“Listening In” to Find Unmet Customer Needs and Solutions

Paper 156

Glen L. Urban
John R. Hauser

July 2002

For more information,
please visit our website at http://ebusiness.mit.edu
or contact the Center directly at ebusiness@mit.edu or 617-253-7054
“Listening In” to Find Unmet Customer Needs and Solutions

Glen L. Urban

and

John R. Hauser

July 1, 2002

Glen L. Urban is the David Austin Professor of Marketing, Sloan School of Management, Massachusetts Institute of Technology, E56-305, 38 Memorial Drive, Cambridge, MA 02142, (617) 258-0679, fax (617) 253-7597, glurban@mit.edu.

John R. Hauser is the Kirin Professor of Marketing, Sloan School of Management, Massachusetts Institute of Technology, E56-314, 38 Memorial Drive, Cambridge, MA 02142, (617) 253-2929, fax (617) 253-7597, jhauser@mit.edu.

This research was supported by the Sloan School of Management, the eBusiness Center, the Center for Innovation in Product Development at M.I.T., and the General Motors Corporation. We gratefully acknowledge the contributions of our industrial collaborators, research assistants, and faculty colleagues: Vince Barabba, Iakov Bart, Ahmed Benabadji, Rupa Bhagwat, Brian Bower, Brian Chan, Hann-Ching Chao, Mitul Chatterjee, Shyn-Ren Chen, Thomas Cheng, Stanley Cheung, Frank Days, Benson Fu, Salman Khan, Christopher Mann, Joseph Kim, Ken Lynch, Bill Qualls, James Ryan, Bilal Shirazi, Jonathon Shoemaker, Fareena Sultan, Andy Tian, Xingheng Wang, and Irene Wilson. This paper has benefited from presentations at the Marketing Science Conferences in Wiesbaden Germany and in Edmonton, the MIT Marketing Workshop, the New England Marketing Conference, and the Stanford Marketing Workshop. An Adobe Acrobat version of this paper is available at mitsloan.mit.edu/vc.
“Listening In” to Find Unmet Customer Needs and Solutions

Abstract

We explore a practical methodology to identify new high-potential “fishing grounds” for product development by “listening in” to ongoing dialogues between customers and web-based virtual advisors. Customers naturally seek out these virtual advisors to aid their purchasing decisions, hence customers have the incentive to express their true needs to these advisors. We study a representative virtual advisor that uses Bayesian updating methods to select maximum probability recommendations for customers. This virtual advisor selects its questions efficiently through a two-step look ahead that maximizes the information potential of each question.

We show that, for this virtual advisor, the maximum (forecast) probabilities of choice are indicators of underlying utility. Drops in underlying utility indicate that no existing product fulfills the conflicting needs that led to the drop. By defining a trigger mechanism and examining correlations among expressed customer desires, we identify the conflicting needs that remain unmet by the current marketplace. Once unmet needs are identified, an automated virtual engineer probes the antecedents of the unmet needs to gather information that is relevant to the product-development team. To explore the unmet needs further, a design palette enables the customer to express his or her own solutions.

We examine the internal validity of the listening-in methodology with Monte Carlo simulation and demonstrate that the methodology can recover known unmet-need segments. We then apply the automated system by listening in to a “Truck Town” virtual advisor. This application, with over 1,000 web-based customers, identified at least two new opportunities for pickup-truck platforms. Together these opportunities represent significant incremental revenues for the truck manufacturer.
Unmet Customer Needs Represent New Opportunities

The successful marketing of a product or service begins with the design of a competitive offering that meets or exceeds customer needs. Within the field of marketing many important methods have proven valuable to identify customer needs including: voice of the customer methods, conjoint analysis to identify important product features, perceptual mapping to position products strategically, pretest and prelaunch analyses to identify winning products prior to market introduction, and tracking analyses to optimize launch (cf. Crawford 1991; Dolan 1993; Green and Srinivasan 1990; Griffin and Hauser 1993; Lehmann and Winer 1994; Narasimhan and Sen 1983; Shocker and Srinivasan 1979; Urban and Hauser 1993; Wind 1982). We continue in this tradition, but focus on the fuzzy front end of the product development funnel where, arguably, the greatest leverage exists for identifying breakthrough product (or service) concepts which have the potential for significant revenue growth.

Specifically, we seek to uncover, understand, and evaluate the opportunities for new products that address previously unarticulated and unidentified customer needs. First, we identify new “fishing grounds” for product development by listening in to web-based dialogues between customers and virtual advisors. We then use a virtual engineer to probe these (previously) unarticulated customer needs so that the product-development team can better understand the nature of the needs and gather the information that is critical for design decisions. Finally, we use design palettes with which the customer attempts to self-design a virtual product to fulfill these needs.

Our methods complement, not replace existing methods. “Listening in” represents a natural source of new information that is there for the taking (since the dialogues occur as the customer searches for product information on the web). “Listening in” rounds out more formal voice-of-the-customer methods. While initial clustering of customers based on the identified needs provides a rough sizing of the product-development opportunities, we expect these unmet-need segments to become seeds for further analysis by product-development teams, not final forecasts. Indeed, the information obtained by listening in provides a natural input to qualitative ideation methods and to quantitative methods such as conjoint analysis (Altschuler 1996; De Bono 1995; Green and Srinivasan 1990; Goldenberg, Mazursky, and Solomon 1999; Kolpasky 2002; Prince 1970).
We begin by defining the problem relative to the product-development funnel. We then describe a representative virtual advisor that uses Bayesian methods to focus quickly on key customer needs. Next we identify a trigger mechanism which senses unmet needs and invites the virtual engineer to join the dialogue. Finally, we discuss the design palette and the initial clustering used to size the identified opportunity. After introducing the listening-in method we use Monte Carlo simulation to assess its internal validity and we illustrate application in the context of the “Truck Town” advisory system.

