Integrating Gap Analysis

and Utility Theory

in Service Research

By Robert F. Bordley

MC482-D30-B24
General Motors Corporation
P. O. Box 100
Renaissance Center
Detroit, Michigan 48265-1000

(313)667-9162(Work)
(313)667-9598(Fax)
(248)619-9699(Home)

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Abstract

Conventional utility theory models customer preferences in terms of actual performance and does not use benchmarks. But empirical work in gap analysis shows that customer preferences clearly depend upon the disparity between performance and some benchmark.

To resolve this apparent discrepancy between theory and experiment, this paper shows that a simple reinterpretation of utility makes utility a function of the uncertainty-discounted gap between actual performance and a benchmark. We interpret the benchmark as reflecting customer product expectations.

The resulting formulation is used to derive a consumer choice model where customer choice depends upon how perceived performance compares to expectations and upon customer uncertainty about performance and expectations. In this model, increasing information on a product or service `tends' to increase its sales if its performance is above customer expectations and to decrease its sales if its performance is below customer expectations.

1. Utility Analysis and Gap Analysis

(1.1) Modeling Customer Demand using Gap Analysis

Since Oliver's early work(1980), it's become widely recognized that customer satisfaction depends upon the individual's prior expectations. As a result, both service quality and customer satisfaction are now defined relative to benchmarks. Thus Parasuram,Zeithaml and Berry(1985) write:

"Service quality as perceived by consumers stems from a comparison of what they feel service firms should offer (i.e., from their expectations) with their perception of the performance of firm providing the services. Perceived service quality is therefore viewed as the degree and direction of discrepancy between consumer's perceptions and expectations….In the service quality literature, expectations are viewed as desires and wants of consumers, i.e., what they feel a service provider should offer rather than would offer"(pg.16-17)

Their views are strongly supported by many other studies(Gronroos,1982; Sasser,1978; Parasuraman, Zeithaml and Berry,1988).

This work has led to gap analysis. Gap analysis defines service quality in terms of the gap between what the service should provide and the customer's perception of what the service actually provides(Boulding, Kalra, Staelin and Zeithaml,1993). It assumes the smaller the gap, the higher the quality of service.

This notion of gap also describes customer satisfaction. As Tse and Wilton(1988) write:

"Postconsumption customer satisfaction/dissatisfaction(CS/D) can be defined as the consumer's response to the evaluation of the perceived discrepancy between prior expectations(or some other norm of performance) and the actual performance of the product as perceived after its consumption…Three approaches to conceptualizing a pre-experience comparison have been suggested in CS/D literature:

(1) Equitable performance…represents the level of performance the consumer ought to receive, or deserves, given a perceived set of costs…The construct is likely to be affected by the price paid, effort invested and previous product experiences.
(2) Ideal product performance represents the optimal product performance a consumer ideally would hope for…It may be based on previous product experiences, learning from advertisement and word-of-mouth communication
(3) Expected product performance represents a product's most likely performance …It is the most commonly used postconsumption standard in CS/D research…It is affected by the average product performance and advertising effort".(pg.204-205).

This perspective is likewise supported by considerable empirical research. As Rust and Oliver(1994) noted,

"Research has shown that this paradigm is fairly robust across various contexts, including product experiences, interpersonal dealing with, e.g., salespeople and many services, including restaurant dining, health care, security transactions and telephone service."

Hence customer demand for both service equality and customer satisfaction is best modeled in terms of the gap between actual performance and some benchmark performance. As Boulding et al(1993) noted, "Service quality and customer satisfaction/dissatisfaction(S/D)…Expectations and perceptions play an important role in both literatures. Two main standards of expectations emerge. One standard represents the expectations as a predictor of future events. This is the standard typically used in the satisfaction literature. The other standard is a normative expectation of future events operationalized as either desired or ideal expectations. This is the standard typically used in the service quality literature …Expectations and perceptions in both literatures are usually linked via the disconfirmation of expectations paradigm. This paradigm holds that the predictions customers make in advance of consumption act as a standard against which customers measure the firm's performance."

