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KEYWORDS: CRM, Personalization, Marketing, e-commerce

The Role of the Management Sciences in Research on Personalization

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Abstract

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The Role of the Management Sciences in Research on Personalization

1. Introduction

When a customer walks into a traditional store, it is difficult for a salesperson to remember if that person is a repeat customer, and if so, what the customer may have purchased in their previous visits to the store. But in an online store, it is possible to remember! One of the key benefits to companies that are conducting business over the Internet is the ability to gather enormous amounts of data about a customer, process these data into usable information, and deliver superior benefits to that customer. The information is typically used to tailor products or services that best match customers' preferences, which can ostensibly lead to greater satisfaction and loyalty. The process of using a customer's information to deliver a targeted solution to that customer is known as *personalization*. Peppers and Rogers (1997) use the term one-to-one marketing to describe the powerful force of personalization and customization unleashed by the Internet.

The notion of personalized services or products is not new. In small neighborhoods, it was (and, perhaps, still is in some places) not unusual for a storekeeper to be familiar with many of the customers and their preferences. This enabled the storekeeper to recommend items to a customer based on that customer's prior purchase behavior. However, as the retail format shifted towards larger supermarkets and retail outlets, which stock an enormous variety of products and cater to larger number of customers, it has become virtually impossible for sales personnel to provide personalized service. In recent years, the shift towards e-tailing has once again made it possible for firms to personalize products and services at low cost.

Personalization and customization are two important ways in which a firm can create and deliver products or services that are tailored to a customer's needs¹. Customization refers to the ability of a firm to create and deliver a tailor-made product based on heterogeneous customer needs (Anderson et al. 1997). On the other hand, personalization is the process of gathering information explicitly or implicitly about a customer, which enables the firm to target products or recommendations that best match the customer's tastes (Nunes and Kambil, 2001). In many

¹ For expositional simplicity, we use the term products to refer to both products and services in the ensuing discussion.

cases, the customer plays a passive role in revealing her tastes and preferences through her prior shopping and browsing behavior. The following examples help illustrate these concepts.

Some web sites, like *mylook.com* and My Yahoo at *yahoo.com*, provide tools that allow customers to organize the contents of their web site according to their preferences. When a customer signs up for a Hotmail account, they can select to receive emails from various electronic magazines. These are examples of customized services. There are a number of ways in which firms provide personalization. A common form is the use of customer data (e.g., transaction history) to make recommendations about products to customers. These recommendations are typically made in an automated fashion, and systems that provide such services are called *recommendation systems*. For example, *Amazon* uses several diverse techniques to recommend books and gifts, and provide coupons, to their customers. *DoubleClick* uses visitor profiles to target banner advertisements on their clients' sites that are more likely to be of interest to a visitor. *YesMail* specializes in targeting and sending personalized emails regarding special deals.

While the distinction may be clear in the situations discussed above, it may not be so in other situations. In this article, we use the term personalization in a general sense to include customization related activities as well; the term customization is used where the distinction is apparent.

Personalization has become important because of the explosion of choices that are available to customers and the need to lower their search costs. Therefore, firms can add value by providing suggestions to simplify the consumers' decision process. Furthermore, the needs of customers vary considerably, and resource constraints have prevented firms from offering too many versions of the products. With improved technologies in flexible manufacturing and in developing digital products, constraints in providing customized products have been mitigated in several areas. At the same time, improved technologies in assessing customers' preferences facilitate personalization. Therefore, greater customer satisfaction can be achieved by giving customers the product that they desire. In addition, the drastic reduction in costs of information technology (Moore's law), coupled with the development of database technologies, significantly changes the economics of collection, storage, and processing of data about customers. The low costs enhance the ability of firms to deliver customized products, and even more so for digital products.

In this article, we present a review of research studies that deal with personalization and customization, as well as, examine industry developments in these areas. We find that the research on personalization and customization is being addressed in relative isolation in different fields. Based on our review, we synthesize current knowledge about these areas, and identify issues that we envision will be of interest to researchers working in the management sciences. We take an interdisciplinary approach that spans the areas of economics, marketing, information technology, and operations. Such an approach allows us to bring richness and appropriate context to these issues. We believe our approach to this paper will be of interest to a wide spectrum of researchers.

We begin by presenting an overarching framework for personalization that allows us to identify key players in the personalization process, as well as, the key stages of personalization. The framework is a modification of Brandenburger and Nalebuff's (1995) Value Net approach, and enables us to examine the strategic role of personalization in the interactions between a firm and other key players in the firm's value system. We review extant literature on the strategic behavior of firms, and discuss opportunities for analytical and empirical research in this regard. Next, we examine how a firm can learn a customer's preferences, which is one of the key components of the personalization process. We use a utility-based approach to formalize such preference functions, and to understand how these preference functions could be learnt based on a customers interactions' with a firm. We identify well-established techniques in management sciences that can be gainfully employed in future research on personalization.

The primary motivation for this article is to identify research opportunities in the context of online personalization. However, many of these issues are also valid for traditional brick-and-mortar environments. In the conclusion we comment on future developments in the brick-and-mortar context that could reduce the distinction in interactions across these differing environments. We should point out that this article focuses on personalization as it applies to end consumers, and not to businesses. While the business-to-business segment is huge (and outstrips the business-to-consumer segment in dollar terms), it is outside the scope of this study.

The rest of the article is organized as follows. In Section 2, we present the modified Brandenburger and Nalebuff framework. We discuss the strategic implications to firms in Section 3. The important issues in modeling customer preferences, and techniques that can be used in this regard, are discussed in Section 4. Concluding remarks are presented in Section 5.

2. A Framework for Personalization

In examining the impact that personalization may have on a firm, it is important to understand how value is created using personalization technologies, and to recognize the key players in the firm's value chain. We have developed an overarching framework that identifies the key players that strategically impact a firms interaction with it's customers, and also captures the essential components of these interactions in the personalization process. Our framework is a modified version of the Value Net (Brandenburger and Nalebuff 1995), and serves two purposes. First, it helps identify the various ways in which personalization technologies can become important to a firm's strategic behavior. Next, it identifies the important components of the personalization process, and enables us to position our discussion on consumer preference functions in the appropriate context. The framework is presented in Figure 1.

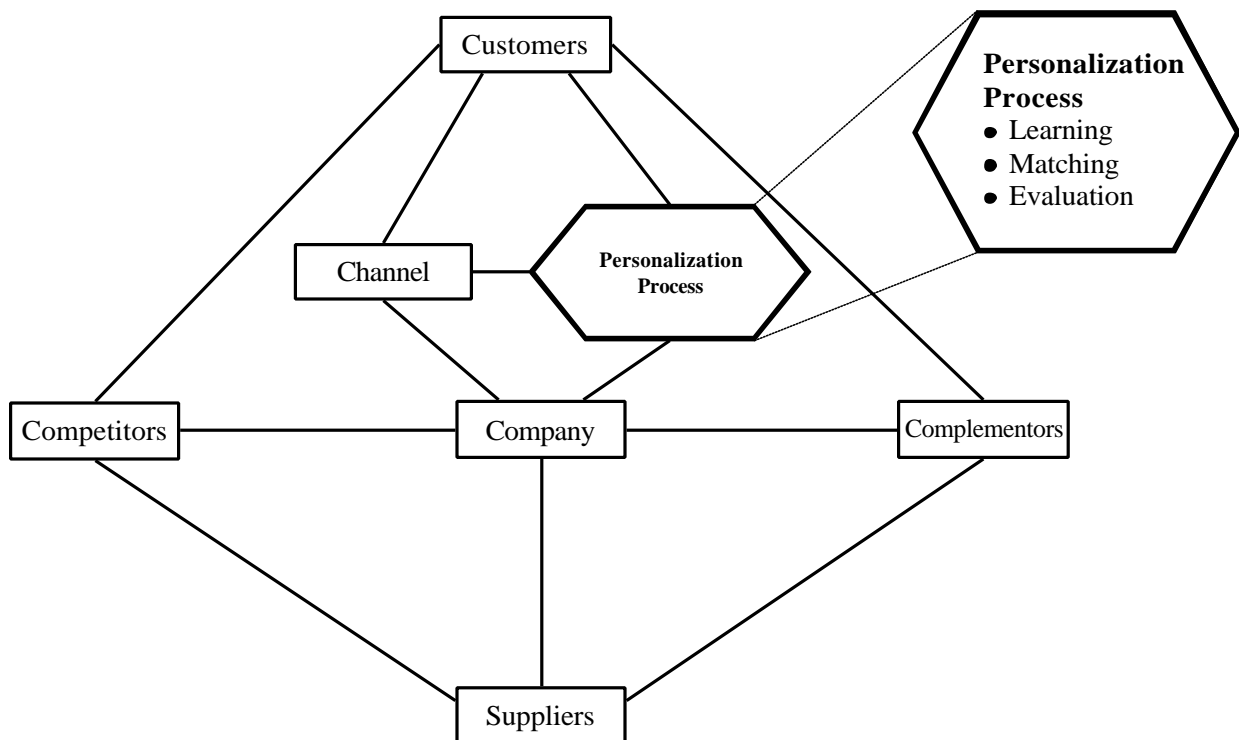


Figure 1: The Enhanced Value Net

2.1. Strategy Overview

The ability to personalize products and services can provide considerable strategic advantage to a firm. The strategic impact can manifest itself in several different ways. For example, personalization can help firms differentiate their services from their competitors,

leading to competitive advantage. Customization and personalization strategies can help a firm perform price discrimination (Dewan et al. 1999, Ulph and Vulcan 2000, Desai 2001, Varian 2001a), and provide, in some industries, first mover advantage (Resnick and Varian 1997). The enhanced Value Net framework enables us to separate out the varied implications of personalization strategies, and examine them in the appropriate context.

In the Value Net approach, a firm interacts with *customers* and *suppliers* in the vertical dimension, and with *competitors* and *complementors* in the horizontal dimension. Typically, transactions occur in the vertical dimension, with products and services flowing from suppliers to customers, and money flowing in the reverse direction (i.e., top-down). Customer information, the critical ingredient for personalization, also flows top-down. Competitors and complementors impact a firm's ability to transact with its customers and suppliers. Since customer information flows to competitors and complementors as well, the ability of a firm to effectively differentiate its products and services is also affected by the actions of these players. We enhance the model of Brandenburger and Nalebuff by including the entity *channel* between the firm and its customers. The channel could, for example, be a retailer for a manufacturing firm, or a portal for a content provider on the worldwide web. Since the flow of customer information to a firm would typically go through such a channel (if such an intermediary exists), the channel can become an important player in a firm's personalization strategies. In some cases, personalization may become the value-added service that the channel provides to the customer. In Section 3 we look at the interactions between a firm and the other players, examine the strategic role of personalization for each of these interactions, and identify opportunities for researchers in the management sciences.

