MEASURING CUSTOMER BEHAVIOR AND PROFITABILITY: USING MARKETING ANALYTICS TO EXAMINE CUSTOMER AND MARKETING BEHAVIORAL PATTERNS IN BUSINESS VENTURES

D. Anthony Miles, Texas A&M University-San Antonio

ABSTRACT

Customer activity and turnover is a critical component in measuring profitability and market performance. Understanding customer behavior is a vital in examining firms the marketplace. The purpose of this study is to examine of the use of marketing analytics to measure customer behavior in small business enterprises (SME). The study used three hypotheses to guide the direction of the research. Building on key theoretical concepts grounded in accounting, finance and marketing literature, this study used analytics to measure both customer behavior and firm behavior patterns. This study examined three significant marketing analytics: (a) customer behavior analytics (customer turnover/frequency; velocity of profit/payment for services); (b) marketing behavior analytics (potential of product/services; economic conditions); and economic behavior analytics (pricing adjustment; market barriers). A random sample (N = 198) of businesses were examined for the study. A quantitative methodology was used to examine data collected from the businesses. The results were calculated using a discriminant analysis and a Pearson's Correlation. Based on the results of the study, the marketing behavior analytic proved to be moderately significant in predicting customer behavioral patterns.

INTRODUCTION

Analytics have been used to measure business performance for many years. Analytics have been mostly used in manufacturing firms and related industries. However, using analytics to measure small-to-medium business enterprises (SME) is still relatively new. The use of analytics to examine SMEs is an emerging approach in research. Considering the lack of research on the use of analytics with SMEs, there is a myriad of opportunities for examining their use with firms. Analytics can be tactical or strategic, depending on the level of decision structures they support. They can be real-time, near real-time or batched, depending on the data they process. Analytic queries can be planned or unplanned, repetitive or non-repetitive. Analytics from multiple customer touch points can help optimize customer interactions with the firm by providing a unified view of a customer (Chan, 2006). Using analytics to measure SME performance has been under-researched. Given the lack of history or prior research in using analytics measure SME, there are untapped opportunities to improve firm performance and possibly minimize enterprise risk.

Drawing on insights from the prior use of analytics in manufacturing industries and others, this study examines SMEs with the use of analytics to measure firm activity and performance. This study contributes to the emerging literature and field of analytics. This study attempts to provide a greater insight into how SMEs operate and examine the impact of analytics as an indicator of firm performance. This study contributes to the emerging literature and the field of entrepreneurship. The importance of this research is threefold. First this study fills a gap in the prior studies with respect to explore the use and impact of analytics in entrepreneurship and SME firm performance. Second, although the use of analytics has been common in the manufacturing industries, this study expands on the prior research and literature by examining their use with SMEs across 11 different industries and sectors. Thus we examine SME firm performance with different industries. Lastly, the utilization of analytics with SMEs is to better understand their performance and its implications on how performance can be improved.

This paper is organized in the following format: (a) the first section provides the background of the study; (b) the second section provides the theoretical foundation for the study with a review of the literature; (c) section three discusses the research process with the development of the theoretical model and conceptual model of the study; (d) section four describes the methodology (statistical research design) for the empirical study; and lastly (e) the last section discusses the results and conclusions from the empirical findings and provides the recommendations for future research.

LITERATURE REVIEW

This research is a continuation of the prior work on small-to-medium business SMEs. The researcher wanted to investigate SME market behavior patterns with analytics. There are four sections in this literature review. Due the fact that there are separate sections within the literature, this will provide a strong basis for the study and theory.

Using Analytics and Measuring Business Performance and Activity

The use of data analytics is emerging. It is emerging in such fields as healthcare, which is a key discipline for healthcare finance. The using business intelligence for competitive advantage is strategic for the execution of business strategy (Giniat, 2011). Historically, the use of analytics with credit scores in small-to-medium lending by community banks is surprisingly widespread (Berger, Cowan & Frame, 2010). In addition, the use of analytics can be forward looking with Customer Relationship Management (CRM) strategies. CRM can leverage customer intelligence created by CRM analytics that enhances CRM operations, and conversely, CRM operations collect critical customer data for CRM analytics (Chan, 2005). The use of analytics is critical in talent management. Conventional workforce planning typically utilizes metrics of people, process and production to recommend hire, reduction and development actions (Shen, 2011).

Analytics have also been used with Continuous assurance (CA) as a methodology for the analytic monitoring of corporate business processes Continuous analytic monitoring-based assurance will change the objectives, timing, processes, tools, and outcomes of the assurance process (Vasarhelyi, Alles & Kogan, 2004). The use of in-memory analytics technology can allow operational data to be held in a single database that can handle all the day-to-day customer transactions and updates, as well as analytical requests – in virtually real time (Acker, Gröne, Blockus, & Bange, 2011). In addition to the real gains in performance and speed offered by in-memory analytics, these new systems can significantly, improve the quality of the business and customer intelligence they generate. The new way to make decisions is to base your thinking on numbers: predictive analytics and statistics. Using analytics is the new way to be smart (Ayres, 2007).

The use of metrics in the study of small-business success is important for both researchers and entrepreneurs. Financial performance is the most cited performance metric. The majority of these were in the financial area, with survival, competitive, and "other" variables also being used (Weinzimmer & Manmadhan, 2009). The retail industry has a history of using analytics and metrics. Scientific methods can be applied to the revenue-driving areas of merchandise such as assortment, pricing, placement, and promotion to obtain further insight and make decisions that are more precise. In addition to the four Ps, there are other decision-making areas of the retail business that can benefit from data-driven analytics. These include placement of stores, allocation of labor, and the option to include services such as free shipping, gift-wrapping, or layaway (Harikumar & Nagadevara, 2012).

Some of the world's most successful companies are driving growth by using analytics to analyze data in extraordinary ways (Davenport & Harris, 2007). There is also the use of analytics in human resources (HR). They can redirect the money they spend today on the wrong employee initiatives to more beneficial employee initiatives. HR departments can be held accountable for impacting the bottom-line the same way business or product leaders are held accountable. Managing HR with data is critical (Mondore, Douthitt & Carson, 2011; Pemmaraju, 2007).

Business process analytics advance risk analysis beyond traditional, retrospective activities such as attribution and decomposition studies and allow an actionable, forward-looking perspective (Eicher & Ruder, 2007). In terms of entrepreneurship, it seems that analytic individuals' intentions toward entrepreneurship rely more strongly on their self-efficacy beliefs concerning the planning, marshalling of resources, and implementation stages of the new venture creation process (Kickul, Gundry, Barbosa, & Whitcanack, 2009). The use of analytics in marketing has been a welcomed innovation. For years, marketing departments could not effectively measure the return on investment (ROI) with advertising campaigns. Now with using analytics, it can be measured. As ROI in marketing is in the priority list for many Chief Marketing Officers today across the globe, knowing where, when, how and on whom to spend becomes very critical (Sathyanarayanan, 2012).

