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Performance implications of deploying marketing analytics

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ABSTRACT

A few well-documented cases describe how the deployment of marketing analytics produces positive organizational outcomes. However, the deployment of marketing analytics varies widely across firms, and many C-level executives remain skeptical regarding the benefits that they could gain from their marketing analytics efforts. We draw on upper echelons theory and the resource-based view of the firm to develop a conceptual framework that relates the organizational deployment of marketing analytics to firm performance and that also identifies the key antecedents of that deployment. The analysis of a survey of 212 senior executives of *Fortune* 1000 firms demonstrates that firms attain favorable and apparently sustainable performance outcomes through greater use of marketing analytics. The analysis also reveals important moderators: more intense industry competition and more rapidly changing customer preferences increase the positive impact of the deployment of marketing analytics on firm performance. The results are robust to the choice of performance measures, and, on average, a one-unit increase in the degree of deployment (moving a firm at the median or the 50th percentile of deployment to the 65th percentile) on a 1–7 scale is associated with an 8% increase in return on assets. The analysis also demonstrates that support from the top management team, a supportive analytics culture, appropriate data, information technology support, and analytics skills are all necessary for the effective deployment of marketing analytics.

1. Introduction

A recent Google search for "marketing analytics" returned more than 500,000 hits. Marketing analytics, a "technology-enabled and model-supported approach to harness customer and market data to enhance marketing decision making" (Lilien, 2011, p. 5) consists of two types of applications: those that involve their users in a decision support framework and those that do not (i.e., automated marketing analytics). During the past half century, the marketing literature has documented numerous benefits of the use of marketing analytics, including improved decision consistency (e.g., Natter, Mild, Wagner, & Taudes, 2008), explorations of broader decision options (e.g., Sinha & Zoltners, 2001), and an ability to assess the relative impact of decision variables (e.g., Silk & Urban, 1978). The common theme in this literature is the improvement in the overall decision-making process (e.g., Russo & Schoemaker, 1989, p. 137).

Rapid technological and environmental changes have transformed the structure and content of marketing managers' jobs. These changes include (1) pervasive, networked, high-powered information technology (IT) infrastructures, (2) exploding volumes of data, (3) more sophisticated customers, (4) an increase in management's demands for the demonstration of positive returns on marketing investments, and (5) a global, hypercompetitive business environment. In this changing environment, opportunities for the deployment of marketing analytics to increase profitability seemingly should abound. Indeed, an entire stream of research in marketing documents the positive performance implications of deploying marketing analytics (e.g., Hoch & Schkade, 1996; Kannan, Kline Pope, & Jain, 2009; Lodish, Curtis, Ness, & Simpson, 1988; McIntyre, 1982; Natter et al., 2008; Silva-Risso, Bucklin, & Morrison, 1999; Zoltners & Sinha, 2005).

However, there continue to be many skeptics with regard to the "rational analytics approach" to marketing. For example, in a recent interview with one of the authors, a (former) senior executive at one of the world's leading car manufacturers claimed that "…marketing analytics-based results usually raise more questions than they answer," and he asserted that "the use of marketing analytics often slows you down." He also claimed that the "…performance implications of marketing analytics are at best marginal." When we inquired about documentation for his views, he referred us to Peters and Waterman's (1982) highly influential book, *In Search of Excellence*, in which the authors denounce formal analysis because of its abstraction from reality and its tendency to produce "paralysis through analysis" (p. 31). More recently, a study of 587 C-level executives of large international companies revealed that only approximately 10% of the firms regularly employ marketing analytics (McKinsey & Co., 2009). And Kucera and White (2012) note that only 16% of the 160 business

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leaders who responded to their survey reported using predictive analytics, although those users "significantly outpace those that do not in two important marketing performance metrics[3]" (p. 1).

John Little diagnosed the issue more than 40 years ago as follows: "The big problem with … models is that managers practically never use them. There have been a few applications, of course, but the practice is a pallid picture of the promise" (Little, 1970, p. B-466). Revisiting the issue, Little (2004, p. 1858) reports that "The good news is that more managers than ever are using models … what has not changed is organizational inertia." Winer (2000, p. 143) concurs: "My contacts in consumer products firms, banks, advertising agencies and other large firms say that [model builders] are a rare find and that models are not used much internally. Personal experience with member firms of MSI indicates the same."

