Chapter 3
Innovation and New Products Research: A State-of-the-Art Review, Models for Managerial Decision Making, and Future Research Directions

Tingting Fan, Peter N. Golder and Donald R. Lehmann

3.1 Introduction

Innovation is the lifeblood of economies. It spawns new firms, revitalizes established organizations, enriches entrepreneurs, builds professional reputations, and raises living standards throughout the world. Over the years, innovation has received considerable attention in the marketing literature, which is not surprising given its importance to both companies and consumers.

Our purpose in writing this chapter is threefold. First, we provide a literature review of major papers in the field of new products research. We organize our review into four tables, one for each of the four stages of the new product development process, and then by topic within each of these stages. Moreover, we provide a short summary of each paper in the tables. These tables and short summaries provide an overview of research and findings in the field, plus direct readers to papers particularly suited to their interests. Second, we highlight specific models within each stage of the new product development process. These models are useful for marketing researchers and managers tackling challenges in the new products domain. Third, after reviewing the literature, we suggest numerous general research directions as well as specific research questions to guide future investigations in this area. We believe this will be particularly useful to those new to the field of new products research, especially those interested in applying quantitative models (e.g., business school Ph.D. students, consultants, practitioners).

T. Fan
The Business School of Chinese University of Hong Kong, Sha Tin, Hong Kong

P.N. Golder (✉)
Tuck School of Business at Dartmouth, Hanover, NH, USA
e-mail: Peter.N.Golder@tuck.dartmouth.edu

D.R. Lehmann
Columbia Business School, New York, NY, USA

B. Wierenga and R. van der Lans (eds.), *Handbook of Marketing Decision Models*, International Series in Operations Research & Management Science 254, DOI 10.1007/978-3-319-56941-3_3

Several researchers have previously documented the innovation subfield of the marketing discipline.[1] In addition to this chapter, we refer interested readers to chapters by Lehmann and Golder (2014) and Rao (2014), prior journal articles by Hauser et al. (2006) and Peres et al. (2010), and the entire *Handbook of Research* on New Product Development (Golder and Mitra 2017). Next, we briefly summarize these writings, and then provide the motivation and positioning of our chapter.

Lehmann and Golder (2014) wrote their chapter on new products research for the *History of Marketing Science*. In it, they organize important new products research beginning in the 1960s going through the 2010s. They find that research is limited on the topics of opportunity identification and concept generation. However, they find that researchers have paid greater attention to design and development (particularly conjoint analysis), sales forecasting, and some aspects of strategy (e.g., competitive response, order of entry).

Rao (2014) provides a focused, comprehensive review of conjoint analysis, in contrast with other authors who discuss conjoint analysis as part of the broader new products literature. Rao's (2014) chapter updates earlier reviews by Wittink and Cattin (1989), Green and Srinivasan (1990), and Wittink et al. (1994).

Hauser et al. (2006) organize research on innovation into five fields of inquiry: (i) consumer response to innovation (e.g., consumer innovativeness, new product growth models, network externalities), (ii) organizational impact (e.g., contextual drivers, adoption of new methods), (iii) market entry strategies (e.g., technological evolution, portfolio management), (iv) prescriptive techniques for product development (e.g., fuzzy front end, design tools), and (v) outcomes from innovation (e.g., market rewards, defending against new entrants, internal rewards for innovation).

Peres et al. (2010) review research on innovation diffusion. Building on prior reviews (e.g., Mahajan et al. 1995), they incorporate more recent research on interpersonal influence, network externalities, and social signals. Their review covers within-market effects, cross-market effects, and cross-country effects for all social influences, not just word of mouth.

The *Handbook of Research on New Product Development* (Golder and Mitra 2017) contains 19 chapters that provide depth on specific aspects of new product development and innovation. These chapters describe the frontiers of new products research as well as offer numerous insights for extending these frontiers of our knowledge base.

Empirical findings across a range of new products research studies can be found in *Empirical Generalizations about Marketing Impact* (Hanssens 2015). Topics in this book of interest to new products researchers include customer satisfaction and product reviews, objective and perceived quality, order of entry, sales diffusion and social influence, product innovation, and competitive reaction.

[1]The *Journal of Product Innovation Management* is also a valuable repository of new products research.

Our chapter for this handbook provides a unique perspective on innovation and new products research. In contrast with earlier works, we organize our review by the major stages of the new product development process: (i) opportunity identification, (ii) product design and development, (iii) sales forecasting, and (iv) commercialization. Our review is more comprehensive than Lehmann and Golder (2014) since their purpose was to provide exemplars of research themes illustrating the historical evolution of the field. One aspect of innovation covered in Lehmann and Golder (2014) that we do not cover is how to value innovations. Most importantly, we focus on models useful for managerial decision-making in various innovation and product development contexts. Therefore, we provide details of several models so that managers and researchers can better understand how these models could be used and the insights that can be generated for informing their decision making.

Overall, our chapter has three overriding objectives: (i) to organize the vast marketing literature on innovation and new products according to the four stages of the new product development process, (ii) to provide detailed discussions of decision-making models useful for each stage of the new product development process, and (iii) to identify the most promising opportunities for future research in each of these stages. Next, we discuss research categorized into the four stages of the new product development process. Within each of these stages, we elaborate on key models. We conclude with our agenda for future research.

3.2 Organizing Research on Innovation and New Products

The new product development process can be broken down into four stages: (i) opportunity identification, (ii) product design and development, (iii) sales forecasting, and (iv) commercialization. The first stage subsumes idea generation and idea screening, which are sometimes treated as separate stages. The final stage, commercialization, includes some research on post-commercialization activities but does not attempt to cover the vast literature on the product management of mature products.

3.2.1 Opportunity Identification

Current research on opportunity identification focuses on three areas: (i) opportunities identified by investigating lead users, (ii) opportunities identified by using online platforms, and (iii) opportunities identified through innovation templates (see Table 3.1). Research on lead users began in the 1980s and is largely associated with the work of Eric von Hippel. Lead users are consumers who have needs ahead of the general market and also create make-shift solutions for those needs. When firms can identify lead users, they benefit in two ways. First, they become aware of unmet needs that exist in the marketplace. These needs are important enough that

Table 3.1 Opportunity identification

Topics	Literature	Summary
Opportunity identified from lead users	Von Hippel (1986)	Lead users are "users whose present strong needs will become general in a marketplace months or years in the future". Lead users can help companies forecast emerging needs, provide new product concepts, and expedite new product development.
	Urban and Von Hippel (1988)	Apply the lead user methodology in the development of a new industrial product (i.e., computer-aided systems for the design of printed circuit boards (PC-CAD)). The authors demonstrate that lead users provide useful data and people prefer the new product concepts generated from lead users.
	Lilien et al. (2002)	Test the effect of lead users in a natural experiment conducted in the 3M Company. The authors found that the forecast annual sales of lead user projects are more than eight times higher than those for the traditional projects and that divisions funding lead user projects generated their highest rate of major product lines in the past 50 years.
Opportunity identified from online platforms	Urban and Hauser (2004)	The authors develop a method which "listens in" to conversations between customers and web-based virtual advisers and demonstrates its value to identify valuable opportunities.
	Bayus (2013)	New product ideas can come from crowdsourcing communities where a dispersed crowd of consumers generates ideas. They found that serial ideators are more likely than consumers with a single idea to generate valuable ideas, but they are unlikely to repeat their early success once their ideas are implemented.
	Stephen et al. (2015)	When new product ideas come from consumers through online platforms, higher clustering/interconnectivity among consumers generate less innovative ideas because ideas from clustered consumers are more likely to be similar or redundant.
	Luo and Toubia (2015)	On online idea generation platforms, high-knowledge consumers generate better ideas when they are exposed to abstract cues such as problem decomposition, while low-knowledge consumers generate better ideas when they see concrete cues such as other consumers' ideas.

(continued)

Table 3.1 (continued)

Topics	Literature	Summary
Opportunity identified from innovation templates	Goldenberg et al. (1999)	Identify five "innovation templates" that most successful new products fit into. These templates are based on product attributes: inclusion, exclusion, linking, unlinking, joining, and splitting.
	Goldenberg et al. (2001)	New product success can be predicted by inspecting the new product idea (innovation templates) and the circumstances of its emergence (protocol). In particular, successful products tend to conform to one of the templates and solve customer problems. New products that are developed only by the inventor or mimicking popular trends are likely to fail.
	Goldenberg et al. (2003)	Apply the "innovation templates" on new products (e.g., DVD player—subtraction, Gillette double-bladed razor—multiplication, Caesarea Creation Industries' rug for children's rooms—division, defrosting filament in an automobile windshield with enhanced radio reception—task unification, Elgo's indoor sprinkler kit—attribute dependency change).
	Boyd and Goldenberg (2013)	Successful applications of the new product templates are discussed.
Opportunities identified from other ways	Chandy and Tellis (1998)	How willingness to cannibalize prior investments may be more important than firm size as a driver of radical product innovation.
	Moorman and Miner (1997)	Greater organizational memory dispersion increases new product creativity and performance.
	Ofek and Sarvary (2003)	How leaders and followers will invest in R&D versus advertising with next-generation technology products. They find that firm investments depend on whether current leadership is based on R&D competence or reputation.
	Kornish and Ulrich (2011)	Parallel search is a common approach to innovation. Firms identify a large number of opportunities and then select some to develop, with only a few successful cases. The authors develop a method to extrapolate unique ideas from a lot of redundant ideas.
	Burroughs et al. (2011)	Firms can enhance creativity by leveraging the monetary reward program and a creative training program in combination.

consumers actively generate their own solutions. Second, potential new product ideas are generated through lead users' solutions. While often these rudimentary solutions are not firms' final solutions, they can be very useful in contributing to firms' attempts to develop products for a broad market. Research has identified many successful market applications of the lead user concept.

Another area of research on opportunity identification to emerge was the development and application of innovation templates. This research stream offered a structured approach to what might otherwise be an undefined process with random outcomes. For example, by identifying five templates of innovation that most successful products belong to, Goldenberg et al. (2001) show how future new products can be identified and refined more easily.

A third and more recent area of research on opportunity identification is the use of online platforms such as Dell's Idea Storm (Bayus 2013). This research tends to investigate how the structure and process of online communities contribute to or detract from opportunity identification and idea generation. Unlike the previous two areas of research, we need better documentation of the marketplace success of new products generated through online platforms.

3.2.1.1 Modeling Opportunity Identification

The most common goal in this research area is to predict the success of new product ideas. Here, researchers have usefully employed logit models (e.g., Bayus 2013; Goldenberg et al. 2001). For example, Bayus (2013) used an individual-effects logit model where the dependent variable (y_{it}) is a binary variable that indicates whether ideator i proposes an idea that is eventually implemented (1 for yes and 0 otherwise).

$$\Pr(y_{it} = 1) = \Lambda(\alpha_i + \beta x_{it} + \gamma z_i), \tag{3.1}$$

where Λ is a logit model $\Lambda(w) = e^w/(1 + e^w)$. The independent variables (x_{it} and z_i) include the past success of this ideator in generating implemented ideas, the diversity of this ideator's past comments, and control variables such as the ideator's demographic information.