**Finding New Opportunities is Important to Product Development**

Figure 1a is a stylized view of the typical product-development funnel used in the automotive industry. Such funnels, also know as phase-review, stage-gate, or waterfall processes, recognize that product development begins with a focus on opportunities and then proceeds to detailed design and engineering, testing, and launch. In Figure 1, the ovals represent product concepts that are refined as they move through the process. The horizontal dotted lines represent alternative platforms that are under development simultaneously. Each platform represents a sizable investment. For example, a typical platform, say light pickup trucks, requires approximately one billion dollars investment of which about half is new capital (tools and assembly) and about half is expendable materials (hand-built prototypes) and engineering time – approximately 1,200 person-years of effort.\(^1\) Typically, platforms are targeted based on extensive segmentation studies involving thousands of customer interviews and sophisticated preference modeling and statistical clustering. The engineering team is well-supported with focus groups, voice-of-the-customer analyses, and other market research methods (e.g., Barabba and Zaltman 1991; Griffin and Hauser 1993; Zaltman 1997). Once designed new products are tested with formal prelaunch analyses (e.g., Urban, Hauser, and Roberts 1990; Urban, Weinberg, and Hauser 1996). The process has evolved over many years of continuous improvement and is, on average, quite effective.

\(^1\) Private communications with automotive executives at various manufacturers.
Identifying a platform opportunity begins the funnel process as shown on the left-most side of Figure 1a. Moreover, experience suggests that a new opportunity that “scoops” the market can lead to significant share growth and profit. These opportunities come in many flavors as illustrated with Figure 2. For example consider the automotive industry, in the mid-1960s Ford identified the trend of teenagers and young adults to customize inexpensive vintage Fords with V8 engines. To meet this opportunity they launched the 1964½ Mustang, which captured the hearts of a new generation of baby boomers just reaching driving age. This small, inexpensive sports car with a powerful V8 engine sold 420,000 units in the first year and went on to launch the lucrative “pony” segment (classicponycars.com/history.html). In 1983 Chrysler introduced the Dodge Caravan and Plymouth Voyager minivans – downsized vans for now-growing families, built on a car-like K platform with comfort features such as power windows, locks, seats, and quality sound systems. This new vehicle could carry a 4’x 8’ sheet of plywood but, unlike existing vans, could fit easily in customers’ garages, had a side door for small children, and had a sedan-like liftgate for shopping. Minivans fulfilled these needs by exploiting front-wheel drive to avoid high floors and to avoid an engine that tunnelled into the cabin. Chrysler sold 210,000 units in the first year and dominated this new segment for years to come (allpar.com/model/m/history.html). A final historical example of an automotive opportunity is the 1990 Miata. This sports car was built to tap the traditional British sports-car market (e.g., TR-3, MG). The car was designed with sports-car handling and a sports-car look. Even the acoustics of the muffler were engineered to match the original British sound. It sold over 30,000 units in 1990 and over 200,000 units before it was restyled in 1999. The Miata tapped a need segment for low-priced, open-bodied sports car and opened up the small sports-car segment of the 1990’s and 2000’s. Examples of such platform “stars” in other industries include the original IBM PC, Mariott’s
Courtyard Hotel (suites hotel), bicycles for off-road use, and Fidelity’s direct-to-consumer money-market funds with check-writing privileges.

Figure 2
Examples of Significant New Automotive Platform Opportunities

(a) 1964½ Ford Mustang     (b) 1983 Dodge Caravan

The listening-in methodology is designed to find opportunities for new platforms. We illustrate this goal in Figure 1b where the “stars” represent significant, but not yet fully defined, new vehicle ideas that might evolve into a new platform. We hope to find these stars by tapping a newly available, yet relatively untapped source of ideas – web-based searches. We expect that these opportunities will have a high probability of passing through the process of design-to-testing-to-launch because they reflect important basic needs that are not fulfilled by existing platforms.

The advent of internet has given customers more information about products in diverse industries such as travel, health, autos, computers, home entertainment, and financial services. Consider the automotive industry where buying services such as Kelley Blue Book (kbb.com), Microsoft’s CarPoint (carpoint.com), Edmund’s (edmunds.com), and Auto-by-tel (autobytel.com) have changed the way that customers search for information on cars and trucks. For example, 62% of all new-vehicle buyers search on-line before buying a vehicle (J. D. Powers 2001). This search rate has increased from 54% in 2000 and 40% in 1999. According to J. D. Powers, “the average automotive Internet user visits 6.8 automotive sites before purchase – 80% visit at least one independent site and 71% visit at least one manufacturer Web site.” The most-important and most-accessed Internet content was information about vehicle options and features. Interestingly, while customers prefer independent sites for pricing and general evaluation, they prefer manufacturers’ sites, by more than a two-to-one margin, for feature and option in-

Because web-based searches are now prevalent (and growing) and because they are incentive compatible – the customer is honestly seeking information relevant to his or her purchasing decision, such searches are a natural source of information. However, because the information flow is so extensive, we need a system to systematically filter this information in order to identify the potential platform stars in Figure 1b.

We illustrate the listening-in methodology with a representative virtual trusted advisor. Such trusted advisors are relevant to a wide range of customer purchases (Urban, Sultan and Qualls 2000). Some virtual advisors are independent (e.g., Kelley Blue Book, AOL’s Personalogic.com, ActiveBuyersGuide.com, and CFI) and some are manufacturer sponsored (e.g., General Motors’ Autochoiceadvisor.com and Michelin-Uniroyal-BFGoodrich’s tireadvisor.com). The goal of each virtual advisor is provide unbiased information on vehicle features and options and to help customers find the vehicle or option that is right for them. If the website is successful in building trust, then customers articulate feature and option needs accurately. New platform opportunities are indicated by those feature and option tradeoffs desired by customers for which no existing or planned vehicles exist. If the number of customers articulating such opportunities is large, such new platform ideas can turn into a major new vehicle category.

A number of analytic approaches are available to form recommendations including attribute matching, selection based on self-explicated importances of features, and full- and partial-profile conjoint analysis. While the listening-in methodology can be adapted to most virtual advisors, we focus, for illustration, on a virtual advisor developed in cooperation with a major automotive manufacturer. This advisor-based system is called “Truck Town.”

