New Product Development: Trade-offs, Metrics, and Successes

Teck-Hua Ho and Dayoung Kim

Abstract This chapter reviews Morris Cohen's scholarly contributions to new product development (NPD) and the other areas at the interface of marketing and production. Specifically, we examine how Morris and his co-authors' pioneering work in NPD has generated follow-up work by a number of scholars, demonstrating the frequent tension between the marketing and production functions. The authors provide rigorous support for performance metrics used by practitioners in the NPD process. Their work on a data-driven decision support system shows the usefulness of their research to industry. In summary, this work on NPD reveals who Morris Cohen is as a scholar—someone with the rare ability to link rigorous research with practical implementation.

Keywords New product development (NPD) · Marketing-operations interface · Time-to-market · NPD metrics · Forecasting

1 Introduction

New product development (NPD) is central to the success of any product or service company. This chapter describes Professor Morris Cohen and his co-authors' scholarly contributions to NPD, a field of study that lies at the interface between marketing and production. This review is not comprehensive; it is intentionally restricted to work done by Morris Cohen and his co-authors. In addition, we focus on work done by Teck-Hua Ho, which has been influenced by Morris Cohen's work.

T.-H. Ho (✉)
National University of Singapore, Singapore, Singapore

D. Kim
Global Asia Institute, National University of Singapore, Singapore, Singapore

Department of Management, California State University at Fullerton, Fullerton, CA, USA
e-mail: dayoungkim@nus.edu.sg

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We apologize in advance to authors who feel their work has not been included or mentioned.

The chapter is organized into three sections:

1. Trade-offs, which reviews studies on the trade-offs that arise at the interface between marketing and operations, paying specific attention to NPD and how Cohen et al. (1996) have shaped research on NPD.
2. Metrics, which reviews metrics used by firms and how the metrics can be understood within a rigorous modeling framework.
3. Successes, which reviews two prevailing forecasting approaches used by firms for new product successes: (a) data-driven statistical methods and (b) prediction markets.

2 Trade-offs

Matching demand and supply in a dynamic and uncertain market is challenging and can create tensions between a company's marketing and production functions. Frequently, marketers focus on *maximizing demand from customers* while production managers focus on *minimizing production costs to meet a demand*. Sombultawee and Boon-itt (2018) provide a recent review of the literature on the interface between marketing and production, while Tang (2010) systematically documents the models that researchers have developed to analyze the trade-offs that arise from coordinating marketing and production. Some of these trade-offs are discussed in detail in Eliashberg and Steinberg (1987, 1993), Porteus and Whang (1991), Karmarkar (1996), Kulp et al. (2004), Yalabik et al. (2005).

Shapiro (1977) provides a good overview of these tensions, outlining eight areas where coordination is necessary between marketing and production. In this section, we focus on four of those areas: (a) capacity planning and sales forecasting, (b) the breadth of the product line, (c) service quality assurance, and (d) NPD. Note that these tensions are still relevant in many operations management settings. The development of new technologies and the outbreak of the Covid-19 pandemic have shifted emphasis somewhat towards capacity flexibility and operations innovations in order to respond to rapid disruptions in supply chains.

2.1 *Capacity Planning and Sales Forecasting*

Since it can take time for a firm to adjust its manufacturing capacity for a new product, it is crucial that the firm obtain accurate long-term demand forecasts. Marketers frequently use the celebrated Bass diffusion model (Bass 1969) to estimate such demand. Thorough reviews of the use and extension of the model in marketing contexts are given in Mahajan and Muller (1979) and Mahajan et al. (1990). One of the practical limitations of early Bass-related models is their assumption that firms have unlimited capacity to fulfil any level of demand. This assumption often does not hold because firms have a fixed manufacturing capacity which can lead to supply constraints, backorders, and lost sales.

Consequently, several operations researchers incorporated supply-side constraints into the Bass diffusion model to make it more realistic. For example, Ho et al. (2002) endogenize demand dynamics to study how a firm should plan its capacity for a new product with backlogs and lost sales. Kumar and Swaminathan (2003) extend the Bass model to capture the effect of lost sales (due to supply constraints) on future demand and show that if a firm wants to maximize total sales during the lifecycle of a product, a myopic marketing plan that maximizes sales at each instance is not optimal.

These revised Bass diffusion models have been made more realistic by removing the assumption that customers generate positive word-of-mouth. This is particularly relevant in the age of social media, where word-of-mouth communication and real-time consumer reviews (i.e., social learning) can have a huge effect on sales. Hu et al. (2016) and Davis et al. (2021) investigate the influence of social learning on stocking (capacity) decisions, while Feldman et al. (2019) investigate the influence of social learning on optimal product design and pricing. This line of work is important and likely to generate much follow-on research.

