Goals of Professional Purchase Using Queuing Theory

Rajesh kumar M. Chaudhary
Research Scholar, Department of Mathematics
JJT University, Jhunjhunu-333001, Rajasthan, India

Jayeshkumar J. Patel
Research Scholar, Department of Mathematics
JJT University, Jhunjhunu-333001, Rajasthan, India

Pragnesh A. Patel
Research Scholar, Department of Mathematics
JJT University, Jhunjhunu-333001, Rajasthan, India

Abstract- **We see that a consumer's Buying behavior represents a cognitive framework such that an appropriately selected queuing model can be used to assess the credibility of a consumer's expression of Buy intention to proceed into Buying action. The modeling idea is to envision that the customer has a mental queue of needs, and the surfacing of a need represents a new arrival to this queue while a buy satisfying a need represents a departure from the queue. Using queuing formulae (and/or readily available tables on queuing), several statistics known as "operating characteristics" can be computed to capture and describe the individual's current need status. Hence, a description of the customer's state of readiness or prospect of actually executing the expressed purchase intention for a product (good or service) whose future sales are of interest in a market survey may be obtained. In this paper, such a description is termed Individual Buyer Profile (IBP), and IBP is offered as a buy intention qualifier.**

Keywords – Watermarking, Haar Wavelet, DWT, PSNR

I. Introduction

Marketers of consumer goods and services have a too much interest to predict the purchase behavior of customers. Normally, these predictions contribute to market forecasts and related generalizations for both existing and new products.

In addition, predicting purchases rests on the stage preceding actual purchase, and is referred to as "intention to purchase" (Howard and Sheth, 1967). According to various theories of buyer behavior, buy objectives helps predict subsequent purchase (Howard and Sheth, 1969). Information about purchase intention is typically drawn from a purchase intent scale or an 11-point purchase probability scale which are designed to elicit a response to the question how likely an item will be purchased within a specific time period. Both purchase intent and probability scales are reported as empirically unbiased, with the latter offering greater precision.

The professional-buy relationship has attracted a number of empirical studies highlighting significant inconsistencies between purchase intention and purchase behaviour (Ferber and Priskie 1965; Kalwani and Silk, 1982). For example, Tull and Hawkins (1987) note that results for private surveys have shown moderate discrepancy between intent and purchase for industrial goods. The results for consumer goods are more disappointing. In public surveys, the results have not been any more encouraging. The United States Bureau of the Census Consumer Buying Expectations Survey has been discontinued (McNeil, 1974). The Canadian Buying Intentions Survey was also questioned as noted by Murray (1969) who states "...buying intentions, when used alone, have limited predictive ability..."

II. BUY INTENDERS AND NON-INTENDERS

From survey, the predictive ability of a buy intention survey dependent on the truthfulness of each survey participant's response. There are two situations when an intention will fail to be truthful: 1) if a positive response --i.e., intention to buy-- is not followed by a purchase action, or 2) if a negative response --i.e., intention not to buy -- is followed by a purchase action (each, during the time period as specified in the survey). The former situation corresponds to an "**intender-non buyer**," denoted herein by $(B^- | I^+)$, which represents the intention by the respondent to purchase the product (I^+). However, what is observed within the study period (B^-) is that the respondent did not follow through with his or her intention and actually buys the product (for whatever reasons, and whether the respondent consciously or unconsciously introduces this discrepancy to be observed eventually). On the other hand, the latter situation corresponds to a "**nonintender-buyer**," $(B^+ | I^-)$, which, though representing a negative intention by the respondent, (I^-), nevertheless, the respondent buys it, $(B+)$ during the observation period of the survey.

Here above two cases have their respective complements; viz., $(B^- | I^-)$, and $(B^+ | I^+)$, corresponding to "truthful" respondents; i.e., "**nonintender-non buyers**" and "**intender-buyers**," respectively.