In addition to predicting the success of an idea, researchers are also interested in the number of ideas generated by an ideator. One model used in this context is the Poisson model. For example, Bayus (2013) uses an individual-effect Poisson model where the dependent variable (y_{it}) is the number of ideas generated by ideator i. This count variable takes on positive integer values, which are assumed to follow the Poisson distribution. The model is specified as follows.

$$\Pr(y_{it}) = \lambda^{y_{it}} e^{-\lambda}/y_{it}! \tag{3.2}$$

where λ is an empirically-estimated parameter.

3.2.2 *Product Design and Development*

Once firms have identified potential opportunities, generated new product ideas, and screened those ideas for the most promising alternatives, firms need to move these ideas into product design and development. Unlike opportunity identification, product design and development has a rich and reasonably large literature in marketing (see Table 3.2 for an overview organized by topic). Much of this literature is due to one model-based area of research: conjoint analysis. Over several decades, many researchers have made important contributions to this literature, which in turn has had a substantial impact on management practice. Conjoint analysis may be the most impactful method developed in marketing research and it almost certainly is such within the area of innovation and new products research. Rao (2014) provides a focused, comprehensive review of conjoint analysis, which updates earlier reviews by Wittink and Cattin (1989), Green and Srinivasan (1990), Wittink et al. (1994), and Rao (2008).

One of the key challenges in conducting conjoint analysis research is that so many product variants exist in multi-attribute product space. As a result, much of the research in conjoint analysis has dealt with methodological and practical approaches by asking consumers about a subset of alternatives while still being able to estimate their preferences across the multi-attribute space.

Besides conjoint analysis, researchers have proposed other approaches for incorporating customers' preferences into product design and development. These approaches include quality function deployment (QFD) (Hauser and Clausing 1988) and voice of the customer (VOC) (Griffin and Hauser 1993). More recently, the idea of heterogeneous design or product morphing has been proposed as a way to take advantage of flexible production in order to better satisfy consumers' specific preferences.

3.2.2.1 *Models for Product Design*

Homogeneous Product Design. Traditional models of product design often use McFadden's (1974) random utility model of consumer choice where all consumers have the same value for attributes. Specifically, the utility u_{sj} for alternative j in choice set s is

$$u_{sj} = x_{sj}^{'}\beta + \varepsilon_{sj}, \tag{3.3}$$

where x_{sj} is a vector of the attribute levels and β captures the corresponding weights (or part-worths) consumers have for each attribute level. β s are homogeneous across consumers and therefore assume that the product design is the same for all consumers. ε_{sj} is an error term following an extreme value distribution. The maximization of consumer utility generates the probability that alternative j is chosen from choice set s:

Table 3.2 Product design and development

Topics	Literature	Summary
Concept and measurement	Homburg et al. (2015)	Product design is measured along three dimensions: aesthetics, functionality, and symbolism. Product design has positive influence on consumer willingness to pay, purchase intention, and word of mouth.
Technology evolution	Fisher and Pry (1971)	Technological evolution follows an S-shape path.
	Sood and Tellis (2005)	The authors challenge the traditional S-shaped technological evolution and found that technological evolution follows a step function with sharp improvements in performance following long periods of no improvement.
	Golder et al. (2009)	Examine 29 radical innovations from initial concept to mass-market commercialization and report findings on when (duration times), by whom (product development leaders), and how (technology borrowing) radical innovations are developed.
Successful product designs	Landwehr et al. (2011)	Prototypical but complex car designs are more preferred and generate more sales than unusual and complex designs.
	Koukova et al. (2012)	The design of multi-format digital products depends on usage situation. Consumers prefer complementary formats because they can use the multi-format product in different usage situations.
	Landwehr et al. (2013)	The influence of a product design on product liking depends on the different stages of exposure. Typical design is preferred at lower exposure levels, while atypical design is preferred at higher exposure levels. In the long run atypical designs are more likely to succeed.
	Ma et al. (2015)	Consumers are more likely to adopt a really new innovation as a detachable peripheral component than integrate it into the base product.
New product planning	Cooper (1990, 1994)	Stage-gate method which consists of concept development, design, testing, and launch.
	Ding and Eliashberg (2002)	Investigate how to structure the new product development pipeline by selecting the appropriate number of projects to fund at each stage in order to have a successful product emerge in the end.

(continued)

Table 3.2 (continued)

Topics	Literature	Summary
	Griffin (1997)	Ways to increase the speed and improve the chances of success in moving through the "funnel."
	Sethi and Iqbal (2008)	A strictly applied stage-gate process may inhibit the development of really new products.
	Ederer and Manso (2013)	Examine the effect of pay for performance on innovation. They found that the combination of tolerance for early failure and reward for long-term success is effective in motivating innovation.
Organizational factors that influence new product development	Rindfleish and Moorman (2001)	Different impacts of horizontal and vertical alliances on new product development. They find that alliances with higher overlap in firms' knowledge bases and higher quality relationships lead to higher new product creativity and faster new product development.
	Sethi et al. (2001)	Moving beyond functional boundaries to identify with the cross-functional team promotes the innovativeness of new products.
	Ganesan et al. (2005)	Examine geographic proximity of alliance partners and find that strong relational ties may be more important than simple geographic proximity and that e-mail communication, in contrast to face-to-face communication enhances new product creativity and development speed.
	Slotegraaf and Atuahene-Gima (2011)	The degree of stability in a new product development project team has a curvilinear relationship to new product advantage.
	Cui and O'Connor (2012)	Examine the resource diversity of multiple alliance partners and its contribution to firm innovation.
	Sethi et al. (2012)	Examine how to use micropolitical strategies to win approval for development of new-to-the-firm products (with market and technology newness).
	Borah and Tellis (2014)	Empirically study firms' choice of and payoff from making, buying, or allying for innovations.
	Tracey et al. (2014)	New product outcomes (e.g., product novelty and speed to market) are

(continued)

Table 3.2 (continued)

Topics	Literature	Summary
		influenced by regional cluster's macro-level configuration and its micro-level governance processes.
	Wies and Moorman (2015)	The influence of going public on firms' innovation: after going public, firms innovate at higher levels and introduce higher levels of variety with each innovation while also introducing less risky innovation, characterized by fewer breakthrough innovations and fewer innovations into new-to-the-firm categories.
How to design a new product? Conjoint analysis		
Foundational papers	Luce and Turkey (1964)	The authors developed procedures for simultaneously measuring the joint effects of two or more variables from rank-ordered data.
	Green and Rao (1971)	The foundational paper about conjoint analysis in marketing.
	Green and Srinivasan (1978)	A review paper: traces the development of conjoint method and discusses the implementation of the method.
	Green and Srinivasan (1990)	An update and extension of their 1978 review of conjoint analysis.
Commercial applications	Wind et al. (1989)	Marriott used conjoint analysis to design Courtyard by Marriott.
	Wittink and Cattin (1989)	Document 1062 conjoint applications in the United States between 1981 and 1985.
	Wittink et al. (1994)	Document 1000 conjoint applications in Europe between 1986 and 1991.
Simple products	Johnson (1974)	Application of conjoint using two-attribute trade off analysis.
	Wind (1973)	Application of conjoint method on full profile ratings.
Multi-attribute products	Shocker and Srinivasan (1974)	LINMAP (LiNear programming techniques for Multidimensional Analysis of Preferences) is used to determine individual consumer's ideal point and salience weights for product attributes.

(continued)

Table 3.2 (continued)

Topics	Literature	Summary
	Green et al. (1981)	For complex products that have many attributes, the authors treat the attributes separately and use data based on conjoint analysis to determine consumer choice. The method is called POSSE (Product Optimization and Selected Segment Evaluation).
	Johnson (1987)	Adaptive conjoint: individuals give initial estimates, which are then revised based on choices between pairs of options purposely selected by the researcher to provide the most useful additional information. This approach was popularized commercially by Sawtooth Software.
	Toubia et al. (2003)	A polyhedral, choice-based design and estimation algorithm for adaptive conjoint analysis. This method converges quickly on a respondent's part-worth utilities with a limited number of questions.
	Toubia et al. (2004)	A new polyhedral choice-based conjoint analysis question-design method.
	Netzer and Srinivasan (2011)	A web-based adaptive self-explicated approach for conjoint analysis of products with ten or more attributes.
Incorporate customer preferences	Hauser and Clausing (1988)	Introduce a planning matrix from Quality Function Deployment (QFD), House of Quality, to relate customer preferences to a firm's design, manufacturing, and marketing.
	Griffin and Hauser (1993)	Incorporate the "Voice of Customer" in order to identify, structure, and provide priorities for customer needs.
	Hoeffler (2003)	In order to mimic consumer coping mechanism when facing uncertainty, the author incorporates both mental simulation and analogies into a standard preference measurement technique (e.g., conjoint analysis) and demonstrates its superior predictive accuracy.
	Coviello and Joseph (2012)	Major innovations are more likely to succeed in small and young technology firms when customers are involved with new product development process.

(continued)

Table 3.2 (continued)

Topics	Literature	Summary
	Kim et al. (2014)	Incorporate the influence of peers in conjoint analysis and demonstrate a PIE (P, the physical product attributes; I, the individual characteristics of the choice maker; E, characteristics of an external peer group) framework of preference, which has superior predictive performance in a conjoint task.
Incorporate multi-media tools to create simulated products	Urban et al. (1996)	Incorporate a multi-media virtual-buying environment to predict consumer response to really-new products. The new method conditions consumers for future situations, simulates user experience, and encourages consumers to actively search for information on the product.
	Urban et al. (1997)	Demonstrate that the internal validity of multi-media stimuli is high and its external validity is comparable with traditional lab stimuli.
Heterogeneous designs	Sandor and Wedel (2005)	First to propose the use of heterogeneous designs where different customers get different designs.
	Liu and Tang (2015)	More efficient heterogeneous choice designs for large number of subdesigns.
	Hauser et al. (2014)	Improve web morphing by incorporating switching costs, potential website exit, and the impact of all clicks to decide the optimal timing of morphing for each customer.

$$p_{sj} = \frac{\exp(x'_{sj}\beta)}{\sum_{j=1}^{J} \exp(x'_{sj}\beta)} \tag{3.4}$$

Recent studies incorporate consumer heterogeneity where consumers have different values for the attributes. Here, a common model is the mixed logit, where β s contain random effects. For example, Sandor and Wedel (2002, 2005) assume that β is multivariate normally distributed with mean μ_B and variance Σ. If Σ is assumed to be a diagonal matrix, β can be written as $\beta = \mu_B + V\sigma_B$ with vector $\sigma_B = (\sigma_1, \ldots, \sigma_m)'$, and V is an $m * m$ diagonal matrix. Assuming utility maximization, the probability that product i is chosen from choice set s is

$$\varphi_{sj} = \int p_{sj}(v)f(v)dv, \text{ where } p_{sj}(v) = \frac{\exp\{x_{sj}^{'}(\mu_B + V\sigma_B)\}}{\sum_{j=1}^{J}\exp\{x_{sj}^{'}(\mu_B + V\sigma_B)\}}, \tag{3.5}$$

where v is the vector containing the m diagonal elements of matrix V.