2.2. Process Overview

We view the personalization process itself as consisting of three main stages, *learning*, *matching*, and *evaluation*. In the learning stage, a firm collects data on its customers and uses that data to learn about the customers' preferences and tastes. The firm then uses the knowledge of customer preferences to design products that best reflect the market needs, and target these products to the appropriate market segment in the matching stage. This targeting could be at the aggregate market level, at the level of important segments of the market, or targeted separately to each individual (a segment size of one). Personalization, if delivered effectively, adds value to

consumers over and above that provided by the firm's products and services. The last stage consists of evaluating the effectiveness of personalization efforts in creating value for the firm and its customers, an activity that can help a firm continuously improve upon its personalization processes. In Section 4, we focus on the research opportunities in the learning part of the personalization process. In order to place that discussion in the proper context we briefly overview the activities involved in all three stages of personalization.

2.2.1. Modeling the Customer

A number of techniques exist in marketing for eliciting information about consumer's buying behavior and interpreting it. Marketing research has traditionally relied on consumer feedback through focus groups and surveys to gather information about consumer's preferences. This process imposes a cost on the consumer and in many cases consumers are unwilling participants. Further, the data quality from surveys is error prone because consumers may not recall information accurately. In other instances, consumers either tend to overstate (e.g., involvement in community activities) or understate (e.g., age) certain types of information. The advent of scanner data made it possible to gather richer information about consumer purchases without imposing a heavy cost on the consumer. Scanner data is relatively more reliable and accurate. The Internet allows firms to have even greater flexibility in gathering information about consumers from a number of sources at increasingly lower costs. Firms are linking up databases across credit card companies, online and offline purchases, and web browsing behavior to be able to better understand consumer needs. Thus, the emphasis in data collection has shifted from "asking the consumer" to "observing the consumer" using electronic media.

The availability of large, rich databases allows firms a multitude of opportunities for understanding consumer behavior. Firms can use a number of techniques to uncover an individual customer's preferences for different attributes of a product. They can learn where consumers like to purchase (e.g., offline or online), what terms they prefer, and how they would like their products to be delivered. The data can allow firms to understand consumer decision processes such as information search, brand choice, and post purchase behaviors.

2.2.2. Matching Offerings to Customers

After a firm learns about a customer, it requires tools to use this knowledge to create different types of personalization. There are several mechanisms that are commonly used for personalization. Perhaps the most common form of personalization is product recommendations. A second approach is to send promotional offers to targeted customers using email, surface mail, and telemarketing. Another mechanism is to place customer specific banner advertisements on websites. For example, based on visitor profiles, advertising server software places advertisements for appropriate product categories. Advertising networks (commonly called Ad Networks) schedule banner advertisements for their clients, keeping in mind the site requirements and customer preferences. Companies could price discriminate among their customers by offering different prices². Websites offer personalized web pages with information organized according to a person's tastes.

An important aspect in effectively deploying these mechanisms is the ability to match a product offering to the target customer. *CDNow* and *Amazon* have popularized the use of collaborative filtering techniques to provide recommendations for music and books. The recommendations are based upon purchase information from other customers who match the profile of a given customer. Other recommendation systems use rule-based techniques. Firms that employ rule-based engines include Blaze Software and Broadvision.

There are a whole host of research issues in the context of matching offers to customers. For example, research is being conducted to develop better matching and recommendation algorithms. Mobasher et al. (2000) have used association rule mining to dynamically include interesting links to visitor's web pages based on their browsing behavior. In many cases, maximizing a firm's profit would be the eventual goal for matching. For instance, Adler et al. (2001) and Kumar et al. (2000) have developed scheduling algorithms to maximize advertising revenues for a site. As part of this special issue, Adomivicius and Tuzhilin (2002) provide a thorough review of research opportunities in the matching stage of the personalization process. We refer interested readers to their work.

² As one may recall, Amazon experimented with such a pricing mechanism, which they later withdrew due to pressure from its customers.

2.2.3. Evaluation

While personalization appears to hold great promise, it is not yet clear how much value such efforts are providing to firms (Nunes and Kambil 2001). This highlights the need for careful measurement of the effects of personalization and for quantification of the benefits of different types of personalization efforts. Personalization can directly affect profits by increasing sales, extracting more of the customer surplus, through cross selling, or through accidental discovery of different products through the recommendation process. Further, personalization could lower costs by providing an efficient means for communication to customers, thereby saving on resources spent on traditional advertising. In addition, there are a number of indirect benefits that are attributed to personalization. Personalization could potentially benefit firms by increasing customer loyalty and satisfaction, and generating favorable word of mouth publicity.

Customer satisfaction has traditionally been measured as the gap between expectations and actual performance and many metrics have been developed in the literature (Zeithaml et al. 1988). Recently, two volumes of *Information Systems Research* (June 2002 and September 2002) have been dedicated to articles on metrics as they could apply for evaluating the performance of net-enabled organizations (such metrics are termed *e-metrics* for short). Several articles in those issues touch upon the role of personalization in the context of firm level evaluations (Straub et al. 2002a, 2002b). However, metrics for personalization activities are not explicitly studied. NetGenesis has a white paper on e-metrics in which they define a personalization index, in addition to discussing traditional metrics such as reach, acquisition, conversion and retention. A formal research agenda is needed for personalization-related performance measures. Although it is outside the scope of our current work, we emphasize that it is an important issue and worthy of examination in its own right.

3. Personalization and Firm Strategy

In the following discussion we examine the role of personalization for each of the interactions represented in the Value Net framework, identify extant literature that pertain to the strategic aspects of these interactions, and provide directions for future research.

3.1. Firm and Customer

The important strategic consideration between a firm and its customers is the bargaining power of the customer. Effective personalization strategies can help shift the power in favor of the firm. We examine broadly the following issues: product differentiation, price discrimination, bundling, privacy, and information asymmetry (strategic behavior of customers). We elaborate on how personalization impacts each of these issues, and pose questions in the context of these issues that appear promising for future research.

Personalization techniques enable firms to better differentiate their products or services. Most goods are differentiated to some degree or other and the economic explanation for differentiation rests on two premises. One is that there are differences in consumer preferences between individuals (or even for the same individual over time). These preferences could be based on either quality valuations (vertical differentiation) or tastes (horizontal differentiation) or both (Tirole 1988, Desai 2001). The second premise is that individuals prefer, and sometimes are willing to pay more, for products that are more suited to their own preferences. Firms, therefore, have an incentive to develop multiple variants of a product to satisfy this need for variety.

By developing products that are tailored to customer's preferences, firms can charge a premium price for their product. For example, a custom-made pair of Levi jeans is priced at a premium of \$10 over the standard product's prices; the premium price typically offsets the additional costs incurred, thereby, providing higher margins (Flaherty 1999). This is an example of price discrimination as firms can charge different prices to different customers who have different valuations for products. Personalization techniques can allow firms to precisely estimate their customers' valuations at low costs, and hence enable them to engage in finer price discrimination.

A taxonomy commonly used for price discrimination considers three types (Pigou 1932, Varian 2001a). When a firm is able to charge different prices to different customers, it is termed first-degree price discrimination. A firm engages in second-degree price discrimination when it makes available a set of related offerings with fixed prices associated with each, and customers choose the product that best fit their tastes. This phenomenon is also referred to as product line pricing or versioning (Varian 2001b). Examples include the many versions of Quicken accounting software, different versions of DVDs of movies (basic and collector's edition), and even stock quotes (real time versus 20 minute delayed). In third-degree price discrimination,

firms charge different prices to different groups (as distinct from individuals, which is of course first-degree)³. There exists a large amount of literature on price discrimination in the areas of economics and marketing. Interested readers are referred to Norman (1999) for a collection of seminal articles in these areas.

In the past, first-degree price discrimination was not a practical approach in many markets because it was quite expensive or sometimes impossible for a firm to gauge the consumer's willingness to pay. With access to enormous amounts of customer data in electronic form, and the tools to analyze these data in close to real time, firms are better able to estimate customer valuations. Further, technology now permits the gathering of information about consumer tastes at low costs. By analyzing consumers' click-stream data and purchase history on the Internet, a firm is better able to price its products based upon the willingness to pay of the customer. Thus, personalization enables better differentiation of products offered, which in turn can lead to better extraction of consumer surplus. It is becoming practical for companies to develop a larger number of variants of products and, in some cases, even serve individual customers profitably. Formal analysis of how (under what circumstances and situations) personalization enables first-degree price discrimination under different conditions is needed. For example, it may be possible for a firm to estimate a customer's valuation for a product, and use customized coupons to match the effective price of the product to an individual customer's valuation (Shaffer and Zhang 1995). Under what conditions should we expect to see the proliferation of products and services? Should we expect this to be more or less pronounced for information goods (that usually have close to zero marginal costs)? A related issue for potential research is to understand how personalization technologies can be used to deliver dynamic pricing strategies (over time and across customers) in real time. By understanding a customer's preferences, a firm can increase revenues by selling its products opportunistically. This enhances the ability of a firm to perform price discrimination (by providing an additional dimension to consider in its pricing scheme), and may lead to substantial gains in traditional as well as spot market environments. This kind of personalization would be suitable for travel and entertainment related products (Morris et al. 2001). Kannan and Kopalle (2001) develop several interesting

³ The strategic role of personalization in the context of third-degree price discrimination has not been examined in extant literature. While one may expect this to be quite analogous to first-degree price discrimination for many kinds of products, this deserves further reflection.

propositions regarding dynamic pricing mechanisms over the Internet, and discuss potential research issues in that context.

In many environments there will be a limit to the number of variants that can be produced because of increasing returns to scale, especially for traditional products. To recover the costs of developing and supplying different variants, firms need a sizeable market. In this context, Dewan et al. (1999) have examined the range of standardized and customized products that form the optimal product spectrum for a firm in a monopolistic setting, when the firm engages in second-degree price discrimination. A decrease in technology costs is shown to lead to greater customization efforts at the expense of standardized products. Desai (2001) examines segmentation (product-line) strategies for firms when customers differ in both quality valuations and tastes. He identifies conditions under which lower quality products cannibalize higher quality products (analogous to findings in Moorthy (1984) for quality differentiated markets), and also conditions that lead to a firm's providing efficient quality levels to different segments. Both monopoly and duopoly scenarios are considered.

The Internet allows for the reproduction and distribution of information goods at very low marginal costs. This has interesting implications on the bundling of information goods (Bakos and Brynjolfsson 1999). Chuang and Sirbu (1999) show that allowing customers to self-select a bundle consisting of a subset of goods (rather than pre-designating the goods in a bundle) can often improve a firm's outcome. Hitt and Chen (2001) extend this stream of work to show that for a monopolistic setting, such a mechanism outperforms individual selling and pure bundling when marginal costs of providing the goods are greater than zero and customers have heterogeneous preferences.