(1.2) Utility Analysis as Implicit Gap Analysis

Economics commonly models individuals as maximizing utility with utility defined as a function of a product's actual performance, and not as an explicit function of a gap (Rust, Inman, Jia and Zahorik(1999), Anderson and Sullivan(1993),Thaler(1985)). But as this paper shows:

(1) The utility function can be reinterpreted as describing the gap between the value of that consequence and a random variable. Hence utility analysis can be viewed as a special form of gap analysis with the random variable implicitly representing customer expectations

(2) Reinterpreting the utility function in terms of gap analysis motivates our replacing the conventional concave utility function commonly used in economic analysis by an S-shaped utility function.

(3) The resulting form of utility analysis differs from conventional gap analysis in discounting the gap between actual performance and customer expectations by the degree of uncertainty in actual performance and the individual's risk-sensitivity. Hence utility-based gap analysis has certain empirical implications going beyond conventional gap analysis.

We will illustrate the advantages of using this gap-based utility analysis, or a utility-based gap analysis, in modeling customer demand for service.

The next section of this paper develops the mathematical equivalence between utility analysis and utility-based gap analysis. The third section discusses interpretations of the utility-based gap. The fourth section motivates certain normality assumptions leading to a particularly simple formula for utility-based gap analysis. The fifth section couples this formula with standard random utility model assumptions to develop a formula for customer demand as a function of service performance, customer expectations, uncertainty in service performance and risk-sensitivity. The sixth section applies this formulation to service research.

2. A New Interpretation of Utility

This section shows that the utility of actual performance can always be reformulated explicitly in terms of a gap between actual performance and some benchmark performance. We first define a value function, v, as any function that describes an individual's preferences over known consequences. Thus if the individual prefers consequence x to consequence x*, then $v(x)>v(x^*)$. Note that if v is a value function, then any monotonic function of v will also be a value function preserving an individual's preference ordering over consequences.

The utility function is a special form of value function which describes an individual's preferences over all possible gambles involving known consequences. The utility function is further specified so that the utility of a gamble is the expected utility of its consequences. We now prove the following Lemmas:

<u>Lemma 1</u>: For any value function v, there exists a random variable T such that, for any consequence, the utility of the consequence is the probability that the value of that consequence exceeds T.

<u>Proof:</u> See Appendix

In many service problems, the individual isn't sure about the kinds of benefits which a product might provide. To represent this uncertainty, let X be a random variable where the probability $Pr(X=x)$ describes the likelihood of getting x as our level of service. Let V be a random variable describing the value of the possible levels of service where the probability that $V=v$ is the probability of getting a service level x whose value, $v(x)$, is equal to v.

<u>Lemma 2</u>: Suppose that V and T are independent. Then the expected utility of X is the probability that V exceeds T.

<u>Proof</u>: See Appendix

If we define the gap as the difference between the value of a consequence and some random variable, T, then the utility of a consequence becomes the probability of the gap being nonzero. Hence any utility function can be reformulated as the probability of a gap being nonnegative.

3. Interpreting this Formulation

A critical question in applying this mathematical equivalence is properly interpreting the random variable, T. To illustrate how to interpret T, we consider four different examples.

(3.1) Interpreting T: An Example involving Long-run Objectives

Consider an individual who hopes to achieve some performance objective, G, in the next twelve months. Suppose the individual needs to make a decision now whose consequences x, will be known by the end of this first month. Let $V(x)$ be a random variable representing how much consequence x contributes toward the attainment of the goal. But in the second through twelfth months, there will be other uncertain factors which also contribute to the attainment of the goal. Let Y represent the total contributions these other factors make toward the goal in the second through twelfth month.

Then the individual will achieve the goal if $V(x)+Y$ exceeds G. Unfortunately the individual doesn't know Y. Hence the individual does not know whether or not getting x ensures attainment of the goal. The individual can only look for that decision d whose possible short-term consequences maximize the probability of achieving the long-run goal. In other words, the individual maximizes $Pr(V(x)+Y>G)$ which is equivalent, if $T = G-Y$, to maximizing $Pr(V(x)>T)$. In this case, the random variable T is the uncertain amount which the individual needs to achieve by the end of the first month in order to achieve the long-run objective.