Determining the optimal product design requires evaluating the information matrix of this mixed logit model. A widely used measure of the information matrix is the inverse of the determinant of the Fisher information matrix, which is called the D-error (Sandor and Wedel 2002).

$$D - error = \det[I(\mu_B, \sigma_B|X]^{-1/2K}, \tag{3.6}$$

where I is the Fisher information matrix and K is the number of attribute level combinations. Minimizing this D-error generates the optimal product design.

One limitation of the mixed logit model is the computation infeasibility when the number of possible designs is too large. To address this limitation, Liu and Tang (2015) propose a particular conjoint choice context, which can be specified as $\{(C_k, w_k)\}, k = 1, \ldots, K$, where C_k is a choice set and w_k is the continuous weight for the choice set with the constraint such that $0 \le w_k \le 1$ and $\sum_{k=1}^{K} w_k = 1$. Instead of searching for the globally optimal product design, this approach finds a globally optimal continuous design by minimizing the D-errors over the entire space of continuous designs. It generates completely heterogeneous designs for each individual respondent in the choice experiment and more importantly, it is computationally feasible.

Conjoint Analysis. Traditional choice-based conjoint analysis relies on consumers' evaluations of product attributes, resulting in the desirability of attribute levels and the importance of each attribute. However, there are difficulties when consumers need to evaluate a large number of product attributes at one time. Recent research extends the traditional stated preference methods and solves this problem by adaptively choosing a subset of attribute comparisons and interpolating the importance of other attributes (Netzer and Srinivasan 2011).

In particular, Netzer and Srinivasan (2011) ask respondents to allocate 100 points across attributes to reflect the importance of each attribute. To alleviate the problem of too many product attributes, they break down the constant-sum allocation across the full set of attributes into a subset of constant-sum allocations between two attributes at a time. In order to reduce the number of paired comparison questions, they propose an adaptive approach where respondents are asked to compare only a subset of all possible paired comparison questions. Then researchers interpolate the importance of the attributes not included in the subset of comparison questions. Meanwhile, researchers can select the attributes for the next comparison to minimize the interpolation errors. Then the importance ratios between two attributes ($r_{j_1 j_2} = W_{j_1}/W_{j_2}$, where W_{j_k} is the importance of attribute j_k) can be calculated from the paired comparisons. With the set of attribute importance ratios, a log-linear multiple regression is used to estimate relative attribute importance. The essence of their approach is to improve the estimation of individual-level attribute importances (W_j) in a way that avoids respondent overload.

3.2.3 Sales Forecasting

Forecasting can be done from the time an idea has been generated until after it has been commercialized. However, most research has focused on forecasting sales at the end of the product design and development stage.

Research on the sales forecasting of new products has been conducted in marketing for several decades. The most well known sales forecasting model in marketing is the Bass model which spawned a huge literature on diffusion models. Conceptually, these models are based on the sociological literature on diffusions of innovation, largely driven through a process of communications (e.g., Rogers 2003). We elaborate on this model in discussing one of its extensions later in this section.

The forecasting literature for non-durables primarily uses stochastic models applied to both first-time purchases and repeat sales. Another class of forecasting models, flow models, incorporate test market results to project initial sales to full-market sales. Regression models have also been used to predict new product sales. Yet another approach combines elements of flow models, regression models, and stochastic approaches to forecast the sales of new consumer nondurables. The well known ASSESSOR model has improved forecasting accuracy because researchers and managers can project laboratory results to market results. The most recent research on sales forecasting has either incorporated online-enabled approaches or focused on forecasting approaches for online environments (e.g., online word-of-mouth, online reviews, virtual markets, sentiment analysis, and blogs; e.g., Chevalier and Mayzlin 2006) (Table 3.3).

3.2.3.1 Sales Forecasting Models

In this section, we provide details on diffusion model extensions and customer lifetime analysis.

Extensions of Diffusion Models. The standard Bass (1969) diffusion model incorporates a hazard rate whereby consumers who have not yet adopted a new product do so at time t:

$$h(t) = p + qF(t), \tag{3.7}$$

where $F(t)$ is the proportion of consumers who have adopted this new product at time t; p captures the intrinsic tendency to adopt (coefficient of innovation), which can be influenced by consumer characteristics, innovation appeal, etc.; and

Table 3.3 Sales forecasting

Topics	Literature	Summary
Forecast with consumer panel statistics (model free)	Fourt and Woodlock (1960)	Customer purchase frequency information can be used to predict the success of grocery products.
Forecast with stochastic processes	Kuehn (1962)	Uses stochastic processes to describe and model new product adoption.
	Massy (1969)	Stochastic evolutionary adoption model (STEAM) uses purchase incidence data to simulate household future purchase and forecast sales.
	Parfitt and Collins (1968)	Use a stochastic model with purchase data to predict the market share for newly launched brands and the market share of established brands after promotions.
	Ehrenberg (1972)	Uses stochastic models and repeat purchase data to predict future sales.
	Schmittlein et al. (1987)	Develop the Pareto/NBD model based on the number and timing of the customers' previous purchase to predict future purchase.
	Fader and Schmittlein (1992)	The predicted sales by the Dirichlet model are usually lower than the actual sales of high-share brands. It is probably because distinct consumer segments favor large brands.
	Fader et al. (2005)	The beta-geometric/NBD (BG/NBD) model is developed to predict the future purchase with easier implementation than Pareto/NBD model and similar results.
	Jerath et al. (2011)	The POD (periodic death opportunity) model relaxes the assumption about customer attrition and thus has better prediction of future sales.
	Bemmaor and Glady (2012)	The Gamma/Gompertz/NBD model is developed to better predict future sales.
Forecast with test market results (Flow models)	Urban (1970)	The SPRINTER model, which is based on the behavioral process of the diffusion of innovation, uses test-market data to predict sales of new frequently purchased consumer products.

(continued)

Table 3.3 (continued)

Topics	Literature	Summary
	Urban (1975)	The PERCEPTOR model, which tracks consumers through states of awareness, trial, purchase, and repurchase, helps estimate the market share for alternate new brand designs.
	Assmus (1975)	The NewProd model traces the number of potential buyers who are at one of the 11 stages of adoption process and predicts the market share for the first year after the product is introduced into the market.
Forecast with regression-based models	Claycamp and Liddy (1969)	The AYER new product model, where both advertising recall and trial purchase are modeled and advertising recall is one factor in the trial purchase equation, generates good predictions based on several months of test market data.
	Blattberg and Golanty (1978)	The Tracker model incorporates awareness and repeat sales with other factors (e.g., advertising, price) and predicts year-end test market sales with early (3-month) test market results. It also helps managers with new product positioning, redesign, and market planning.
	Blackburn and Clancy (1980)	The LITMUS model combines early test market results with survey data to forecast new product sales and provides diagnostic information on a new product's strengths and weaknesses, and feedback on a product's entire marketing mix.
	Pringle et al. (1982)	The NEWS model predicts consumer awareness, trial, repeat purchase, usage, sales, and market share for a new brand.
Forecast with pre-test-market model	Silk and Urban (1978)	The ASSESSOR model which has two parts—an awareness-trial-repeat model and a preference model—uses constant sum preference data to predict sales of new packaged goods before they are test marketed.
	Urban and Katz (1983)	Demonstrate that the ASSESSOR model can predict sales accurately and is commercially viable.

(continued)

Table 3.3 (continued)

Topics	Literature	Summary
Forecast with other factors (e.g., word-of-mouth, observational learning)	Godes and Mayzlin (2004)	Online word-of-mouth is measured. Its dispersion across user communities can explain new TV show ratings.
	Chevalier and Mayzlin (2006)	An improvement in a book's reviews leads to an increase in book sales. Negative reviews have greater impact on sales than positive reviews.
	Liu (2006)	The volume of online word-of-mouth can help explain movie box office revenue.
	Dahan et al. (2011)	Securities trading of concepts (STOC) can measure aggregate consumer preferences on new product concepts.
	Chen et al. (2011)	While negative word-of-mouth has more influence on sales than positive word-of-mouth, positive observational learning (OL) increases sales but negative OL has no effect.
	Iyengar et al. (2011)	Social contagion influences new product adoption through network ties. This influence is moderated by both the recipients' perception of their opinion leadership and the sources' volume of product usage.
	Sonnier et al. (2011)	Sentiment analysis of online communication shows that positive and neutral word-of-mouth help sales and negative word-of-mouth hurts sales.
	Sood et al. (2012)	Develop a model called SAQ (Step And Wait) for predicting the path of technological innovation.
	Sun (2012)	Higher variance of a book's online ratings improves its sales rank when its average rating is low.
	Gopinath et al. (2013)	Opening day movie box office is influenced by prerelease blog volume and advertising, whereas postrelease movie box office is influenced by postrelease blog valence and advertising.
	Tang et al. (2014)	Neutral user-generated content has non-neutral impact on product sales and its impact differs between mixed-neutral and indifferent-neutral user-generated content.

(continued)

Table 3.3 (continued)

Topics	Literature	Summary
	Risselada et al. (2014)	The effects of social influence and direct marketing on high-technology product adoption change over time. The effect of social influence from cumulative adoptions decreases from the product introduction onward, whereas the influence of recent adoptions remains unchanged. The effect of direct marketing also decreases from the product introduction onward.
	Gopinath et al. (2014)	The valence of online word-of-mouth influences sales and its impact increases over time, whereas its volume has no impact. The effect of attribute-oriented advertising on sales decreases faster than emotion-oriented advertising.
	Aral and Walker (2014)	Random experiments on the adoption of a Facebook application demonstrate that the influence of peers on new product adoption is moderated by the tie strength and structural embeddedness of the social network.
	Toubia et al. (2014)	Develop an approach for using individual-level data on social interactions to improve the aggregate penetration forecasts made by diffusion models.
	Kornish and Ulrich (2014)	It is important to predict the success of new products from raw ideas. Ideas that are one standard deviation better have 50% higher sales.

q measures the effect of social contagion (coefficient of imitation). The proportion of new product adoption at time t can be written as

$$f(t) = \frac{dF(t)}{dt} = h(t)[1 - F(t)] = [p + qF(t)][1 - F(t)]. \tag{3.8}$$

The solution of this equation can be used to predict the cumulative penetration of a new product, in other words, the proportion of consumers who have adopted a new product at time t. Specifically,

$$F(t) = \left[1 - \exp\left(-g - \frac{p+q}{t}\right)\right] \Big/ \left[1 + \left(\frac{q}{p}\right)\exp\left(-g - \frac{p+q}{t}\right)\right], \tag{3.9}$$

where g is a location parameter.