Using Analytics in the Field of Marketing

Using analytics to measure business performance has been used for many years. However, using analytics to measure marketing is still relatively new. Analytics can be tactical or strategic, depending on the level of decision structures they support. They can be real-time, near real-time or batched, depending on the data they process. Analytic queries can be planned or unplanned, repetitive or non-repetitive. Analytics from multiple customer touch points can help optimize customer interactions with the firm by providing a unified view of a customer (Chan, 2006). With analytics, data about customer's brand preference, shopping frequency, buying patterns can be effectively captured from various sources like retail outlets, web and survey. Data can then be sliced and diced so as to gain useful insights about customers past, present and future buying behavior (Sathyanarayanan, 2007). In response to the pressure on marketers to demonstrate their value to the firm, there have been several high profile calls for more research in the area of marketing performance measurement (Davenport & Harris, 2007; Farris, et al., 2006).

In many cases, marketing effectiveness is hard to determine for organizations of all sizes: (a) marketing activity has both tangible and intangible effects; (b) marketing activity has both short-term and long-term (future) effects; (c) marketing operates within a volatile and uncontrollable external environment that includes its customers, competitors and legislators; (d) marketing operates within an internal environment which is subject to constraint and change; (e) there is corporate confusion between marketing (the total business process) and the what the marketing department does; and (f) when it comes to available metrics for measuring marketing performance and/or effectiveness, marketers are spoilt for choice (Brooks and Simkin, 2011).

The measurement of marketing performance has been a concern in the field of marketing for decades. In order to represent the current situation of companies about marketing measurement, the research identified the actors that are involved in the process. Furthermore, Azam and Qamar, (2011) they concluded from their study that the agents involved in the development of the measures are mainly from the marketing department, followed by finance, market research agencies, IT staff, external agencies and consultants. In the field of marketing, metrics and analytics have not use as like such fields as accounting, finance and management.

Using Analytics in Others Fields For Measurement

Using analytics and data to make market predictions can be used in four broad analytics generated across organizations: (1) market predictions, (2) customer segments, (3) need and opportunity-focused analytics and (4) customer value analytics (Bailey, Baines, Wilson, & Clark, 2009). Solcansky, Sychrova, and Milichovsky (2011) also argued metrics could be divided into two groups – financial metrics and non-financial metrics. Some companies use Marketing dashboard as the comprehensive set of important tools for internal and external synthesis. Furthermore, financial metrics are used more often than nonfinancial metrics. The importance of justifying marketing investments and the metrics necessary to measure marketing performance thus have taken center stage (Grewal, Iyer, Kamakura, Mehrotra & Sharma, 2008).

Finance and marketing have traditionally been on different pages, talking different languages and unable to establish common goals (See, 2007). Customer analytics helps companies to turn data in to knowledge and provides meaningful insights about customers, their buying pattern, campaign effectiveness and so (Sathyanarayanan, 2010). There is a downside of using metrics. The end result of such assumptions can be an over-reliance on statistical modeling techniques: the use of simplistic models in relation to situations that are highly complex, or a search for spurious precision (Ozimek, 2010).

The use of analytics in marketing has been utilized in different ways to understand profitability: (a) analytics to measure lifetime value of a customer (CLV) is becoming popular (Shih & Liu, 2003); (b) analytics used in measuring customer relationship management (Furness, 2001); (c) customer analytics to measure customer retention (Saubert, 2009); (d) using cluster analytic to measure customer relationship management (Panayides, 2002; Chan 2005; Marsella, Stone & Banks, 2005; Dabija, Abrudan, & Anetta, 2006); and lastly (e) the linkage of customer satisfaction, customer retention, and firm profitability as to why customer satisfaction measurement (CSM) has been a focal point in marketing decision making (Wu, DeSarbo, Chen, & Yi Fu, 2006).

The Emerging Use of Analytics and Metrics in Management Decisions

The use of data analytics is emerging. It is emerging in such fields as healthcare, which is a key discipline for healthcare finance. The using business intelligence for competitive advantage is strategic for the execution of business strategy (Giniat, 2011). Historically, the use of analytics with credit scores in small-to-medium lending by community banks is surprisingly widespread (Berger, Cowan & Frame, 2010). The use of analytics can be forward looking with Customer Relationship Management (CRM) strategies. CRM can leverage customer intelligence created by CRM analytics that enhances CRM operations, and conversely, CRM operations collect critical customer data for CRM analytics (Chan, 2005). The use of analytics is critical in talent management. Conventional workforce planning typically utilizes metrics of people, process and production to recommend hire, reduction and development actions (Shen, 2011).

Analytics have also been used with Continuous assurance (CA) as a methodology for the analytic monitoring of corporate business processes Continuous analytic monitoring-based assurance will change the objectives, timing, processes, tools, and outcomes of the assurance process (Vasarhelyi, Alles & Kogan, 2004). The use of in-memory analytics technology can allow operational data to be held in a single database that can handle all the day-to-day customer transactions and updates, as well as analytical requests – in virtually real time (Acker, Gröne, Blockus, & Bange, 2011). In addition to the real gains in performance and speed offered by in-memory analytics, these new systems can significantly improve the quality of the business and customer intelligence they generate.

The use of metrics in the study of small-business success is important for both researchers and entrepreneurs. Financial performance is the most cited performance metric. The majority of these were in the financial area, with survival, competitive, and "other" variables also being used (Weinzimmer & Manmadhan, 2009). The retail industry has a history of using analytics and metrics. Scientific methods can be applied to the revenue-driving areas of merchandise such as assortment, pricing, placement, and promotion to obtain further insight and make decisions that are more precise. In addition to the four Ps, there are other decision-making areas of the retail business that can benefit from data-driven analytics. These include placement of stores, allocation of labor, and the option to include services such as free shipping, gift-wrapping, or layaway (Harikumar & Nagadevara, 2012).

Some of the world's most successful companies are driving growth by using analytics to analyze data in extraordinary ways (Hodge, 2011; Malik & Naeem, 2011). There is also the use of analytics in human resources (HR). They can redirect the money they spend today on the wrong employee initiatives to more beneficial employee initiatives. HR departments can be held accountable for affecting the bottom-line the same way business or product leaders are held accountable. Managing HR with data is critical (Mondore, Douthitt & Carson, 2011; Pemmaraju, 2007). Business process analytics advance risk analysis beyond traditional, retrospective activities such as attribution and decomposition studies and allow an actionable, forward-looking perspective (Eicher & Ruder, 2007). In terms of entrepreneurship, it seems that analytic individuals' intentions toward entrepreneurship rely more strongly on their self-efficacy beliefs concerning the planning, marshalling of resources, and implementation stages of the new venture creation process (Kickul, Gundry, Barbosa, & Whitcanack, 2009).