The low prevalence of marketing analytics use implies that many managers remain unconvinced about the benefits that accrue from that use. In addition, most research studies that document these benefits have focused on isolated firm or business unit "success stories" without systematically exploring performance implications at the firm level. Given the lack of compelling evidence about the performance implications of marketing analytics, the objective of this research is to address two questions: (1) Does widespread deployment[4] of marketing analytics within a firm lead to improved firm performance? and (2) If the answer to (1) is "yes," what leads to the widespread deployment of marketing analytics within firms? With the usual caveats and cautions, particularly with regard to making causal inferences using non-experimental data, we find that the answer to question 1 appears to be "yes" and, hence, the answer to question 2 has high managerial relevance, as well as academic importance.

To address our research questions, we propose a conceptual framework that relies on both the resource-based view (RBV) of the firm (Barney, 1991; Wernerfelt, 1984) and upper echelons theory (Hambrick & Mason, 1984) to model the factors that link marketing analytics deployment to firm performance, as well as the factors that drive the deployment of marketing analytics. We assess the validity and value of that framework with data drawn from a survey of 212 senior executives at *Fortune* 1000 firms, supplemented by secondary source objective performance data for those firms. We find that the deployment of marketing analytics has a greater impact on firm performance when the industry is characterized by strong competition and when customer preferences change frequently in the industry. We also find that top management team (TMT) advocacy and a culture that is supportive of marketing analytics are the keys to enabling a firm to benefit from the use of marketing analytics, and our analyses suggest that the benefits realized by marketing analytics deployment may be sustainable.

We proceed as follows: We first present our conceptual framework and hypotheses and, then, describe our data and our methodology. We then present our findings and discuss their theoretical and managerial implications, as well as the limitations of our research.

2. Conceptual framework

The conceptual framework in Fig. 1 depicts what we refer to as the marketing analytics chain of effects. The framework articulates our predicted relationships, including the hypothesized relationship between the deployment of marketing analytics and firm performance.

We propose that marketing analytics deployment, which we define as the extent to which insights gained from marketing analytics guide and support marketing decision making within the firm, has a positive impact on firm performance. However, this positive impact on firm performance is likely to be moderated by three industry-specific factors: (1) the degree of competition faced by the firm, (2) the rate of change in customer preferences, and (3) the prevalence of marketing analytics use within the industry. Furthermore, we identify TMT advocacy of marketing analytics as a vital antecedent of the deployment of marketing analytics. We suggest that a firm's TMT must not only commit adequate resources in the form of employee analytic skills, data, and IT but also nurture a culture that supports the use of marketing analytics. Such a culture can ensure that the insights gained from marketing analytics are deployed effectively.

In the following section, we first elaborate on the link between the deployment of marketing analytics and firm performance. Next, we consider the antecedents of the deployment of marketing analytics; i.e., the resources and organizational elements that we posit must be in place for marketing analytics to be deployed effectively.

2.1. The performance implications of deploying marketing analytics

A few authors (primarily authors writing for non-academic journals) suggest that the use of marketing analytics can slow firms down, leading to missed market opportunities that are seized by more agile and non-analytics-oriented competition. For example, citing General Colin Powell's leadership primer, Harari (1996, p. 37) suggests that "excessive delays in the name of information-gathering breeds analysis paralysis," which leads to missed opportunities and, hence, subpar firm performance. Peters and Waterman (1982) predict an analogous effect. Additionally, based on our discussions with executives, we conclude that many top managers share similar notions regarding the performance outcomes of marketing analytics use.

However, there are many firm-specific case studies that describe the positive performance impact of marketing analytics use. For example, Elsner, Krafft, and Huchzermeier (2004) demonstrate how Rhenania, a medium-sized German mail order company, used a dynamic, multilevel response modeling system to answer its most important direct marketing questions: When, how often, and to whom should the company mail its catalogs? The model allowed the company to increase its customer base by more than 55% and quadrupled its profitability during the first few years following implementation, and the firm's president asserted that the firm was saved by deploying this model.

Marketing analytics can also significantly improve a firm's ability to identify and assess alternative courses of action. For example, in the 1980s, Marriott Corporation was running out of adequate downtown locations for its new full-service hotels. To maintain growth, Marriott's management planned to locate hotels outside downtown areas to appeal to both business and leisure travelers. A marketing analytics approach called conjoint analysis facilitated the company's design and launch of its highly successful Courtyard by Marriott chain, establish a multibillion dollar business, and create a new product category (Wind, Green, Shifflet, & Scarbrough, 1989).