One limitation of the original Bass model is that consumers are homogeneous and influenced by the same factors. One extension is the asymmetric influence model (AIM) where two consumer segments, i.e., influentials and imitators differ in the factors that drive their adoption behavior (Van den Bulte and Joshi 2007). The hazard functions for these two segments are

$$\text{For influentials (denoted as 1)}, h_1(t) = p_1 + q_1 F_1(t); \tag{3.10}$$

$$\text{For imitators (denoted as 2)}, h_2(t) = p_2 + q_2[wF_1(t) + (1-w)F_2(t)], \tag{3.11}$$

where w denotes the relative importance that imitators attach to influentials' versus other imitators' adoption behavior ($0 \le w \le 1$). Assuming the proportion of influentials is θ and the proportion of imitators is $1-\theta$, the overall cumulative market penetration is:

$$F_m(t) = \theta F_1(t) + (1-\theta)F_2(t). \tag{3.12}$$

And the fraction of population adopting at time t is:

$$f_m(t) = \theta f_1(t) + (1-\theta) f_2(t). \tag{3.13}$$

From Eqs. 3.6 and 3.7, the population hazard function can be derived as

$$h_m(t) = f_m(t)/[1 - F_m(t)] = [\theta f_1(t) + (1-\theta) f_2(t)]/(1 - F_m(t)). \tag{3.14}$$

As individual consumer level social interaction data become available, researchers have extended the Bass model by incorporating data such as social ties and new product recommendations among consumers (Toubia et al. 2014). Assume that consumer i receives r_{it} recommendations in period t. r_{it} is assumed to follow a binomial distribution specified as:

$$\begin{aligned} & r_{it} \sim Bin(ties_i, aF_{t-1}) \\ & \Rightarrow P(r_{it}|ties_i) = \binom{ties_i}{r_{it}} (aF_{t-1})^{r_{it}} (1 - aF_{t-1})^{ties_i - r_{it}} \end{aligned} \tag{3.15}$$

where $ties_i$ is the number of consumer i's social ties, F_{t-1} is the cumulative penetration in period $t-1$, and a is the probability that a given tie would recommend the product to consumer i conditional on the tied consumer having adopted.

The hazard rate is influenced by the social recommendation r_{it} and is specified as

$$h(r_{it}) = 1 - (1-p)(1-q)^{r_{it}} \tag{3.16}$$

where p and q have similar interpretation as in the Bass model.

Toubia et al. (2014) show that the aggregate diffusion process can be derived from Eqs. 3.9 and 3.10. Let $P(ties)$ be the probability mass function of the number of social ties, and let f_t^{ties} and F_t^{ties} be the marginal and cumulative aggregate penetration in period t among consumers with ties. The marginal penetration f_t^{ties} is equal to the proportion of non-adopters, $1 - F_t^{ties}$, multiplied by the expected value of the hazard rate in period t among these consumers:

$$\begin{aligned} f_t^{ties} &= \left(1 - F_{t-1}^{ties}\right) E_{r_t}[h(r_t)|ties] \\ &= \left(1 - F_{t-1}^{ties}\right) \sum_{r_t=0}^{ties} h(r_t) P(r_t|ties) \end{aligned} \tag{3.17}$$

The Bass model can be further extended by incorporating the number of consumer recommendations (Toubia et al. 2014).

Extensions of Customer Lifetime Models. Another common model used to predict sales is the customer lifetime model, where statistical models predict how long a customer will stay with a company and how much he will buy (i.e., purchase rate). For more information about customer lifetime models and related issues, we refer to Chap. 10 of this Handbook: "Marketing Models for the Customer-Centric Firm" by Ascarza, Fader, and Hardie. The most influential model in this stream is the Pareto/NBD model (Schmittlein et al. 1987). Here, the time at which a customer becomes "dead" (i.e., no longer buy from a company) is denoted τ. For any time $T > 0$, if the customer is still alive at T (so $\tau > T$), the number of purchases (x) in $(0, T]$ is assumed to follow the Poisson distribution:

$$P[X = x|\lambda, \tau > T] = e^{-\lambda T} \frac{(\lambda T)^x}{x!}; \quad x = 0, 1, 2, \ldots, \tag{3.18}$$

where the purchase rate λ is assumed to follow a gamma distribution:

$$\mathrm{g}(\lambda|\mathrm{r}, \alpha) = \frac{\alpha^{\mathrm{r}}}{\Gamma(\mathrm{r})} \lambda^{\mathrm{r}-1} \mathrm{e}^{-\alpha\lambda}; \quad \lambda > 0; \quad r, \alpha > 0. \tag{3.19}$$

The time τ until becoming "dead" is assumed to follow an exponential distribution:

$$f(\tau|\mu) = \mu e^{-\mu\tau}; \quad \tau > 0, \tag{3.20}$$

where the death rate μ is also assumed to follow a gamma distribution:

$$h(\mu|s, \beta) = \frac{\beta^s}{\Gamma(s)} \mu^{s-1} e^{-\beta\mu}; \quad \mu > 0; \; s, \beta > 0. \tag{3.21}$$

With these equations, the purchases made while a customer is "alive" follow the NBD model and have the distribution:

$$P[X = x|r, \alpha, \tau > T] = \binom{x + r - 1}{x} \left(\frac{\alpha}{\alpha + T}\right)^r \left(\frac{T}{\alpha + T}\right)^x; \quad x = 0, 1, 2, \ldots \tag{3.22}$$

"Deaths" for a sample of customers follow the Pareto distribution:

$$f(\tau|s,\beta)=\frac{s}{\beta}(\frac{\beta}{\beta+\tau})^{s+1}, \quad r>0 \tag{3.23}$$

Overall, this combined purchase event/duration model is called the Pareto/NBD. One challenge with this model is its complicated likelihood function and numerous evaluations of the Gaussian hypergeometric function. To address this limitation, Fader et al. (2005) develop a beta-geometric/NBD (BG/NBD) model, a variation of the Pareto/NBD, which is easier to implement. Similar to the Pareto/NBD model, the BG/NBD model assumes that the number of purchases follows the Poisson distribution and the purchase rate follows the gamma distribution. The difference between the Pareto/NBD and BG/NBD is how/when customers become inactive. The Pareto/NBD assumes that customers can "die" at any point in time, independent of the occurrence of actual purchases, whereas the BG/NBD assumes that customers "die" immediately after a purchase. Specifically, the BG/NBD assumes that after any purchase, a customer becomes "dead" with a probability p which follows a beta distribution with p.d.f:

$$f(p|a,b)=\frac{p^{a-1}(1-p)^{b-1}}{B(a,b)}, \quad 0\le p\le 1, \tag{3.24}$$

where $B(a, b)$ is the beta function, which can be written as $B(a,b)=\Gamma(a)\Gamma(b)/\Gamma(\mathrm{a,b})$.

The point at which the customer "dies" is distributed across purchases according to a (shifted) geometric distribution with p.m.f

$$\begin{aligned} &P(\text{inactive immediately after } j\text{th transaction}) \\ &=p(1-p)^{j-1}, \quad j=1,2,3,\ldots \end{aligned} \tag{3.25}$$

Fader et al. (2005) show that the BG/NBD model can be estimated easily in Microsoft Excel and therefore is usable in most business applications.

Researchers also extend the Pareto/NBD model by making it more flexible and more powerful for sales prediction. For example, Bemmaor and Glady (2012) develop the gamma/Gompertz/NBD (G/G/NBD) model. Similar to the Pareto/NBD model, the G/G/NBD model assumes that the number of purchases follows the Poisson distribution and the purchase rate follows the gamma distribution. The difference between the Pareto/NBD and G/G/NBD is that the probability that a customer dies before time τ is assumed to follow a Gompertz distribution:

$$F(\tau|\eta)=1-\exp\left(-\eta\left(e^{b\tau}-1\right)\right), \quad \eta,b>0,\tau>0 \tag{3.26}$$

Compared with the Pareto/NBD model, the G/G/NBD model is more flexible because the p.d.f. of the Gompertz distribution can be skewed left or right and it can exhibit a mode at zero or an interior mode. Bemmaor and Glady (2012) also show that the G/G/NBD predicts sales better than the Pareto/NBD model.

3.2.4 Commercialization

The final stage of the new product development process is commercialization. This stage has received much attention in marketing because it lies at the nexus of firm strategy and consumer response to new products (e.g., Boulding and Christen 2003; Golder and Tellis 1993; Min et al. 2006; Robinson and Fornell 1985). Research on commercialization can be categorized into several areas.

First, there is a large and rich literature on entry timing strategies. Initial research in this area found that market pioneers or first movers enjoyed substantial advantages over later entrants. However, this research suffered from several limitations including survivor bias and misclassifying successful firms. Correcting for these limitations resulted in the finding that market pioneers tend to have much higher failure rates, lower market shares, and lower rates of market leadership than previously believed.

Second, another stream of research has attempted to identify the factors associated with new product success. These include differentiation (both meaningful and seemingly meaningless) (Carpenter et al. 1994), introducing innovative product attributes (Shankar et al. 1998), and market characteristics like network effects (Wang et al. 2010). A related stream of research looks specifically at the marketing mix variables associated with new product success (e.g., Bruce et al. 2012; Kopalle and Lehmann 2006; Spann et al. 2015).

Finally, another stream of research examines how incumbents defend against new entrants. Much of this work is analytical (theoretical) in nature (e.g., Hauser and Shugan 1983). Some of these papers make strong prescriptive recommendations of strategies for firms to follow. Surprisingly, some empirical research shows that firms actually do very little to respond to competitors' innovations (Table 3.4).

3.2.4.1 Modeling Commercialization

In this section, we provide details on models of channel acceptance and customer lifetime value.

Channel acceptance of new products. When a new product is introduced to a market, there are two major challenges: how to position it so that consumers will choose it over alternative products and how to convince retailers to accept it. Luo et al. (2007) develop an approach to positioning and pricing a new product that directly incorporates the consumers' preferences and retailer's acceptance criteria.

The authors propose two frameworks of market estimation before and after a new product's entry (see Figs. 3.1 and 3.2). In these two frameworks, consumers' preferences are first estimated with a random utility choice model for a

Table 3.4 Commercialization

Topics	Literature	Summary
Entry timing	Robinson and Fornell (1985)	Market pioneers have higher market shares because of firm-based superiority (better marketing mix and more cost savings) and consumer information advantages.
	Urban et al. (1986)	Market pioneers have higher market shares across 24 categories.
	Robinson (1988)	Market pioneers have higher market shares in industrial goods industries because of their stronger products compared with competitors' products and the characteristics of the industrial goods industries.
	Carpenter and Nakamoto (1990)	Market pioneers have advantages in acculturating consumers' preferences for the pioneer rather than for later entrants.
	Kalyanaram and Urban (1992)	Later entrants suffer a long-term market disadvantage in 8 categories of consumer packaged goods.
	Golder and Tellis (1993)	A historical analysis shows that 47% of market pioneers fail and their market share is overstated in the literature because of a survival bias whereby failed pioneers are not included in the data sets and successful later entrants are misclassified as pioneers.
	Kalyanaram et al. (1995)	Main conclusions: (1) for consumer packaged goods, order of market entry has stronger negative relationship with trial penetration than with repeat purchase; (2) pioneers have broader product lines than late entrants; (3) skill and resource profiles differ across market pioneers, early followers, and late entrants; and (4) order of market entry is not related to long-term survival rates.
	Narasimhan and Zhang (2000)	Firm with a larger pioneering premium may choose to wait, while a firm with a smaller pioneering premium speeds to the market.
	Bohlmann et al. (2002)	Pioneers are better off in product categories where consumers value variety, whereas pioneers are worse off in categories where consumers value quality.
	Boulding and Christen (2003)	Market pioneers may suffer a long term profit disadvantage because of greater average cost.
	Min et al. (2006)	Pioneers have first-mover advantages with incremental innovations, but they are likely to fail with a really new product.