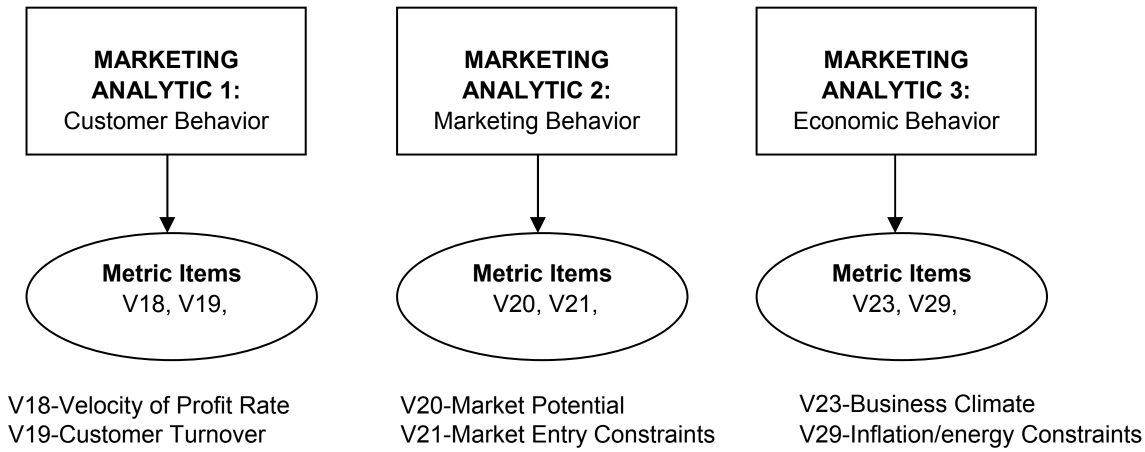
The use of analytics in marketing has been a welcomed innovation. For years, marketing departments could not effectively measure the return on investment (ROI) with advertising campaigns. Now with using analytics, it can be measured. As ROI in marketing is in the priority list for many Chief Marketing Officers today across the globe, knowing where, when, how and on whom to spend becomes very critical (Sathyanarayanan, 2012).

THEORETICAL FRAMEWORK OF THE STUDY

Theoretical Framework Model

In this section, the conceptual relationship between the marketing analytics and variables are displayed. What is illustrated is the three marketing analytics and metrics. The following theoretical model is presented in more detail with the specific variables for the study. The model that follows gives the both the analytics and variables and thus appropriated separated by the three categories (see Figure 1).

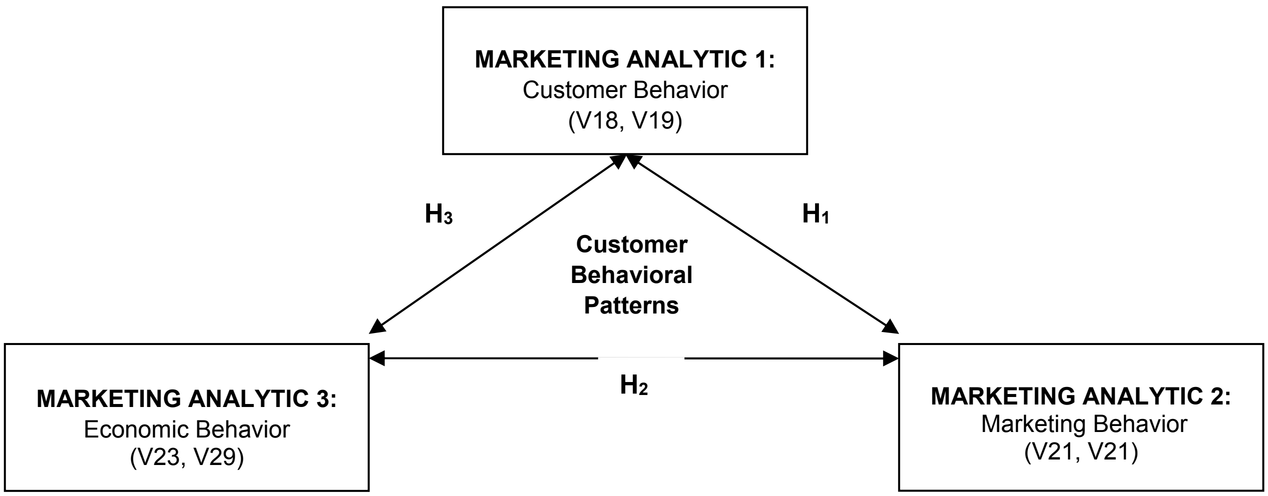
**Figure 1 Theoretical Framework of the Study:
Marketing Analytics and Metric Items**



Conceptual Model of the Study

In this section, the conceptual relationship between the marketing analytics and customer behavior are displayed. In Figure 2 we present our conceptual model of marketing analytics. The model includes three contributors to customer behavioral patterns. These analytics provide a predictor into customer behavior in SMEs. The following theoretical model is presented in more detail with the specific variables for the study. To establish the theoretical model and conceptual model, the researcher tried to meet three criteria: (a) internally, the theory must be logically consistent; (b) must be in agreement with known data and facts; and (c) the theory must be testable; ultimately be subject to empirical evaluation (Jaccard & Jacoby, 2010).

Figure 2 Conceptual Framework Model of the Study:
Marketing Analytics and Their Effect on Customer Behavior Patterns



Theory and Hypotheses

Our first three hypotheses suggest that customer behavior in SMEs is positively influenced by three marketing analytics: (a) customer behavior analytic (V18-Velocity of Profit Rate, V19-Customer Turnover); (b) marketing behavior analytic (V20-Market Potential; V21-Market Entry Constraints); and (c) economic behavior analytic (V23-Business Climate; V29-Inflation/energy Constraints).

The research suggests that an emphasis on some differentiating the effects on customer behavior in SMEs (see Figure 1). It is proposed that these three analytics directly influences customer behavior in SMEs. Accordingly, the following hypotheses are submitted:

H_1: *Customer behavior analytics can positively predict customer behavioral patterns in small business enterprises (SME).*
H_2: *Marketing behavior analytics can positively predict customer behavioral patterns in SMEs.*
H_3: *Economic behavior analytics can positively predict customer behavioral patterns in SMEs.*

In summary, our proposed model consists of the three marketing factor analytics that influence that impact customer behavior. Our three hypotheses suggests those relationships are most critical to the examining the influences on customer behavior in SMEs and the hypothesized relationships.

METHODOLOGY AND STATISTICAL RESERCH DESIGN

Research Design Strategy

This study is an extension of previous research on small business enterprises (SME). The researcher will examine customer behavioral patterns and marketing patterns in SMEs. The study used a *survey research strategy*. First, the study utilized a quantitative approach as a methodology. Second, this study used a *non-experimental, exploratory research design*. Third, the study used a *cross-sectional research design strategy*, which attempts to collect quantifiable or quantitative data with two or more variables.

The researcher made the decision to use a survey research design for the following reasons: (a) typically, survey research is guided by logical constraints (Allen & Yen, 1979; Babbie, 1973; Campbell & Stanley, 1963; Dunn-Rankin et al., 2004); (b) survey research has the tendency to be deterministic, especially when a researcher attempts to explain the reasons for and sources of observed events (Keppel, 1982; Kerlinger,1985); (c) survey research is economical when a researcher can carefully examine the relevance of each variable; and (e) survey research is precise (Afifi & Clark, 1984; Converse, & Presser, 1986)

ANALYSIS

To test our hypotheses, we conducted a discriminant analysis, and regression analysis with the data. It was determined that these were most appropriate for the statistical analysis. We used SAS (Statistical Analysis System) version 9.0 (2011) and SPSS (Statistical Package for Social Sciences) version 17.0, for the analyses. After the data collection was completed, a data-cleaning process was implemented prior to the data analysis. When errors were detected, the original source was located and corrected. The majority of the data-cleaning problems were the following types: (a) data entry or input errors, (b) misspellings, and (c) duplicate or redundancy of input. Other data cleaning issues concerned incomplete surveys. For each equation, the dependent variables were measured with the independent variables.