Protecting the privacy of individuals has become a very important issue because of the low costs associated with collecting and disseminating information on the Internet and otherwise. Currently, the market on personal information is based on the notion that the institution that has gathered the information also owns the information (Laudon, 1996). While privacy laws are being enacted to guard against unauthorized use of personal information, there is likely to remain a significant market in personal information. For a customer to be willing to share personal information with a firm, she must have a clear idea about benefits she can expect to receive, about how the information will be used by the firm, and about how it may be shared with other organizations. Laudon suggests the possibility of creating a National Information Market in

which information about individuals is bought and sold at a market-clearing price. In this kind of a market, an individual would have the ability to grant to institutions the right to use their personal information for a predetermined period of time and specified nature of use. There are several interesting research issues that warrant examination in this context. For instance, a firm would like to obtain as much information on a customer as possible before engaging in a transaction with her. The customer, on the other hand, would like to obtain perfectly personalized service by providing as little information as possible. It would generally be beneficial for the customer to share information that would enable the firm to provide the right product to her. At the same time, the customer would not like to provide information that would reveal her reservation price for the product. The firm should provide incentives to the customer in order to convince her to share some of this information. Incentives could be, for instance, of a monetary nature or a mandatory requirement for receiving recommendations (Resnick and Varian 1997). A related phenomenon is that of users deliberately providing incorrect personal data in an effort to obtain the desired recommendations without divulging those details that they consider too personal. Therefore, incentives must be such that users do not falsify their data. Implications for one-time purchase products and repeat purchase situations need to be examined. Yet another topic for study is the impact of such an information market on transaction costs associated with personalized products, and thereby its impact on the social welfare.

Many sites such as *IMDb*, *CDNow*, and *Amazon* base their recommendations on ratings of products obtained from users. The ratings provided are useful in identifying customers with similar tastes. Since users are typically able to provide their ratings anonymously, it is possible for interested parties (e.g., producers of these products) to manipulate the ratings. An interesting question here is what kinds of incentive mechanisms are required to elicit unbiased ratings.

3.2. Firm and Competitors

Competitors pose the threat of substitutes to a firm. This is clearly a very important aspect of the personalization and customization strategies that a firm has to consider, and consequently has many important research implications. The issues we examine here are: differentiation, price discrimination and price competition, switching costs and lock-in, first-mover advantage, and network effects. We briefly survey the existing literature, and then identify some questions that warrant additional research.

A firm's personalization and customization efforts have the strategic effect of increasing differentiation, which in turn helps reduce price competition (Shaked and Sutton 1982), generate greater loyalty among consumers, and in some cases, generate price premiums (by extracting greater consumer surplus). Shaked and Sutton have shown that increased product differentiation leads to reduced price competition in equilibrium.

However, as more firms start personalizing their services, there is also an enhanced competition effect, which reduces the benefits of surplus extraction (Ulph and Vulkan 2000). This intensified competition comes about because firms are competing for smaller and smaller segments of consumers. Ulph and Vulkan show that when consumers are homogeneous in taste, the competition effect dominates the surplus effect making firms worse off with personalized pricing. Using a duopoly setting, they characterize when it is profitable for both firms to engage in first-degree price discrimination, and when the firms are both worse off. In related work (Ulph and Vulkan, 2001), they examine situations where firms are able to customize a range of products at constant marginal costs without having to incur additional fixed costs on every differentiated brand they offer. Under such situations, they show that a firm is always better off using price discrimination if it also mass-customizes.

Their results are along the same lines as those of Dewan et al. (2000a) who show that when firms in a duopoly simultaneously adopt customization there is reduced differentiation, which should lead to greater price competition. However, firms charge higher prices on customized products and this compensates for the lower prices due to price competition. In their model, the authors assume that firms incur an additional cost in order to customize their products. They further assume that the firms price discriminate to the second-degree. They show that when one firm adopts a customization strategy, it is able to improve its market share and profits at the expense of other firms. However, it then becomes optimal for other firm's to also adopt customization, which, in turn, leads to excessive investments in customization leading to lower profits for all the firms.

Several other articles have also demonstrated that one-to-one promotions by competing firms can lead to lower profits to all firms (Shaffer and Zhang 1995, Fudenberg and Tirole 2000). In all of these works, it is assumed that firms are identical. Recently, Shaffer and Zhang (2002) have examined a scenario where firms offering one-to-one promotions differ in size and consumers have heterogeneous brand loyalty. They find that while this always leads to increased

price competition, it can also affect the market share of the firms. The firm with a larger market share and a more loyal following can be better off when both firms offer promotions as compared to when neither does so. Desai and Purohit (2002) investigate situations where a firm can adopt a fixed price policy or allow haggling (negotiations) when different customer segments differ in their costs of haggling. They identify, in a competitive setting, when the negotiation policy is more profitable than a fixed-price policy.

In another related line of work, Dewan et al. (2000b) examine if there exist any first-mover advantages for a firm to adopt customization, and find that when firms adopt customization sequentially, there is an advantage for the early adopter. Further, they show that by investing heavily in customization, a firm can deter entry of potential rivals.

The above studies provide a good starting point for future research on the competitive effects of personalization and customization. There are a number of interesting research issues that deserve attention. Existing studies assume that all firms have full information and do not allow some firms to possess greater knowledge about customers than other firms. Even though switching costs are lowered on the Internet, customers may find it costly to provide information about their preferences to firms and therefore be unwilling to engage in such exercises with many firms. When does a firm lock-in its customers using personalization? How will this affect the market equilibrium when switching costs are common knowledge? What happens when switching costs borne by customers are not known to the firm, and are heterogeneous? What kinds of contracts would be optimal in such environments? In a related vein, for repeat purchase environments, a firm can over time acquire customer information that enables the firm to be able to better customize their product offering, as well as, improve their ability to discriminate on prices. How should a firm invest in personalization and customization technologies to ensure that they can sustain their advantage over their competitors? Finally, does market growth rate impact the ability of a firm to use personalization as a lock-in strategy? As suggested by Liebowitz and Margolis (1990), should we expect to observe this phenomenon for firms operating in relatively slower growth markets?

Many personalization techniques (most notably collaborative filtering) are more effective when implemented with a large customer base. Consequently, for products with high search costs where personalization adds significantly to the value of the product, there are indirect network effects to customers for shopping at sites that are well established. Therefore, there may

exist important first mover advantages. What implications does this have on the market structure in equilibrium? Resnick and Varian (1997) speculate about the competition across recommendation systems themselves, positing that one or two systems would emerge as survivors in each product category. More formal analysis needs to be done in this regard.

Firms can differentiate from competition by using other strategies such as developing a strong brand, and partnering with strong and highly visible companies. Research is needed to quantify the magnitude of differentiation that can be obtained from personalization relative to other sources of differentiation. We need to understand the conditions under which personalization is a significant source of differentiation relative to other alternatives. In other words, which products and services would most benefit from personalization? What environmental conditions (consumer characteristics, market structure, etc.) enhance the effect of personalization in a competitive setting? What kinds of interaction effects exist between the multiple sources of differentiation? For instance, does personalization enhance or diminish the effect of branding?

3.3. Firm and Suppliers

The bargaining power of suppliers is the important strategic consideration here. Of interest here is how personalization strategies of a firm impact its suppliers. While the impact is indirect in nature, the following issues appear to have interesting implications: product proliferation, information sharing, and forward and backward integration.

The ability of a firm to provide personalized service may be dependent on the firm's ability to harness its supply chain in an effective manner. An important assumption often made in the literature on customization is that it can be performed at uniform marginal costs, and these costs are low. For a firm to be able to achieve this efficiently, it is important that the product proliferation that typically results from customization should not require very high fixed costs (Varian 2001b). There are several unanswered questions in this context. How does product proliferation for a firm impact the firm's ability to transact efficiently with its suppliers? Does it require the firm to use a larger number of suppliers with higher costs of engaging in such supplier relationships? What kind of revenue sharing would be optimal for a firm to align its supplier's incentives to its own?

Another important set of issues revolves around a firm's willingness to share customer information with its suppliers. Similar issues are being studied in the context of information sharing in supply chains (such sharing is termed vertical information sharing). The value of information sharing in a supply chain has been studied in a variety of contexts (Gavirneni et al. 1999, Lee et al. 2000). Lee et al. demonstrate that information sharing in a supply chain can help counter the "bullwhip effect," that leads to demand distortion when suppliers do not have timely access to end-customer demand data. Specifically, they find that a supplier can experience great savings when demand correlations over time is high or the demand variation over a period is high. Lee and Whang (2000) have pointed out the limitation to information sharing in the presence of competition. In a recent article, Li (2002) examines the direct effect and leakage effect of vertical information sharing when firms possess some private information about downstream market demand or about its own cost. The direct effect deals with payoffs to the parties engaged in sharing information, and discourages information sharing. The leakage effect can occur when competing firms infer information about each other based on their actions with a common supplier. Li shows that the leakage effect can discourage the sharing of demand information while encouraging the sharing of cost information, and goes on to identify conditions under which the firms benefit from sharing the cost information. Customer information used for personalization and costs of personalization may be expected to display similar characteristics, and needs to be carefully examined. While these questions are interesting in general, they are even more so for digital products. Consider a portal that has contracted out the delivery of content. Should the portal make the customer data available to the content providers? This could have important implications on the competitive landscape, as this may allow the content provider to compete for the customers directly. Over time, this may even enable the content provider to gather knowledge about its competitors that are also supported by the portal (the leakage effect). Finally, if the transaction costs become too high due to product proliferation, it may be worthwhile for either the firm or the supplier to consider vertical integration.

3.4. Firm and Complementors

Complementors could play an important role in a firm's customization and personalization strategies. The bargaining power of the complementor is the primary strategic

consideration for the firm. We identify bundling and information sharing as the important issues in this interaction.

By engaging in strategic partnerships with its complementors (e.g., hardware from Dell bundled with MS Windows software from Microsoft), a firm can greatly increase the ability to customize its products for a large customer base. The coverage of the product space can increase substantially, provided the complementary firms ensure that different versions of their respective products are compatible. This can lead to a very fine-grained level of customization at relatively low costs, leading to a higher ability to price-discriminate than traditional bundling of complementary products.

There are several questions of interest here. How should the additional consumer surplus extracted by the complements be shared? If versioning is more costly for one firm than the other, how should it impact revenue sharing? How do customization capabilities drive the choice of a complementor, when several possibilities exist? What incentives should a firm provide to its complementors to achieve compatibility of offerings? When would firms want exclusive rights over its complementors' products?

Another related, but distinct, set of issues pertain to how information should be shared across complementors. At first sight it would appear that the firms would benefit from sharing customer information as they would be better able to customize their offerings, and also engage in cross-selling their products. However, sharing of this information could lead to a shift in the balance of power between these firms. Should any customer information be even shared with the complementors? Or would there exist some intermediate level of sharing that would be optimal for the firms? It is possible that one firm can sell its customer information to the other. For example, Microsoft may find Dell's customer list quite valuable, as this would enable Microsoft to target these customers for software upgrades.