(continued)

Table 3.4 (continued)

Topics	Literature	Summary
	Boulding and Christen (2008)	Market pioneers benefit from two cost advantages—experience curve effects and preemption of input factors, while they suffer from three cost disadvantages—imitation, vintage effects, and demand orientation.
	Wang et al. (2010)	In markets with strong network effects, pioneer survival advantage occurs when their product is cross-generation compatible but within-generation incompatible. In contrast, in markets with weak network effects, pioneer survival advantage is likely to occur when their product is cross-generation incompatible but within-generation compatible.
Strategies to succeed	Carpenter and Nakamoto (1990)	Examine optimal positioning, advertising, and pricing strategies for a late entrant and conclude that a differentiated strategy is optimal and a "me-too" positioning is often sub-optimal.
	Carpenter et al. (1994)	Meaningless differentiation can result in a meaningfully differentiated brand.
	Montoya-Weiss and Calantone (1994)	Meta-analysis of the factors that contribute to the success of new products.
	Nowlis and Simonson (1996)	Introducing new product features adds substantial value and increases brand choice.
	Shankar et al. (1998)	For a later entrant, being innovative can create advantages with higher market potential and a higher repeat purchase rate than either the pioneer or non-innovative late entrant.
	Henard and Syzmanski (2001)	Meta-analysis of the factors that contribute to the success of new products.
	Haenlein and Libai (2013)	Demonstrate that when targeting potential adopters of a new product, firms should target customers with high lifetime value, or "revenue leaders".
Marketing mix in new market	Horsky and Nelson (1992)	An analysis of the optimal positioning and pricing strategy of a new brand using game theory.
	Cooper (2000)	An approach to marketing planning for radically new products.
	Kopalle and Lehmann (2006)	Examine optimal advertised quality, actual quality, and price for a firm entering a market. They found that it is optimal to overstate quality when customers rely relatively less on advertising to form quality expectations and

(continued)

Table 3.4 (continued)

Topics	Literature	Summary
		customers' intrinsic satisfaction with a product is high.
	Hitsch (2006)	Explore optimal entry and exit policy when demand of a new product is uncertain.
	Luo et al. (2007)	Develop an approach to positioning and pricing a new product that incorporate the retailer's acceptance criteria into the development process.
	Narayanan and Manchanda (2009)	Examine the optimal allocation of marketing communication across consumers and over time for the launch of a new product.
	Bruce et al. (2012)	Study the dynamic effects of advertising and word-of-mouth on demand for new products at different stages. They found that increased advertising is more effective at an earlier stage and increased word-of-mouth is more effective at a later stage.
	Spann et al. (2015)	Analyze dynamic pricing strategies in the introduction and early growth phases of new products.
Strategies to defend against a new entrant	Hauser and Shugan (1983)	Analyze how a firm should adjust its marketing expenditures and price to defend its position when attacked by a competitive new product.
	Robinson (1988)	Incumbents' most common response to a new entrant is either no response or only a single reaction with one marketing variable.
	Bowman and Gatignon (1996)	Investigate the influence of order-of-entry on the effectiveness of a firm's marketing mix and found that late entry reduces sensitivity to price, promotion, and quality.
	Gatignon et al. (1997)	Empirically examine the effectiveness of different defensive strategies against new product entry and found that faster reaction is more successful whereas greater breadth of reaction (number of marketing mix variables used) is less successful.
	Roberts et al. (2005)	Develop a model to set an incumbent's defensive marketing strategy prior to a new entrant's launch.
Strategies to shift away from a failing new product	Boulding et al. (1997)	Managers remain committed to a new product launch even when confronted with strong evidence of failure. This commitment is lessened by precommitment to a predetermined stopping rule or introducing a new decision maker.

(continued)

Table 3.4 (continued)

Topics	Literature	Summary
	Biyalogorsky et al. (2006)	Develop and test a conceptual framework that explains why new product managers maintain or escalate their commitment to a failing new product. They argue that it may not be possible to eliminate commitment bias at the individual level, and that organizational processes must be used instead.
The outcomes of innovations	Gielens (2012)	Explore when and to what extent new products change national brands' market position.
	Rubera and Kirca (2012)	A meta-analysis of the effect of firm innovativeness on its value and financial position.
	Dotzel et al. (2013)	Examine the determinants of service innovativeness and its interrelationships with firm-level customer satisfaction, firm value, and firm risk.
	Rubera (2015)	Empirically study the effect of design innovativeness (i.e., the degree of novelty in a product's design) on new product sales' evolution.

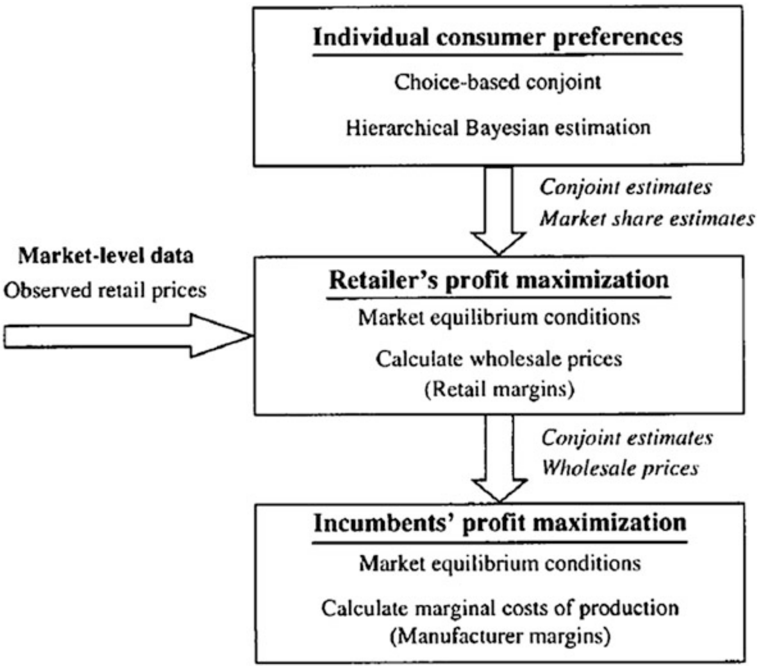

Fig. 3.1 Estimation of market specifics—before entry. *Source* Luo et al. (2007)

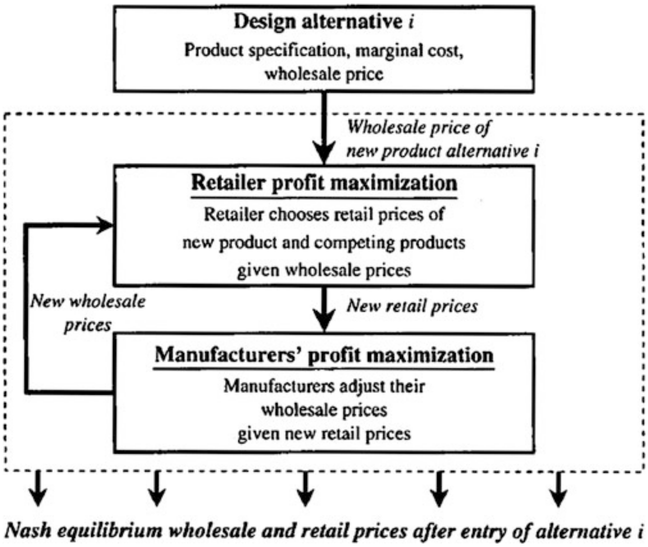

Fig. 3.2 Market scenario development—after entry of design alternative. *Source* Luo et al. (2007)

conjoint choice experiment with N individual consumers evaluating K choice sets with G alternative product designs. The utility of consumer i for product design g in choice k is defined as:

$$U_i(x_{gk}, p_{gk}) = \left(x'_{gk}\beta_{ix} + p_{gk}\beta_{ip}\right) + \varepsilon_{igk,} \tag{3.27}$$

where x_{gk} is a vector of product attributes of design g, p_{gk} is the price, and $\varepsilon_{igk,}$ is the random component of the utility. The probability of consumer i choosing design g can be derived from Eq. (3.1). Specifically, it is expressed using the logit expression.

$$\Pr_{igk} = \frac{\exp(x'_{gk}\beta_{ix} + p_{gk}\beta_{ip})}{\sum_{g'=1}^{G}[\exp(x'_{g'k}\beta_{ix} + p_{g'k}\beta_{ip})] + \exp(a_i)}, \tag{3.28}$$

where a_i is the utility of no-choice option for consumer i.

The next step is to estimate wholesale prices and marginal costs of incumbent products. First, the wholesale prices can be determined by maximizing the retailer's profits. In particular, before a new product is introduced to the market, the retailer's profit maximization is specified as:

$$\max_{p_1, p_2, \ldots, p_J} \pi^r = \left\{\sum_{j=1}^{J} \left[m_j * (p_j - w_j) * S\right]\right\} - sc * J, \tag{3.29}$$

where π^r is the retailer's profit, m_j is product j's market share, w_j is its wholesale price, S is market size, and sc is the marginal shelf cost.

Alternatively, the marginal costs of incumbent products can be estimated by maximizing manufacturer's profits. That is,

$$\max_{w_j} \pi_j^m = \left(w_j - c_j\right) * m_j * S - F_j \quad j - 1, \ldots, J, \tag{3.30}$$

where c_j is product j's marginal cost, and F_j is its fixed cost.

The manufacturer's goal is to select a product design and a wholesale price so that the product will be accepted by retailers, and be more profitable than other designs. As shown in Fig. 3.2, we need to estimate the new market scenario after the entry of the new product by estimating new wholesale and retail prices. The procedure includes solving two optimization problems iteratively: the retail profit maximization problem (second block in Fig. 3.2) and the manufacturer profit maximization problem (third block in Fig. 3.2). The maximization equations are similar to Eqs. 3.29 and 3.30 but with new wholesale and retail prices.