In another example, Kannan, Kline Pope, and Jain (2009) report how marketing analytics at the National Academies Press (NAP) led to a better understanding of customers and to a better manner of reaching the customers. The NAP was concerned about the best way to price and distribute its books in print and in pdf format via the Internet. It built a pricing model that allowed for both substitution and complementarity effects among the two formats and calibrated the model using a choice modeling experiment. The results permitted the NAP to launch its entire range of digital products with a variable pricing scheme, thereby maximizing the reach of its authors' work.

The common theme of the above firm-specific examples is that the deployment of marketing analytics allows firms to develop and offer

[3] The metrics are "incremental lift from a sales campaign" and "click through rate (for mass campaigns)." Those firms that use customer analytics also report a significantly greater ability to measure customer profitability and lifetime value and are also more likely to have staff dedicated to data mining.

[4] We use the term "deployment" or "to deploy" to mean "to put into use, utilize or arrange for a deliberate purpose," without reference to the financial, human, or technical investment that might be necessary for the enablement of such deployment.

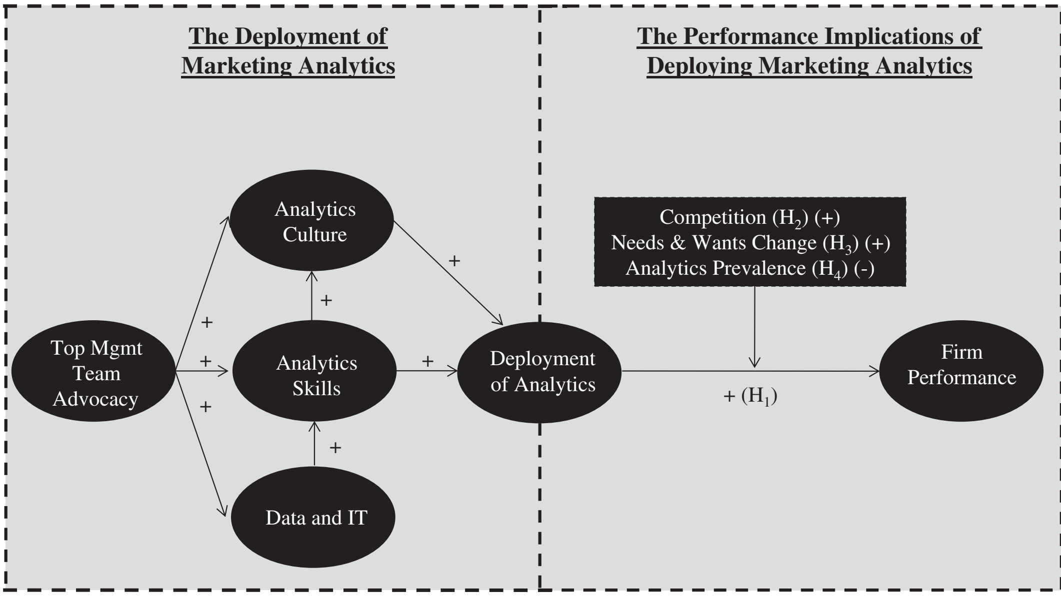


Fig. 1. Conceptual framework.

products and services that are better aligned with customer needs and wants, which, in turn, leads to improved firm performance. Thus, we propose the following main effect:

H1. The greater the deployment of marketing analytics, the better the firm's performance.

2.1.1. Competitive industry structure

Most firms compete with a number of rivals (Debruyne & Reibstein, 2005), although the degree of rivalry varies considerably across industries (DeSarbo, Grewal, & Wind, 2006). The level of competition that a firm faces also has many concomitant effects, including the degree of customer satisfaction that the firm must attain to operate successfully. For example, Anderson and Sullivan (1993) find that firms with less satisfied customers that face less competition perform approximately the same or even better than firms with more satisfied customers that operate in more competitive environments. Thus, firms that confront more competition must strive for higher levels of customer satisfaction to perform well.