1) ***Descriptive Statistical Analysis.*** The study used descriptive statistics (mean, median, and standard deviation) to summarize the overall trends in the data and compare the scores (Creswell, 2005). In addition, descriptive statistics were used to compute and assess the general pattern in the data. The following demographic and professional variables were reported from the data: industry type group, and the three analytics groups.
2) ***Inferential Statistical Analysis.*** Inferential statistics were used to make inferences about the data's population based on different analyses (linear regression, discriminate analysis,

correlation). Inferential statistics were employed to draw conclusions about the population based on the representative sample in the study.

Variables: Measurement of Independent and Dependent Variables

Our empirical analysis involves six variables, each measured through self-reported survey items. The survey is primarily based on a 5-point scale, with both an anchor and a middle variable. A Cronbach's alpha was used to determine reliability of the variables in the survey.

Dependent Variables. There are three sets of dependent variables. The three analytics were used as dependent variables to test the three hypotheses in the study: (a) Customer Behavior (Velocity of Profit Rate; Customer Turnover), Economic Behavior (Business Climate; Inflation/Energy Constraints) and (c) Marketing Behavior (Market Potential; Market Entry Constraints).

Independent Variables. A 32-item, multi-item scales, and a 5-point Likert scale were used. Primarily the 5-point point scale was used to measure three marketing analytics (customer behavior, marketing behavior and economic behavior). *Industry type* was used as the independent variable for the study.

1) *Consumer monopoly-type industries.* These are businesses in industries that have little to no competition; monopolistic and have a strong identifiable niche; price is not an important consideration; however value to the consumer is because they are willing to pay the firm's asking price regardless of cost.
2) *Consumer competitive-type industries*. These industries have a few competitors, but are not monopolistic and have strong an identifiable niche in the marketplace. Price is not an important consideration; but market position is important. They have a strong competitive advantage.
3) *Commodity-type industries*. These industries that have an excessive amount of competitors and price is the single most important consideration; examples are textile manufacturers, producers of raw materials such as corn and rice, steel producers, gas and oil companies, lumber industry and paper manufacturers; the product or services in these types of industries do not have any defining characteristics to the consumers.
4) *Semi-commodity type industries.* These are businesses that have a somewhat common product or service that have a fair amount of competitors in the marketplace. Price is somewhat an important characteristic and market position is not important. They do not have a strong competitive advantage (Buffett & Clark, 1997; Buffett & Cunningham, 2001). This study used this framework and taxonomy to classify businesses by market saturation.

These analytics consist of six items (metrics) of the survey questionnaire. The measure model was tested by examining each of the item's significance. For measuring the dependent variables, we measure six variables in the three analytic groups. We used the analytics as three indicators in measuring the three behaviors within the businesses.

RESULTS OF STUDY

The results of the findings are presented. The descriptive statistics of the study's key variables, along with the mean and standard deviations are presented in Tables 1. Table 1 shows the frequency and percentages of the industry types with the firms. Also, the data in Table 1 shows that 45.5% of the businesses were commodity-type businesses. The descriptive statistics for the main analytics and its variables of interest are presented in Tables 2 to 7. Tables 2 to 7 summarizes the results of the cross tabulations in the data. A cross tabulation was conducted with each of the marketing analytics. The industry type and items in the appropriate the analytics.

Table 1: Results: Industry Type by Market Saturation *(N = 198)*

Industry Type Variable	Competitors in Marketplace	Frequency	% of Total
1. Consumer monopoly-type industry	0 – 4	40	20.2
2. Consumer competitive-type industry	5 – 10	39	19.7
3. Semi-commodity-type industry	11 – 20	29	14.6
4. Commodity type-industry/product	21 and higher	90	45.5
Total		**198**	**100.0**

Table 2: Velocity of Profit: How Rapid the Customer Pays for Goods and Services and Rapid the Firm Makes Money in Industry Types *(N = 198)*

		Industry Type					
	Velocity of Profit Metric	**Consumer-Monopoly Type Industry**	**Consumer Competitive Type Industry**	**Semi – Commodity Type Industry**	**Commodity Type Industry**	**Total**	**% of Sample**
V19-Velocity of Profit	Paid immediately	22	15	11	37	85	42.9
	A day or more than 24 hours	0	2	1	10	13	6.6
	Neutral; not sure	3	2	9	5	19	9.6
	A week or more	7	6	4	9	26	13.1
	A month or more (invoicing)	8	14	4	29	55	27.8
	Total	**40**	**39**	**29**	**90**	**198**	**100.0**

Results of Marketing Analytic 1: Customer Behavior and Patterns

Table 3:Customer Turnover Behavior in Business Enterprises Money in Industry Types *(N = 198)*

	Customers Per Day Metric	Consumer-Monopoly Type Industry	Consumer Competitive Type Industry	Semi - Commodity Type Industry	Commodity Type Industry	Total	% of Sample
V19-Customer Turnover	20 or more customers per day	9	10	5	12	36	18.2
	15 or customers per day	3	2	2	8	15	7.6
	Neutral; not sure	4	11	14	20	49	24.7
	10 or less customers per day	5	4	2	6	17	8.6
	5 or less customers per day	19	12	6	44	81	40.9
	Total	**40**	**39**	**29**	**90**	**198**	**100.0**

Results of Marketing Analytic 2: Marketing Behavior and Patterns

Table 4: Market Potential of Product/Services Money in Industry Types *(N = 198)*

	Market Potential Metric	Consumer-Monopoly Type Industry	Consumer Competitive Type Industry	Semi-Commodity Type Industry	Commodity Type Industry	Total	% of Sample
V20-Market Potential	Product/service has existed 6 years or more	25	29	14	79	147	74.2
	Product/service has existed 3 -5 years	5	3	3	5	16	8.1
	Not sure; neutral	3	2	5	3	13	6.6
	Product/service is nearly new; 2 years in existence	0	3	3	3	9	4.5
	New product/service; none exist on the market	7	2	4	0	13	6.6
	Total	**40**	**39**	**29**	**90**	**198**	**100.0**

Table 5: Market Entry Barriers Effect on Business Enterprises Money in Industry Types *(N = 198)*

	Market Entry Metric	Consumer-Monopoly Type Industry	Consumer Competitive Type Industry	Semi-Commodity Type Industry	Commodity Type Industry	Total	% of Sample
V21-Market Entry	Barriers highly unlikely	9	3	3	15	30	15.2
Barriers	Barriers unlikely	7	9	5	17	38	19.2
	Not sure; neutral	3	4	12	9	28	14.1
	Barriers likely	12	11	6	25	54	27.3
	Barriers highly likely	9	12	3	24	48	24.2
	Total	**40**	**39**	**29**	**90**	**198**	**100.0**

Results of Marketing Analytic 3: Economic Behavior and Patterns

Table 6: Economic/Business Climate of Business Enterprises Money in Industry Types *(N = 198)*

	Economic/Business Climate Metric	Consumer-Monopoly Type Industry	Consumer Competitive Type Industry	Semi-Commodity Type Industry	Commodity Type Industry	Total	% of Sample
V23-Business Climate	Highly thriving	16	11	9	23	59	29.8
	Somewhat thriving	13	16	6	33	68	34.3
	Not sure; neutral	9	9	13	26	57	28.8
	Somewhat declining	2	3	1	7	13	6.6
	Highly declining	0	0	0	1	1	.5
	Total	**40**	**39**	**29**	**90**	**198**	**100.0**

Table 7: Business Enterprises: Inflation/Energy Cost Influence on Pricing Controls Money in Industry Types *(N = 198)*

	Inflation/Energy Metric	Consumer-Monopoly Type Industry	Consumer Competitive Type Industry	Semi-Commodity Type Industry	Commodity Type Industry	Total	% of Sample
V29-Inflation/Energy	Can adjust pricing freely	28	20	16	45	109	55.1
	Can adjust pricing with some constraints	9	12	4	30	55	27.8
	Not sure; neutral	2	3	5	4	14	7.1
	Cannot adjust pricing with some constraints	0	1	4	4	9	4.5
	Cannot adjust pricing freely	1	3	0	7	11	5.6
	Total	**40**	**39**	**29**	**90**	**198**	**100.0**

Discriminant Analysis of Customer Behavior and Patterns

A discriminant analysis is a statistical method that is used in predicting to a dichotomous criterion variable; it is a group membership analysis used to distinguish between groups with predefined characteristics (Vogt, 1993). A discriminant analysis has two basic purposes: (1) to describe major differences among groups following a MANOVA analysis; and (2) to classify subjects into groups based on a combination of measures (Stevens, 1992).