(3.2) Interpreting T: An Example Involving Uncertain Requirements

As Rust, Zahorik and Keiningham(1995) noted, customers form expectations of a product on the basis of its attributes and observe the performance of a product based on its attributes. As an example, consider an individual who wants to buy a car which will satisfy all of the family's performance needs for the next five years. Suppose we let x denote the vehicle. We also let $v(x)$ denote the performance of the vehicle, which is measured by how many miles the vehicle can travel in five years before breaking down. In order to determine whether this vehicle meets the family's performance needs, we need to assess the amount of performance that the family will require over the next five years.

Let T be the amount of performance which the family will require over the next five years. Most families don't know how many trips---and thus how many miles---they will drive in the next five years. Hence T will be a random variable. Thus if the family is only interested in satisfying its performance requirements, it will choose that vehicle whose performance has the greatest chance of exceeding T.

The performance of the vehicle is likewise a random variable. Hence if we replace $v(x)$ by V, we conclude that the probability of the vehicle meeting the family's requirements is $Pr(V>T)$. The family chooses that vehicle with the maximum value of $Pr(V>T)$.

(3.3) Interpreting T: Hedonic versus Concrete Attributes

Most products are characterized by many (often hundreds) of attributes(Griffin and Hauser(1993)). The previous example focused on a case in which the attribute in question---miles driven before the vehicle breaks down---is concrete and measurable. Suppose we consider a hedonic attribute, e.g., comfort. Unlike mileage, how one individual may assess a vehicle's comfort may differ from another vehicle's assessment of comfort. As a result, we will define the comfort of a specific vehicle, x, by arbitrarily picking some reference individual and specifying the comfort of vehicle, x, as the comfort, $v(x)$, which this reference individual assigns to vehicle x.

Because this reference individual was chosen arbitrarily, there will be some random deviation, Y, between the value which the reference individual assigns to the vehicle and the value which a randomly chosen individual would assign to the same vehicle. (Hence Y reflects variation across individuals.) Thus $v+Y$ will reflect the comfort which this randomly chosen individual would assign to the vehicle. If we let G denote the threshold determining whether a vehicle is comfortable or not, then the probability a randomly chosen individual finds vehicle x comfortable is $Pr(v+Y>G)$.

Now vehicle x denotes a specific vehicle nameplate(e.g., Pontiac Grand Am.) Since there are generally tens of thousands(or hundreds of thousands) of vehicles produced under the nameplate, the reference individual's valuation $v(x)$ is based on that individual's experience of only one of those Pontiac Grand Am's (a `test' vehicle). If the reference individual had based on his valuation on a different Pontiac Grand Am, his valuation may have been slightly different. To reflect this variation across vehicles, let V be a random variable with $Pr(V=v)$ being the probability that the reference driver will assign a comfort level of v to a randomly chosen vehicle. Since the actual vehicle the driver buys will differ from the `test' vehicle, the driver, instead of getting a vehicle whose comfort level is $v(x)$, will get a vehicle whose comfort level is described by the random variable V.

Thus the probability of the driver being comfortable is the probability that $V+Y$ exceeds G. If we define $T=G-Y$, then the probability of the driver being comfortable with the vehicle is $Pr(V>T)$. Since V and T are presumed independent, this implies that how a driver's comfort-sensitivity differs from the reference individual does not affect the comfort characteristics of the vehicle he gets. Since this assumption of independence is not necessarily realistic, our next example discusses a way in which this independence condition can be dramatically relaxed.

(3.4) Interpreting T: An Example Involving `Should' Expectations

Suppose an individual has `should' expectations, $ES$, i.e. expectations of what the product should provide(Boulding,Kalra, Staelin,Zeithaml(1993)). These `should' expectations partially reflect the individual's past experiences with similar products(denoted by Q_j) and partly reflect underlying needs(or ideal expectations,I). We write this as

$$ES_j = k_j Q_j + (1-k_j) I$$

Suppose the customer wants to choose the product that has the maximum chance of exceeding his should expectations. Then the customer maximizes

$$Pr(V>ES) = Pr(V>kQ + (1-k)I)$$

It's tempting to think that this objective function is equivalent to our target-based model with $T=kQ+(1-k)I$. As we now show, this isn't generally true.