Assuming that marketing analytics provide better insights about customer needs, firms in industries with greater competition should earn higher returns (because of more clearly targeted offerings, for example, which result in greater customer satisfaction) than firms in less competitive industries. Thus, we propose:

H2. The more intense the level of competition among industry participants, the greater the positive impact of marketing analytics deployment on firm performance.

We note that if “analysis-paralysis” is a serious concern associated with the deployment of marketing analytics, then the corresponding negative performance implications should be even greater in competitive environments because competitors move more swiftly in such environments (e.g., DeSarbo et al., 2006). Under these circumstances, we should observe a negative interaction between marketing analytics deployment and level of competition (as opposed to our predicted positive interaction).

2.1.2. Customer preference changes

Customer preferences regarding product features, price points, distribution channels, media outlets, and other elements of the marketing mix change over time (e.g., Kotler & Keller, 2006, p. 34). The rate of such change varies: fashions change seasonally, whereas preferences for consumer electronics appear to change almost monthly (e.g., Lamb, Hair, & McDaniel, 2009, p. 58), but preferences regarding construction equipment, hand tools, and agricultural products appear to be much more stable over time.

The more customers' needs fluctuate, the greater is the uncertainty that firms face in making decisions and the more critical scanning and interpreting the changing environment becomes (Daft & Weick, 1984). Marketing analytics offer various means to assist firms in monitoring the pulse of the market and providing early warning of preference changes. Additionally, a stable, predictable environment reduces the need for marketing analytics because such an environment requires a limited number of decision variables to manage for organizational success (Smart & Vertinsky, 1984). Therefore, we propose:

H3. The more rapidly customer preferences change in an industry, the greater the positive impact of the deployment of marketing analytics on firm performance.

2.1.3. Prevalence of marketing analytics use

The prevalence of the use of marketing analytics within an industry may attenuate their positive performance implications. Porter (1996, p. 63) notes that as firms evolve, “staying ahead of rivals gets harder,” partially because of the diffusion of best practices, facilitated, for example, by inputs from strategy consultants. Competitors are quick to imitate successful management techniques, particularly if they promise superior methods of understanding and meeting customers' needs. Such imitation eventually raises the bar for everyone (e.g., Chen, Su, & Tsai, 2007; D'Aveni, 1994; MacMillan, McCaffery, & Van Wijk, 1985). Thus, the greater the overall use of marketing analytics in an industry, the lower is the upside potential for a firm to increase its use. Hence, we propose:

H4. The more prevalent the use of marketing analytics in an industry, the lower is the positive impact of the deployment of marketing analytics on the performance of individual firms in that industry.

To summarize our hypotheses regarding research question #1, we predict that the deployment of marketing analytics has positive performance implications in general[5] and that this effect is even stronger

[5] A concave (downward sloping) response function would admit diminishing returns to deployment and would model a “paralysis of analysis effect”. We report a test for such an effect in Section 4.3.4 and do not find that effect.

in industries characterized by strong competition and in which customer preferences change frequently and weaker in industries in which the deployment of marketing analytics is commonplace.

We next discuss the factors that lead to the deployment of marketing analytics.

2.2. Antecedents of the deployment of marketing analytics

Adapting a resource-based view (RBV—Barney, 1991; Wernerfelt, 1984), Amit and Schoemaker (1993) suggest that firms create competitive advantage by assembling, integrating, and deploying their resources in a manner that allows them to work together to create firm capabilities. Firm capabilities can provide a sustainable competitive advantage when they are protected by isolating mechanisms that thwart competitive imitation (Rumelt, 1984).

Building on the RBV literature, we suggest that marketing analytics must be appropriately assembled and embedded within the fabric of the firm to be deployed effectively, which potentially results in a sustainable competitive advantage. Furthermore, we single out TMT advocacy of marketing analytics as a key driver of that process.

2.2.1. TMT advocacy, analytics culture, and sustainable competitive advantage

According to upper echelons theory (Hambrick & Mason, 1984), organizations are a reflection of their TMT; thus, for marketing analytics to become an integral part of a firm's business routines and, ultimately, its culture, it must be strongly supported by the firm's TMT (Hambrick, 2005).