2.2 Breadth of the Product Line

Marketers often want to extend a product line to satisfy customers' heterogenous needs and/or customers' variety-seeking behavior. Extending a product line comes at a cost. For example, broadening a line may incur setup costs, and as a consequence, reduce effective capacity. Similarly, a wider product line requires higher levels of inventory and transportation costs. These tensions are discussed in the book *Product variety management: research advances* (Ho and Tang 1998), which collects articles by a group of leading interdisciplinary researchers, including economists, engineers, marketers, and operational management researchers. The early chapters of the book explain what motivates a firm to broaden its product line, while the later chapters examine leading industry practices to manage product variety in terms of design, pricing, and manufacturing.

The book led to several streams of research. Kim et al. (2002) extend the standard choice models used in marketing by allowing for multiple varieties of a product to be bought at the same time. Cachon et al. (2005) consider how a firm should optimize its product assortment when a customer exhibits heterogenous behavior. Gaur and Honhon (2006) and Kök and Fisher (2007) investigate the same assortment problem when consumers can substitute for a product that is out of stock, a similar product that is available. Alptekinoğlu and Corbett (2008) discuss the implications of an extremely large product line (i.e., mass customization) with price competition. Broda and Weinstein (2006) use trade data from the USA to show how increasing the product line by importing a variety of products has contributed to national welfare gains in that country.

2.3 Service Quality Assurance

Service quality assurance is another area where marketing and production must align their decisions. Guaranteeing a high level of customer service requires balancing (a) the service capacity and the speed at which service is provided and (b) the customers' degree of preference for service quality. So (2000) and Ho and Zheng (2004) examine the effect of guaranteeing customer delivery times under competitive rivalry. So (2000) considers an oligopolistic scenario where firms compete on a delivery time guarantee. If firms are heterogenous in capacity, larger firms tend to offer a shorter delivery time guarantee. Ho and Zheng (2004) consider a duopoly scenario where firms choose delivery time guarantees to influence customer expectations. They show that the optimal guarantee requires a balance between service capacity and customer sensitivity to the guarantee. So and Tang (1996) consider a setting where firms can choose both the number of servers and a service guarantee. The authors quantify the benefits of dynamically adjusting the number of servers and evaluate the interactions between the number of servers and the level of guaranteed service.

2.4 NPD

The pressure on firms to develop and launch new products rapidly has intensified because product life cycles have become significantly compressed. As a consequence, the decisions on *when* to introduce the new product and *what* its performance level should be, cannot be overemphasized.

Until the early 1990s, little attention was devoted to analytically modeling the trade-offs between time-to-market and product performance. Cohen et al. (1996) was the first to present a comprehensive model of the complex NPD process by analyzing trade-offs that arise within a fixed NPD time horizon. The authors demonstrate how firms should strike a balance between time-to-market, product performance, and cost in order to maximize lifecycle profits. The proposed model allows for product performance to be enhanced over multiple stages. The authors show that the optimal NPD policy is for firms to concentrate efforts on the most productive stage of the multistage NPD process. The paper generated much follow-up work and significant interest among practitioners. As of October 4, 2021, it has been cited 674 times on Google Scholar.

Indeed, a review paper on product development decisions, Krishnan and Ulrich (2001), evaluated the main contribution of Cohen et al. (1996) as "sorting the relative priority of development objectives" and "showing that performance measures are often traded off against one another." Tatikonda and Montoya-Weiss (2001) also added how Cohen et al. (1996) created new avenues of research by examining "the advantages and disadvantages of being first (or faster) to market, depending on demand, product life cycle, growth stage, competitive context and behavior, consumer behavior, and elements of the marketing mix." Table 1 is a summary of papers that build on Cohen et al. (1996) and which have received more than 250 citations on Google Scholar. In these papers, the term "product performance" and "product quality" are used interchangeably.

3 Metrics

To help NPD teams to make optimal decisions and maximize the chance of a new product's success, quantifiable metrics must be developed and used. Bill Hewlett, co-founder of Hewlett-Packard (HP), once said, "You cannot manage what you cannot measure." House and Price (1991) describe how HP used quantifiable performance metrics[1] such as break-even-time to maximize the chance of a new product's success.