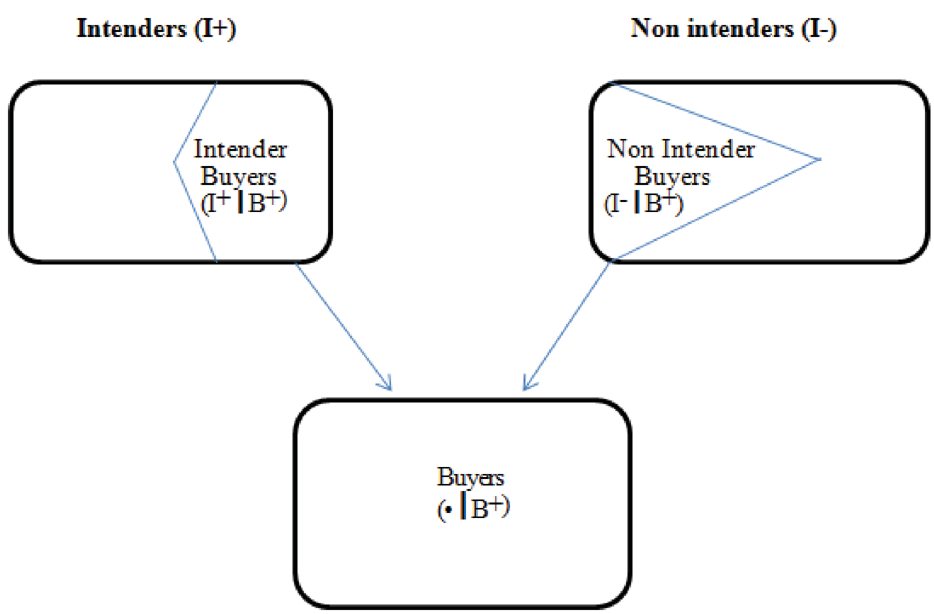

Figure 1. A Representation of Intention-Buyers Relationship

The intent-purchase discrepancy varies in magnitude as reported by a number of studies. For example, Ferber (1965) notes that an average of about 72 percent of nonintenders act in accord with their intentions, while only 47 percent of intenders are consistent with their intentions to purchase. Hence, as probabilistic estimates, we can write Pr $(B^- | I^-) = 0.72$ (i.e., given a respondent who expresses a negative purchase intention, the probability that the respondent is a nonbuyer-to-be is 0.74), and Pr ($B^+ | I^+$) = 0.47 (i.e., given a respondent who expresses a positive purchase intention, the probability that the respondent is a buyer-to-be is 0.43). Accordingly, Pr ($B^+ | I^-$) = 0.28, and Pr ($B^- | I^+$) = 0.53; i.e., there is a 28% chance that the respondent will buy, given that s/he may have said otherwise, and there is a 53% chance that a respondent will not buy, although they may have responded positively, expressing intention to buy. Thus, for a sample of respondents surveyed, the intention and Buying relationship may be represented as shown in above Figure 1.

Possible causes for the gap between Buyers intention and actual Buyers include the survey itself ;failure to predict future preferences (Lowenstein and Adler, 1995), effect of information acquisition bias in measuring and reporting intentions (Fisher, 1993; Mittal and Kamakura, 2001), perceived quality of the product and product satisfaction (Cronin and Taylor, 1992; Sweeny et al, 1999).

III. Purpose of the Study

Finding the gap between stated and actual Buyers has resulted in remarkable depth, sophistication and complexity, in lieu of parsimony much desired by the marketing practitioner. The practitioner is faced with quite a dilemma when conducting an intentions study. One approach might be to develop a mathematically complex model able to incorporate every researched influence and so offer a result in terms of a range of purchase probability. Alternatively, to encourage researchers to uncover an integrated and comprehensive model able to reduce the stated to actual purchase gap. It is the latter which forms the basis for this paper. That is, the purpose of this paper is to describe how queuing theory might be used to help improve the credibility, and hence, the predictive quality of consumer intention to purchase.

We envision that every consumer has a cognitive queue of needs. The arrivals to this queue are the needs that surface or emerge and the departures are the needs that are satisfied by appropriate purchase action.[1] Hence, a properly chosen queuing model can capture and reflect the individual's current need status (e.g., whether the individual already has a lengthy queue of unsatisfied needs; what the average waiting time for a need is, etc.). Based on the values of such statistics, we can come up with a description of the individual's readiness for --or prospect of-- actually completing the intended purchase within the survey period, and so, assess the fidelity of the response s/he gives. In this paper, we call such a description Individual Buyer Profile (IBP), and offer IBP as a purchase intention qualifier. This qualification or assessment of response fidelity (or truthfulness) across all respondents would facilitate and lead to an improvement in the predictive quality of the survey.

While queuing theory is studied in the stochastic processes literature its use in marketing as suggested in this paper for Professional Buy Objectives is, to the best of our knowledge, a new attempt. However, various existing stochastic and other buyer behavior models and related topics can be found in Howard and Sheth (1969), and Lilien and Kotler (1983).