We posit that a culture that is supportive of marketing analytics is critical for its effective deployment because that culture carries the logic of how and why “things happen” (Deshpande & Webster, 1989, p. 4). These norms are especially important because the person (or organizational unit) that carries out the marketing analytics (e.g., marketing analyst or researcher) frequently is not responsible for implementing the insights gained, namely, executives in marketing and other functions (Carlsson & Turban, 2002; Hoekstra & Verhoef, 2011; Van Bruggen & Wierenga, 2010; Wierenga & van Bruggen, 1997). An analytics culture provides decision makers with a pattern of shared values and beliefs (Deshpande, Farley, & Webster, 1993; Ouchi, 1981), which in turn, should positively influence the degree to which they incorporate the insights gained from marketing analytics in their decisions. Furthermore, culture is sticky, difficult to create, and even more difficult to change (e.g., Schein, 2004), suggesting that it may protect against competitive imitation of a firm's analytics investments, thus delivering sustainable rewards from a firm's marketing analytics investments.

2.2.2. Analytics skills

To deploy marketing analytics within a firm, the firm must also have access to people (either internally or among its partners) who have the knowledge to execute marketing analytics. Thus, the TMT must ensure that people with the requisite marketing analytics skills are present within the company or available outside the firm. We distinguish between technical marketing analytics skills and other individual-level, analytics-based knowledge structures that are tacit (Grant, 1991). Technical marketing analytics skills likely derive primarily from classroom or other structured learning situations and consist of the range of marketing models and related concepts that the analyst could deploy. In contrast, tacit knowledge of marketing analytics includes skills acquired primarily through real-world learning.

We anticipate that higher levels of marketing analytics skills will increase the extent of marketing analytics deployment because people use the tools and skills they understand and with which they are comfortable (Lounsbury, 2001; Westphal, Gulati, & Shortell, 1997). Additionally, better skills should lead to more useful results from using those skills, thus facilitating the organization-wide marketing analytics adoption process. Therefore, a firm's employees' analytics skills should have both a direct, positive impact on the organizational deployment of analytics and an indirect effect on organizational deployment through the positive impact on analytics culture.

2.2.3. Data and IT resources

A firm's physical IT infrastructure and data resources are two other critical tangible assets that the TMT must implement to allow for the effective deployment of marketing analytics. Physical IT resources form the core of a firm's overall IT infrastructure and include computer and communication technologies and shared technical platforms and databases (Ross, Beath, & Goodhue, 1996). Data result from measurements and provide the basis for deriving information and insights from marketing analytics (Lilien & Rangaswamy, 2008). Marketing analytics are often based on vast amounts of customer data (Roberts, Morrison, & Nelson, 2004), which require sophisticated IT resources to effectively obtain, store, manipulate, analyze, and distribute across the firm. Therefore, IT and data are closely related tangible resources, such that one would be significantly less valuable without the other. Building on this mutual dependence, we posit that both IT and data resources are important prerequisites for marketing analytics use.

To summarize our hypotheses regarding research question #2, we propose that TMT advocacy of marketing analytics is an important precursor to the effective deployment of marketing analytics. We further propose that a firm's TMT must not only ensure that employees with the requisite analytics skills and an adequate data and IT infrastructure are in place but also nurture a culture that supports the use of marketing analytics. Such a culture can ensure that the insights gained from marketing analytics are deployed effectively.

3. Data and methods

3.1. Scale development

We adapted existing scales when they were available. However, our study is among the first to empirically explore the performance implications of marketing analytics, and scales for several of our constructs were not available. We developed the missing scales, following a four-phase iterative procedure, as recommended in the literature (Churchill, 1979): First, we independently generated a large pool of items for each of the constructs from an extensive literature review. Second, we engaged fifteen senior-level, highly regarded marketing academics to expand our list of items and evaluate the clarity and appropriateness of each item. Third, we personally administered pretests to six top managers to assess any ambiguity or difficulty that they experienced when responding. Fourth, we conducted a formal pretest with 31 senior managers. Because the fourth stage/pretest revealed no additional concerns, we finalized the scale items, which are listed in Appendix A.[6]

3.2. Data collection procedure

We conducted a mail survey among executives of *Fortune* 1000 firms. We first randomly selected 500 entries from the *Fortune* 1000