Suppose we view the performance of a product, V, as differing from one's previous experience with the product, Q, by some random deviation e. Then we can write

$V=Q+e$. In this case, V and $(kQ+(1-k)I)$ are correlated. However the equivalence with utility theory discussed in section 2 requires that T and V be uncorrelated. Hence we cannot generally interpret T as describing `should expectations'.

Instead we need to define $V^*=(V-kQ)/(1-k) = Q + e/(1-k)$. If we also define $T=I$, then the customer maximizes

$$Pr(V>ES) = Pr(V^*>T)$$

Thus our formulation can describe situations involving `should' expectations with appropriate transformations of V and T.

(3.5) The Appropriate Interpretation of T

Our previous section showed how maximizing expected utility was equivalent to maximizing the probability of performance exceeding some random threshold, T. In this section, we showed that T could generally be interpreted as what the customer must receive from the product in order to be satisfied with the product. As we noted, T will usually be uncertain because the customer will not definitely know what is required in order to be satisfied.

When T is highly uncertain(e.g. when T is uniformly distributed),

$$u(x) = Pr(x>T) = x$$

i.e., the individual is risk-neutral and acts as if he had no expectations. Conversely when T is not uncertain, $u(x)$ is the probability that x exceeds those known expectations.

4. The Discounted Gap

(4.1) Specifying the Function F

As section 2 noted, for every function, F, there exists a different random variable $T=F[U^*]$ where U^* is a uniform random variable. If we specify F to be the inverse cumulative normal distribution, then T will be normally distributed. Specifying F also specifies how the value function $v(x)$ is related to the utility, $u(x)$, of various consequences x. The uncertainties associated with the consequences,X, imply a probability distribution over $u(x)$ and, likewise, a probability distribution, over $v(x)$. Following common practice(e.g., Boulding, Kalra, Staelin,2000), we will assume that V, which describes the probability distribution over $v(x)$, is normally distributed.

(4.2) The Uncertainty-Adjusted Gap

If we let:

(1) V_i denote the random variable associated with the value of alternative i's payoff

(1) EV_i denote the mean of V_i

(2) s_i denote the standard deviation of V_i

(3) s_0 denote the standard deviation of T

then we can define the uncertainty-adjusted gap by:

$$G_i = (EV_i\text{-}ET)/[1+s^2{}_i/s^2{}_0]^{1/2}$$

As the Appendix shows:

<u>Lemma 3</u>: The utility of product i exceeds the utility of product j if and only if $G_i > G_j$.

<u>Proof</u>: See Appendix

Note that

$$R_i = [1+s^2{}_i/s^2{}_0]^{1/2} - 1$$

could be interpreted as the variance in product performance, adjusted to reflect the individual's uncertainty about his expectations. This adjusted variance is zero for a risk-neutral individual (for whom $s^2{}_0$ is infinite) and is large for a very risk-averse individual (for whom $s^2{}_0$ is small.) When there is no variance in product performance, R_i is zero regardless of the individual's risk-preferences.

Given this definition,

$$G_i = (EV_i\text{-}ET)/(1+R_i)$$

and is just the standard formula for the gap discounted by this adjusted variance, R_i.

5. Modeling Customer Choice

(5.1) The Random `Gap' Model

Random utility models(Benakiva and Lerman,1986) are widely used to relate the value of an alternative to its probability of being chosen. Most random utility models assume that there is a double exponential error in the observer's estimate of utility. Suppose we assume, instead, that there is a double exponential error in the measurement of `the gap'. In this case, the random utility model gives us a choice probability of

$$P_i = exp(G_i/s^*)/\{\sum_j exp(G_j/s^*)\}$$

where s^* is the scaling factor associated with the double exponential error term. Hence the logarithm of the relative probability of choosing alternative i over alternative 1 is

$$ln(P_i/P_1) = (1/s^*)\{G_i\text{-}G_1\}$$

Note that

(1) increasing the expected quality of a product, $EV_{i,}$, without changing anything else, always improves market share

(2) reducing the uncertainty about a product's quality, $s_{i,}$ will increase that product's market share if $EV_i>ET$, i.e., if the product is expected to meet customer requirements. Otherwise it will decrease market share.