Similarly, leading Japanese companies use target unit cost as a tool to manage NPD teams (Cohen et al. 1996). The target costing approach provides a structured way to constrain the NPD process so that the new product will not be too costly to produce by quantifying the cost of the potential new product early in the development process (Cooper and Slagmulder 2017). As a consequence, NPD teams avoid developing low-margin products and bring only highly profitable products to market. Cooper and Chew (1996) provide a successful application of the target costing approach at Olympus, a market leader in single-lens reflex (SLR) cameras in 1980s. The company had no competitors in Japan until the early 1980s but began to lose market share and money when competitors produced a compelling alternative. In response, Olympus adopted the target costing approach to drive NPD, with the NPD team having to measure the cost of adding a new feature. Using this process, Olympus reduced its production costs by about 35% in the 1990s (Cooper and Chew 1996). Note that target costing may mitigate the level of product performance and lengthen the time to market.

Cohen et al. (1996, 2000) provide an integrated framework for analyzing the implications of using simple and measurable performance metrics in NPD. Cohen

[1] HP successfully reduced break-even-time by one-half for new products through the effective use of metrics. Four key metrics they adopted are break-even-time (BET), time-to-market (TM), break-even-after-release (BEAR), and return factor (RF). BET is a measure of the total time until the break-even point on the original investment is reached. TM is the total development time spent from the start of product development to manufacturing release. BEAR is the time from manufacturing release to when project investment costs are recovered in the form of profit from a product. RF is a calculation of profit dollars divided by investment dollars at a specific point in time after a product has moved into manufacturing and sales.

Table 1 Papers that have expanded on the research in Cohen et al. (1996)

Method	Bibliography	Description	Relevance to Cohen et al. (1996)
Empirical investigation	Shankar et al. (1998), *Journal of Marketing Research*	Empirical analysis of 13 brands across two ethical drug categories suggests a trade-off between innovativeness and entry timing. The authors identify the mechanism through which innovative late movers can outsell pioneers and suggest new strategies for late entry.	The authors use the same assumption as Cohen et al. (1996), that firms often have conflicting objectives in terms of cost, timeliness, and innovativeness. They also focus on how different metrics such as time-to-market and cost are often traded off against one other.
Empirical investigation	Moorman and Slotegraaf (1999), *Journal of Marketing Research*	Controlling for the effects of external market information, the authors investigate the relationship between a firm's organizational capabilities and NPD outcomes. They find that marketing and product development capabilities jointly influence the speed of product development.	The authors include product development cost as a variable in the model to control for the trade-off between the efficiency of development and cost, as discussed in Cohen et al. (1996, 1997).
Empirical investigation	Tatikonda and Montoya-Weiss (2001), *Management Science*	Using the data from 120 development projects for assembled products, the authors find that an organization's information processing factors and capabilities are associated with the speed of NPD. As a result, the factors and capability are linked to achieving a target for product performance, unit cost, and time-to-market.	The authors consider time-to-market, cost, and product performance to be key objectives for NPD. They demonstrate that achieving the time-to-market objectives improves customer satisfaction and product success.
Framework for new service development	Menor et al. (2002), *Journal of Operations Management*	The authors provide a review of research areas in new service development (NSD), highlight areas for further refinement and exploitation, and identify areas for new study and discovery.	The authors devise performance metrics for NSD and highlight that total development cost, as suggested by Cohen et al. (1996), is important for managing NSD.

(continued)

Table 1 (continued)

Method	Bibliography	Description	Relevance to Cohen et al. (1996)
Model application in different industry	Plambeck and Wang (2009). *Management Science*	The authors use a stylized model to investigate the impact of e-waste regulation on introducing new products in the electronics industry. Specifically, they explore the effects of e-waste regulations on the NPD process, the quantity of e-waste generated, social welfare, consumer surpluses, and manufacturer profits.	As in Cohen et al. (1996, 2000), the standard Cobb–Douglas production function was used to formulate the relationship among expenditure, speed, and quality in NPD. Manufacturers choose the development time and expenditure for a new product, which together determine its quality.
New framework and empirical validation	Pavlou and El Sawy (2011), *Decision Sciences*	The authors propose a structural model where dynamic capabilities influence product success by reconfiguring existing operational capabilities in the context of NPD. Dynamic capabilities were found to be important for higher environmental turbulence.	As in Cohen et al. (1996), the authors view NPD success as the achievement of product performance (quality, innovativeness) and process efficiency (time-to-market, low cost).

et al. (2000) generalize the modeling framework from Cohen et al. (1996) by allowing the level of resources used in NPD to vary over time. Cohen et al. (2000) rigorously analyze the pros and cons of setting a target on each of the three simple and measurable metrics: (1) time-to-market, (2) product performance, and (3) total development cost. The authors derive optimality conditions to enable firms to become aware of the potential impact of setting a target on one of these metrics. For example, the paper shows that setting a compressed time-to-market target can lead to downward bias in product performance and suboptimal product success. The authors demonstrate that the target total development cost approach can also result in a similar bias. Finally, the target total performance approach was shown to lead to extended development times and a shorter sales cycle.