[6] We note that we employed single-item measures for some of our constructs. Several researchers have demonstrated that in certain contexts, measures that comprise one item generate excellent psychometric properties (e.g., Bergkvist & Rossiter, 2007; Drolet & Morrison, 2001; Robins, Hendin, & Trzesniewski, 2001; Schimmack & Oishi, 2005). In particular, single-item measures have been found to be very useful when the construct is unambiguous (Wanous, Reichers, & Hudy, 1997). Furthermore, single-item measures are also useful when participants are busy (which certainly applies to top executives) and perhaps dismissive of and/or aggravated by multiple-item measures that, in their view, measure exactly the same construct (Wanous et al., 1997). Such respondent behavior has been found to inflate across-item error term correlation (Drolet & Morrison, 2001). Our pretests revealed that three of our constructs (i.e., competition, needs and wants change, and marketing analytics prevalence) are unambiguous in nature, leading us to employ single-item measures for them.

list and then leveraged the corporate connections of two major U.S. universities to obtain the names of 968 senior executives (primarily alumni) working at these firms.

We addressed these respondents using personalized letters, in which we asked them to complete the survey in reference to either their strategic business unit (SBU) or their company, whichever they felt was more appropriate. We also provided a nominal incentive (1 USD, called a token of thanks, which emerged as the most effective incentive in a pretest). Of the 968 executives contacted, 36 returned the surveys and indicated they were not qualified to respond and 20 surveys were returned because of incorrect addresses. We obtained 212 completed surveys (of the 912 remaining surveys), which yielded an effective response rate of 23.25%. We controlled for possible nonresponse bias by comparing the construct means for early and late respondents (Armstrong & Overton, 1977) but found no significant differences. As we show in Table 1, most (71%) of the respondents in our sample had titles of director or higher, which suggests that they should be knowledgeable about their firms' capabilities and actions.

We also asked the respondents to report their confidence levels with regard to the information they provided (Kumar, Stern, & Anderson, 1993). The sample mean score was 5.59 (out of 7 [SD = .81]), indicating a high level of confidence. Additionally, we received multiple (either two or three) responses from 35 firms/SBUs in our sample, allowing us to cross-check the responses when we received more than one response from a firm.[7,8]

3.3. Scale assessment

We assessed the reliability and validity of our constructs using confirmatory factor analysis (Bagozzi, Yi, & Phillips, 1991; Gerbing & Anderson, 1988). We included all independent and dependent latent variables in one confirmatory factor analysis model, which provided satisfactory fit to the data (comparative fit index [CFI] = .97; root mean square error of approximation [RMSEA] = .05; 90% confidence interval [CI] of RMSEA = [.033; .068]). On the basis of the estimates from this model, we examined the composite reliability and discriminant validity of our constructs (Fornell & Larcker, 1981). All composite reliabilities exceed the recommended threshold value of .6 (Bagozzi & Yi, 1988); the lowest reliability is .75. The coefficient alphas of our constructs are all greater than .7. We also assessed discriminant validity using the criteria proposed by Fornell and Larcker (1981). The results demonstrate that the squared correlation between any two constructs is always lower than the average variance extracted (AVE) for the respective constructs, providing support for discriminant validity. Finally, the correlations between the respective constructs are all significantly different from unity (Gerbing & Anderson, 1988). Overall, the results indicate that our latent constructs demonstrate satisfactory levels of composite reliability and discriminant validity. We present the correlations among the constructs in Table 2 and the AVE and coefficient alphas in the Appendix A along with the scale items.

Although we were able to establish discriminant validity, some of our constructs are highly correlated. For example, the correlation between analytics skills and analytics culture is 0.825. As per our measures, "analytics skills" refer to the type of analytics skills that the employees possess, whereas "analytics culture" indicates shared beliefs with regard to how analytics will influence the company. Although one would expect these two constructs to be highly correlated, we assert that they do not measure the same thing, much in the same manner that a physician who measures a patient's height and weight, two highly correlated items, might argue that height and weight measure different important things and thus both should be measured.

Table 1
Profile of *Fortune* 1000 firm respondents.