3.5. Firm and Channel

Two strategic considerations are important here, the bargaining power of the channel, and also the threat of substitution. Important issues in this context are information sharing and coopetition. Some issues are analogous to those discussed in the context of interactions between a firm and its suppliers, and are not repeated here.

Many firms find it necessary to use some intermediary in order to reach their eventual customers. These intermediaries, or distribution channels, traditionally include wholesalers, retailers, and agents. While wholesalers and retailers typically resell the firm's merchandise, agents usually negotiate with customers on behalf of the firm. Since these intermediaries have first hand information on the customers, they play an important role in personalization of products and services.

The first question that arises is how much of the customer information should a channel share with the firm? Information regarding customers' tastes would help the firm in identifying important market segments and thereby in better targeting its products. At the same time, information on a customers' valuation of products may enable the firm to negotiate better terms with the channel. With the relatively low costs associated with setting up storefronts on the Internet, a firm may find it profitable to directly target its customers and compete with its existing channels. Therefore, the channel may well find it disadvantageous to share all of the customer information.

In some situations, channels could serve as intermediaries that enable competitors to share data that is mutually beneficial. For example, an electronic mall can track visitors' movements across all storefronts, and make that information available to participating stores, perhaps at a nominal price. Going one step further, the mall could also collect transactional data from the stores, and provide information at some level of aggregation back to all of the stores (resulting in some amount of coopetition across these stores). This would enable the stores to better assess the customer's preferences, and help them determine what products to recommend to them. Several research issues emerge in this kind of a marketplace. When would it be worthwhile for the marketplace to engage in provisioning this type of personalization services? How should the personalization provider charge for their services? What are the implications to firms who do not participate (or, stated differently, what kinds of firms would prefer to not participate)? How does it impact the customer, and what are the privacy implications in this context?

As discussed in Section 3, there are a number of research questions that need to be addressed when considering the role of personalization in a firm's strategic behavior. Analytic frameworks could be used to model some of the interactions in order to obtain insights into how a firm should develop its personalization strategy, or respond to similar strategies of its

competitors and partners. These issues also provide ample opportunities for management science researchers to empirically study personalization-related phenomenon, such as its impact on branding or customer retention. Table 1 provides a summary of the key research issues identified in this article.

Table 1: Impact of personalizing on firm strategy

Interaction	Broad Areas	Research Issues	References & representative articles
Customer	Differentiation	Under what conditions would we expect to see the proliferation of goods and services? What is the optimal product mix for a firm? How does this differ for information goods as compared to traditional goods?	Dewan et al. 1999, Varian 2001b, Desai 2001
	Price discrimination	How can first-degree price discrimination be effected? When are dynamic pricing strategies viable?	Norman 1999, Shapiro and Varian, 1999
	Bundling	What is the impact of personalization on bundling strategies?	Bakos and Brynjolfsson 1999, Chuang and Sirbu 1999, Hitt and Chen 2001
	Privacy	What are an individual's rights to personal information? What incentives are necessary to get customers to provide such information? Can a market mechanism be used to balance the benefits to customers and to firms?	Laudon 1996, Resnick and Varian 1997
Competitors	Price discrimination under competition	How will a firm's personalization strategy change with under competition? Which products and services will most benefit from personalization? Will recommendation systems proliferate, or a few emerge as dominant (like search engines)?	Shaked and Sutton 1982, Shafer and Zhang, 1995, 2002, Dewan et al. 2000a, 2000b, Ulph and Vulcan 2000
	Lock-in, first mover advantage, and network effects	When can a firm lock-in customers using personalization? How does this affect market equilibrium? What happens when switching costs borne by customers are not known to the firm, and are heterogeneous? What kinds of contracts would be optimal in such environments? When personalization is being achieved using collaborative filtering techniques, are there sustainable first mover advantages?	Farrell and Shapiro 1989, Liebowitz and Margolis 1990, 1994
Suppliers	Transaction cost economics	How does product proliferation from customization impact a firm's ability to transact efficiently with its suppliers?	Varian 2001b
	Incentives for information sharing	Should a firm share customer information with its suppliers? Should a supplier share with a customer the information it gathers from its other customers?	Gavirneni et al. 1999, Lee et al. 2000, Li 2002

	Vertical integration	Would we expect to see vertical integration for information goods? Other goods?	
Comple-mentors	Bundling	How is bundling of complementary products (e.g., hardware and software) impacted by personalization? How does the relative market power of a firm affect the degree of personalization (customization) of a complementor's product offerings?	Schmalensee 1984, Chuang and Sirbu 1999,
	Information sharing	How will the sharing of consumer surplus be tied to the sharing of information?	
Channel	Information sharing	How much customer information should a channel share with the firm?	Lee and Whang 2000
	Coopetition	Should a channel share customer information across its vendors? When would firms participate in this kind of sharing? Will the need to share customer information lead to co-opetition among competitors? What are the privacy implications for customers?	

4. Modeling the Customer for Personalization

The modeling of customer preferences poses many interesting challenges for management science researchers. We first highlight the issues related to data collection. Subsequently, we discuss relevant models that can be used to understand consumers' preferences with the help of available data. There is currently little published literature that employs established methods in the management sciences in the context of personalization. We provide a review of models that we believe are relevant to personalization research, and discuss issues that researchers need to address in developing new models or in applying existing models to personalization.

4.1. Data Collection

Several sources of data are available to a firm to learn about a customer's tastes and preferences. The data can be collected either by directly asking the customer or by tracking the customer's interactions with the firm. In the direct approach, firms seek customer input using online surveys and registration forms. In tracking (that we call the indirect approach), data on consumer interactions are gathered from transaction histories, web-logs and application server logs, cookies, and databases from external sources. Some of these data, like transactional data, are common across brick-and-mortar stores and web-based ones. When customers interact with a firm through its web site, all such interactions can be stored as well. These interactions can provide information that would typically be not available in conventional databases. We

summarize for the two approaches the important data, their sources, and their uses in the personalization process. We refer the interested reader to (Mena, 2001) for additional details. Research issues that pertain to the effectiveness of different data collection methods are discussed.

4.1.1. Asking the Customer

Many websites employ a registration form or an online survey form to gather information about the customer. These are popular among online portals, in the online travel industry, and in the financial services sector especially for purchase of insurance, loans, and stock brokerage services. The data collected is often of a demographic nature, and used to profile customers based on characteristics such as age, gender, and income level. Physical and email addresses can also be used to help in profiling a user. For instance, advertising servers use ZIP codes to target advertisements for companies in that neighborhood. Demographic data can also be obtained from direct marketing companies, typically based on phone numbers and physical addresses.

In addition to demographic data, a variety of other types of information could also be collected in this manner. For instance, to obtain an email account at Hotmail.com, a customer needs to fill out a survey regarding free online magazine subscriptions and another survey of interest in promotional information in various categories. This information is used to understand a customer's preferences directly. Info Harvest Inc. is an example of a company that specializes in doing preference surveys using secure data gathering methods.

An issue in directly asking is that consumers are unwilling to provide much information unless they can see a clear benefit (Schwartz 1997, p72). A solution is to offer free products or services in return for more information about themselves. For example, Knowledge Networks offers use of a free Internet appliance, WebTV, for browsing and surveys (Rivers and Fallat 2000). Another solution is to gather information sequentially over time. Initially, at the time of registration, consumers are asked for minimal information, and over time more information is obtained. These techniques highlight interesting research issues regarding the efficacy of alternate schemes for gathering information from customers in different situations.

Another important issue is to understand the potential biases when gathering information online, and developing techniques to properly account for such biases. There is evidence that 40% of frequent and experienced Internet users provide false information on *online surveys* about 25% of the time (GVU 1998). At the same time, there is evidence that *online interviews*

yield better quality data than telephone or in person interviews (Saris, 1991, Kalfs 1993). Research is needed to understand the areas (what kind of questions) and contexts in which people are prone to misrepresent information? Geng et al. (2001) propose an interesting approach to eliciting accurate valuations of new products from potential customers using a two-round auction setting.

Direct methods are being increasingly employed for understanding segment or market level behavior. Studies report the advantages of online market research to include speed of completion, lower costs, and the ability to reach “harder to reach” respondents such as busy executives, mobile salespeople, and those at remote locations. In these situations, how representative are the samples of the target population (Miller, 1999)? The use of self-selected panels of customers is common, which is an important source of bias (Montgomery 2000). Initial online respondents were not representative of the US population, as they tended to be more highly educated, and technologically sophisticated. This is further complicated because of the global nature of the Internet. For these reasons, it is hard to define a sampling frame. Weighting methods are sometimes employed to ensure that the demographics match that of the population. While such methods are useful for matching gender, age, and income distributions, it is not clear how to account for differences in attitudes and experience.

Given that people use different bandwidth and different technologies to access the Internet, another pertinent question is whether everybody views a survey instrument in the same way (Miller and Dickson, 2001). Surveys can be administered either through email or by providing a web link. E-mail surveys are not appropriate for long surveys or those with skip patterns (Miller and Dickson 2001). The difference in data quality and response rates between different methods of administration of surveys is not well established. A related issue is whether the use of adaptive surveys (i.e., those in which responses to prior questions are employed to ask more pertinent questions or customized questions) improves the quality of data and the response rates. Similarly, the effectiveness of using rich media such as video, sound, and interactivity in surveys needs to be assessed and quantified.

Since provision of information is closely related to issues of privacy and trust, it is important to understand how trust in the firm can be enhanced. What data collection methods work best for mitigating a customer’s perceived risk (e.g., either through loss of privacy or

misuse of personal information). What activities enable a firm to credibly signal their privacy policy to customers? How does trust affect data quality and response rates?

Smith and Leigh (1997) and Miller and Dickson (2001) provide good reviews of online market research techniques and associated research issues. Researchers from MIT have developed a virtual shopping environment to conduct experiments (Urban, Weinberg, and Hauser, 1996; Urban et al, 1997). Wilke (2000) has reported a parallel testing program where he found that online concept and product tests were methodologically sound, and obtained high correlation between mail and online product tests. Online studies also had high test-retest reliability, provided more extensive open-ended comments, and respondents were more willing to express negative feelings. In another series of 60 parallel tests, Schafer and Wydra (2000) found high correlations between mail and online surveys. They point out that since early responses were likely to be from people with no time constraints, surveys should remain online for at least four days.

4.1.1. Tracking the Customer

We summarize below the important types of data available from tracking a customer's interactions with a firm. Since the original intent for collecting these data is often for purposes other than personalization, the research issues have to do primarily with integration of data from different sources, and its impact on modeling customer preferences. We defer the discussion of such issues till Section 4.2.