The task of conducting the discriminant analysis included using four independent variables that were used in the study. The four independent variables (IV) were industry saturation variables: (a) consumer monopoly-type industry; (b) consumer competitive-type industry, (c) semi-commodity-type industry, and (d) commodity type-industry/product. The six dependent variables (DV) were used for the discriminant analysis as follows: (a) velocity of profit rate, (b) customer turnover, (c) market potential, (d) market entry constraints, (e) business climate, and (f) inflation/energy constraints. When the six variables and their coefficients are combined to create the discriminant score, the analytic will serve as a way to classify the data points.

Discriminant analysis is a mathematical maximization procedure. The goal of the procedure is to find uncorrelated linear combinations of original (predictor) variables that maximize the between-to-within association, as measured by sum-of-squares and cross-products (SSCP) matrix. The logic behind discriminant analysis involves finding the function with the largest eigenvalue-this results in maximum discriminate among groups (Stevens, 1992). The first discriminant function is the linear combination that maximizes the between-to-within association if illustrated by the following equation (Mertler & Vannatta, 2002):

$$DF_1 = a_{10}x_0 + a_{11}x_1 + a_{12}x_1 + a_{11}x_2 + a_{13}x_3 + \ldots + a_{1p}x_p \quad (1.1)$$

Where DF = discriminate function
v = the discriminant coefficient or weight for that variable
x = respondent's score for that variable
a = a constant
i = the number of predictor variables

The second discriminant function is illustrated. The analytic procedure then proceeds to find the second linear combination—uncorrelated with the first linear combination—that serves as the next best separator of groups. This is illustrated by the following equation (Mertler & Vannatta, 2002):

$$DF_2 = \mathrm{a}_{20}\mathrm{x}_0 + a_{21}x_1 + a_{22}x_2 + a_{23}x_3 + a_{24}x_4 + \ldots + a_{2p}x_p \quad (1.2)$$

The third discriminant function is illustrated. It is constructed so that it is uncorrelated with the first two and it serves as the third best separator of the groups (Mertler & Vannatta, 2002):

$$^{r}\, DF_1 \bullet DF_2 = 0 \quad (1.3)$$

For this study, Discriminant Analysis was used to conduct a multivariate analysis of variance test of the hypotheses for the study. The study investigated the possibility of predicting (with a meaningful degree of accuracy) which variables would be significant with industry types and customer behavior. A sample of (N = 198) small business enterprises (SME) were used to measure customer behavioral patterns with three predictive analytics.

Table 8 presents the standardized discriminant function coefficients. Table 8 shows the Wilk's, λ *F* -ratios, degrees of freedom and the significant function. The *F*-test was employed to determine the level of significance of the computed discriminant analysis equation. This is equivalent to *F* ratios (.800 to 8.560) and 3 degrees of freedom (*df*). As a result of the analysis, it was determined the market potential variable is significant, and yielded a significant *F* ratio (F = 8.56; df = 1; and p = .000).

Table 8: Tests of Equality of Group Means Table *(N = 198)*					
Predictor Analytics	**Wilks's λ**	***F***	***df1***	***df2***	***p***
Customer Behavior Analytic					
V18-Velocity of Profit Rate	.967	.819	3	194	.485
V19-Customer Turnover	.971	1.911	3	194	.120
Marketing Behavior Analytic					
V20-Market Potential	.883	8.560	3	194	.000
V21-Market Entry Constraints	.988	.800	3	194	.495
Economic Behavior Analytic					
V23-Business Climate	.985	1.000	3	194	.394
V29-Inflation/energy Constraints	.975	1.679	3	194	.173

Note: CI = confidence interval for odds ratio

Application of the Wilks' Lambda Test

Before the discriminant functions can be generated, it must be ascertained if, indeed, the four industry type groups differ significantly on the across three analytics (six variables). This is a text of equality of industry type groups and is conventionally measured by the Wilks' Lambda statistics. The Wilks's λ was calculated to be from .817 to .980.

The scales do discriminate among the industry types among the variables. Table 9 shows the overall Chi-square test was significant (Wilks λ = .817, Chi-square = 38.838, df = 18, p <. 003; the two functions extracted accounted for nearly 80% of the variance in the analytics, confirming the hypotheses. Table 10 shows the tests of equality between the group means. The table shows the eigenvalues, variances and canonical correlations. Based on the results of the canonical correlations, it shows as highly successful: 71.6% of the cases were correctly reclassified into their original categories.

Table 9: Wilk's Lambda Table and Tests of Functions *(N = 198)*				
Test of Functions	Wilk's Lambda	Chi-square	*df*	*p*
1 through 3	.817	38.838	18	.003
2 through 3	.942	11.486	10	.321
3	.980	3.792	4	.435

Table 10: Eignevalues and Tests of Equality of Group Means *(N = 198)*				
Function	Eigenvalue	% of Variance	Cumulative %	Canoncial Correlation
1	$.153_a$	71.6	71.7	.364
2	$.041_a$	19.1	90.7	.198
3	$.020_a$	9.3	100.0	.140

Note: a. First 3 canonical discriminate functions were used in the analysis.

Discriminant Function Coefficients and Group Centroids Results

Table 11 shows the standardized canonical discriminant function coefficients. The discriminant functions were calculated. The table gives the deriving discriminant function scores from standardized predictors. Table 12 shows the three functions at the group centroids. This indicates the average discriminant score (aka centroid or multivariate mean) for each group on each function.

Table 11:Standardized Canonical Discriminant Function Coefficients			
	Function		
Analytics and Variables	**1**	**2**	**3**
Customer Behavior Analytic			
V18-Velocity of Profit Rate	-.022	.410	-.467
V19-Customer Turnover	-.251	-.594	.393
Marketing Behavior Analytic			
V20-Market Potential	.913	.064	.145
V21-Market Entry Constraints	.022	.041	-.569
Economic Behavior Analytic			
V23-Business Climate	-.217	.394	.364
V29-Inflation/energy Constraints	-.197	.506	.549

Table 12: Functions at Group Centroids			
	Function		
Industry Type	**1**	**2**	**3**
Consumer monopoly-type industry	.391	-.334	-5.39
Consumer competitive-type industry	5.08	.215	-.238
Semi-commodity-type industry	.589	.237	.203
Commodity type-industry/product	-.389	-2.12	6.19

Note: Unstandardized canonical discriminate functions evaluated at group means.