Listening In to a Virtual Advisor

Truck Town combines two methods to recommend a set of four vehicles to customers – a segmentation “gearbox” and a Bayesian advisor. The segmentation gearbox divides people into segments based on grouping and assignment rules. In this case the grouping is based on a cluster analysis of a 76-item questionnaire sent to 100,000 respondents. The original study by the

---

2 The colorful industry term, gearbox, is an analogy. Just as the gearbox in a car matches engine speed to wheel speed, the segmentation questions match the manufacturer’s vehicles to the customer.
automotive manufacturer identified forty-six segments of which twenty-five were relevant to pickup trucks and used in Truck Town. Customers were assigned to segments based on answers to the virtual advisor’s questions – answers about the customer’s desire for features and options such as comfort, passenger capacity, and prestige as well as about the customer’s anticipated use of the truck. The answers to these questions assign respondents to a group of similar people. In Truck Town one of the four recommended vehicles is the vehicle bought most often by the segment to which the customer is assigned. Like collaborative filtering, the segmentation gearbox provides reasonable recommendations based on the preferences of similar customers. It is based on extant marketing research methods, but it does not identify new opportunities. Thus, to identify new opportunities, we focus on the Bayesian advisor which Truck Town uses to identify three of the four vehicles.

**Bayesian Advisor**

The basic concept behind the Bayesian advisor is (1) to select sets of questions, known as question banks, such that the answers provide the most information about which vehicle to recommend and (2) after each question bank to update the probabilities that describe the likelihoods that each vehicle will be most preferred by the customer. Figure 3a illustrates the opening screen of the Truck Town advisor (a neighbor who has bought many trucks over the years) and Figure 3b illustrates one of the question banks asked of customers. We describe first the Bayesian updating mechanism and then describe how this mechanism can be used to select the maximum-information question. We later indicate how the conditional probabilities and first-question prior probabilities are obtained. We begin with the notation.

Let Q be a set of question banks indexed from $q = 1$ to $N$. For each question, $q$, let $r_q$ index the potential responses to that question bank where $r_q$ is a nominal variable with values from 1 to $n_q$. If there is more than one question in a question bank, then $n_q$ represents the number of possible combinations of answers. If one of the questions includes a continuous sliding scale, it is discretized to a finite number of categories.
For each customer the order of the questions is chosen adaptively. For a given customer, let $R_q$ be the set of questions up to, but not including, question $q$. Let $v_j$ indicate vehicles from 1 to $V$. We are interested, at any point in the advisor’s questioning sequence, in the likelihood that the customer will prefer vehicle $j$ after having been asked question $q$. We indicate this likelihood by $P(v_j | R_q, r_q)$.

Suppose that we have available the conditional probabilities of how customers who prefer vehicle $v_j$ will answer the $q^{th}$ question bank. Then, to the extent that this conditional probability, $P(r_q | v_j)$, approximates $P(r_q | v_j, R_q)$, we can use Bayes Theorem to update recommendations.  

$$P(v_j | R_q, r_q) = \frac{P(r_q | v_j, R_q) P(v_j | R_q)}{\sum_{j=1}^{V} P(r_q | v_j, R_q) P(v_j | R_q)} \approx \frac{P(r_q | v_j) P(v_j | R_q)}{\sum_{j=1}^{V} P(r_q | v_j) P(v_j | R_q)}$$  

where $P(v_j | R_q)$ was the virtual advisor’s recommendation probability to the customer for vehicle $v_j$ prior to asking the $q^{th}$ question bank. $P(v_j | R_q)$ is obtained by the recursive use of Equation 1. Figure 4 gives on example for one customer of the evolution of the recommendation probability. The current recommendation is given on the left and the probability that the customer will purchase that recommended vehicle is given on the right. Also listed on the left are the question and the answer. For example, after the second question on engine size, the customer answers “4 cylinders.” If the customer were to stop answering questions and request a recommendation, the

\[^{3}\text{In all equations, we suppress the individual customer subscript, } i, \text{ for simplicity.}\]
advisor would recommend the Mazda B2300 and forecast a 0.0735 probability that the customer would purchase the Mazda B2300. In Figure 4 the probability of purchase increases for the most preferred truck after each question is answered. Note that the recommended vehicle changes after the fifth question bank and again after the eighth question bank.

Figure 4
Evolution of Updated Recommendation Probabilities After Question Banks

<table>
<thead>
<tr>
<th>Recommendation/Question</th>
<th>Maximum Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mazda B2300, Prior (Points *)</td>
<td>0.0533</td>
</tr>
<tr>
<td>Mazda B2300, Engine Size (4 cyl)</td>
<td>0.0735</td>
</tr>
<tr>
<td>Mazda B2300, Transmission (Auto, 2WD)</td>
<td>0.0861</td>
</tr>
<tr>
<td>Mazda B2300, Size (Compact)</td>
<td>0.1105</td>
</tr>
<tr>
<td>Mazda B2300, Towing/Hauling (no)</td>
<td>0.1123</td>
</tr>
<tr>
<td>Toyota Tacoma, Construction Plowing (no)</td>
<td>0.1200</td>
</tr>
<tr>
<td>Toyota Tacoma, Brand (All)</td>
<td>0.1243</td>
</tr>
<tr>
<td>Toyota Tacoma, Bed Length (Short)</td>
<td>0.1328</td>
</tr>
<tr>
<td>GMC Sierra 1500, Tallest Person (6'-6.5')</td>
<td>0.1376</td>
</tr>
<tr>
<td>GMC Sierra 1500, Passengers (2)</td>
<td>0.1376</td>
</tr>
<tr>
<td>GMC Sierra 1500, Maneuverability (Important)</td>
<td>0.1400</td>
</tr>
<tr>
<td>GMC Sierra 1500, Big, Quiet (Not Important)</td>
<td>0.1400</td>
</tr>
<tr>
<td>GMC Sierra 1500, Styling (Sporty)</td>
<td>0.1458</td>
</tr>
<tr>
<td>GMC Sierra 1500, Price (20-22K)</td>
<td>0.1467</td>
</tr>
</tbody>
</table>