Transaction data/Point of sale data

This includes all information on items purchased, their prices, time of purchase, and all other information associated with a transaction. These data are typically captured directly in databases at the time the transaction occurs. A customer's transaction history is a very important source of knowledge about the customer's tastes. In traditional brick-and-mortar environments, the information on the customer, if at all collected, may be hard to deploy for personalization of services (particularly during the shopping process). With electronic stores, the customer information is usually mandatory (for payment and delivery of products), and the site can connect the customer information with prior purchase history. Identifying that a visitor is an existing customer is performed by requiring user registration or with the help of cookies, as discussed below.

Web and application server logs

Web and application server log files record all visitor interactions at a site. Web log files were originally designed to track server traffic, and some of the data can be useful for personalization and customization related activities. Data captured include (i) the browser host IP (Internet Protocol) address; (ii) authentication information such as an ID or a password; (iii) date and time of the interaction; (iv) the Uniform Resource Locator (URL) for the page requested by the user; (v) the referrer field if any (e.g., search engine and keyword used to navigate to the site); and (vi) a cookie field that identifies if a visitor is new or a returning one. IDs and passwords are often used to customize a visitor's site. The set of URL's requested by a user is often referred to as clickstream data. Application server log files can include additional information as specified by the application code. This could include information such as the data queried from back-end databases, the thread-id for the code (applet) that was executed, and special events that may have occurred during the interaction.

Cookies

Cookies are small text files that a web site server places on the hard disk of a browser host machine (client machine). A cookie helps the web site server identify a user both within a session, as well as across sessions. Cookies typically include (i) the domain name of the server; (ii) how the cookie was created; (iii) the expiration date for the cookie; (iv) the name of the cookie; and (v) the cookie value that helps identify the browser host machine to the server. Cookies can be used in a variety of ways in the personalization process. Browsing behavior within a session can help the server understand the immediate needs of the customer. Across sessions, a cookie helps the server track repeat visits of users, which is very useful for sites that do not require authorization for access. Furthermore, the information in a cookie can help the server link a visitor to transactional and demographic data stored on that individual. This can enable the server to tailor content or recommendations to the user. In addition to tracking behavior within a site, cookies from third parties can be used to track a customer at multiple sites. For example, advertising servers (or Ad Networks, as they are referred to in the popular press) track a person's visits to all those sites that are serviced by that server. These data enable the Ad Network to learn aspects of a customer's preferences that cannot be gleaned from navigation within a single site. The Ad Network (e.g., Doubleclick) can use that knowledge to better target advertisements and manage advertising campaigns.

In addition to the above, there exist other sources of data on customers that could help in the personalization process. These include customer service databases, warranty claims databases, and any other point of contact with the customer that is recorded by the firm. Firms are investing heavily in Customer Relationship Management (CRM) software to capture all information about customers' interactions, which can enable the firms to arrive at a single unified view of each customer.

Table 2 summarizes the key research issues in collecting data for personalization applications.

Table 2. Issues in data collection

Issue	Research Questions	References & representative articles
Incentive mechanisms	When are monetary incentives required, and when are non-monetary incentives appropriate? How can accurate customer valuations be obtained? What is the role of permissions in collecting personal data?	Geng et al. 2001.
Potential Biases	In which questions and in which situations are bias aggravated? Which methods are better in what situations? How can online information gathering be improved?	GVU Survey (1998), Saris (1991), Kalfs (1993)
Adaptive surveys	What is the effect of adaptive surveys on data quality and response rates?	
Privacy and trust	How can a firm credibly signal their good intentions? How does trust affect data quality?	Miller and Dickson (2001)
Sampling Issues	How can samples representative of the population be drawn? When that is not possible, how should adjustments be made?	Miller (1999), Miller and Gupta (2001)
Reliability and validity of measures	Are results obtained from online surveys consistent with those obtained by traditional methods? If not, what are the causes for these differences? What are the benefits and limitations of alternate forms of delivery (e.g., email / web-based) of surveys?	Wilke (2000), Schafer and Wydra (2000),
Role of Technology	Download times vary with different connection bandwidth, affecting response rates differentially. How does this distort how people view the same survey?	Miller and Dickson (2001)

4.2 Learning Customer Preferences

The data collected on customers has to be analyzed to obtain insights about customer behavior. In this section, we discuss models that can be used to understand consumers' preferences. We review established models in economics, marketing and operations research that we believe are relevant to personalization research, and point out opportunities for developing new models. We classify the models into four categories. These categories are:

Preference models: These models are used to understand consumer preferences for different attributes of a product or service.

Prediction / Response models: In these models, the goal is to predict consumer behavior such as a purchase and understand the responsiveness of a customer to marketing and other influences.

Stochastic models: The objective here is to model time-related customer behavior such as how many purchases a customer is likely to make in a given period of time, or the time between purchases.

Segmentation models: These models are used to cluster consumers into homogeneous groups.

Table 3 provides an overview of these four categories of models with some representative applications.

Table 3: Model Categories and Representative Applications

Model categories	Techniques	Representative applications
Preference Models Understand consumer preferences	Expectancy value model Conjoint analysis Ideal point model	How much does a customer value different attributes? What is the utility of alternate combinations of attributes to a customer?
Prediction / Response models Predict probability of purchase, measure response to price and promotions	Regression analysis Logit / Probit models	How much will this customer buy given a targeted offer? What is the effect of price and promotions on the probability of purchase? How likely is a customer to click on a given advertisement?
Stochastic Models Predict when a customer will do a task	Hazard rate models Purchase incidence model	How frequently does a customer visit a web site? What factors affect the duration of stay on a web site? Which customer has ceased to be active? What action is needed?
Segmentation models Classify customers into segments and target accordingly	AID / CHAID Clustering Latent class segmentation	Which segment does a customer belong to? What level of personalization to provide to each segment?

The above classification helps to organize our discussion of specific models that are useful for personalization. The models categories are presented in order of their importance to personalization research. In each category, we provide a brief overview of the important techniques and related literature. Since work in personalization is still evolving, we present techniques that have worked well in the offline world, and point to good review articles for the interested reader. We then discuss new modeling opportunities in personalization research.

4.2.1 Preference Models

Utility theory is the dominant paradigm employed in economics, marketing, and operations research to understand and represent individual preferences. In marketing literature, learning customer preferences is often viewed as determining the utility function of the customer for a given product (Lancaster 1979, Srinivasan 1979, Horsky and Rao 1984). While a large variety of models have been developed based on the utility paradigm, there are three that have been widely used to estimate individual preferences. They are the *expectancy value model*, *conjoint analysis*, and the *ideal point model*. We first provide an overview of basic utility models and assumptions, and then describe the above three variants. We note at the outset that, strictly speaking, the term utility function is used to refer to preference representations under uncertainty, while value functions refer to preference representations under certainty (Dyer and Sarin 1979). For expositional convenience, in this paper we use the term utility function to include value functions as well.

For most product categories, the utility to customers is a function of multiple attributes of a product (Lancaster 1971). Let $\mathbf{X}=(X_1, X_2, \dots, X_n)$ represent the set of attributes that constitute the utility function of a customer, and $U(\mathbf{x}) = U(x_1, x_2, \dots, x_n)$ refer to the utility function of the customer. Each X_i is assumed to be bounded, and $U(\mathbf{x})$ is assumed to be continuous. The difficulty lies in identifying the specific nature of the utility function, and then determining procedures for estimating the function parameters from available data. The common approach has been to make one or more assumptions about the preferences, and identify functional forms that satisfy these assumptions. To make the estimation task simple, the additive and the multiplicative (log-additive) functional forms shown below have been widely used, as they are separable in the utilities over the different attributes (Keeney 1974, Dyer and Sarin 1979).

Additive utility function:

$$U(\mathbf{x}) = \sum_i w_i * u_i(x_i).$$

Multiplicative utility function:

$$U(\mathbf{x}) = \prod_i [(1 + K * w_i * u_i(x_i)) - 1] / K.$$

In the above expressions, w_i refers to the weight assigned to the i^{th} attribute, $u_i(x_i)$ is the utility for level x_i of the i^{th} attribute, and K is a scaling constant.

Knowledge of a customer's utility function enables a firm to understand which of several choices would be most preferred by the customer. This knowledge, in turn, can enable the firm to determine which product (or product set) should be recommended to the customer, or for that matter, how much to charge a customer for the product. Firms also use this knowledge to design optimal sets of attributes for different market segments. In some situations, these models are estimated at an individual level and then aggregated to understand market behavior, while in others models are directly estimated at a market or a segment level.

In assessing multi-attribute utility functions, researchers have typically examined ways in which the weights of the attributes can be elicited from individuals assuming that the utility functions are separable (Keeney 1974, Farquhar 1984). These weights then indicate the relative importance the individual places on each attribute. A straightforward approach to determining such weights is to ask the individual to directly assign weights to the attributes, often requiring that the weights add up to 1.

The use of self-explicated importance weights is not usually recommended, as individuals often find it difficult to articulate such weights, and the procedure does not have built in checks to ensure the validity of the weights obtained. More effective approaches to determining weights include, among others, the ratio method (Edwards 1977), the swing weighting method (von Winterfeldt and Edwards 1986), the tradeoff method (Keeney and Raiffa 1976), and the pricing out method (Keeney and Raiffa 1976). These approaches do allow for the checking of internal consistency of the weights provided by the individual. Nevertheless, the weights obtained using such techniques have been found to be dependent on the elicitation method (Schoemaker and Waid 1982, Borchertding et al. 1991), and the question of validity of such weights remains partially unresolved.

The Analytic Hierarchy Process (AHP) has been widely used in modeling multi-criteria decision problems (Saaty 1986). A key aspect of this approach is to decompose a problem into smaller constituent parts, each of which in turn may be decomposed in a similar manner until the elemental attributes are obtained. Weights of attributes within a single sub-hierarchy are obtained via pair-wise comparison. The weights assigned to the sub-hierarchies are similarly elicited by comparing their relative importance with other sub-hierarchies within a common parent. More recently, Barron and Barrett (1996) have considered three schemes for deriving weights from the rankings of the importance of attributes. Such techniques are easy to implement since only the

rankings are needed from the individual thereby simplifying the assessment process. The three schemes are the rank-sum, the rank reciprocal, and the rank-ordered centroid. In their experiments, Barron and Barrett find the rank-ordered centroid scheme to be more accurate than the other two.

The *expectancy value model* was one of the first utility-based used to estimate consumer preferences in marketing. It is a compositional model and computes a score based on a customer's importance weights and beliefs. For instance, a popular version of this model computes a consumer's attitude score A_b for a branded product b , as a weighted average of consumer beliefs about the attribute i of the brand b , B_{bi} , weighted by the importance weight of each attribute w_i (Fishbein 1963, Bass and Talarzyk 1972). The importance weights sum to 1 across all attributes. It is mathematically similar to the additive utility model and is expressed as:

$$A_b = \sum_i w_i B_{bi}.$$

Both the importance weights and beliefs are sought from the respondent using a rating scale. This score is then used to predict that individual's choice in a category. Such self-explicated measures have been employed in market research to compute the attitude score of an individual, that is then used to predict an individual's choice in a category as well as the expected market share for products (Hoepfl and Huber 1970).