An Application of Customer Lifetime Value (*CLV*). When a new product is introduced to the market, managers can use customer lifetime value (CLV) to identify and target the most profitable customers. Customer lifetime value (CLV) is the present value of all future profits obtained from a customer over his life of relationship with a firm. It is specified as (Gupta et al. 2004; Reinartz and Kumar 2003):

$$CLV = \sum_{t=0}^{T} \frac{(p_t - c_t) r_t}{(1+i)^t} - AC \tag{3.31}$$

where p_t is the price paid by the customer at time t, c_t is the direct cost of serving the customer at t, i is the discount rate for the firm, r_t is the probability of a customer being "alive" at time t, AC is the acquisition cost, and T is the time horizon for estimating CLV. If the margin $(p_t - c_t)$ and retention rate are constant over time and the time horizon is assumed to be infinite, CLV can be simplified to (Gupta and Lehmann 2003):

$$CLV = \sum_{t=0}^{\infty} \frac{(p - c) r^t}{(1+i)^t} = m \frac{r}{(1 + i - r)} \tag{3.32}$$

Haenlein and Libai (2013) use CLV to identify profitable customers ("revenue leaders"). They argue that targeting "revenue leaders" can accelerate these customers' new product adoption and therefore create an earlier and larger cash flow. More important, these customers can create higher-than-average social value. This effect is due to "network assortativity"—a phenomenon whereby people tend to be connected with others who are like them.

In order to assess the value of "revenue leaders," Haenlein and Libai (2013) use stochastic network-based cellular automata, an ABM (Agent-Based Model) technique, to simulate new product adoption based on local interactions among individual customers. The basic idea of the ABM technique is to start with a social network where no customer has yet adopted the product. Then the utility of buying the product is randomly generated and assigned to each customer and customers whose utility is larger than the product price will adopt the new product. Customers who have adopted the new product influence other customers by word-of-mouth and thus more customers adopt the new product in their social network. Details of the ABM technique are given in Goldenberg et al. (2002). One benefit of using the ABM technique is that it allows researchers to explore the effectiveness of various seeding programs and helps mangers target the most profitable customers. In Haenlein and Libai (2013), the value created by a seeding program is:

Total value = Direct value (i.e., new product adoptions by customers who are seeded) + Social value (i.e., new product adoptions by customers who are connected with the seeded ones) − Cost of the seeding program. Haenlein and Libai (2013) demonstrate that targeting "revenue leaders" is more profitable than targeting "opinion leaders."

3.3 Future Research Opportunities

While prior research has contributed much to our understanding of innovation and new products, many opportunities remain to fulfill the potential in this important area of research. We begin by discussing key areas of emphasis that transcend particular stages of the product development process.

One key topic of future research should be to focus more on metrics than models. Prior research has already done much to develop useful models. However, going forward, developing appropriate metrics for firms to use systematically over time offers great potential benefits. With these metrics, researchers would be able to enhance our understanding of new product development, show firms how they should reduce the inherent inefficiencies, and help them deliver successful innovations on a more regular basis.

A second key topic of future research is business model innovation. Nearly all marketing research use the new product as the level of analysis. However, the product is only one part of the overall offering delivered to customers. Firms can grow through other elements of the marketing mix (i.e., pricing, communication, channels) and other aspects of their business model (e.g., financing, sourcing, partnering), and are influenced by actions that lie outside the firms' control.

A third key topic of future research is to more thoroughly document the process of generating and commercializing the most innovative new products. Currently, we mainly know anecdotes and selected pieces of complete innovation success stories. The first step in repeating these successes is to at least thoroughly understand how they occurred in the past and to see what differentiates them from failures.

Next, we outline some more specific questions for future research. We organize these using the same four stages of new products research that we used to organize prior research: (i) opportunity identification, (ii) product design and development, (iii) sales forecasting, and (iv) commercialization.

3.3.1 Opportunity Identification

The following research questions are most important to address in the area of opportunity identification:

1. How should firms identify the most relevant lead users?
2. Which lead users are predictive of the future preferences of the general consumer market?
3. How can online platforms (e.g., user groups, Facebook, snapchat, and Instagram) be used to identify potential opportunity areas, generate new product ideas, and screen those ideas?
4. What are the best approaches for generating or moderating business-to-consumer communications and consumer-to-consumer communications?
5. When and how are new technologies incorporated into new products? Do these new technologies lead or lag firms' efforts to identify new opportunities?

3.3.2 Product Design and Development

Research questions important to address in the area of product design and development include:

1. How do firms document and learn from failures during the new product development process? How should they do this?
2. How should firms make use of online platforms to design and develop their new products? What are the best ways to involve consumers at various points during design and development? What are the downsides of doing so?
3. What are the similarities and differences in designing and developing new products versus new services versus integrated products and services?
4. When is it appropriate for firms to rely on product champions versus cross-functional teams?
5. How should intrapreneurship be encouraged within organizations? How should firms fund and reward innovators? When and how should firms use think tanks or skunk works?
6. How and when should firms pursue joint development projects with other firms or with potential customers (especially business customers)?

7. When and how should firms abandon new products during design and development?
8. When and how should firms incorporate new technologies into new products?
9. When and what should new products borrow from past products, e.g., to be compatible with behavior or expectations?
10. Are portfolio approaches useful for managing risks in new product development projects?

3.3.3 Sales Forecasting

The following research questions are important to address in the area of sales forecasting:

1. How should firms use online platforms and social media (e.g., Facebook, Instagram, snapchat, etc.) to forecast sales?
2. How should the use of these platforms vary for business-to-business versus business-to-consumer products?
3. How can sales forecasting techniques be more diagnostic by decomposing the overall sales forecasts into the various elements of each new product or service offering?
4. What testing techniques provide better information about ultimate market acceptance earlier in the product design and development process?
5. How can firms generate better estimates of cannibalization across their product lines?
6. How do forecasts themselves impact strategy and success?

3.3.4 Commercialization

While this stage is typically ignored by academics, it is often the most critical one. Important questions to address in this area include:

1. How should firms document, learn from, and apply lessons learned from failed new product launches?
2. How should firms use social media to promote new product launches? How should these efforts differ between business and consumer markets?
3. What is the role of opinion leaders in markets with high social media activity?
4. Who are the opinion leaders in markets with high social media activity and how do they differ from opinion leaders in markets with low social media activity?
5. When and how should firms kill new products after commercialization?

6. What does the concept of relative product advantage really mean? How is it measured? How much does it contribute to a new product's success?
7. How do new categories obtain their names? Should firms be more proactive about promoting new category names?
8. How important are informational cascades in driving new product adoption?
9. What are the contextual factors that determine when being fast to market is more or less important? What are the differences between incremental innovations and radical innovations?
10. What is the appropriate scale of entry for new products? What are the factors that determine when it should be large or small?
11. How should firms manage consumer disadoption and disposal?

3.4 Conclusion

This review has highlighted some key marketing research on innovation and new products. Where we provided less extensive coverage, we refer readers to other useful references. For each of the four stages of the new product development process (opportunity identification, product design and development, sales forecasting, and commercialization), we organize literature by sub-topics within each of these stages. This hopefully will give readers a good sense of the state-of-the-art in each of these research areas. We also provide thoughts on some important research to conduct going forward. Overall, much has been learned already. Nonetheless, given the importance of new product innovation to firms, to individuals, and to societies, we hope that tomorrow's researchers continue to generate newer and richer insights in this vitally important field of investigation.

References

Aral, Sinan, and Dylan Walker. 2014. Tie strength, embeddedness, and social influence: A large-scale networked experiment. *Management Science* 60 (6): 1352–1370.

Assmus, G. 1975. NEWPROD: The design and implementation of a new product model. *Journal of Marketing* 39 (1): 16–23.

Bass, Frank M. 1969. A new product growth model for consumer durables. *Management Science* 15 (5): 215–227.

Bayus, Barry L. 2013. Crowdsourcing new product ideas over time: An analysis of the Dell IdeaStorm community. *Management Science* 59 (1): 226–244.

Bemmaor, Albert C., and Nicolas Glady. 2012. Modeling purchasing behavior with sudden 'Death': A flexible customer lifetime model. *Management Science* 58 (5): 1012–1021.

Blackburn, J.D., and K.J. Clancy. 1980. LITMUS: A new product planning model. In *Proceedings: Market measurement and analysis,* ed. Robert P. Leone, 182–193. Providence, R.I.: The Institute of Management Sciences.

Blattberg, R., and J. Golanty. 1978. Tracker: An early test market forecasting and diagnostic model for new product planning. *Journal of Marketing Research* 15 (2): 192–202.

Biyalogorsky, E., W. Boulding, and R. Staelin. 2006. Stuck in the past: Why managers persist with new product failures. *Journal of Marketing* 10 (2): 108–121.

Bohlmann, Jonathan D, Peter N. Golder, and Debanjan Mitra. 2002. Deconstructing the pioneer's advantage: Examining vintage effects and consumer valuations of quality and variety. *Management Science* 48 (9): 1175–1195.

Borah, Abhishek, and Gerard J. Tellis. 2014. Make, buy, or ally? choice of and payoff from announcements of alternate strategies for innovations. *Marketing Science* 33 (1): 114–133.

Boulding, W., and M. Christen. 2003. Sustainable pioneering advantage? Profit implications of market entry order. *Marketing Science* 22 (3): 371–392.

Boulding, William, and Markus Christen. 2008. Disentangling pioneering cost advantages and disadvantages. *Marketing Science* 27 (4): 699–716.

Boulding, W., R. Morgan, and R. Staelin. 1997. Pulling the plug to stop the new product drain. *Journal of Marketing Research* 34 (1): 164–176.

Bowman, D., and H. Gatignon. 1996. Order of entry as a moderator of the effect of the marketing mix on market share. *Marketing Science* 15 (3): 222–242.

Boyd, D., and J. Goldenberg. 2013. *Inside the box*. New York, NY: Simon and Schuster.

Bruce, Norris I., Natasha Zhang Foutz, and Ceren Kolsarici. 2012. Dynamic effectiveness of advertising and word of mouth in sequential distribution of new products. *Journal of Marketing Research* 49 (4): 469–486.

Burroughs, James E., Darren W. Dahl, C. Page Moreau, Amitava Chattopadhyay, and Gerald J. Gorn. 2011. Facilitating and rewarding creativity during new product development. *Journal of Marketing* 75 (4): 53–67.

Carpenter, G.S., R. Glazer, and K. Nakamoto. 1994. Meaningful brands from meaningless differentiation: The dependence on irrelevant attributes. *Journal of Marketing Research* 31 (3): 339–350.

Carpenter, G.S., and K. Nakamoto. 1990. Competitive strategies for late entry into a market with a dominant brand. *Management Science* 36 (10): 1268–1278. Focused Issue on the State of the Art in Theory and Method in Strategy Research.

Chandy, R.K., and G.J. Tellis. 1998. Organizing for radical product innovation: The overlooked role of willingness to cannibalize. *Journal of Marketing Research* 35 (4): 474–487.

Chen, Yubo, Qi Wang, and Jinhong Xie. 2011. Online social interactions: A natural experiment on word-of-mouth versus observational learning. *Journal of Marketing Research* 48 (2): 238–254.

Chevalier, J.A., and D. Mayzlin. 2006. The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research* 43 (3): 343–354.

Claycamp, H.J., and L.E. Liddy. 1969. Prediction of new product performance: An analytical approach. *Journal of Marketing Research* 6 (4): 414–420.

Cooper, L.G. 2000. Strategic marketing planning for radically new products. *Journal of Marketing* 64 (1): 1–16.