Question Selection

To select the next question bank the virtual advisor attempts to gain as much information as possible from the customer. For example, if, after reviewing the responses, the advisor decides that a question bank on towing capacity is likely to make one truck more highly probable and all other trucks less probable, then that question bank might be a good candidate to ask next. To do this formally, we turn to formal theory in which information is defined as the logarithm of the relative odds (e.g., Gallagher 1968). That is, the information, $I(v_j | r_q, R_q)$, provided by the response to question bank $q$, equals $\log \left[ P(v_j | R_q, r_q) / P(v_j | R_q) \right]$. This definition has a number of nice theoretical properties including that (1) under an equal proportional loss rule, information always increases when the probability of the maximum-choice truck increases, (2) the expected
information is maximized for the true probabilities, and (3) the information measure rewards systems that provide more finely-grained estimates.

In order to compute the expected information, we need to take the expectation over all possible responses to question bank $q$ and over all possible vehicles. Thus, the information that we expect from question bank $q$ is given by Equation 2.\(^4\)

$$
EI(q|R_q) = \sum_{j=1}^{V} P(v_j | R_q) \sum_{r_q=1}^{n_q} P(r_q | v_j, R_q) \log \frac{P(v_j | r_q, R_q)}{P(v_j | R_q)}
$$

In a myopic world, the virtual advisor simply chooses the question bank for which Equation 2 is maximized.

We can improve upon Equation 2 with an $m$-step look ahead. To date, the computational demands of Equations 1 and 2, coupled with the potentially large number of responses for each question bank has limited the Truck Town look-ahead algorithm to two steps. Basically, for each potential question bank and response on Step 1, the advisor computes the best second question and the expected information for that question. It then selects the Step-1 question with the highest contingent expected information.

**Initial Calibration**

Two estimates are necessary for the virtual advisor to begin: conditional response probabilities, $P(r_q | v_j)$, and prior probabilities, $P(v_j)$. The conditional response probabilities are based on a combination of prior surveys and judgments including those by experienced managers and engineers and the cooperating automotive manufacturer. The virtual advisor obtains the prior probabilities for each individual from a logit model based on five truck characteristics: price, fuel economy, performance, reliability, and safety. Each customer is asked initial constant-sum, self-explicated importance weights for these characteristics. (In Figure 4 these prior weights or points are obtained in the first question.) The prior probabilities are estimated with Equation 3 where the $w_c$ is the importance for the $c^{th}$ characteristic for each individual obtained from a constant-sum allocation of 100 importance points across the five scales, $x_{jc}$ is the value of characteristic $c$ for vehicle $v_j$, and $\beta$ is a scaling parameter.

\(^4\) As in Equation 1, we assume that $P(r_q | v_j, R_q) \approx P(r_q | v_j)$. This applies through the remainder of the paper.
The characteristic values for each existing vehicle and the scaling parameters are obtained from archival data and judgments by managers and engineers.

**Trigger Mechanism to Identify New Opportunities**

Equation 2 enables the virtual advisor to select a question order that leads to the most rapid convergence toward recommendations. For many customers an existing vehicle will fulfill their needs and the updated recommendation probabilities will evolve smoothly as in Figure 4. However, for some customers, new questions could reveal inconsistencies. For example, suppose that (1) the customer has already answered constant-sum importance questions that indicate reliability and low price are most important (price 30 points, performance 10 points, fuel economy 20 points, reliability 30 points, and safety 10 points) and (2) his or her subsequent answers suggest interest in a small truck with a 4-cylinder engine, two-wheel drive, and automatic transmission. The Mazda B2300 fits these preferences best (see Figure 5 – Questions 1 to 4). Given these answers the virtual advisor decides to ask next about towing and hauling. Suppose the customer says that he or she plans to use the truck to haul heavy materials and tow a motor boat (weighing 6,500 pounds). No existing truck can fill all the requirements expressed in Questions 1-5. This may be an opportunity worth investigating.

The intuition in this example is that the new question bank revealed something about the customer’s underlying needs. Based on this new information the customer is probably not going to be satisfied with existing trucks and the virtual advisor will have to revise its best-truck recommendation probability downward. This drop in the maximum recommendation probability becomes a trigger mechanism for further investigation. We illustrate the trigger mechanism by an arrow in the dialogue in Figure 5. Question 5, towing and hauling, causes the most preferred vehicle to change from the Mazda to a Ford Ranger (a slightly larger and more-powerful compact truck). The utility drops because this more powerful compact truck cannot fully meet the towing requirements and because it cannot meet the requirements expressed in Questions 1-4. (It has a 6-cylinder engine and is more expensive.) A full-sized truck, such as the Chevrolet Silverado 1500, could fulfill the towing requirements, but the advisor does not recommend the Silver-
ado because it does poorly on the other desired features. After further questions the recommendation probabilities in Figure 5 increase because the Ford Ranger fulfills the additional requirements.

A Formal Derivation of the Trigger Mechanism

To put this concept in perspective we pause to derive the trigger mechanism from more fundamental properties. Suppose that there are two vectors of truck characteristics, $\bar{x}_j$ and $\bar{y}_j$.

The utility of the first set of characteristics can be measured directly such as in the exponents of Equation 3. The utility of the second set of characteristics is revealed through the answers to the virtual advisor’s questions. If $\bar{x}_j$ and $\bar{y}_j$ are modeled as a utility tree, then we can write the joint utility as a separable function (Blackorby, Primont and Russell 1975), $u(\bar{x}_j, \bar{y}_j) = u_x(\bar{x}_j) + u_y(\bar{y}_j) + \varepsilon$, where $\varepsilon$ is a Gumbel-distributed error term that represents the uncertainty in utility.