IV. Personal Objectives and Predictions

Morrison (1979) emphasizes the gathering of actual purchase data as a follow-up to stated intentions to facilitate an evaluation of stated intentions versus actual purchases. This would be useful for estimating future purchase rates, as well. Clearly, there is an understandable anticipation of a difference between the intention to purchase and the actual behavior. There might be a variety of reasons for this difference or discrepancy ─ factors such as intervening time, unforeseen event(s), influence of others, new information, etc., may well suppress or enhance the intention resolution. The question is whether one can qualify or evaluate the individual-level purchase intentions in light of additional information about, and mostly from, the individual at the time of initial data collection, allowing for a-priori identification of the inherent potential for the outcome of no purchase.

By identifying those purchase intentions unlikely to be realized, and so eliminating them from further consideration in the estimation of actual purchases, one can reduce the intention-purchase discrepancy due to the intender-non buyer group; the main group Responsible for the discrepancy. Forecasts may be improved in the conservative sense; that is, the lower bound of the forecast representing the purchases expected from intenders can be sharpened. As the actual sum of purchases is likely to include a (small) portion from the nonintender-buyer group, a forecast adjusted/corrected for the intention-purchase discrepancy from the intender-nonbuyer group should offer a realistic lower bound on sales.

V. Queueing Mechanism in a Cerebral Context

Suppose that in an intention study, respondent **R** honestly indicates a positive response to buy the product (good or service) in question; call this product **P**. However, the investigator would not really know whether the response is honest and realistic. After allowing a reasonable period of time[2] for the purchases to occur, let us assume the investigator establishes that **R** did not make the purchase. From the investigator's point of view, **R's** intention was, in one sense or another, not truthful. Perhaps, respondent **R's** intention to purchase, although genuine or honest, could not be realized. How likely or ready was **R** to buy product **P** at the time the intention to purchase was expressed? It is possible that respondent **R** already had too many incumbent needs waiting for their turn to be satisfied (i.e., waiting to be serviced) via the purchase of relevant product(s) for the satisfaction of each need to occur.

In other words, **R's** need-satisfaction mechanism or capacity might have been in a state of backlog or congestion (i.e., in a state with too many needs to satisfy within a time period) when indicating an honest positive response to buy **P**. That is, respondent **R** may not have been fully cognizant of the underlying self-need-status at the time the intention was solicited. And later, a variety of these inadequately-perceived needs versus perhaps overestimated means --such as financial expectations-- may have prevented **R** the opportunity (i.e., the "room") to service the need for product **P** by a purchase action. Such a situation is analogous to the case of a fully occupied (or busy) queuing system that is unable to accommodate any more customers. Hence, it is possible to visualize the presence of a queuing mechanism couched within a cognitive framework. Needs are recognized by the consumer as they emerge or surface, constituting the arrivals to this cognitive queue, while the consumer's purchases which successfully satisfy these needs represent service completions and departures from this queuing system. Upon satisfaction, each need disappears, opening up room or the opportunity for another (the next) need to be satisfied.

In the likely event a survey respondent is not in full appreciation of the juxtaposition of incumbent personal needs and means, such an individual may honestly, but perhaps unrealistically, indicate a positive response to buy **P** within the period the intention study covers. It is certainly desirable to control or account for this intention-purchase discrepancy at the outset.

VI. Queueing and Personal Buyer Profiles

With regard to the preceding discussion, assume that products belonging to category **C** are purchased by a customer at an average rate of μ (mu). Furthermore, suppose that **P** is a product classifiable into this category. Let us also assume there exists an average need emergence of λ (lambda) for the customer concerning category C products. With regard to the queuing construct outlined earlier, an appropriate model can be selected, and its standard formulae and/or tabulated results can be employed to obtain certain statistics that will capture the customer's current outlook of needs, and reveal his/her prospect for actually executing the purchase of **P** which was responded to with a positive intention.

Obviously, characterizing the product concept into its groups (convenience, shopping, specialty, unsought) may require separate treatment --such as using a different queuing model and/or λ and μ parameter values-- for each product based on the classification provided by the respondent.

VII. Model Implementation

In numerous purchase behavior models, the Poisson process appears as a standard assumption (Chatfield and Goodhart, 1973; Gupta and Morrison, 1991; Schmittlein and Morrison, 1985; Wagner and Taudes, 1986). In keeping with this mainstream assumption and following Kendall's (1953) standard queuing notation for model designation, consider the M/M/1 queuing model. It is very likely that, due to its "completely" random nature, the M/M/1 model would be appropriate for products that are likely to invoke impulse purchases (for staples, the D/M/1 model is suggested).