Self reported measures suffer from halo effects (Beckwith and Lehmann 1973), and methods have been employed to deduce the importance weights. Prominent among these methods are monotonic regression (Johnson 1975), linear programming (Shocker and Srinivasan 1979), and monotonic analysis of variance (Green and Wind 1973). Unlike the expectancy value models, perceptual or underlying dimensions (obtained from a factor analysis) are employed as explanatory variables in these models. Wilkie and Pessemier (1973) provide a good review on this subject.

When assessing customer preferences, it has been well documented that individuals are more easily able to provide information on their preferences of brands as compared to directly specifying the relative importance of different attributes (Srinivasan and Shocker 1973, Horsky and Rao 1984, among others). In many cases (such as in low involvement grocery products), consumers may not be able to provide meaningful information about their beliefs or importance weights of attributes. A variety of models and methods have been proposed in the literature that use brand preferences provided by individuals to estimate the attribute weights. Of these, the

most popular model employed to understand consumer's preferences, especially for new products, is conjoint analysis (Green and Rao 1971, Green et al. 1972, Srinivasan and Shocker 1973). The basic model is represented by the following formula:

$$U(\mathbf{X}) = \sum_{i=1, m} \sum_{j=1, r_i} u_{ij} * x_{ij}$$

where $U(\mathbf{X})$ is the overall utility of an alternative, u_{ij} is the part-worth contribution or utility associated with the j^{th} level of the i^{th} attribute, x_{ij} is one if the i^{th} attribute is present and zero otherwise, m is the number of attributes, and r_i is the number of levels of attribute i . Customers are asked to compare and rank multiple product descriptions, which specify combinations of different attribute levels. These product descriptions are developed according to a specific experimental design. Assuming that the rank order reflects the inverse of preferences of the consumer, it is used as a dependent variable in a dummy variable regression to estimate the importance weights of attributes. The utilities derived from different combinations of attributes are calculated for each customer, which are then used in predicting which brand a customer will buy. The parameters can be used to simulate market shares of new products, find different segments of customers, and design optimal products. These models have been found to work well for products with a small number of attributes, and also with a small number of levels within an attribute.

When the valuation of an attribute is not monotonic (i.e., more is not always considered to be better), such as sweetness of a candy or roominess of a car, consumers are assumed to have an ideal point for this attribute. Preference is then modeled as an inverse function of the distance from the ideal point, and such models are called *ideal point models*. Horsky and Rao (1984) formulate the preference function in terms of the distance between a choice object from that of an ideal object as shown below:

$$D_b = K + \sum_i w_i * d_{bi} + \epsilon_i.$$

Here, D_b is the distance of a brand b from the ideal brand, w_i is the weight of attribute i , d_{bi} is distance of the b^{th} brand from the ideal point on attribute i , K is a constant, and ϵ_i is an error term. The functional form of their distance measure is separable in weights, although the d_{bi} 's can take on any number of forms, for instance the weighted city-block or Euclidean distance. Each pair-wise comparison results in an inequality equation that follows from the above distance function. Horsky and Rao show that if a cardinal (interval-scaled) value function is to be

determined, then it is necessary to collect not only pair-wise preference comparisons, but also comparisons of pairs of pairs. The comparisons of pairs of pairs lead to additional inequalities. They present a mathematical programming approach that minimizes the violations to the inequalities that are implied by the two sets of comparisons. They go on to identify the number of comparisons that would be required at a minimum, in order to have any degrees of freedom for estimation purposes. They also discuss how their approach could be extended to estimate the ideal points on each attribute in addition to the weights.

A common problem in applying conjoint analysis and other related techniques is respondent fatigue. For example, the number of all possible combinations of three levels each for five attributes is 3^5 or 243. It is a daunting task for any respondent to rank so many alternatives. In practical studies, respondents evaluate only a subset of alternatives, which limits the estimation of some parameters. As a result, hybrid conjoint models have been developed that employ both a self-explication task (in which customers indicate acceptable and unacceptable levels of important attributes) and a ranking task (using fewer combinations of a reduced set of levels and attributes) to reduce fatigue. Green and Krieger (1996) present a hybrid model for a customer n who rates r product descriptions (or profiles), each with i attributes and l levels per attribute, as:

$$U_r = \sum_i w_i \sum_l D_{il} I_{il}, \text{ and}$$

$$S_r = a + b U_r + \sum_i \sum_l B_{il} I_{ril} + e_i,$$

where U_r is the utility from the self explicated task, w_i is the importance weight of an attribute and D_{il} is the evaluation of level l of attribute i . I_{il} is an indicator variable, which takes the value 1 if that combination of attributes is evaluated by the respondent. The value of an alternative r , S_r , is modeled as a function of U_r and indicator variable I_{ril} for the profile evaluated by the respondent. The regression coefficients a , b , and B_{il} are estimated at the pooled-sample level. Other extensions of the above model allow for estimation of individual level intercepts and coefficients as well as interactions between attributes. An alternate solution to reduce consumer fatigue is adaptive conjoint analysis (Johnson 1987, 1991). A good review of hybrid models appear in Green and Krieger (1996), and of adaptive conjoint models in Green and Srinivasan (1990).

Another variant of conjoint analysis, called choice based conjoint analysis (CBA) uses customer choice as the dependent variable. The estimation of parameters of this model requires a large number of observations and hence data is typically pooled across several customers to obtain aggregate level model parameters (see Louviere and Woodworth 1983, Mahajan et al. 1982, Batsell and Louviere 1991). The models employ the multinomial logit or probit framework and are estimated using maximum likelihood techniques or simulation techniques (we discuss these models in some detail in Section 4.2.2).

While the use of utility-based models in personalization is limited at present, some works have recently appeared in the academic literature. Conjoint analysis has been used in designing personalized websites (Dreze and Zufryden 1997), and testing product concepts on the Internet (Dahan and Srinivasan 1998). Montgomery (2000) describes other works that use conjoint analysis related techniques for Internet based applications. There are a host of issues in modeling customer preferences that should be of interest to researchers working in the management sciences. We describe a few promising avenues.

The vast majority of preference functions are based on the additive or log-additive models, as they are easy to estimate with relatively few observations. These models assume two types of independence, mutual preferential independence and mutual utility independence (alternatively, mutual difference independence for value functions) (Keeney 1974, Dyer and Sarin 1979). These assumptions are often violated in many application domains. In applications where large amounts of observations are available (e.g., browsing related applications, or repeat purchase scenarios), it should become feasible to consider other classes of preference functions that make less restrictive assumptions. Desirable characteristics of such functions need to be identified, and estimation issues examined in those contexts.

In some environments, the personalization process is desired during real time interactions (e.g., during negotiation, serving advertisements, etc.). In these scenarios, each interaction could be viewed as a stochastic process that is used to learn a customer's preferences. Then, based on the interaction, one could determine the conditional utility function of the customer. The modeling challenge here would be to identify utility functions that can be easily updated based on new interactions, instead of having to re-estimate all of the parameters of the utility function based on previous interactions. It would be desirable to characterize the customer profile using a utility function that is compact, easy to calculate on the fly, and easy to update. Hazen et al.

(1996) discuss three classes of compact preference summaries with such properties in the context of stochastic decision trees: memoryless, Markovian, and semi-Markovian. An interesting area of future research is to identify under what situations such preference functions are reasonable in the personalization context, and to determine appropriate functional forms.

To apply choice based conjoint analysis to tracking data, researchers need to determine the length of purchase history needed to obtain stable estimates of an individual's preference function. The length of the purchase history limits the applicability of such techniques to frequently purchased goods and services. Under what conditions and for what products can one estimate individual level preference models on the Internet? How would one use the models for durable goods or for newer customers? What is the magnitude of bias relative to aggregate models? Another important issue in using some of the existing models is how to obtain an individual-specific utility function from an aggregate preference function. This is often the case when data available for an individual consumer is sparse. When using conjoint analysis, Lenk et al. (1996) have combined data across different households to estimate individual level parameters using a hierarchical Bayes random effects model. They show that their model can use shorter questionnaires and can accommodate complex product categories with a large number of attribute values or a large number of choices. The Bayesian methods incur a significant computation cost and so may not be good for real-time personalization. In environments where an individual's preference function is relatively stable, the model parameters can be re-estimated periodically. The periodicity of estimation, and the time horizon for data used, are important issues for investigation. Berger (1985) provides a good review of hierarchical Bayes models, and some representative applications in marketing are discussed by Lenk and Rao (1990) and Allenby and Lenk (1994).

What experimental designs are feasible for conducting conjoint analysis on the web? For example, hybrid conjoint models (Green and Krieger 1996) that reduce respondent fatigue could be adapted for online environments. How can preference functions obtained from conjoint studies (based on survey data) be used in conjunction with preference functions estimated from tracking data? These are some of the open research questions that need experimentation.

There are several elements of the environment that can affect a consumer's decision process. Family members, friends, salespersons, and other people often influence decisions in many ways. In addition, marketing variables, competitive factors, and situational factors affect

the purchase process. This raises interesting issues for personalization that have not been currently addressed. In group-decision making situations (such as when a family makes a decision regarding purchase of a car or insurance), if firms had data on both the wife and husband, how could they combine the different pieces of information to provide a personalized recommendation? What models are relevant for aggregating preferences of the members of a household or a group?

Another interesting aspect of the Internet is the development of virtual communities, where consumers go online to community spaces to gather or share information about vendors, prices, products, recommendations, and experiences of other consumers. Chat rooms, instant messaging, and bulletin boards are all online tools that are made available by firms to facilitate discussion among its customers. For instance, AOL has 33 million customers, and over 120 million registered users of ICQ, the instant messaging software. AOL members generate 1.2 billion messages everyday and spend 10 million hours per week in chat rooms. Given the widespread popularity of online communities and active participation by many members, firms find it attractive to build and maintain online communities (Hagel and Armstrong, 1997). There is very little research on how communities shape beliefs and perceptions about products and whether firms can manage these communities to their advantage. Balasubramaniam and Mahajan (2001) suggest that economic activities must be embedded within the interactions across community members for organizations to leverage these communities. What role do social interactions play in an individual's utility function? Can providing access to communities enhance differentiation, and can this differentiation be used to enhance personalization to individual consumers? How can one quantify the network externality that may accrue due to membership in a community.

In cross-selling applications, it will be useful to study how a customer's preference function for one product can be adapted to reflect that same customers' preference function for another related product. What should be done when some of the attributes are common across the two products and others are not? How should this adaptation differ for complementary and substitute products? When a customer's preference functions are available for several products, how can they be combined to estimate the preference function for the target product? Should a consumer's preference function be derived from preference functions of other customers (akin to collaborative filtering techniques)? If so, how? Ansari et al. (2000) discuss, in the context of

providing recommendations, a hierarchical Bayes approach that considers both customer choice as well as product characteristics. Preference functions can be used to generalize such approaches.