Cooper, R.G. 1990. Stage-gate systems: A new tool for managing new products. *Business Horizons* 33 (3): 44–54.

Cooper, R.G. 1994. Perspective third-generation new product processes. *Journal of Product Innovation Management* 11 (1): 3–14.

Coviello, Nicole E., and Richard M. Joseph. 2012. Creating major innovations with customers: Insights from small and young technology firms. *Journal of Marketing* 76 (6): 87–104.

Cui, Anna S., and Gina O'Connor. 2012. Alliance portfolio resource diversity and firm innovation. *Journal of Marketing* 76 (4): 24–43.

Dahan, E., A.J. Kim, A.W. Lo, T. Poggio, and N. Chan. 2011. Securities trading of concepts (STOC). *Journal of Marketing Research* 48 (3): 497–517.

Ding, M., and J. Eliashberg. 2002. Structuring the new product development pipeline. *Management Science* 48 (3): 343–363.

Dotzel, Thomas, Venkatesh Shankar, and Leonard L. Berry. 2013. Service innovativeness and firm value. *Journal of Marketing Research* 50 (2): 259–276.

Ederer, Florian, and Gustavo Manso. 2013. Is Pay for Performance Detrimental to Innovation? *Management Science* 59 (7): 1496–1513.

Ehrenberg, A.S.C. 1972. *Repeat-buying: Theory and application*. Amsterdam: North Holland Press.

Fader, P.S., B.G.S. Hardie, and K.L. Lee. 2005. Counting your customers the easy way: An alternative to the Pareto/NBD model. *Marketing Science* 24 (Spring): 275–284.

Fader, P.S., and D.C. Schmittlein. 1992. Excess behavioral loyalty for high-share brands: Deviations from the Dirichlet model for repeat purchasing. *Journal of Marketing Research* 30 (November): 478–493.

Fisher, J.C., and R.H. Pry. 1971. A simple substitution model of technological change. *Technological Forecasting and Social Change* 3: 75–88.

Fourt, L.A., and J.W. Woodlock. 1960. Early prediction of market success for new grocery products. *Journal of Marketing* 25 (2): 31–38.

Ganesan, S., A.J. Malter, and A. Rindfleisch. 2005. Does distance still matter? Geographic proximity and new product development. *Journal of Marketing* 69 (4): 44–60.

Gatignon, H., T.S. Robertson, and A.J. Fein. 1997. Incumbent defense strategies against new product entry. *International Journal of Research in Marketing* 14 (2): 163–176.

Gielens, Katrijn. 2012. New products: The antidote to private label growth? *Journal of Marketing Research* 49 (3): 408–423.

Godes, D., and D. Mayzlin. 2004. Using online conversations to study word-of-mouth communication. *Marketing Science* 23 (4): 545–560.

Goldenberg, Jacob, David Mazursky, and Sorin Solomon. 1999. Toward identifying the templates of new products: A channeled ideation approach. *Journal of Marketing Research* 36 (2): 200–210.

Goldenberg, J., R. Horowitz, A. Levav, and D. Mazursky. 2003. Finding your innovation sweet spot. *Harvard Business Review* 81 (3): 120–130.

Goldenberg, Jacob, Donald R. Lehmann, and David Mazursky. 2001. The idea itself and the circumstances of its emergence as predictors of new product success. *Management Science* 47 (1): 69–84.

Goldenberg, Jacob, Barak Libai, and Eitan Muller. 2002. Riding the saddle: How cross-market communications can create a major slump in sales. *Journal of Marketing* 66 (2): 1–16.

Golder, Peter N., and Debanjan Mitra (editors). 2017. *Handbook of research on new product development*. Edward Elgar.

Golder, Peter N., Rachel Shacham, and Debanjan Mitra. 2009. Innovations' origins: When, by whom, and how are radical innovations developed? *Marketing Science* 28 (1): 166–179.

Golder, Peter N., and Gerard J. Tellis. 1993. Pioneer advantage: Marketing logic or marketing legend? *Journal of Marketing Research* 30 (May): 158–170.

Gopinath, Shyam, Pradeep K. Chintagunta, and Sriram Venkataraman. 2013. Blogs, advertising, and local-market movie box office performance. *Management Science* 59 (12): 2635–2654.

Gopinath, Shyam, Jacquelyn S. Thomas, and Lakshman Krishnamurthi. 2014. Investigating the relationship between the content of online word of mouth, advertising, and brand performance. *Marketing Science* 33 (2): 241–258.

Green, P.E., J.D. Carroll, and S.M. Goldberg. 1981. A general approach to product design optimization via conjoint analysis. *Journal of Marketing* 45 (Summer): 17–37.

Green, P.E., and V.R. Rao. 1971. Conjoint measurement for quantifying judgmental data. *Journal of Marketing Research* 8 (August): 355–363.

Green, P.E., and V. Srinivasan. 1978. Conjoint analysis in consumer research: Issues and outlook. *Journal of Consumer Research* 5 (2): 103–123.

Green, P.E., and V. Srinivasan. 1990. Conjoint analysis in marketing: New developments with implications for research and practice. *Journal of Marketing* 54 (4): 3–19.

Griffin, A. 1997. PDMA research on new product development practices: Updating trends and benchmarking best practices. *Journal of Product Innovation Management* 4 (6): 429–458.

Griffin, A., and J.R. Hauser. 1993. The voice of the customer. *Marketing Science* 12 (1): 1–27.

Gupta, Sunil, and Donald R. Lehmann. 2003. Customers as assets. *Journal of Interactive Marketing* 17 (1): 9–24.

Gupta, Sunil, Donald R. Lehmann, and Jennifer A. Stuart. 2004. Valuing Customers. *Journal of Marketing Research* 41 (1): 7–18.

Haenlein, Michael, and Barak Libai. 2013. Targeting revenue leaders for a new product. *Journal of Marketing* 77 (3): 65–80.

Hanssens, Dominique M. 2015. *Empirical generalizations about marketing impact*, 2nd ed. Cambridge, MA: Marketing Science Institute.

Hauser, J.R., and D. Clausing. 1988. The house of quality. *Harvard Business Review* 66 (3): 63–73.

Hauser, John R., Guilherme Liberali, and Glen L. Urban. 2014. Website morphing 2.0: switching costs, partial exposure, random exit, and when to morph. *Management Science* 60 (6): 1594–1616.

Hauser, John R., and S.M. Shugan. 1983. Defensive marketing strategies. *Marketing Science* 2 (4): 319–360.

Hauser, John R., Gerard J. Tellis, and Abbie Griffin. 2006. Research on innovation: A review and agenda for marketing science. *Marketing science* 25 (6): 687–717.

Henard, D.H., and D.M. Szymanski. 2001. Why some new products are more successful than others. *Journal of Marketing Research* 38 (3): 362–375.

Hitsch, G.A. 2006. An empirical model of optimal dynamic product launch and exit under demand uncertainty. *Marketing Science* 25 (1): 25–50.

Hoeffler, Steve. 2003. Measuring preferences for really new products. *Journal of Marketing Research* 40 (4): 406–420.

Homburg, Christian, Martin Schwemmle, and Christina Kuehnl. 2015. New product design: Concept, measurement, and consequences. *Journal of Marketing* 79 (3): 41–56.

Horsky, D., and P. Nelson. 1992. New brand positioning and pricing in an oligopolistic market. *Marketing Science* 11 (2): 133.

Iyengar, Raghuram, Christophe Van den Bulte, and Thomas W. Valente. 2011. Opinion leadership and social contagion in new product diffusion. *Marketing Science* 30 (2): 195–21.

Jerath, Kinshuk, Peter S. Fader, and Bruce G.S. Hardie. 2011. New perspectives on customer 'death' using a generalization of the Pareto/NBD model. *Marketing Science* 30 (5): 866–880.

Johnson, R.M. 1974. Tradeoff analysis of consumer value. *Journal of Marketing Research* 11 (2): 121–127.

Johnson, R.M. 1987. *Adaptive conjoint analysis.* Paper presented at the Sawtooth Software Conference.

Kalyanaram, G., W.T. Robinson, and G.L. Urban. 1995. Order of market entry: Established empirical generalizations, emerging empirical generalizations, and future research. *Marketing Science* 14 (3 Supplement): G212–G221.

Kalyanaram, G., and G.L. Urban. 1992. Dynamic effects of the order of entry on market share, trial penetration, and repeat purchases for frequently purchased consumer goods. *Marketing Science* 11 (3): 235–250.

Kim, Hye-Jin, Young-Hoon Park, Eric T. Bradlow, and Min Ding. 2014. PIE: A holistic preference concept and measurement model. *Journal of Marketing Research* 51 (3): 335–351.

Kopalle, P., and D.R. Lehmann. 2006. Setting quality expectations when entering a market: What should the promise be? *Marketing Science* 25 (1): 8–24.

Kornish, Laura J., and Karl T. Ulrich. 2011. Opportunity spaces in innovation: Empirical analysis of large samples of ideas. *Management Science* 57 (1): 107–128.

Kornish, Laura J., and Karl T. Ulrich. 2014. The importance of the raw idea in innovation: Testing the sow's ear hypothesis. *Journal of Marketing* 51 (1): 14–26.

Koukova, Nevena T., P.K. Kannan, and Amna Kirmani. 2012. Multiformat digital products: How design attributes interact with usage situations to determine choice. *Journal of Marketing Research* 49 (1): 100–114.

Kuehn, A.A. 1962. Consumer brand choice as a learning process. *Journal of Advertising Research* 2: 10–17.

Landwehr, R., Aparna A. Labroo, and Andreas Herrmann. 2011. Gut liking for the ordinary: Incorporating design fluency improves automobile sales forecasts. *Marketing Science* 30 (3): 416–429. http://pubsonline.informs.org/action/doSearch?text1=Landwehr%2C+J+R&field1=ContribJan.

Landwehr, Jan R., Daniel Wentzel, and Andreas Herrmann. 2013. Product design for the long run: Consumer responses to typical and atypical designs at different stages of exposure. *Journal of Marketing* 77 (5): 92–107.

Lehmann, Donald R., and Peter N. Golder. 2014. New products research. In *The history of marketing science*, ed. Russell S. Winer and Scott A. Neslin, now publishers.

Lilien, G.L., P.D. Morrison, K. Searls, M. Sonnack, and E.V. Hippel. 2002. Performance assessment of the lead user idea-generation process for new product development. *Management Science* 48 (8): 1042–1059.

Liu, Y. 2006. Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of Marketing* 70 (3): 74–89.

Liu, Qing, and Yihui Tang. 2015. Construction of heterogeneous conjoint choice designs: A new approach. *Marketing Science* 34 (3): 346–366.

Luce, D.R., and J.W. Turkey. 1964. Simultaneous conjoint measurement: A new type of fundamental measurement. *Journal of Mathematical Psychology* 1: 1–27.

Luo, L., P.K. Kannan, and B.T. Ratchford. 2007. New product development under channel acceptance. *Marketing Science* 26 (2): 149–163.

Luo, Lan, and Olivier Toubia. 2015. Improving online idea generation platforms and customizing the task structure on the basis of consumers' domain-specific knowledge. *Journal of Marketing* (forthcoming).