Based on some statistics (known as "operating characteristics") that describe a queuing model's expected (i.e., average) behavior, the following **IBP** description can be obtained for the M/M/1 model. First consider:

$$Pr\ (0) = 1 - (\lambda/\mu) \tag{1}$$

Where Pr (0) is the probability that the individual's cognitive queuing system is empty (i.e., idle). An individual with a high Pr (0) value who also states an intention to buy P is more likely to make the purchase than if the respondent's Pr (0) values were low. This is because when Pr (0) is high, the respondent's set of needs is near empty (or idle), and consequently, a respondent with a positive purchase intention and an idle or near empty set of needs is apt to act and purchase product P without having to worry about satisfying many other incumbent needs first, which would be the case with a respondent whose Pr(0) value is low. Now consider:

$$Lq = \lambda^2 / \mu\ (\mu - \lambda) \tag{2}$$

Where, Lq is the average number of unsatisfied incumbent needs that are already waiting in the individual's cognitive queuing mechanism (i.e., needs in line). A large Lq value would qualify a consumer who indicates an intention to buy product P a less likely buyer-to-be (with high potential to join the intender-nonbuyer group) than if the Lq values were small. This is simply because when Lq is large, the currently unsatisfied and queued up needs for other products would take precedence, thereby delaying, precluding and/or averting the purchase of product P (in a timely way). Next, consider:

$$Wq = \lambda / \mu\ (\mu - \lambda) \tag{3}$$

Where Wq is the average time a need waits before it is served. For a purchase intention to be more credible, it would be desirable to have a low Wq value. The reason is that a large Wq value implies a lengthy waiting time, on average, until a need gets its turn to be serviced by the purchase of a relevant product. There are two immediate problems associated with a large Wq regarding the credibility of a respondent's indication of an intention to buy P (i.e., positive response). One of these problems has to do with the purchase time, in that the customer's purchase of P may occur far too late to be of any use to the survey. The other problem is that the purchase may not occur at all due to a long waiting time, and this may cause forgetfulness and/or create various other obstacles to purchase action such as loss of interest.

Finally, we could also consider Δ (delta), the so-called "traffic intensity factor" in queuing terminology, for further characterization of IBP:

$$\Delta = (\lambda / \mu) \tag{4}$$

This will indicate if the respondent's queuing mechanism to serve his/her needs is at a high or low state of being busy. If the Δ value is high, this should be taken as yet another indicator that the respondent's ability to satisfy and dispense with his/her product needs is slow in coming. Hence, such a respondent's positive intention to purchase the product in question in the survey should not be viewed as being quite realistic and/or credible.

VIII. A Practical Example and Comparison

To give a more concrete picture of the foregoing discussion, consider the scenario presented in Table 1 for purposes of **IBP** description and comparison. It should be noted that a data given in Table 1 has to be product category specific. Also note it is assumed that both respondents in Table 1 have expressed a positive intention to purchase product **P** in a purchase-intention survey.

It is also noted that λ and μ are average rates (average input parameter values). As such, they are measured in "number of needs" — that is, "average number of needs surfacing" and "average number of needs that can be serviced," respectively, per unit time (per week, month, etc.). Consequently, L_q is measured in number of needs and W_q is measured, for each need, in the time unit used for λ and μ. On the other hand, Pr (0) and Δ are unit less quantities.

Table -1 Hypothetical Data for Practical Comparison

	Respondent 1	**Respondent 2**
	9.000	5.000
μ	10.000	30.000
Pr(0)	0.100	0.830
Nq	8.100	0.030
Wq	0.900	0.007
Δ	0.90	0.17

Based on the foregoing discussion, we can develop the **IBP** descriptions of these two respondents, and qualify the credibility of each respondent's intention to buy **P**.

Accordingly, we see that Respondent 1 with Pr (0) =0.10 (or Δ=0.90) already has a "very busy" cognitive queue compared to Respondent 2 whose mental queue of needs has a high Pr (0)=0.83 value for being idle (i.e., for having no incumbent need), or alternatively, a low Δ value of 0.17 for being busy. Indeed, Respondent 1 already has 8.1 unsatisfied needs waiting in the queue for their turn for service to come, while Respondent 2, with a low L_q of 0.03, has practically no need waiting (as supported by the high probability, Pr (0) =0.83, of zero incumbent need for this respondent). As a result, Respondent 2 is much more likely to make the purchase of product **P** (on average, within W_q=0.007 time units), whereas respondent 1, with W_q=0.9, has to keep the servicing of each need waiting almost a complete time unit. The obvious conclusion resulting from this comparative **IBP** description is that, Respondent 1's purchase intention is not very credible; and certainly far less credible than Respondent 2's.