Information products, that are emerging as a dominant segment of goods served over the Internet, provide several important research challenges. Technological advances are making it possible to customize such products at finer and finer levels of granularity, all in close to real time. At the same time, different customers may have vastly different valuations for an information product. A key challenge will be to determine preference functions for such products with sufficient accuracy to enable first-degree price discrimination, perhaps using micro-payments. Of particular interest here would be to recognize the difference in the nature of consumption of information products as compared to traditional goods and services. As the Internet becomes the delivery medium for multi-media applications (e.g., experience goods), we expect to see many new issues emerge in this domain as well. DeZemmer (2002) mentions how universities are considering using tracking software that can help them send customized mailings to potential students who have visited virtual tours provided on the university web sites. The next step would be to personalize such tours based on a student's profile.

4.2.2. Prediction / Response models

The main objective of these models is to predict customer behavior such as whether a customer will purchase or not, or which one of several brands will a customer choose. In addition, these models have been used to determine the responsiveness of the customer to prices, promotions, and other variables. This knowledge can enable a firm to improve the effectiveness of these marketing variables. The two most widely used sets of techniques are regression models and discrete choice models.

Regression models typically employ continuous dependent variables such as sales, profits, or any other such attribute. The explanatory variables could include variables such as prices, promotional offers, as well as demographic or behavioral (e.g., loyalty) attributes. These models are widely used in marketing and other areas and well researched. Interested readers are referred to Greene (2000) for a good review of such techniques.

Logit and probit models are applicable in the context of modeling discrete dependent variables. When a firm wants to understand the impact of factors that affect consumer decisions

such as the choice of a brand, these models are appropriate. In these models, a latent variable, such as utility U_{jkt} , is defined for a customer k choosing alternative j on purchase occasion t . This utility is assumed to consist of a deterministic component V_{jkt} and a random error ϵ_{jkt} as shown below (Guadagni and Little 1983):

$$U_{jkt} = V_{jkt} + \epsilon_{jkt}.$$

The deterministic component of utility V_{jkt} is typically modeled as a linear-in-parameters function of explanatory variables, i.e., $V_{jkt} = \alpha_j + \beta X_{jkt}$. Under the assumption of a type II Gumbel distribution for the random error term ϵ_{jkt} , the logit model gives the probability of a customer k choosing an alternative j on occasion t as:

$$\text{Prob}_{kt}(j) = \frac{\exp(V_{jkt})}{\sum_{i=1}^J \exp(V_{ikt})}.$$

On the other hand, if one assumes that ϵ_{jkt} are distributed according to a Normal distribution, it leads to the probit model. Both models are estimated using maximum likelihood estimation techniques. The advantage of the logit model is that it is easy to compute. The probit model allows the specification of a flexible variance covariance structure, but is computationally burdensome for a large number of alternatives. Recent advances in estimation techniques using simulation of multivariate normal probabilities (such as Method of Simulated Moments (McFadden 1989) and Gibbs Sampling (McCullogh and Rossi 1994)) have made it possible to estimate probit models involving a large number of alternatives. The flexible covariance structure allows a researcher to model dependencies between the alternatives, and between the effects of the explanatory variables, and thus overcome the *independence of irrelevant alternatives* (IIA) problem associated with the logit model. Rossi and Allenby (1993) provide a method to obtain individual level estimates using hierarchical Bayesian estimation.

The logit model can be estimated for each individual if a sufficient number of purchases have been made in a given category. When enough data points on an individual customer are not available, the choice models can be estimated at an aggregate level by combining data from many customers. When grouping customers, the estimates of the choice model will be biased if differences between individuals (such as differences in their preferences or in their response to marketing variables) are ignored (Guadagni and Little 1983). This issue is called heterogeneity and has been addressed using mixture models (Kamakura and Russell, 1989), random intercept

models (Chintagunta et al. 1991), random coefficient models (Gonul and Srinivasan 1993) or multinomial probit models (Rossi and Allenby, 1993). Degeratu et al. (1999) use choice models to model online grocery purchases.

These discrete choice models can be used to determine a customer's preferences based on factors such as pages visited or links traversed, the duration of stay on a page, or advertisements clicked. When purchase history is also available, the models can help predict choices that a customer may make on their next visit or how likely the customer is to respond to a discount offered. An important issue in this context is the appropriate modeling of endogeneity in such environments. In traditional response models, the explanatory variables are assumed to be exogenous. However, in the context of personalization, prices and promotions could be tailored to an individual customer and hence it is important to consider these variables as endogenous (Leeflang and Wittink, 2000). This necessitates the specification of models for the endogenous variables and estimation of a system of equations. Villas-Boas and Winer (1999) have developed a model to account for endogeneity of marketing mix variables using scanner data. Similar extensions are needed for personalization applications.

When estimating aggregate models it is important to control for heterogeneity. Observed heterogeneity can be modeled by allowing the coefficients to be a function of demographic and other variables. In addition, unobserved sources of variation across consumers, across choices, across stores, and across time need to be controlled for in order to avoid biased estimates. Unobserved heterogeneity in regression models can be incorporated using fixed or random effects (Greene 2000). In discrete choice models, unobserved heterogeneity is modeled by defining random intercepts and random coefficients. A typical approach is to specify a decomposition of the error term (Heckman, 1981). For instance, to incorporate random intercept in the model, the intercept α_0 is specified as:

$$\alpha_0 = \underline{\alpha}_0 + \delta_n + \xi_{nk},$$

where $\underline{\alpha}_0$ measures the mean intrinsic utility, δ_n represents the random deviation for a customer n from the mean, and ξ_{nk} represents the deviation from the mean for a customer on a given occasion. Researchers then assume a parametric distribution for the random variables δ_n and ξ_{nk} (e.g., Normal or Gamma). The mean of the distribution is zero, and the variance can be estimated. For a good discussion of these models see Chintagunta et al. (1991), Rossi et al. (1996), and Gonul and Srinivasan (1993).

Heckman and Singer (1984) suggest that parameter estimates may be sensitive to the assumed functional form of the random distribution and propose a nonparametric specification to capture the unobserved heterogeneity. In this specification, they assume a discrete distribution with r ($r=1,2,\dots,R$) support points for the random variables. Each support point has a location parameter (A_r) and a probability mass (P_r). These are estimated using maximum likelihood techniques. Applications of the method are reported in Vilcassim and Jain (1991) and Gonul and Srinivasan (1993).

A customer's click-stream data from a firm's website, does not provide information about their browsing behavior on other sites. This information could have important implications regarding the customers purchase behavior. Using site-centric data could lead to significant bias in results relative to interpretations drawn from data on browsing behavior collected across multiple web sites. Research needs to examine the nature of bias and develop models to correct for such bias.

Resnick and Varian (1997) point to the modeling challenges in personalization using Internet data, which is typically of high dimensionality (i.e., a large number of attributes are needed to describe the product space). Further, data on an individual is sparse. This necessitates pooling of data across different customers, different sources, and even different categories. Recommendation agents often use data from multiple sources – e.g., ratings from customers, demographic data, product characteristics, and tracking history. Robust models are needed to combine data from such diverse sources for purposes of predicting customer behavior. Russell and Kamakura (1994) have presented an approach to refine a choice model using data from individual level scanner data and merge it with store level data; similar extensions are needed for combining data from heterogeneous sources for personalization applications.

One of the important limitations of the discussed models is that they predict a single, most preferred, item for a customer. In many situations (e.g., groceries, music, movies, news items on a web site), a customer is interested in buying a group of items, or consuming a set of information products. McAlister (1979) has shown how, using preference judgements given by subjects, models of preference for groups of items can be inferred by applying linear programming techniques. A practical limitation of their approach is the restriction on the number of items that are in the consideration set. Models for understanding preferences for groups of items from large itemsets deserve special attention.

The models discussed in this section are practical for datasets that have about a few thousand observations (typically under 10000). However, when the dataset is in millions of records, some of these models may not scale up. It is important to identify which models are appropriate for smaller samples of data and which should be used with larger samples. Techniques are needed that scale up well without sacrificing much accuracy.

4.2.3. Stochastic models

Purchase incidence models and *purchase timing models* have been widely used to model stochastic aspects of a customer's behavior. Purchase incidence models have been employed in marketing to understand, for instance, how many purchases a customer will make in a given time period. These models are useful in evaluating the success of promotions, and can be used to target communication and promotional offers to customers at the time that they are likely to purchase or the time that they are likely to switch. Purchase timing models are closely related to purchase incidence models and are often used to model the time between purchases.

In purchase incidence models, the number of units purchased by consumer i in time period t is assumed to follow a Poisson distribution with parameter λ , which can be interpreted to be the rate of the Poisson process. To model consumer heterogeneity, it is assumed that λ is distributed over the population according to a gamma distribution with parameters (\mathbf{a}, \mathbf{b}) . The number of purchases for a randomly selected individual then follows a Negative Binomial Distribution (NBD) as shown below (Ehrenberg 1959):

$$f(y_{it} | \mathbf{a}, \mathbf{b}) = \binom{y_{it} + \mathbf{b} - 1}{y_{it}} \left(\frac{\mathbf{a}}{\mathbf{a} + t} \right)^{\mathbf{b}} \left(\frac{t}{\mathbf{a} + t} \right)^{y_{it}}.$$

The mean of the NBD is $E[Y_{it}] = \beta t / \alpha$ and the variance is $\text{Var}[Y_{it}] = (\beta t / \alpha) + (\beta t^2 / \alpha^2)$. The model parameters (α, β) can be estimated by the method of moments (i.e., by matching the mean and variance to the observed mean and variance of the number of purchases) or by using maximum likelihood estimation techniques. While the former is easy to compute and use, the latter method is more effective (Gupta and Morrison 1991).

The purchase incidence model can be used to compute the probability of at least one purchase during a given time interval. These models have been extended to account for “never buyers” (Morrison and Schmittlein 1988), incorporate marketing variables (Gupta 1991), and unobserved heterogeneity (Wedel et al. 1993). In the context of the Internet, such a model can be

used to predict the number of visits or the number of downloads in a given time interval. Firms can understand the effect of marketing variables on the duration of stay at a website or the timing of the next visit. Fader and Hardie (1999) and Moe and Fader (2001) use the purchase incidence model framework to model customer trial and repeat purchase over time at the Internet music retailer *CDNow*.

The purchase timing models can be used to predict and understand the time between purchases, and model the duration of visits to web sites. A major advantage of these models over the purchase incidence models is that they account for right censoring, which occurs if a sample of consumers is observed for a fixed length of time causing longer inter-purchase times to have a larger probability of falling outside the observation period. Biased estimates are obtained if one does not control for censoring. In the continuous time model of Jain and Vilcassim (1991), the probability of purchase during a certain time interval $t+Dt$, given that one has not purchased until time t (called the hazard function), is specified as:

$$h(t | X, \theta) = h_0(t) \phi(X) \phi(\theta),$$

where $h_0(t)$ is the baseline hazard function, $\phi(X)$ is a function of explanatory variables, and $\phi(\theta)$ is the specification of the unobserved heterogeneity. All these functions are non-negative. The authors use the Box-Cox formulation of Flinn and Heckman (1982) to specify the baseline hazard function. These models are estimated using maximum likelihood estimation procedures (Heckman and Singer 1984, Cox 1972, Lancaster 1979).