(3) increasing the customer's benchmark, ET, will enhance the relative market share of products whose product quality is less certain(i.e. for which $s_i>s_1$).

(4) increasing the uncertainty about the benchmark, s_0, will have a more complicated effect. It will tend to favor those products with a smaller gap and a large uncertainty,i.e., it will favor product i if

$$G_i /[1+(s_i/s_0)]^2 < G_j/[1+(s_1/s_0)]^2$$

An important special case of this model emerges when $s_j=s_1$ for all j. In this case, the model becomes

$$ln(P_i/P_1) = \{ G_i \text{-}G_1 \}/s^* = \{EV_i\text{-}EV_1\}/s^*(1+R_1)$$

Note that mean ideal expectations becomes irrelevant although the variance in those expectations still matter. Increasing the variance in the ideal expectations(or equivalently decreasing the variance in each product's performance) will cause the market share of the higher-value product to increase. This, of course, is intuitive. When it's easier to observe the higher performance product, the higher performance product's market share increases.

(5.2) Comparisons with the Logit Model

Equation(5.1) was derived by assuming that there was a double exponential error in the certainty equivalent. In contrast, the conventional logit model is derived by assuming a double exponential error in the utility function. Hence the logit model would write relative market shares as:

$$ln(P_i/P_1) = (1/s^*)\{EU_i - EU_1\}$$

Making direct comparisons between the two models is difficult since our model is expressed in terms of the value function and the logit model is expressed in terms of the utility function.

But in many applications of the logit model, the utility function is estimated using a value function. In these cases, the logit model becomes equivalent to

$$ln(P_i/P_1) = (1/s^*)\{EV_i - EV_1\}$$

which corresponds to our model when all alternatives have the same variance.

This model, unlike ours, implies that relative shares are independent of changes in the customer's benchmark or of relative changes in the variance of each product. Since gap analysis shows that frequently choice is based on a comparison between actual performance and a benchmark, we believe this model is frequently unrealistic.

Note that increasing the uncertainty about the benchmark, or decreasing the average variance of each product, decreases s^*. In the logit model, this increases the market share of more highly valued products and decreases that of less highly valued products. But our model gives more complicated predictions. The previous section already discussed the implication of changing the uncertainty about the benchmark.

In addition, since each product i's gap, in our model, is discounted by $[1+s^2_i/s^2_0]^{1/2}$, a unit change in the variance of each product will have a greater impact on products with smaller variance. Thus consider two products whose expected performance exceeds expectations. Suppose we reduce the variance of both products by a unit and suppose this eliminates all uncertainty about the performance of the less highly valued product. Then our model suggests that it's possible that the less highly valued product will see its market share increase more than the more highly valued product.

6. Customer Satisfaction Application

(6.1) Extensions to Modeling Customer Satisfaction

As in our model, Rust, Inman, Jia and Zahorik(1999) supposed that the perceived quality of a product, V, was normally distributed about EV, the brand's average quality, with variance s^2. But they further assumed that the customer was uncertain about average quality, EV. They modeled this uncertainty by treating EV as normally distributed with mean μ and variance σ^2. By doing so, they were able to describe how a customer's past experience with the product would update his beliefs about EV and thus alter his propensity to buy future products. In this section, we now incorporate these extensions into our model.

We first define the certainty equivalent of uncertain performance V as a product having a known level of performance, C, which is considered just as desirable as the product with uncertain performance V. If EV is normally distributed with mean μ and variance σ^2, then V is normally distributed with mean μ and variance $s^2 + \sigma^2$. Thus the certainty equivalent for the product is

$$C=[\mu-ET]/[1+(s^2+\sigma^2)/s^2{}_0]^{1/2}$$

Now suppose the customer has just had one experience with one version of the product. Let V be the experienced quality. Then the customer revises his estimate of the mean of EV from μ to $\mu + w(V-\mu)$ where

$$w= (1/s^2)/[(1/s^2)+(1/\sigma^2)]$$

(This corresponds to Rust, Inman, Jia and Zahorik(1999) 's result if we scale $s^2+\sigma^2=1$.) Similarly the customer's uncertainty about EV now changes from σ^2 to $1/[(1/s^2)+(1/\sigma^2)]$ or $\sigma^2(1-w)$.