IX. Cautions and Discussion

The appropriateness of standard queuing formulae and/or tabulated values is subject to a general stationary and steadiness of purchase behavior in a given marketing environment. In most cases, this is unlikely to be compromised since customers included in an intention study have probably purchased a variety of products over a lengthy period of time. However, for an innovative product which is totally new in the experience of customers, it could be difficult to contend with the appropriateness of this assumption.

It is also worthwhile to note that the arrivals (or calling units) in this cognitive queuing framework are the needs which are inanimate/abstract beings. That is, they are one's (product) needs that the individual is aware of (at some level of awareness). As such, the needs are "patient customers" in the terminology of queuing. However, reneging on intentions might still occur as a result of such factors as the consumer's forgetfulness and change in need(s) over time. Indeed, this point relates to the "reasonable" time requirement mentioned in footnote 2 (also see Schmittlein and Morrison 1985).

The estimation of rates λ and μ would require empirical investigation that is beyond the scope and purpose of this conceptual paper. We acknowledge that, of these two parameters, it seems λ is the more challenging to estimate being the more abstract one in nature. However, in today's world of extensive consumer databases, scanner data, and data mining techniques, together with an increasingly viable micro segmentation, the estimation of these parameters should be possible with a reliable degree of accuracy. Writing on a related topic, Schmittlein and Morrison, (1985) indicate that in most real settings, it is impractical to estimate parameter μ separately for each individual. Instead, Schmittlein and Morrison (1985) suggest an estimation procedure based on a sample of customers. The context of the Schmittlein and Morrison (1985) article is on actual purchases rather than intentions, and is not couched in a cognitive framework. However, the approach they suggest would be helpful. Note that rate μ obtained from a sample can be adjusted up or down, capable of being individualized based on a consumer's demographic and income data.

An argument on the dependence and/or independence of λ and μ might be raised. We tend to think that need recognition occurs independently of purchase action. On the other hand, the requirement of arrival rate being smaller than the service rate, ($\lambda < \mu$), needs careful verification for the M/M/1 model to be used. This might be a vulnerable constraint in a number of cases, especially if the independence of λ and μ assumption is to be accepted. But such a violation presents no problem for us, because if λ is found to be greater than μ for a respondent, then this finding could be viewed as a definite signal to discredit such an individual's positive purchase intention. This is because, if $\lambda > \mu$, then the respondent would already be experiencing serious difficulty in servicing his/her ever-increasing backlog of incumbent needs, let alone address the new needs that surface (except for emergency needs). Therefore, from the marketing point of view, the **IBP** interpretations based on this queuing approach preserve integrity by being robust to the violation of the M/M/1 requirement of ($\lambda < \mu$).

The approach suggested in this paper is not limited to the Poisson process case, although the Poisson category of queuing models --such as the M/M/1 model-- would be versatile, convenient and simple in addressing nonlinearities that exist in buyer behavior (Laroche and Howard, 1980). In fact, as we pointed out earlier, for different product categories, different queuing models could be adopted with careful selection. Furthermore, given the well-grounded presumption that consumers classify products/services (convenience, shopping, etc.) into processing categories (routinized response, high and low involvement), we can view --at any given moment in time-- an individual's overall purchase disposition for several different products as a complex collection --or perhaps, a network-- of queues, where each queue is considered appropriate for a particular category of product and/or need. To capture the different levels of urgency of needs, this collection may also include "priority queue" models. That is, the queuing approach, in general, offers richness. Nonetheless, we advocate that single server queuing model should be appropriate in most cases, since a respondent would ordinarily service his/her own needs by his/her own means (i.e., the occasional receipt of gifts, contributions, etc. should not compromise the use of single server models).

Finally, the approach can readily lend itself to an evaluation of managerial variables and marketing decisions, as they can have a direct effect on μ. For example, price reductions and/or promotional activities might lead to changes in the **IBP**s.