Classification Results of Predicted Group Membership Results

Table 13: Classification Results of Predicted Group Membership

		Predicted Group Membership				
	Group: Industry Type	**Consumer Monopoly-Type Industry**	**Consumer Competitive-Type Industry**	**Semi-Commodity-Type Industry**	**Commodity Type-industry/**	**Total**
Original Count	Consumer monopoly-type industry	4	2	5	29	40
	Consumer competitive-type industry	0	2	5	32	39
	Semi-commodity-type industry	1	1	7	20	29
	Commodity type-industry/product	3	0	2	85	90
%	Consumer monopoly-type industry	10.0	5.0	12.5	72.5	100.0
	Consumer competitive-type industry	.0	5.1	12.8	82.1	100.0
	Semi-commodity-type industry	3.4	3.4	24.1	69.0	100.0
	Commodity type-industry/product	3.3	0	2.2	94.4	100.0
Cross-validated Count	Consumer monopoly-type industry	3	2	6	29	40
	Consumer competitive-type industry	1	0	5	33	39
	Semi-commodity-type industry	2	1	6	20	29
	Commodity type-industry/product	3	0	3	84	90
%	Consumer monopoly-type industry	7.5	5.0	15.0	72.5	100.0
	Consumer competitive-type industry	2.6	.0	12.8	84.5	100.0
	Semi-commodity-type industry	6.9	3.4	20.7	69.0	100.0
	Commodity type-industry/product	3.3	.0	3.3	93.3	100.0

Note: (a) Cross validation is done only for those cases in the analysis in cross validation. Each case is classified by the functions derived from all cases other than that case; (b) 49.5% of original grouped cases correctly classified; and (c) 47.0% of cross-validated grouped cases correctly classified.

Table 13 shows the predicted group membership. The rows represent actual group membership and columns represent predicted group membership. Within each cell, the number and percent of cases correctly classified are shown. For this example, all of the diagonal cells show perfect classification (100.0%).

Correlation Matrix and Results of Study

A Pearson's correlation was used to measure any intercorrelations between the variables in the data. The Pearson's correlation coefficient is used to show a linear relationship between two variables that been measured on an interval or ratio scales (Vogt, 1993). A Pearson correlation analysis was conducted between the variables to be used in the linear regression analyses, namely, Velocity of Profit Rate, Customer Turnover, Market Potential, Market Entry Constraints, Business Climate and Inflation/energy Constraints. This is illustrated by the following equation:

$$r = \frac{\sum XY - \frac{\sum X \sum Y}{N}}{\sqrt{\left(\sum X^2 - \frac{(\sum X)^2}{N}\right)\left(\sum Y^2 - \frac{(\sum Y)^2}{N}\right)}} \tag{1.4}$$

The correlations are presented in Table XX. Notably, the variables that were significantly correlated with the other variables at $p < 0.001$ are illustrated. Of note, the strong intercorrelations were between the variables Business Climate and Customer Turnover. There was a significant correlation (.009).

Table 14: Correlation Matrix of Variables and Means and Standard Deviations *(N = 198)*

Variable	Mean	*SD*	1	2	3	4	5	6
1-Velocity of Profit Rate	2.76	1.727	—					
2-Customer Turnover	3.46	1.524	.179	—				
3-Market Potential	1.61	1.199	-.086	-.112	—			
4-Market Entry Constraints	3.26	1.408	.145	-.067	-.189	—		
5-Business Climate	2.14	.938	-.049	.009	.020	-.066	—	
6-Inflation/energy Constraints	1.78	1.123	.206	-.106	-.038	.217	.053	—

Note: $^*p < 0.001$

DISCUSSION

The primary goal of this research was to assess whether marketing analytics can act as a predictor of customer behavioral patterns in small business enterprises (SME). Our study attempts to provide empirical evidence and theoretical arguments to support the idea that marketing analytics can predict customer, economic, and marketing behavior in SMEs.

In examining the support for our first hypothesis, we tested it with a discriminant analysis. We need to evaluate our results to determine if it supported the first hypothesis. Our first hypothesis suggests that customer behavior analytics can act as a predictor of customer behavioral patterns in small business enterprises (SME). Based on the discriminant analysis, the results do not support Hypothesis 1. As a result of the findings, the Consumer Behavior Analytic (Velocity of Profit; Customer Turnover) was not a significant influence on customer behavior in SMEs. Nor was the analytic a strong predictor variable (p = .582; p = .323). Therefore, the hypothesis could not be supported.

The second hypothesis suggests that marketing behavior analytics acts as a moderate predictor of customer behavioral patterns. In examining the support for the second hypothesis, based on the results of the linear regression analysis, it partially supported Hypothesis 2. As a result of the findings, the Marketing Behavior Analytic (Market Potential; Market Entry Constraints) proved to be a moderate predictor variable (p = .001; p = .879). Therefore, the hypothesis could be supported.

Lastly, the third hypothesis suggests that economic behavior analytics can act as a predictor of customer behavioral patterns. Based on the results analysis, did not support Hypothesis 3. as a result of the findings, the Economic Behavior Analytic (Business Climate; Inflation/energy Constraints) results indicated that it was not a predictor variable (p = .101; p = .076). Therefore, the hypothesis could be supported. In conclusion, our study proved there is a need to conduct more research on marketing analytics. While the results were not positive, this study took an ambitious step in examining customer behavior in SMEs.

CONCLUSIONS AND CRITICAL OBSERVATIONS

The objectives of the study were to determine whether marketing analytics can act as a predictor of customer behavioral pattern. Focusing on the customer behavioral patterns in small business enterprises (SME), we attempted to use three marketing analytics (customer behavior analytics; marketing behavior analytics; and economic behavior analytics) as constructs.

First we applied the development the conceptual models to the examination and review of customer behavior patterns to the data. This type of examination is necessary for the sound development of the three constructs in the customer behavior in SMEs. Furthermore, it would be premature to explore the proposed theoretical model without first maintaining the soundness of the conceptual model, in this case customer behavior. In developing the conceptual model we tried to meet three essential criteria in development of the theory (Jaccard & Jacoby, 2010).

Second, we identified six areas of customer behavior that need further elaboration to advance the theory through development. Our examination concluded that the unique behavioral and social resources of the customers could not be identified. Based on the results of the discriminant analysis, only the marketing behavior analytic proved to be moderately significant. This is a test of equality of the industry type groups and is conventionally measured by the Wilks' lambda statistics. Nevertheless, the scales do discriminate among the industry types among the variables (see Table 9).

Third, to test our hypotheses we conducted a Pearson correlation to investigate intercorrelations with the variables in the marketing analytics. The implication here is that more research needs to be conducted on the analytics and that our results bore little fruit on that. The results also suggest the three analytics will need some development to become better predictors of customer behavior patterns.

These results have a least two implications. First, the research begins to provide some insight on customer behavior in business enterprises. Our study suggests that marketing analytics can moderately predict customer behavior. Second, our results shed some light on the need for refining the use of marketing analytics as a measurement tools for examining customer behavior. Furthermore, more research needs to be done to refine marketing analytics to ensure better measurement of customer behavior patterns.

In summary, this research contributes to the development of a theory of marketing analytics to measure customer behavior. The results of our study make several contributions to the literature. This study adds to the foundation of marketing theory and the potential advantages of using analytics as a measure tool. Although the results were not what we anticipated, this study could be a start in using analytics to measure customer behavior in firms. There is much more that can be investigated in terms of using marketing analytics.