Hence given one product experience, the certainty equivalent becomes

$$C' = [\mu-ET + w(V-\mu)]/[1+(s^2+\sigma^2)/s^2{}_0 - w\sigma^2/s^2{}_0]^{1/2}$$

(6.2) How Information Affects the Certainty Equivalent

Suppose we define the relative uncertainty about product quality by

$$k = (\sigma^2/s^2{}_0)/[1+(s^2+\sigma^2)/s^2{}_0]=\sigma^2/[s^2{}_0 + (s^2+\sigma^2)]$$

Likewise we define the relative discrepancy

$$D=(\mu -V)/(\mu-ET)$$

as the deviation between experience and expected experience relative to the deviation between ideal expectations and expected experience

We can then rewrite the certainty equivalent as

$$C'=C[1-wD]/[1-wk]^{1/2}$$

Since k is always nonnegative, increasing w always decreases the denominator.

Now suppose that D is negative. This means that either:

(a) $\mu>ET$ and $V>\mu$, i.e., the product is expected to exceed ideal expectations and the information suggests the product is even better than the consumer expected.

(b) $\mu<ET$ and $V<\mu$, i.e., the product is expected to fall short of ideal expectations and the information suggests the product is even worse than that consumer expected.

In this case, increasing w always increases the magnitude of the numerator. Hence increasing the weight,w, of new information makes a negative certainty equivalent become more negative and a positive certainty equivalent more positive.

Now suppose that D is positive. Then the information is either suggesting that an unacceptable product(i.e., $\mu<ET$) is better than expected or that an acceptable product(i.e., $\mu>ET$) is worse than expected. We can rewrite the certainty equivalent as

$$C'=C[\ 1+\ w\ (k-2D+wD)/(1-wk)\ \ ]^{1/2}$$

First suppose that $k>D(2-w)$. This means that uncertainty about quality is large. Then increasing w always increases the absolute magnitude of the certainty equivalent. Since $k<1$ and $w<1$, this also implies $D<1$. Since the numerator is proportional to $1-wD$, this implies that increasing information can never make the certainty equivalent change sign.

Now suppose that $k<D(2-w)$. In this case, the effect of reducing uncertainty is outweighed by the disconfirmation effect. Hence increasing w tends to shrink the magnitude of the certainty equivalent---as the disconfirmation effect outweighs the

reduction in uncertainty provided by the new information. If $D>1$, then eventually w exceeds $(1/D)$ and the sign of the certainty equivalent changes.

(6.3) Comparison with Previous Work

Rust, Inman, Jia and Zahorik(1999) 's original work focused only on concave utility functions. But our model is only concave when V and μ both exceed ET. Hence our model also makes predictions in cases not considered by Rust, Inman, Jia and Zahorik.

To illustrate these extensions, we first slightly generalize Rust, Inman, Jia and Zahorik(1999) 's formulation slightly by supposing that the customer, instead of having one experience with the product, has n experiences with the product. Let V denote the average quality in those experiences. This provides an estimate of average product quality which---assuming independent experiences----has variance (s^2/n). Hence our formula for w will increase as n increases.

We now compare the implications of our formula with Rust et al.'s propositions:

(1) If a better than expected outcome is observed, they predicted that the probability of choosing the option will increase. This holds in our formalism when the product is expected to exceed expectations. Otherwise, it's possible that a better than expected outcome---by reducing our uncertainty about an outcome that is expected to miss expectations---could reduce the probability of choosing the option.

(2) If an expected outcome is observed, they predicted that the probability of choosing that option will increase. In this case, $D=0$. Our model predicts that the probability of choosing that option will increase if expected quality exceeds ideal expectations(i.e.$\mu > ET$) and will decrease if expected quality is less than ideal expectations.

