplines—when tackling the complicated problem of designing for the Marketing Mix. It is our hope that this paper serves as a framework that drives *Design for Market Systems* research over the next decade.

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