Limitations of Study

As with any research study, this study is not without its share of limitations. The limitations that were an influence on this study were not significant, yet there were challenges. First, the findings of this study are based on a non-experimental design. Because of that, it does not establish the issue of causality between the research variables in the study. This will need to be further developed.

Second, we had time constraints for collecting data and it may have been a limitation to collecting more data. It is possible that we could have collected more data and possibly attained different results. Furthermore, this study may present a limited representation of the target population we were looking for. Third, the findings of this study are based on a self-reported data. Hence, these findings cannot be generalized to other industries, or beyond the geographic scope of this study.

Fourth, we recognize that we had a limited amount of marketing analytics to work with. We are confident that if more analytics were used we could have taken in consideration other variables that have an impact the firms. Nevertheless, the results of our study need to be interpreted with some level of caution. Thus, this study does provide a significant contribution to the body of the prior research in marketing.

Directions for Future Research Opportunities

This study extends our prior studies on small business enterprises (SME). The results of this can possibly lead to future work on marketing analytics. This study could be expanded to determine further firm characteristics with marketing analytics in terms of firm performance. There are many opportunities for future research that could extend beyond the scope of our research.

First, one example is this study could be repeated with modification in order to reexamine the relationship between dependent variables and independent variables in terms of developing more analytics for measurement of firm dynamics. Second, another example would be that future research could examine firm analytics in terms of minority business enterprises and if they are different or more successful than their non-minority, counterparts are. Third, despite the positive findings, it is important that future research extend the work to a larger samples size.

Fourth, a longitudinal study would provide another opportunity and have the added advantage of measuring firms and the analytics over a long period. Fifth, a future research could further examine customer turnover analytic its relationship to firm profitability. Lastly, the results of our study could be expanded to determine what specific types of marketing analytics are more critical to firm dynamics and profitability. In addition, there is room to extend this study to specific sub-demographic populations (women owned businesses, minority owned businesses etc).

REFERENCES

Acker, O., Gröne, F., Blockus, A., & Bange, C. (2011). In-memory analytics - strategies for real-time CRM. *Journal of Database Marketing & Customer Strategy Management*, *18*(2), pp. 129-136. doi:10.1057/dbm.2011.11

Afifi, A. & Clark, V. (1984). *Computer-Aided Multivariate Analysis.* Belmont, CA: Lifetime Learning Publications.

Allen, J. & Yen, W. (1979). *Introduction to Measurement Theory.* Belmont, CA: Wadsworth.

Ambler, T., Kokkinaki, F., & Puntoni, S. (2004). Assessing marketing performance: Reasons for metrics selection. *Journal of Marketing Management*, *20*(3/4), 475-498.

Ayres, I. (2007). *Super Crunchers: Why Thinking By Numbers Is The New Way To Be Smart.* New York: Bantam.

Azam, Z., & Qamar, I. (2011). Quantifying the role of marketing productivity metrics in marketing performance measurement. *Interdisciplinary Journal of Contemporary Research in Business*, *3*(4), 428-440.

Babbie, E. (1973). *Survey Research Methods.* Belmont, CA: Wadsworth Publishing.

Bailey, C., Baines, P. R., Wilson, H., & Clark, M. (2009). Segmentation and customer insight in contemporary services marketing practice: why grouping customers is no longer enough. *Journal of Marketing Management*, *25*(3/4), pp. 227-252.

Bednall, D. (2012). Effective research. *Australasian Journal of Market & Social Research*, 20(1), 8.

Berger, A., Cowan, A., & Frame, W. W. (2011). The surprising use of credit scoring in small business lending by community banks and the attendant effects on credit availability, risk, and profitability. *Journal of Financial Services Research*, 39(1/2), pp. 1-17.doi:10.1007/s10693-010-0088-1

Brooks, N., & Simkin, L. (2011). Measuring marketing effectiveness: An agenda for SMEs. *Marketing Review*, *11*(1), 3-24. doi:10.1362/146934711X565260

Buffett, M. & Clark, D. (1997). *Buffettology.* New York: Rawson Associates.

Buffett, W. & Cunningham, L. (2001). *The Essays of Warren Buffett: Lessons for Corporate America* (2nd ed.). New York: University Press.

Babbie, E. (1973). *Survey Research Methods.* Belmont, CA: Wadsworth Publishing.Carpenter, S. (2012). From cookies to consumers to the bottom line; Understanding and applying concepts. *Advances in Management*, *5*(7), pp. 5-7.

Chan, J. O. (2005). Toward a unified view of customer relationship management. *Journal of American Academy of Business, Cambridge*, *6*(1), 32-38.

Chan, J. O. (2006). A conceptual model for operations-analytics convergence. *Journal of American Academy of Business, Cambridge*, *8*(1), pp. 48-54.

Converse, J. & Presser, S. (1986). *Survey Questions: Handcrafting the Standardized Questionnaire.* Thousand Oaks: Sage.

Dabija, D., Abrudan, I. N., & Anetta, A. (2009). Retail marketing instruments -- an analytic approach. *Young Economists Journal / Revista Tinerilor Economisti*, 785-796.

Dasari, S. & Kurhekar, A. S. (2011). Retail analytics using SAS: Experience of fresh greens Pvt. Ltd., Bangalore. *IUP Journal of Supply Chain Management*, *8*(1), pp. 7-22.

Davenport, T. & Harris, J. (2007). *Competing on Analytics: The New Science of Winning* Boston: Harvard Business School Press.

Dunn-Rankin, P., Knezek, G., Wallace, S. & Zhang, S. (2004). *Scaling Methods* (2nd ed.).Hilllsdale: Erlbaum. Eicher, J., & Ruder, D. (2007). Business process analytics: A new approach to risk. *Journal of Alternative Investments*, *10*(2), pp. 76-84.

Farris, P., Bendle, N., Pfeifer, P., & Reibstein, D. (2006). *The Marketing Metrics: 50+ Metrics Every Executive Should Master.* Upper Saddle River: Wharton School Publishing.

Farzinnia, N., & McCardle, K. F. (2010). Bayesian updating with confounded signals. *Communications in Statistics: Theory & Methods*, *39*(6), pp. 956-972. doi:10.1080/03610920902827299

Furness, P. (2001). Techniques for customer modeling in CRM. *Journal of Financial Services Marketing*, *5*(4), 293.

Giniat, E. J. (2011). Using business intelligence for competitive advantage. *Hfm (Healthcare Financial Management)*, *65*(9), pp. 142-146.

Gnatovich, R. (2007). Making a case for business analytics. *Strategic Finance*, *88*(8), pp. 47-51.

Grewal, D., Iyer, G. R., Kamakura, W. A., Mehrotra, A., & Sharma, A. (2009). Evaluation of subsidiary marketing performance: combining process and outcome performance metrics. *Journal of the Academy Of Marketing Science*, *37*(2), 117-129.

Harikumar, L., & Nagadevara, V. (2012). Analytics: A competitive edge for a retail portal. *Journal of The Academy of Business & Economics*, *12*(1), pp. 43-48.