Ma, Zhenfeng, Tripat Gill, and Ying Jiang. 2015. Core versus peripheral innovations: The effect of innovation locus on consumer adoption of new products. *Journal of Marketing Research* 52 (3): 309–324.

Mahajan, Vijay, Eitan Muller, and Frank M. Bass. 1995. Diffusion of new products: Empirical generalizations and managerial uses. *Marketing Science* 14 (3): G79–G88.

Massy, W.F. 1969. Forecasting the demand for new convenience products. *Journal of Marketing Research* 6 (4): 405–412.

McFadden, Daniel. 1974. Conditional logit analysis of qualitative choice behavior. In *Frontiers in econometrics*, ed. Zarembka, 105–42. New York: Academic Press.

Min, S., M.U. Kalwani, and W.T. Robinson. 2006. Market pioneer and early follower survival risks: A contingency analysis of really new versus incrementally new product-markets. *Journal of Marketing* 70 (1): 15–33.

Montoya-Weiss, M.M., and R. Calantone. 1994. Determinants of new product performance: A review and meta-analysis. *Journal of Product Innovation Management* 11 (5): 397–417.

Moorman, C., and A.S. Miner. 1997. The impact of organizational memory on new product performance and creativity. *Journal of Marketing Research* 34 (1): 91–106.

Narasimhan, C., and Z.J. Zhang. 2000. Market entry strategy under firm heterogeneity and asymmetric payoffs. *Marketing Science* 19 (4): 313–325.

Narayanan, Sridhar, and Puneet Manchanda. 2009. Heterogeneous learning and the targeting of marketing communication for new products. *Marketing Science* 28 (3): 424–441.

Netzer, O. and V. Srinivasan. 2011. Adaptive, self-explication of multiattribute preferences. *Journal of Marketing Research* 48 (1): 140–156.

Nowlis, S.M., and I. Simonson. 1996. The effect of new product features on brand choice. *Journal of Marketing Research* 33 (1): 36–46.

Ofek, E., and M. Sarvary. 2003. R&D, marketing and the success of next generation products. *Marketing Science* 22 (3): 355–370.

Parfitt, J.H., and B.J.K. Collins. 1968. Use of consumer panels for brand-share prediction. *Journal of Marketing Research* 5 (2): 131–145.

Peres, Renana, Eitan Muller, and Vijay Mahajan. 2010. Innovation diffusion and new product growth models: A critical review and research directions. *International Journal of Research in Marketing* 27 (2): 91–106.

Pringle, L.G., R.D. Wilson, and E.I. Brody. 1982. News: A decision-oriented model for new product analysis and forecasting. *Marketing Science* 1 (1): 1–29.
Rao, Vithala R. 2014. Conjoint analysis. In *The history of marketing science*, ed. Russell S. Winer and Scott A. Neslin. World Scientific - Now Publishers Series in Business.
Rao, V.R. 2008. Developments in conjoint analysis. In *Handbook of marketing decision models*, 1st ed, ed. Berend Wierenga, 23–53. New York: Springer Science+Business Media.
Reinartz, Werner J., and Vita Kumar. 2003. The impact of customer relationship characteristics on profitable lifetime duration. *Journal of Marketing* 67 (1): 77–99.
Rindfleisch, A., and C. Moorman. 2001. The acquisition and utilization of information in new product alliances: A strength-of-ties perspective. *Journal of Marketing* 65 (2): 1–18.
Risselada, Hans, Peter C. Verhoef, and Tammo H.A. Bijmolt. 2014. Dynamic effects of social influence and direct marketing on the adoption of high-technology products. *Journal of Marketing* 78 (2): 52–68.
Roberts, John H., Charles J. Nelson, and Pamela D. Morrison. 2005. a prelaunch diffusion model for evaluating market defense strategies. *Marketing Science* 24 (1): 150–164.
Robinson, W.T. 1988. Marketing mix reactions to entry. *Marketing Science* 7 (4): 368–385.
Robinson, W.T., and C. Fornell. 1985. Sources of market pioneer advantages in consumer goods industries. *Journal of Marketing Research* 22 (3): 305–317.
Rogers, Everett M. 2003. *Diffusion of innovation*, 5th edn. Free Press.
Rubera, Gaia. 2015. Design innovativeness and product sales' evolution. *Marketing Science* 34 (1): 98–115.
Rubera, Gais, and Ahmet H. Kirca. 2012. Firm innovativeness and its performance outcomes: A meta-analytic review and theoretical integration. *Journal of Marketing* 76 (3): 130–147.
Sándor, Zsolt, and Michel Wedel. 2002. Profile construction in experimental choice designs for mixed logit models. *Marketing Science* 21 (4): 455–475.
Sándor, Zsolt, and Michel Wedel. 2005. Heterogeneous conjoint choice designs. *Journal of Marketing Research* 42 (2): 210–218.
Schmittlein, David C., Donald G. Morrison, and Richard Colombo. 1987. Counting your customers: Who are they and what will they do next? *Management Science* 33 (1): 1–24.
Sethi, R., and Z. Iqbal. 2008. Stage-gate controls, learning failure, and adverse effect on novel new products. *Journal of Marketing* 72 (1): 118–134.
Sethi, Rajesh, Zafar Iqbal, and Anju Sethi. 2012. Developing new-to-the-firm products: The role of micropolitical strategies. *Journal of Marketing* 76 (2): 99–115.
Sethi, R., D.C. Smith, and C.W. Park. 2001. Cross-functional product development teams, creativity, and the innovativeness of new consumer products. *Journal of Marketing Research* 38 (1): 73–85.
Shanker, V., G.S. Carpenter, and L. Krishnamurthi. 1998. Late mover advantage: How innovative late entrants outsell pioneers. *Journal of Marketing Research* 35 (February): 54–70.
Shocker, A.D., and V. Srinivasan. 1974. A consumer-based methodology for the identification of new product ideas. *Management Science* 20 (6): 921–937.
Silk, A.J., and G.L. Urban. 1978. Pre-test-market forecasting of new packaged goods: A model and measurement methodology. *Journal of Marketing Research* 15 (2): 171–191.
Slotegraaf, Rebecca, and Kwaku Atuahene-Gima. 2011. Product development team stability and new product advantage: The role of decision-making processes. *Journal of Marketing* 75 (1): 96–108.
Sonnier, Garrett P., Leigh McAlister, and Oliver J. Rutz. 2011. A dynamic model of the effect of online communications on firm sales. *Marketing Science* 30 (4): 702–716.
Sood, Ashish, Gareth M. James, Gerard J. Tellis, and Ji Zhu. 2012. Predicting the path of technological innovation: SAW vs. Moore, Bass, Gompertz, and Kryder. *Marketing Science* 31 (6): 964–979.
Sood, A., and G.J. Tellis. 2005. Technological evolution and radical innovation. *Journal of Marketing* 69 (3): 152–168.
Spann, Martin, Marc Fischer, and Gerard J. Tellis. 2015. Skimming or penetration? Strategic dynamic pricing for new products. *Marketing Science* 34 (2): 235–249.

Stephen, Andrew T., Peter Pal Zubcsek, and Jacob Goldenberg. 2015. Lower connectivity is better: The effects of network structure on redundancy of ideas and customer innovativeness in interdependent ideation tasks. *Journal of Marketing* (forthcoming).

Sun, Monic. 2012. How does the variance of product ratings matter? *Management Science* 58 (4): 696–707.

Tang, Tanya, Eric Fang, and Feng Wang. 2014. Is neutral really neutral? The effects of neutral user-generated content on product sales. *Journal of Marketing* 78 (4): 41–58.

Toubia, Olivier, Jacob Goldenberg, and Rosanna Garcia. 2014. improving penetration forecasts using social interactions data. *Management Science* 60 (12): 3049–3066.

Toubia, Olivier, John R. Hauser, and Duncan I. Simester. 2004. Polyhedral methods for adaptive choice-based conjoint analysis. *Journal of Marketing Research* 41 (1): 116–131.

Toubia, O., D.I. Simester, J.R. Hauser, and E. Dahan. 2003. Fast polyhedral adaptive conjoint estimation. *Marketing Science* 22 (3): 273–303.

Tracey, Paul, Jan B. Heide, and Simon J. Bell. 2014. Bringing 'Place' back in: Regional clusters, project governance, and new product outcomes. *Journal of Marketing* 78 (6): 1–16.

Urban, G.L. 1970. SPRINTER MOD III: A model for the analysis of new frequently purchased consumer products. *Operations Research* 18 (5): 805–854.

Urban, G. L. 1975. PERCEPTOR: A model for product positioning, *Management Science*, 21 (8): Application Series, 858–871.

Urban, G.L., T. Carter, S. Gaskin, and Z. Mucha. 1986. Market share rewards to pioneering brands: An empirical analysis and strategic implications. *Management Science* 32 (June): 645–659.

Urban, G.L., and J.R. Hauser. 2004. "Listening In" to find and explore new combinations of customer needs. *Journal of Marketing* 68 (2): 72–87.

Urban, G.L., J.R. Hauser, W.J. Qualls, B.D. Weinberg, J.D. Bohlmann, and R.A. Chicos. 1997. Validation and lessons from the field: Applications of information acceleration. *Journal of Marketing Research* 34 (February): 143–153.

Urban, G.L., and E. Von Hippel. 1988. Lead user analysis for the development of new industrial products. *Management Science* 34 (5): 569–582.

Urban, G.L., and G.M. Katz. 1983. Pre-test-market models: Validation and managerial implications. *Journal of Marketing Research* 20 (3): 221–234.

Urban, G.L., B.D. Weinberg, and J.R. Hauser. 1996. Premarket forecasting of really new products. *Journal of Marketing* 60 (1): 47–60.

Van den Bulte, Christophe, and Yogesh V. Joshi. 2007. New product diffusion with influentials and imitators. *Marketing Science* 26 (3): 400–421.

Von Hippel, E. 1986. Lead users: A source of novel product concepts. *Management Science* 32 (7): 791–805.

Wang, Qi, Yubo Chen, and Jinhong Xie. 2010. Survival in markets with network effects: Product Compatibility and order-of-entry effects. *Journal of Marketing* 74 (4): 1–14.

Wies, Simone, and Christine Moorman. 2015. Going public: How stock market listing changes firm innovation behavior. *Journal of Marketing Research* (forthcoming).

Wind, Y. 1973. A new procedure for concept evaluation. *Journal of Marketing* 37 (4): 2–11.

Wind, J., P.E. Green, D. Shifflet, and M. Scarbrough. 1989. Courtyard by Marriott: Designing a hotel facility with consumer-based marketing models. *Interfaces* 19 (1): 25–47.

Wittink, D.R., and P. Cattin. 1989. Commercial use of conjoint analysis: An update. *Journal of Marketing* 53 (3): 91–96.

Wittink, D.R., M. Vriens, and W. Burhenne. 1994. Commercial use of conjoint analysis in Europe: Results and critical reflections. *International Journal of Research in Marketing* 11: 41–52.