---

5 Following the modeling traditions in marketing we subsume price into the utility function by assuming the customer maximizes utility subject to a budget constraint and by representing price as being weighted by its Lagrange multiplier. Indeed, this is explicit in Equation 3. See also Srinivasan (1982) and Hauser and Urban (1986).
due to question banks that have not yet been asked (or may never be asked). Now when the customer answers that he or she wants to tow and haul, this answer reveals information about the customer’s utilities. For example, we might expect that the utilities for compact trucks to decrease and the utilities for full-sized trucks to increase. Let $V'$ be the set of all trucks for which $u_i(\bar{y}_j)$ increases and let $V$ be the set of all trucks for which $u_i(\bar{y}_j)$ decreases. Then the updated recommendation probability for the maximally preferred truck, written in utility terms, is given by Equation 4. Here $m$ indexes the truck that the advisor would have recommended prior to the $q^{th}$ question bank.

$$P(v_j | r_q, R_q) = \frac{\sum_{j=1}^{V'} e^{u_i(\bar{y}_j) + u_i(\bar{y}_j)} + \sum_{j \in V', j \neq m} e^{u_i(\bar{y}_j) + u_i(\bar{y}_j)} + \sum_{j \in V, j \neq m} e^{u_i(\bar{y}_j) + u_i(\bar{y}_j)}}{\sum_{j=1}^{V'} e^{u_i(\bar{y}_j) + u_i(\bar{y}_j)} + \sum_{j \in V', j \neq m} e^{u_i(\bar{y}_j) + u_i(\bar{y}_j)} + \sum_{j \in V, j \neq m} e^{u_i(\bar{y}_j) + u_i(\bar{y}_j)}}$$

Straightforward calculus demonstrates that if the recommended truck is in $V'$, then the recommendation probability increases and if the recommended truck is in $V$, then the recommendation probability decreases. In summary, and in non-technical terms, this derivation demonstrates that the virtual advisor can identify changes in the underlying utilities by monitoring the updated probability of the recommended truck. If this probability drops, then the question bank has revealed that the customer’s preferences for underlying truck characteristics, measured implicitly by the question bank, are in conflict with the customer’s preferences for the existing trucks identified by all prior question banks. These conflicts are the opportunities that may lead to the new platform stars in Figure 1b.

**Identifying Potential Root Causes of the Utility Drops**

When the trigger mechanism identifies a potential conflict, we need further information to determine whether or not it is a true opportunity. We first identify which truck characteristics are in conflict and then gather clarifying information from the customer. For example in Figure 5 the customer’s (forecast) utility drops after the fourth question (towing/hauling) is answered.

Conflicts happen when no existing truck simultaneously satisfies all of the customer’s needs. To diagnose such conflicts it is tempting to rely on “product archeology” to examine the correlations among the characteristics of trucks that are now on the market (Ulrich and Pearson 1998). However, such “ecological” correlations represent more than customer preferences; they

---

6 Technically, the derivation needs to consider also the case where the identity of the recommended truck changes based on answers to the $q^{th}$ question bank. However, this does not change the basic intuition.
represent the efficient frontier of the equilibrium responses by competing truck manufacturers. Instead, we must examine correlations in the underlying customer preferences that drive the responses to the virtual advisor’s question bank. We obtain indicators of these correlations from the virtual-advisor dialogue.

Let $\rho_{r_q \, r_p}$ be the correlation across vehicles of the conditional probabilities of answering $r_q$ to question bank $q$ and answering $r_p$ to question bank $p$. Let $P$ be the matrix of these correlations. For example, an element in this matrix might be the correlation across vehicles of the probabilities of a customer indicating that he or she (1) will use the truck for trailering heavy loads and (2) prefers a rugged body style for that vehicle. Based on existing truck segments we expect these example characteristics to be positively correlated. On the other hand, a priori, we expect a customer’s need to pull a trailer to be negatively correlated with a preference for a small truck. That is, we do not expect that customers who prefer small trucks will also value hauling and towing. (If the example motivating the drop in utility in Equation 4 occurs often in the data, we may want to re-examine this a priori belief.) Thus, whenever the trigger mechanism suggests a potential opportunity, the listening-in algorithm examines all correlations corresponding to the customer’s answers to the first $q$ question banks ($R_q \cup r_q$). It flags those which are highly negative (less than $-0.30$ in Truck Town). Such negative correlations trigger the virtual engineer.

**A Virtual Engineer Clarifies the Opportunity**

Once triggered, the virtual engineer (VE) explores the opportunity further. The concept of a VE is simple; its implementation difficult. To be useful to the product-development team, the VE must ask the customer those questions that inform the engineering design decisions that would be necessary should a star platform opportunity be identified. To be credible to the customer, the VE must ask questions in a non-technical manner that relates to how the customer uses the truck. Naturally, the VE evolves through application, but we describe here the process by which the initial VE questions are created.

For each potential conflict (negative $\rho_{r_q \, r_p}$), an engineering design team from a major auto manufacturer considered the basic engineering problem imposed by the conflicting needs. The team then generated the questions that would need to have answered to enable it to decide among basic solutions to that conflict. The engineers formulated the questions that they would ask the customer if they were participating in the dialogue between the advisor and customer. For ex-
ample, if the customer wants a small truck that can tow a boat, then the engineering team would ask about the type of boat (e.g., small sailboat, large motor boat, or jet ski) and the weight of the boat that the customer plans to tow. The engineering team would also ask the customer why he or she wants a small truck (e.g., low price, tight parking, high maneuverability, fuel economy, etc.). All engineering questions are then rephrased into customer language.

In addition to the questions identified by the engineering team, the VE includes open-ended dialogues which enable the customer to elaborate further the reasons underlying the previously-unidentified need. Figure 6 illustrates a sample dialogue in which the VE introduces himself, asks about a conflict, gathers quantitative data, and asks for open-ended comments. In this example, the unmet-need conflict is between a compact truck and the need to tow a large load.