(3) They predicted that a rational customer might choose an equally priced option for which the expected quality is worse. This occurs in our model. If expected quality exceeds ideal expectations, we prefer options with lower variance. If expected quality falls short of ideal expectations, we prefer options with higher variance.

(4) They predicted that a worse than expected quality outcome may still increase the probability of choosing that option. (This postulate was not supported in their analysis.) Our model predicts that this effect may hold only if expected quality exceeds ideal expectations. If expected quality is less than ideal expectations, then a worse than expected quality outcome will always decrease the probability of choice.

(5) They predicted that a negative disconfirmation would evoke a greater relative chance in preference than a positive disconfirmation of equal magnitude. This will only happen in our model if expected quality exceeds ideal expectations. On the other hand, if expected quality falls short of ideal expectations, the reverse will happen.

(6) Given diffuse priors and an equal historically observed mean and variance, they predict that a sufficiently large negative disconfirmation will cause a greater preference shift in a less experienced customer. This is consistent with our model where we can model a less experienced customer by assuming a larger value of w.

Thus some of Rust, Inman, Jia and Zahorik's results extend to the case of initially convex and then concave utility functions. In other cases, they are dramatically violated.

(6.4) The Variance-Reduction Effect

Rust, R. J. Inman, J. Jia and A. Zahorik(1999) emphasized that customer behavior, in response to new information or experience with a product, depended upon the interaction of *the disconfirmation effect* which measures, how the mean estimate of product quality was changed and *the variance-reduction effect* which measures how uncertainty about product quality changes. In our model, the variance-reduction effect always serves to amplify the value of the certainty equivalent. Hence if expected performance, given the new information, exceeds ideal expectations, then the variance-reduction effect amplifies this positive certainty equivalent and makes the product even more attractive. Conversely if expected performance given the new information, falls short of ideal expectations, the variance reduction effect amplifies the negative certainty equivalent and makes the product even less attractive.

7. Managerial Implications

This paper highlights the importance of knowing how well the product or service meets ideal expectations. Suppose that the performance of our product is consistent with current customer expectations. Then encouraging individuals to try our product will:

(1) Enhance their view of the product if they currently feel the product exceeds their target expectations. (This was consistent with the original Rust et al. model.)

(2) Degrade their view of the product if they currently feel the product falls short of their target expectations. (This differs from what the original Rust et al model suggested.)

Thus if our service is good---and people generally believe it is good---encouraging individuals to try our service will only confirm those expectations and increase their willingness to try our service in the future. On the other hand, if our service is inadequate---and if people generally believe it is inadequate----encouraging individuals to try our service will only confirm those expectations and reduce their willingness to try our service in the future. (In other words, `better to be silent and thought a fool than to open one's mouth and remove all doubt.')

This finding complements earlier results from Mittal, Ross & Baldarasar(1998) and DeSarbo, Huff, Rolandelli and Choi(1994) which show that negative performance on an attribute has a greater impact on repurchase intentions than positive performance on the same attribute. Like these earlier results, our finding is an application of prospect theory, which observed that individuals were risk-averse for gains and risk-prone for losses.

Since information tends to reduce the riskiness of a gamble, their results imply that information will tend to enhance the attractiveness of gambles involving gains and will tend to degrade the attractiveness of gambles involving losses. In our formulation, a product whose performance is expected to exceed expectations is offering customers a potential gain while a product whose performance is expected to fall short of expectations is offering customers a potential loss. Hence, not surprisingly, we found that information tends to enhance the attractiveness of products expected to exceed expectations and reduce the attractiveness of products expected to fall short of those expectations.

8. Discussion and Conclusions

It's common to specify a customer's utility function as a linear or concave function. In part, this reflects the lack of information on customer preferences. But as this paper showed, a customer's utility can be interpreted as the probability distribution over a customer's ideal expectations. Since managers often have considerable information about customer expectations, it becomes critical to specify a utility function, which reflects this information.

When we focus on a more general class of S-shaped utility models, we find that the conventional concave utility function commonly used in applications is only appropriate when products and services are expected to exceed customer ideal expectations. As this paper showed, the predictions of our models can change dramatically when we move to a more general S-shaped utility model.