X. Summing up

Although the purchase intention discrepancy is well documented, there does not appear a method addressing its a-priori control at the time of data collection. Available works advocate follow up (ex-post) studies to enhance the experiential value of a survey that was completed, rather than add a discrepancy-reducing practicality to a survey that is currently under way.

The contribution of queuing theory as outlined in this paper also helps to overcome a problem that is part and parcel of existing purchase-intention assessment. The determination and availability of **IBP** avoids the highly subjective practice of adjusting downward purchase-intention survey results by some rule-of- thumb (e.g., 50% of "will definitely purchase" will purchase, etc.). That is, **IBP** provides a quantified basis in describing/assessing a respondent's prospect of being truthful to his/her response (particularly when the response is positive, which is the main source of purchase- intention discrepancy).

The remarkable contribution of consumer databases together with an increasingly viable micro segmentation strategy (particularly for electronic commerce over the Internet, and use of scanner data) makes the step from intention to purchase ever more important. That is, marketers have access to individual consumers that significantly helps to facilitate the estimation of λ and μ, and enhance the use of the queuing approach we offer in this paper.

In summary, queuing and **IBP** descriptions may be a valuable tool to assess a credible versus an unrealizable purchase intention. Such assessments may lead to the elimination of unlikely purchase intentions in advance (i.e., reduce intention gap), and so, improve market forecasts drawn from intention studies, thereby resulting in cost savings in market research and promotion. Queuing models seem to offer potential for this purpose. Furthermore, the versatility of this approach in view of the rich collection of queuing models and the availability of numerous results (i.e., formulae and/or tabulated values) suggests a new and useful application of queuing theory. Therefore, it is hoped that this work will stimulate further research in an area where need for improvement is unquestionably evident. Purchase-intention discrepancy is of serious dimensions, and requires some (a- priori) control and reduction.

REFERENCES

[1] Chatfield, C. and Goodhart G.J., " A Consumer Purchasing Model with Erlang Inter-Purchase Times", Journal of the American Statistical Association, vol. 68, pp. 828-835, 1973.

[2] Cronin, J. and Taylor S., " Measuring Service Quality: A Re-examination and Extension, Journal of Marketing", vol. 56, 1992, pp. 55-58.

[3] Ferber, R. and Priskie R, "Subjective Probabilities and Buying Intentions, Review of Economics and Statistics", vol. 47, 1965, pp. 322-325.

[4] Fisher, R.J., " Social Desirability Bias and Validity of Indirect Questioning, Journal of Consumer Research", vol. 20, 1993, pp. 303-326.

[5] Gupta, S. and Morrison D.G., " Estimating Heterogeneity in Consumers' Purchase Rates", Marketing Science, vol. 10, 1991, pp. 264-269.

[6] Howard, J.A. and Sheth J. N., "A Theory of Buyer Behavior", in Moyer, R. (ed.) "Changing Marketing System", Proceedings of the 1967 Winter Conference of the American Marketing Association AMA, 1967, pp.253-262.

[7] Kalwani, M.U. and Silk A.J., "On the Reliability and Predictive Validity of Purchase Intention Measures", Marketing Science, vol. 1, 1982, pp. 243-287.

[8] Kendall D.G., "Stochastic Processes Occurring in the Theory of Queues and their Analysis by the Method of the Imbedded Markov Chain", Annals of Mathematical Statistics, vol. 24, 1953, pp. 338-354.

[9] Loewenstein, G., and Adler D. A, "Bias in Predictions in Tastes", The Economic Journal, vol. 105, 1995, pp. 929-937.

[10] Mittal, V., and Kamakura W.A., "Satisfaction, Repurchase Intent, and Repurchase Behaviour: Investigating the Moderating Effect of Customer Characteristics", Journal of Marketing Research, vol. 38, 2001, pp. 131-142.

[11] McNeil J., "Federal Programs to Measure Consumer Purchase Expectations, 1946-73: A Post-Mortem", Journal of Consumer Research, December 1974, pp. 1-15.

[12] Morrison D.G., "Purchase Intentions and Purchase Behaviour", Journal of Marketing, vol. 43, 1979, pp. 65-74.

[13] Murray J., "Canadian Consumer Expectations Data: An Evaluation", Journal of Marketing Research, February 1969, p. 60.

[14] Schmittlein, D.C. and Morrison D.G., "Is the Customer Still Active?", American Statistician, vol. 39, 1985, pp. 291-295.

[15] Tull, D.S. and Hawkins D.I., "Marketing Research, Measurement and Method", New York,MacMillan Publishing Company, 1987.