**Figure 6**
Virtual Engineer

(a) Introductory Screen  
(b) Example Dialogue  
(c) Specific Questions to Elaborate  
(d) Open-ended Questions
A Design Palette Solicits Customer Solutions to Potential Conflicts

If the unmet customer need is truly a new star platform opportunity, then it is important to explore that opportunity from multiple perspectives. One perspective is the customer’s own solutions – customers have proven to be sources of new solutions in many categories including software, windsurfing, and mechanical fasteners (von Hippel 1986; 1988; 2001a). Even for trucks, new ideas often come from user innovations at construction sites, trailering, camping, and racing (NASCAR’s Craftsman Truck Series). Furthermore, such user solutions can be accelerated with innovation “tool-kits” which enable customers to mix and match features (Franke and von Hippel 2002; von Hippel 2001b). Such tool-kits are not unlike the mass-customization configurators used by Dell.com and Timbuk2.com in which customers pick and choose the features they want as they order their computer or luggage products. Such toolkits, known as user-design methods, have been used successfully in market research for instant cameras, laptop computer bags, crossover vehicles, ski resorts, high-speed copiers, and Internet Yellow Pages (Dahan and Hauser 2002; Leichty, Ramaswamy and Cohen 2001).

We illustrate one such “design palette” in Figure 7. Here the customer (a) receives instructions, (b) changes the size of the truck, and (c) changes the color. For brevity, we have not shown the many intermediate steps, some of which include new state-of-the-art truck features such as four-wheel steering and extra-wide frames. However, changes do not come free. There are sophisticated engineering/cost models underlying the design palette. For example, if the customer changes the size of the truck, then the cost, fuel economy, and towingpayload capacity change accordingly. Once the customer completes the redesign he or she is given the opportunity to indicate whether, and by how much, he or she prefers the new design. (The customer may not prefer the new design because of accumulated “sticker shock” or because of an holistic judgment of the final truck.) Nonetheless, in the empirical application described later in this paper, 73% of the respondents who completed the exercise indicated that they would purchase their custom-designed truck were it available.7

7 Due to self-preference learning, memory accessibility, and context effects the preference for the self-designed truck might be inflated (Bickart 1993; Feldman and Lynch 1988; Nowlis and Simonson 1997; Simmons, Bickart and Lynch 1993; Tourangeau, Rips and Rasinski 2000). However, this does not diminish the value of the design palette as a means to identify opportunities that will be explored in more depth as the product-development team cycles through an iterative process.
The virtual engineer and the design palette are triggered automatically whenever a probability drop is detected that is larger than a preset threshold. The virtual engineer is triggered for at most six of the flagged conflict pairs to keep the respondent’s task relatively short.\(^8\) (This means no more than six input screens, such as Figure 6c, are presented to the customer).

While “listening in” can, in theory, identify all unmet-need combinations, not all such combinations will justify further investigation. To make the decision on further investigation, a truck manufacturer requires an initial estimate of the size of the opportunity. This estimate of potential can be a rough indicator because “listening in” is just part of the fuzzy front end of an it-

---

\(^8\) The trigger level is set judgmentally. If it is set to be very sensitive, the virtual advisor is triggered on measurement error. But, if it is set too conservatively, platform opportunities will be missed.
erative product development process. The manufacturer will evaluate any opportunities further before any sizable investment. Fortunately, the listening-in methodology provides a method for initial sizing that appears to be sufficient to distinguish the few big winners.

Subject to the caveats of self-selected customers and the approximations in Equations 1-4, we can identify patterns of unmet needs within the population. Each customer answers a custom-designed set of questions. These questions and the corresponding answers identify the customer’s needs. Let $A_i$ represent customer $i$’s answers. Then $A_i$ corresponds to a subset, $P_i$, of the correlation matrix, $P$. We then cluster respondents on $P_i$ to identify groups of customers with similar needs. If the size of the similar-unmet-need cluster is large, as a fraction of the initial sample, then this unmet-need segment is likely to be worth further investigation.⁹

Suppose we have identified an unmet-need segment. We then “design” a truck for that segment by defining a truck concept by the needs it fulfills. To estimate market share for the truck concept we include it in the set of existing trucks available to the virtual advisor. By using the Bayesian model in Equation 1, we calculate revised posterior probabilities for all trucks, including the new truck concept. Averaging the revised posterior probabilities over all respondents provides a rough estimate of market share for the concept.

In the US truck market, a single share point in the truck market is worth $800 million in annual revenues. In our application, the cooperating manufacturer considers any segment above a few percent of the initial population to be worth further investigation as a new platform star. Even a one- or two-percent segment is worth further investigation if the needs of the unmet-need segment can be fulfilled with a minor redesign (typical cost of $300 million).

Monte Carlo Simulations to Test the Internal Validity of the Listening-In Methodology

In order to test the internal validity of the listening-in methodology we generated nine customer segments of 500 respondents each – a total of 4,500 simulated respondents. For six of the generated customer segments, existing trucks do not satisfy all the customers’ needs. If there were no error, customers in those segments would answer the virtual advisor’s questions accordingly and the listening-in methodology should correctly identify their unmet needs. For example in Segment 1 we define an answer profile consistent with customers who want a small truck that

---

⁹ “Listening in” is based on dialogues with virtual advisors. Because customers choose to initiate these dialogues, there is self-selection. However, given the large fraction of truck customers who search for information on the web and given the growth in virtual advisors, we expect the self-selection issues to diminish. At minimum, a large fraction of even the self-selected customers might still be a star opportunity.
tows. Customers in this segment would answer “yes” to “compact truck” and “yes” to the towing questions. If no existing truck meets both needs simultaneously, these answers would trigger a drop in the posterior probability and indicate unmet needs. In the simulation, we created segments to represent customers who want (1) small trucks that can haul and tow, (2) sporty full-sized trucks with short beds, (3) small trucks with diesel engines, (4) full-sized trucks with an extra-short bed and 4-cylinder engines, (5) small trucks with 10-cylinder engines, and (6) full-sized trucks with high maneuverability. For the other three segments, we created profiles where existing trucks do satisfy the customers’ needs (e.g., full-sized trucks that can haul or tow large loads).