The approach of using the above-mentioned NPD metrics has been expanded in several ways. Researchers in operations management have started to focus on developing resilience in capacity planning in anticipation of unforeseeable market shifts and technology disruptions. Such resilience-oriented metrics will cost more and take longer to develop but will be meaningful additions to the above-mentioned NPD metrics. These new metrics extend the existing framework by allowing for a longer time horizon and more variability and disruption in demand conditions (Steenburgh and Ahearne 2018).

4 Successes

In this section, we describe two methods of new product success forecasting. The first is based on well-established statistical methods used in marketing (e.g., econometric analyses, probabilistic models, individual choice models), and the second is based on prediction markets.

4.1 Statistical Methods

Since the 1980s, marketing researchers have advanced the statistical models used in demand forecasting (Hogarth and Makridakis 1981; Makridakis et al. 2008). Guadagni and Little (1983) created a fundamentally new approach to demand forecasting by pioneering the use of panel-level scanner data to develop individual choice models. For a review, see Rossi et al. (1996), and for two well-known applications, see Erdem and Keane (1996) and Erdem and Winer (1998). Individual choice models have also been used to forecast the success of new products in the market (Neelamegham and Chintagunta 1999). To address a challenge posed by product categories that have hundreds of stockkeeping units (SKUs), Ho and Chong (2003) developed a parsimonious model to forecast demand at the SKU-level.

Cohen et al. (1997) demonstrate how statistical methods can be used in the NPD process in practice. The authors develop a decision support system based on an analysis of historical data from 51 new products launched at a major food manufacturer. The system evaluates the financial prospects of extending a new product line and provides shipment forecasts at various stages of the NPD process. The authors demonstrate how taking a "product line" perspective system (instead of a "product" perspective) can improve the success of new products.

Another method of forecasting new product success is the Bass diffusion model (Bass 1969). Srinivasan and Mason (1986) show that this model can be advanced to forecast new product diffusion in retail, industrial technology, and durable consumer goods among others. See Mahajan et al. (1990) for a comprehensive review of this stream of literature.

The strong emphasis on empirical analysis in marketing has significantly influenced the development of the field of operations management. In the 1990s, academics in operations management began to place strong emphasis on empirical analysis. For example, they frequently use the random utility model (Ben-Akiva and Lerman 1985) to capture demand substitution within a product assortment. As a consequence, researchers can now analyze how inventory stocking and pricing decisions change as a result of demand substitution (e.g., Vulcano et al. 2012; Fisher and Vaidyanathan 2014; Rusmevichientong et al. 2014). For comprehensive reviews, see Ho et al. (2017) and Fisher et al. (2020).

4.2 Prediction Markets

A separate and complementary stream of research focuses on using prediction markets to predict the success of new products. Ho and Chen (2007) describe a market-based method of demand forecasting to leverage on the "wisdom of the crowd" in a so-called prediction market. A prediction market is a price-discovery mechanism designed to aggregate information by allowing a large group of individuals to bet on possible outcomes in the form of shares. The authors describe the history and the scientific foundations behind the prediction market and present step-by-step approaches for setting one up. They show how a prediction market can be used in the motion picture, information technology, and healthcare industries, all of which involve high uncertainty in demand and a short product lifecycle.

The prediction market has been used to improve prediction accuracy in presidential elections (Snowberg et al. 2007; Chen et al. 2008) and the seasonal influenza epidemic (Polgreen et al. 2007; Tung et al. 2015). More recently, it has been used to predict the progression of the Covid-19 pandemic (Ho et al. 2021), demonstrating that a prediction market can be a promising forecasting tool, even in the case of one-off, disruptive events. However, prediction markets only work well when participants in the market have experience or knowledge of the topic being forecasted and have views that are sufficiently independent (Ho and Chen 2007).

5 Conclusion

This chapter focuses on Morris Cohen's contributions to the marketing-operations interface, specifically in NPD. Cohen and his co-authors pioneered research in this area and laid some of the foundations for subsequent work. They demonstrate how a combination of rigorous modeling, empirical analysis, and practical insights can help to shift the development of research not only in operations management but also at the interface between marketing and production.

Personal Note
I (Teck-Hua Ho) have had the great privilege of working on NPD with Morris (production/operations) and Professor Jehoshua (Josh) Eliashberg (marketing). Both of them are giants in their fields and I benefitted enormously from collaborating with them. They have been great mentors, ardent supporters, phenomenal cheerleaders, and, most importantly, true friends. I am forever grateful to them.

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