Hodge, N. (2011). Harnessing analytics. *Financial Management (14719185)*, pp. 26-29. Hill, R. P., & Moran, N. (2011). Social marketing meets interactive media. *International Journal of Advertising*, *30*(5), 815-838. doi:10.2501/IJA-30-5-815-838

Jaccard, J. & Jacoby, J. (2010). *Theory Construction and Model-Building Skills: A Practical Guide for Social Scientists.* New York: The Guilford Press.

Keppel, G. (1982). *Design and Analysis: A Researcher's Handbook* (2nd ed.). Englewood Cliffs, NJ: Prentice-Hall. Kerlinger, F. (1985). *Foundations of Behavioral Research* (3rd ed.). New York: Holt Rinehart and Winston.

Kickul, J., Gundry, L. K., Barbosa, S. D., & Whitcanack, L. (2009). Intuition versus analysis? Testing differential models of cognitive style on entrepreneurial self-efficacy and the new venture creation process. *Entrepreneurship: Theory & Practice*, *33*(2), pp. 439-453. doi:10.1111/j.1540-6520.2009.00298.x

Lee, Y. (2012). A fuzzy analytic network process approach to determining prospective competitive strategy in China: A case study for multinational biotech pharmaceutical enterprises. *Journal of Business Economics & Management*, *13*(1), pp. 5-28. doi:10.3846/16111699.2011.620165

Marsella, A., Stone, M., & Banks, M. (2005). Making customer analytics work for you! *Journal of Targeting, Measurement & Analysis For Marketing*, *13*(4), pp. 299-303.

Mertler, C. & Vannattta, R. (2002). *Advanced and Multivariate Statistical Methods* (2nd ed.) Los Angeles: Pyrczak Publishing.

Miles, D. (2011). *Assessing Business Risk: Development of the Entrepreneurial Risk Assessment Scale*. (University of the Incarnate Word). ProQuest Dissertations and Theses, 231. Retrieved from http://search.proquest.com/docview/854859878?accountid=7058. (854859878).

Mondare, S., Douthitt, S., & Carson, M. (2011). Maximizing the impact and effectiveness of HR analytics to drive business outcomes. *People & Strategy*, 34(2), pp. 20-27.

Ozimek, J. (2010). Issues with statistical forecasting: The problems with climate science – And lessons to be drawn for marketing analytics. *Journal of Database Marketing & Customer Strategy Management*, 17(2), 138-150. doi:10.1057/dbm.2010.12

Panayides, P. M. (2002). Identification of strategic groups using relationship marketing criteria: A cluster analytic approach in professional services. *Service Industries Journal*, *22*(2), 149-166.

Pemmaraju, S. (2007). Converting HR data to business intelligence. *Employment Relations Today (Wiley)*, *34*(3), pp. 13-16. doi:10.1002/ert.20161

Sathyanarayanan, R. S. (2012). Customer analytics -- The genie is in the detail. *Journal of Marketing & Communication*, *7*(3), pp. 28-33.

Saubert, W. M. (2009). Using customer analytics to improve customer retention. *Bank Accounting & Finance (08943958)*, *22*(3), pp. 33-38.

See, E. (2006). Bridging the Finance-Marketing Divide. *Financial Executive*, *23*(6), 50-53.

Shen, K. F. (2011). The analytics of critical talent management. *People & Strategy*, *34*(2), pp. 50-56.

Solcansky, M., Sychrova, L., & Milichovsky, F. (2011). Marketing effectiveness by way of metrics. *Economics & Management*, *16,* 1323-1328.

Stevens, J. (1992). *Applied Multivariate Statistics for the Social Sciences* (2nd ed.) Boston: Allyn and Bacon. Vasarhelyi, M. A., Alles, M. G., Kogan, A., & O'Leary, D. (2004). Principles of analytic monitoring for continuous assurance. *Journal of Emerging Technologies in Accounting*, *1*pp. 1- 21.

Weinzimmer, L. G., & Manmadhan, A. (2009). Small business success metrics: The gap between theory and practice. *International Journal of Business Research*, *9*(7), pp. 166-173.

Wu, J., DeSarbo, W., Chen, P., & Fu, Y. (2006). A latent structure factor analytic approach for customer satisfaction measurement. *Marketing Letters*, *17*(3), pp. 221-238. doi:10.1007/s11002-006-7638-1

Ya-Yeuh, S., & Chung-Yuan, L. (2003). A method for customer lifetime value ranking – Combining the analytic hierarchy process and clustering analysis. *Journal of Database Marketing & Customer Strategy Management*, *11*(2), pp. 159-172.

Zikmund, W. (2003). *Exploring Market Research* (8th ed.) New York: Thomson-Southwestern.

APPENDIX A: USING LINEAR REGRESSION FOR PREDICTIVE ANALYTICS WITH CUSTOMER BEHAVIOR

Linear Regression Predicting Customer Behavior and Patterns

We wanted to further measure the customer behavior patterns to support the discriminant analysis findings. So we used a linear regression to determine the behavioral patterns in the data. The case *with* a reference group will be denoted Linear regression attempts to model the relationship between two variables by fitting a linear equation to observed data (Vogt, 1993). This is illustrated by the following equation:

$$y_i = \beta_1 x_{i1} + \ldots + \beta_p x_{ip} + \varepsilon_i = x_i^{T}\beta + \varepsilon_i, \qquad i = 1,\ldots, n, \qquad (1.5)$$

where ^{T} denotes the transpose, so that $\boldsymbol{x}_i^{T}\boldsymbol{\beta}$ is the inner product between vectors $\boldsymbol{x}_i$ and $\boldsymbol{\beta}$.

The regression analysis was conducted utilizing the six analytic variables (Velocity of Profit Rate, Customer Turnover, Market Potential, Market Entry Constraints, Business Climate, and Inflation/Energy Constraints) as the dependent variables (DV). Industry type was used as the independent variable (IV).

The analytic variables explained a significant portion of variance in relationship with industry types, $R^2 = 0.16$, SE = .066, $p < 0.001$. The variable Market Potential moderately predicted the relationship with industry types, $\beta = 0.39$, t (552), $p = 0.001$. The other analytics variables, Velocity of Profit Rate, Customer Turnover, Market Entry Constraints, Business Climate, and Inflation/Energy Constraints did not significantly predict a relationship with industry types (see Table 15). Table 16 illustrates the logistic regression determinants with the IV (industry types).

Table 15: Linear Regression Determinants for Industry Types *(N = 198)*

Predictor Variables	β	SE	95% CI	*df*	*t*	*R²*	*p*
Customer Behavior Analytic							
V18-Velocity of Profit Rate	.039	.103	.259	1	.552	.002	.582
V19-Customer Turnover	.071	.090	.268	1	.991	.005	.323
Marketing Behavior Analytic							
V20-Market Potential	-.226	.069	-.089	1	-3.254	.051	.001
V21-Market Entry Constraints	.011	.084	.178	1	.152	.000	.879
Economic Behavior Analytic							
V23-Business Climate	.117	.055	.200	1	1.647	.014	.101
V29-Inflation/energy Constraints	.126	.066	.248	1	1.781	.016	.076

Table 16:Linear Regression Determinants for Industry Types *(N = 198)*		
Industry Type Variable	**Rank**	**Log Determinant**
Consumer monopoly-type industry	1	.847
Consumer competitive-type industry	1	.374
Semi-commodity-type industry	1	.830
Commodity type-industry/product	1	-.811
Pooled within-groups	1	.253