For each respondent we generated consistent responses, $r_q$’s, to each question bank and consistent self-explicated importances, $w_c$’s for their segment profile. We then added errors to the customer’s responses. There are two classes of questions – questions with nominal categories and constant-sum self-explicated importance questions. Because the $r_q$’s are nominal variables we assume that 5% are answered incorrectly and that the incorrect answers are uniformly distributed among the remaining categories. For example if the respondent truly wants a compact truck we simulate the a 10-percent error by having 10 percent of the respondents answer that they want a large truck. In Segment 1 (small and tow), such errors would not trigger a utility drop because there would be existing vehicles consistent with their expressed needs (i.e., a large truck that can tow and haul large loads). Because the $w_c$’s are interval-scaled variables estimated by allocating 100 points across the five truck characteristics, we simulate response error in the these answers by adding a zero-mean, normally-distributed response error such that the standard deviation of the error equals a specified number of points ($e$). For simplicity we truncate negative self-explicated importances which, fortunately, occur with low probability. We then apply the listening-in equations to the simulated respondents.

Whenever a trigger point occurs we record the negative conditional-probability correlations, $\rho_{r_q r_p}$, for all unmet needs identified in the complete dialogue with that simulated respondent. If multiple trigger points are identified, unmet needs for all triggers are recorded. Thus, each simulated respondent, who experiences one or more utility drops, is represented by a vector
which has negative $\rho_{r,r'}$ values for any unmet need pair. Finally, we cluster the correlations to identify the unmet-need customer segments.$^{10}$

Table 1 reports the results for a range of errors in both the nominal answers and in the constant-sum answers. Specifically, we simulate errors of 0%, 10%, and 20% for the nominal answers and 0 points, 5 points, and 10 points for the constant-sum answers. The percentages in Table 1 represent the simulated respondents with true unmet needs that were correctly assigned to the appropriate segment.$^{11}$ As expected, the listening-in algorithm identifies the unmet needs perfectly when there are no response errors. Fortunately, the algorithm is still reasonably accurate for higher errors in both the self-explicated importances and the responses to the virtual advisor’s questions. For example, we obtain 83.2% recovery for a 10% error in the nominal responses and a 5-point error in the self-explicated importances. Even in the most severe condition, $E=20%$ and $e=10$ points, the recovery is as high as 71.1%. This level of recovery should be sufficient for the fuzzy front end of product development where the product-development team need only identify new fishing grounds. Final decisions on the potential platform development will be based on more extensive data collected later in the product-development process.

Thus, it appears that, at least in simulation, the triggering mechanism can uncover unmet needs in noisy data that represent some respondents who have unmet needs and other respondents who have their needs satisfied. As a final example of face validity, note that the effect of errors in the self-explicated importances is small relative to the effect of errors in the nominal responses. This is not surprising because the self-explicated importances determine prior probabilities that are updated based on the answers to all subsequent nominal answers. With enough questions, the effect of the prior probabilities diminishes.

---

$^{10}$ For this test we use a k-means non-tree clustering algorithm based on the Euclidean norm. We abstract $n$, $n+1$, and $n+2$ clusters and examine their size and interpret their profiles. If the $n$th cluster is small we abstract more clusters and continue until we do not find a large cluster. To be sure that no large unmet-need cluster is missed, we abstract additional clusters until the last two clusters are small and do not reflect interesting need patterns. This simulates the manner in which the listening-in methodology is applied to actual data.

$^{11}$ There are six unmet-need segments plus one needs-are-fulfilled segment. This last segment is effectively merged because no correlations are flagged (the trigger mechanism is not triggered) when all needs are met.
Table 1
Identification Rate for Unmet-Need Segments

<table>
<thead>
<tr>
<th>Response Errors (updating)</th>
<th>Errors in the Self-Explicated Importances (Priors)</th>
<th>e = 0 points</th>
<th>e = 5 points</th>
<th>e = 10 points</th>
</tr>
</thead>
<tbody>
<tr>
<td>E = 0%</td>
<td>100%</td>
<td>98.5%</td>
<td>99.2%</td>
<td></td>
</tr>
<tr>
<td>E = 10%</td>
<td>86.0%</td>
<td>83.2%</td>
<td>83.4%</td>
<td></td>
</tr>
<tr>
<td>E = 20%</td>
<td>79.4%</td>
<td>77.5%</td>
<td>71.1%</td>
<td></td>
</tr>
</tbody>
</table>

Application to Identify New Opportunities for Pickup Truck Platforms

The initial application of “listening in” occurred in August of 2001 when 1092 customers were recruited from the Harris Interactive Panel.\(^\text{12}\) The customers had purchased a pickup truck in the past four years (1997-2000) and were given a $20 incentive for this initial test. Pickup truck customers are a prime target for virtual advisors. For example, Scott Morton, Zettelmeier, and Silva-Risso (2001) report that the typical pickup buyer saves 2.9% of the purchase price with an on-line service compared to an average of 1.5% for all vehicles.

On average each customer spent 45 minutes with the virtual advisor, design palette, and virtual engineer (when triggered). Most customers found the experience worth their effort. Customers trusted the virtual advisor by an 8-to-1 margin over dealers and would be more likely to purchase a vehicle recommended by the virtual advisor by a 4-to-1 margin over a vehicle recommended by a dealer. For the design palette, 78% found it an enjoyable experience and 82% felt it was a serious exercise. When the virtual engineer was triggered, 88% found the questions easy to answer and 77% felt that the virtual engineer related well to their needs. Interestingly, 56% of the customers reported that they would pay for the advise provided by Truck Town if it were included in the price of the pickup truck that they purchased as a result of using Truck Town.

In this initial application we set the trigger mechanism to be very sensitive to any utility drop. Thus, some respondents, whose needs were already satisfied, answered the virtual engineer’s questions. This sensitivity does not affect the market-size estimates because the data for such respondents will not favor the newly-designed platforms.