An interesting observation in online shopping environments is that a significant proportion of customers do not complete the sale they have initiated by putting items in their shopping cart. Timing and purchase incidence models could be used to predict under what circumstances a customer is likely to abandon her shopping cart, and what inducements under the current circumstances would most likely lead to the customers continued shopping. Factors in addition to price and promotions that affect such behavior, such as site responsiveness and ease of use can be studied in this context. Models need to be developed that capture trade-offs between marketing and non-marketing variables.

These kinds of techniques can be adapted to model the duration of stay on a site by a customer, and link that with the likelihood of purchase. A related issue would be to identify if there are pages of a site that customers typically exit from (such pages are termed killer pages). Churn and switching behavior can be modeled, and these factors incorporated in the

personalization process. The number of active visitors (customers) to a site at a given point of time could be modeled as well (e.g., see Schmittlein et al., 1987). For sites with a large numbers of visitors, timing models can be used to allocate differential computational or other resources to customers based on predicted behavior. All of these scenarios offer modeling and empirical research opportunities for management science researchers.

4.2.4. Segmentation Models

Segmentation has long been recognized as an important aspect of personalization, as it allows viewing a heterogeneous market as a collection of smaller relatively homogeneous groups with distinct preferences (Smith 1956). Products and services can then be designed to cater to specific groups (segments), so that they provide a high level of satisfaction to customers in each group. Over the years a large number of techniques have been developed to cluster customers into groups. Some commonly used techniques are *Automatic Interaction Detection (AID) / Chi-Squared AID (CHAID)*, *cluster analysis*, *Classification algorithms and regression trees (CART)* (Breiman et al. 1984), and *latent class segmentation*. Wedel and Kamakura (1998) discuss different techniques for segmentation and provide a comprehensive evaluation of the suitability of techniques discussed.

Segmentation can be done using observable or unobservable variable. Observable variables include demographic and socioeconomic variables, and purchase history, while unobservable variables include attributes relating to loyalty, perceptions, preferences, and sensitivity to marketing. Wedel and Kamakura classify the methods used for segmentation either as *a priori* or *post hoc* - depending on whether the type and number of segments are determined in advance by the researcher or whether they are determined on the basis of results of data analysis. They further classify the segmentation methods as being descriptive (capture association between variables with no dependent variable) or predictive (association between set of dependent variable and independent variables).

Recent advances in segmentation include use of mixture regression models, which are shown to be generally superior to clustering techniques (Wedel and Kamakura, 1998). Most segmentation procedures are applied to one set of variables (such as product usage). Ramaswamy et al. (1996) develop a latent Markov model to identify segments when multiple types of segmentation bases exist and these bases are not independent (such as product usage and

benefits). Bhatnager and Papatla (2001) present a model to segment customers based on their search behavior, in order to deliver personalized advertisements to customers.

Segment level personalization involves the identification of the relevant segments and the corresponding preference functions, the assignment of a customer to a particular segment, and the delivery of products that best serve the needs of the segment (and, by implication, the customer). Several of the research issues discussed in the sections on preference and prediction models apply here as well. In addition, there exist other interesting issues unique to segmentation. For instance, models could be employed to determine brand-specific effects in the value functions for different segments. Srinivasan (1979) defined the brand-specific effect to be the component of overall preference not explained by the attributes in a multi-attribute model, and showed that the estimation problem can be recast as a minimum cost network flow model. More recently, Brynjolfsson and Smith (2001) have used logistic regression techniques to identify price premiums for branded online retailers of books.

Another practical issue is how often to perform segmentation of your customers? This issue is relevant when markets are dynamic and evolving as on the Internet. Further, could there be trigger events that suggest the need for a fresh segmentation? In Customer Relation Management applications, customers are assumed to evolve from being a prospect, to a customer, to a supporter, and finally to an advocate (Brown, 1999). An issue here is that of dynamic segmentation, in which longitudinal consumer data is used to determine which phase of relationship a customer is in. These phases indicate the growing involvement or satisfaction of a customer with the firm. Depending on the classification of a customer into one of these phases, different marketing strategies may be employed. While a few dynamic segmentation models have been developed (Wedel and Kamakura 1998), little is known about the stability of these methods. Additional research is needed to develop robust methods for dynamic segmentation.

Most studies view segmentation as grouping customers. In a one-to-one marketing situation, firms in some categories (such as information providers like Yahoo) attempt to expand their range of products and services to take advantage of their relationship with the customer. In such cases, an interesting question is to segment one individual's preference across multiple situations. In a recent study, Moe (2001) classifies people into buyers, browsers, and searchers based on the type of information that they were seeking. The same individual can, in fact, be a searcher at some point in time and a buyer at another point in time. If it is possible to classify an

individual as being in a browsing mode or a purchasing mode, then different kinds of inducements may be appropriate. A related question is whether a consumer's behavior is static across categories of service. For example, a customer using Yahoo's services could be a novice information gatherer for high technology products, while an expert information gatherer for stock trading. Ideally, the website should provide different types of personalization if it could make such distinctions accurately. Models for contextual personalization are needed.

In summary, there exist opportunities for developing new models of user preferences for a variety of personalization scenarios that have become feasible with the advent of Internet related technologies. Empirical issues also abound in precisely estimating preferences for products, and attributes of products under consideration. Table 4 summarizes the key research issues that we have identified in learning customer preferences.

Table 4: Model Categories and Representative Applications

Model categories	Research Issues	References & representative articles
Preference Models Expectancy value models Preference regression Conjoint analysis Ideal point model	What functional forms are feasible for different types of personalization applications? What is the length of purchase history needed for obtaining stable estimates of an individual's preference function? When should individual level models be used? Which models are best suited for obtaining individual specific parameters from aggregate models? What is the extent of bias in individual preference models relative to aggregate models? What are feasible experimental designs for conducting conjoint analysis on the web? How can data from surveys be combined with tracking data to understand consumer preference functions? How can preference functions for one product be adapted to derive preference functions for related products? How are preference functions for information products different from those for traditional goods?	Hazen et al. (1996) Green and Srinivasan (1990) Lenk et al. (1996), Allenby and Lenk (1994) Green and Krieger (1996)

Prediction / Response models Regression analysis Logit / Probit models	How should endogeneity of prices and promotions in targeted offers be modeled? How can different types of heterogeneity be controlling for? What models are appropriate for site-centric data? For user-centric data? How can biases in site-centric data be accounted for? What models are appropriate for handling incomplete or missing data (sparse data situations)? What models could be used to predict purchase of groups of items? Which models scale up well?	Villas-Boas and Winer (1999) Chintagunta et al. (1991), Gonul and Srinivasan (1993), Heckman and Singer (1984) Russell and Kamakura (1995), McAlister (1979)
Stochastic Models Hazard rate models Purchase incidence models	What models are appropriate for predicting purchase timing? For predicting the duration of visit to a web site? For predicting when the next visit to a site will occur? Which factors most affect incomplete sales? How could one identify the appropriate inducements to customers for such situations? Which factors affect switching across products (sites)? Which factors characterize killer pages? How can we model the number of active visitors to a site?	Ehrenberg (1959), Gupta (1991), Gupta and Morrison (1991), Jain and Wilcassim (1991) Fader and Hardie (1999) Schmittlein et al. (1987)
Segmentation models AID / CHAID Cluster Analysis Latent class analysis	Are brand-specific effects different for different segments? If so, what is the brand premium for different segments? How often should segmentation be done? What segmentation approaches are appropriate for dynamic segmentation (i.e., capturing the movement of a customer across phases of involvement with a firm)? Can an individual's actions be segmented differently in different contexts? What models are appropriate for such scenarios?	Srinivasan (1979), Brynjolfsson and Smith (2001) Ramaswamy et al. (1996), Wedel and Kamakura (1998)

5. Conclusion

The advent of e-commerce/e-business has generated new opportunities for personalization and customization. The widespread availability of Internet technologies, along with the steeply falling prices of computers, has changed the economics of personalization. With improved technologies in flexible manufacturing and in developing digital products, constraints in providing customized products have been mitigated in several areas. While neither concepts of personalization and customization are new, the shift towards e-tailing has made these phenomena of critical importance to firms in a large number of industries.

In this article, we highlight aspects of personalization and customization that we consider offer significant opportunities to researchers in the management sciences. We have approached research issues at two different levels. First, we look at the role of customization and personalization in a firms value system. The framework we use is a modification of the well-known Value Net framework. We examine the role of personalization in the interactions between a firm and other key players in the firms value system, survey extant research, and suggest

avenues that we consider are promising to management science researchers. Next, we focus on one of the key activities a firm must undertake to effectively provide personalization, namely learning customer preferences. We discuss existing approaches to customer modeling and suggest how these and newer models could be used for personalization applications.

Our focus has been primarily on online environments. However, future developments in wearable computers could reduce the distinction in online and face-to-face interactions. There are three important differences in interactions across these two environments. They are the ability for nearly instantaneous *customer identification* (e.g., through IP address or a cookie), greater ability to *capture more information* about the customer (e.g., through a Web log), and greater ability to *recall more information* about a customer once identified (through real-time database access). An intriguing possibility in the not too distant future is the use of cyborg-like outfits that a sales person could use in a traditional brick-and-mortar store ⁴. Such an outfit could enable the salesperson to overcome the three main differences between online and face-to-face interactions. If socially acceptable, a radio-frequency ID tag embedded in the discount card that many stores issue could enable registered-customer identification as soon as they pass through the door, and non-invasive biometric technology might identify some of the rest. Wireless connectivity to profiling databases could help the sales person in making recommendations based on prior interactions with the customer, and voice recognition systems could capture the new interaction for future use. We should mention here that while this scenario is appealing, several issues in human-computer interactions would need to be resolved before these devices could be successfully deployed.

While we have attempted to provide a reasonably comprehensive survey of the issues involved and extant research, we make no claims that the survey is exhaustive. Our hope is to increase awareness of the importance of personalization in a firms' strategic and operational considerations, and to illustrate some of the important problems and opportunities for researchers in that context. There do exist several challenges to execute high quality research in these areas. Given the interdisciplinary nature of these issues, researchers must be able to view problems from the different perspectives and be able to bring to bear tools and techniques from the different disciplines in order to make significant contributions. The difficulty in doing this well is

⁴ We thank Arthur Geoffrion, one of the guest editors of this special issue, for suggesting the cyborg scenario in this context.

further compounded by the pace at which technology changes are coming about, that lead to newer and more innovative ways in which firms can personalize products and services.

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