Upon making normality assumptions, we find that this formulation will rank alternatives according to how much expected performance exceeds expectations discounted by the uncertainty in that performance and those expectations. Uncertainty in expectations serves to reduce the effective uncertainty in performance. We couple this result with standard random utility models to develop a new choice model which, unlike the logit model, makes choice an explicit function of

(1) Expected performance

(2) Expectations about How the Product Should Perform (Performance Benchmarks)

(3) The uncertainty in perceived performance

(4) The uncertainty about those benchmarks(which can be interpreted as a measure of risk-neutrality.)

This immediately leads to a number of testable propositions about how changes in expectations and performance uncertainty should impact a consumer's likelihood of purchasing a product.

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APPENDIX

Proof of Lemma 1: Suppose we denote the utility function as u and rescale it to lie between zero and one. Also consider an arbitrary value function v. Let *C* denote the set of possible consequences and let x denote a typical consequence in C. Since v and u are both consistent with the same ordering of consequences x, there exists a strictly monotonic function *F* such that $v(x)= F[u(x)]$. Let U^* be a uniformly distributed random variable. Then $u=Pr(u>U^*)$. If we define the random variable *T by* $T=F[U^*]$, then we also have $u=Pr(v>T)$. Thus the utility of a consequence x can be viewed as the probability that the value of that consequence $V(x)$ exceeds some random threshold, *T*.

Proof of Lemma 2: By definition, $u(X) = \sum_x u(x)\, Pr(X=x) = \sum_v Pr(v>T)Pr(V=v)$. Since *V* and *T* are independent, we can then write $\sum_v Pr(v>T)Pr(V=v) = Pr(V>T)$. This proves the result. (This result was originally proven for Von Neumann-Morgenstern utilities by LiCalzi and Castiglione(1996) and extended to Savage utilities by Bordley and LiCalzi(2000).)

Proof of Lemma 3: Let $N(x)$ denote the probability that a standard normal variable is less than *x*. *Let* s_{i0} be the standard deviation of V_i-T. Then

$$Eu(X_i)=Pr(V_i>T) = Pr(Z< (EV_i-ET)/s_{i0})=N\{(EV_i-ET)/s_{i0}\}$$

Thus the expected utility is a function of the ratio $(EV_i-ET)/s_{i0}$.

Now the certainty equivalent, *c,* of any uncertain quantity *V* can be interpreted as the price for which the individual would be willing to see the quantity. Thus an individual would be willing to exchange a product with uncertain performance *V* for a product whose performance was known to be exactly equal to *c* . Then

$$u(c) = Eu(X)$$

Since

$$u(c)=Pr(c>X) = N\{(v(c)-ET)/s_0\}$$

equating $u(c)$ and $Eu(X)$ gives

$$N\{(v(c)-ET)/s_0\}= N\{(EV_i-ET)/s_{i0}\}$$

Since N is monotonic, we have

$$v(c) = (EV_i-ET)\, s_0/s_{i0} + ET$$

Since T and V are independent, $s_{i0} =[s^2{}_i + s^2{}_0]^{1/2}$. If we define the gap between V_i and the individual's expectations by

$$G_i = (EV_i-ET)/[1+s^2{}_i/s^2{}_0]^{1/2}$$

then ranking uncertain quantities by the certainty equivalent gives us the same result as ranking uncertain quantities using the gap.

BIOGRAPHY

Dr. Robert F. Bordley has spent twenty years at General Motors in its Corporate Strategy Staff, its Systems Engineering Center and its Research and Development Center. He has been awarded the R&D Award of Excellence and GM's Presidents Council Award. His assignments at General Motors include being manager of strategic frameworks, manager of R&D portfolio planning, manager of marketing sciences, manager of decision support systems and manager of mission analysis. He has also worked at the National Science Foundation as director of the Decision, Risk & Management Sciences Program where he was involved in creating the current directorate for social sciences. He has also been an adjunct professor at Oakland University for five years and at University of Michigan, Dearborn, for one year.. He has published more than sixty papers in such journals as Marketing Science, Journal of Business and Economic Statistics, Management Science, Operations Research, Journal of Economic Theory, Review of Economics and Statistics.