\(^{12}\) This initial test was based on a stratified random sample of the panel. For this test, all customers were given the opportunity to use the design palette.
Of the 1092 customers in the virtual advisor dialogue, 90% responded in a manner that triggered the virtual engineer based on a triggering criteria of at least a 1.5 percent drop in utility from the previous value. Of those, the most common pairwise conflicts were a maneuverable full-sized truck (38%), a compact truck which could tow and haul heavy materials (14%), and a full-sized truck with a six-cylinder engine (7%). Clustering pairwise conflict profiles, \( P \), identified a segment of customers with unmet needs for large and maneuverable trucks. Of these respondents, ten percent wanted top-of-the-line truck and sixteen percent wanted a standard full-sized pickup. Another segment, thirteen percent of the respondents, had unmet needs for a compact truck that could tow and haul. Given the current engineering frontier, meeting these needs would raise the price of the truck, thus not every respondent in an unmet-need segment would purchase a new concept truck. We provide market share estimates below.

Table 2 provides a perspective on the reasons that respondents cited most when the virtual engineer sought further clarification of the full-sized-maneuverable-truck unmet-need conflict. This qualitative input suggests that respondents are using the full-sized truck for city driving. The large truck fulfills critical needs – they are willing to sacrifice maneuverability for large passenger capacity and large payloads.

<table>
<thead>
<tr>
<th>Why I need a maneuverable pickup truck.</th>
<th>Why I need a full-sized pickup truck.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequent city driving</td>
<td>Large passenger capacity.</td>
</tr>
<tr>
<td>66%</td>
<td>73%</td>
</tr>
<tr>
<td>Tight parking</td>
<td>Large payloads.</td>
</tr>
<tr>
<td>58%</td>
<td>50%</td>
</tr>
<tr>
<td>I make many U-turns</td>
<td>Full-sized style.</td>
</tr>
<tr>
<td>26%</td>
<td>39%</td>
</tr>
<tr>
<td>Too many traffic jams</td>
<td></td>
</tr>
<tr>
<td>28%</td>
<td></td>
</tr>
</tbody>
</table>

When the full-sized-maneuverable-truck segment of respondents were given the opportunity to redesign their most preferred pickup truck, the features that they changed most often were truck height (6’ to 7’), truck width (6’ to 7’), and steering (two-wheel steering to four-wheel steering). This suggests that they are looking for an even larger truck, but that they would be interested in four-wheel steering to gain maneuverability. Using the methods described earlier for market sizing we estimated the potential market share of a full-sized truck with four-wheel steering, for an additional manufacturer’s suggested retail price (MSRP) increase of $3,000. For this
truck concept, the listening-in equations estimate a market-share increase for the manufacturer of 3-4% (the exact value is coded for confidentiality).\textsuperscript{13} Such a $1.6-to-3.2 billion dollar per year opportunity is definitely worth further investigation. In addition, a compact truck with hauling and towing is estimated to be a $1 to 2 billion opportunity (values coded). Such conflicting customer needs could be fulfilled by a small truck platform with a strong frame, transmission, and engine.

Our initial application to pickup trucks illustrates that major new-product opportunities can be identified. After our study was complete we learned (previously unknown to us) that the automotive manufacturer was in the process of introducing four-wheel steering in order to improve maneuverability of its top-of-the-line pickup truck (the 2002 GMC Denali). This truck is selling well. We plan to monitor the sales of this truck and, perhaps a basic full-sized truck with four-wheel steering, to determine whether its sales are in the rough range predicted by the market-sizing equations.

**Summary, Discussion, and Future Research**

The fuzzy front end of product development has, perhaps, the highest leverage for the product-development process. It is in the fuzzy front end that new opportunities, new fishing grounds, are identified. Uncovering new unmet-need segments before competition can do so often provides a significant competitive advantage. This is true in many industries, but particularly true in the automotive industry.

In this paper we investigate a methodology in which a virtual engineer “listens in” to a customer’s Internet dialogue with a trusted, virtual advisor. The use of such advisors is growing as they become more effective, as the Internet itself gains further penetration, and as the value of such advisors becomes recognized by customers. The fraction of people using the Internet for information and advice is large (62% in autos, 70% in travel, and 56% in health) and advisors are becoming more common. “Listening in” provides a means to capture the information in these dialogues.

The listening-in methodology relies on formal quantal choice models for prior probabilities (logit models) and formal Bayesian updating based on the customers’ responses to the virtual

\textsuperscript{13} We obtain rough forecasts by adding a full-sized maneuverable pickup truck to the choice sets of the unmet-need-segment customers. We obtain $P(r_q | v_j)$ for the new vehicle by assuming a profile similar to an existing vehicle except for the critical responses on the size and maneuverability questions, which are changed to be consistent with the vehicle being both full-sized and maneuverable. The iterative use of Equation 1 provides the estimates.
advisor. Information theory assures that the advisor’s dialogue is efficient – an important consideration if we are to impose further burdens with the virtual engineer and the design palette. By monitoring and analyzing the click-stream dialogues, “listening in” identifies unmet needs by drops in the forecast choice probabilities for the recommended vehicle. Once unmet needs are identified, automated interventions (1) gather more detail on the unmet needs and (2) enable the customer to express his or her own solutions. Monte Carlo simulations suggest good internal validity and an initial application suggests the practical power of the methodology.

Like all methodologies, “listening in” will benefit from continuous improvement. The initial application builds on existing methods that are used in new ways. Each component can be improved – better methods to identify priors, more efficient look-ahead algorithms, improved calibration of the trigger mechanism, and better indicators of conflicting needs could all benefit from further research. The dialogues, the user interfaces, and the presentation of stimuli are all areas of potential improvement. For example, work is now underway to put more “stretch” into the design palette and to give the virtual advisors and the virtual engineers personalities based on “talking heads.”

Our initial focus was the automotive industry and pickup trucks. We feel that the methods and concepts are generalizable. They apply to any category in which a virtual advisor is available – the basic concepts go well beyond the specific trusted advisor in Truck Town. If the advisor produces utility estimates for the purchase options (e.g., with conjoint analysis or linear attribute weighting), the Bayesian trigger mechanism still applies. A virtual engineer can still be used to learn more about the unmet-need conflicts. In summary, the listening-in methodology is designed to be a complement, not a replacement, for the many effective marketing-research methodologies used throughout the product-development process.
References