Position	Number of participants	Percentage
President, CEO	7	3
EVP, (Sr.) VP, CMO, CFO, COO	78	37
(Sr.) Director, Executive Director	65	31
(Sr.) Marketing Manager	47	22
Other (e.g., Marketing Strategist)	15	7
Total	212	100

3.3.1. Descriptive statistics

Table 3 contains descriptive statistics for our sample firms and indicates that the sample represents a broad range of firms. Table 4 lists the names of some sample firms. In Table 5, we provide the summary statistics and correlations for our variables and, in Table 6, we present histograms for our focal variables. As the histograms show, the sampled firms display a wide range of values for our focal variables. For example, on the seven-point scale measuring TMT advocacy of marketing analytics, approximately 18% of the sample firms fall within the 6–7 range and 16% within the 1–3 range (M = 4.5; SD = 1.7). Furthermore, with regard to analytics culture, approximately 25% of the sample firms fall within the 6–7 range, and approximately 14% score within the 1–3 range (M = 4.6; SD = 1.6). We also asked the respondents (1) whether their marketing analytics applications are designed primarily in-house or by outside experts and (2) whether the primary day-to-day operations of marketing analytics are managed in-house or outsourced. Table 7 presents the responses to these questions and demonstrates that the majority of the *Fortune* 1000 firms design and manage their marketing analytics (applications) in-house. We also make note of the low percentage of respondents who did not know the answer to these questions, another sign that our respondents are quite knowledgeable about the domain under study.

3.4. Conceptual model testing procedures

Our conceptual model proposes both direct and moderating effects (Fig. 1). To model and test these effects simultaneously, we used structural equation modeling (SEM); recent methodological advances have made it feasible to include multiple interactions in a path model (Klein & Moosbrugger, 2000; Marsh, Wen, & Hau, 2004; Muthén & Asparouhov, 2003). We used Mplus Version 6.11 and estimated our model using the full-information maximum likelihood approach (Klein & Moosbrugger, 2000; Muthén & Muthén, 2010, p. 71).

4. Results

4.1. SEM model fit

Fig. 2 summarizes the results of our SEM, depicting two of the three interactions (i.e., competition and needs and wants change) as statistically significant. Because means, variances, and covariances are not sufficient statistics for our SEM estimation approach, our model does not provide the commonly used fit statistics, such as RMSEA and CFI. Instead, in accordance with Muthén (2010), we assessed fit in two steps. First, we re-estimated our SEM without the interaction terms and compared that model with our original model via a chi-square difference test using the associated loglikelihoods (Muthén & Muthén, 2011; Satorra & Bentler, 1999). This test yielded a χ^2 (3) difference of

[7] We received two responses from 33 firms/SBUs and three responses from 2 firms/SBUs. Because we had contacted 968 executives who worked for 500 randomly selected *Fortune* 1,000 firms, we evidently contacted multiple executives working for the same firms/SBUs, which accounts for most of these multiple responses. In a few instances ($n = 5$), executives also invited their coworkers to participate in the survey.

[8] Although this multiple-response sample is too small for a formal multitrait, multimethod assessment, it enabled us to assess whether the respective respondent groups' means for the key constructs were statistically different (e.g., Srinivasan, Lilien, & Rangaswamy, 2002). *T*-tests indicated that none of the means were statistically significantly different from each other.

Table 2
Construct correlations and variances.

Constructs	Correlations					
	1	2	3	4	5	6
1. TMT Advocacy	**1.257**	*0.649*	*0.570*	*0.188*	*0.476*	*0.047*
2. Analytics Culture	**0.806 (0.03)**	**1.677**	*0.681*	*0.176*	*0.543*	*0.033*
3. Marketing Analytics Skills	**0.755 (0.04)**	**0.825 (0.03)**	**2.777**	*0.318*	*0.608*	*0.070*
4. Data and IT	**0.434 (0.07)**	**0.419 (0.07)**	**0.564 (0.06)**	**0.638**	*0.196*	*0.107*
5. Deployment of Analytics	**0.690 (0.05)**	**0.737 (0.04)**	**0.780 (0.03)**	**0.443 (0.06)**	**1.788**	*0.062*
6. Firm Performance	**0.216 (0.07)**	**0.181 (0.08)**	**0.265 (0.07)**	**0.327 (0.08)**	**0.248 (0.07)**	**0.373**

Note: The correlations and their standard errors (provided in brackets underneath) are in bold, the squared correlations are in italics, and the variances are provided on the diagonal.

28.124, which is highly significant ($p<.0001$) which clearly favors the model with interactions. Second, we (re)estimated the model without interactions with the conventional SEM estimation approach to derive the usual model fit statistics (e.g., RMSEA and CFI). This conventional model (without interactions) fits the data quite well (χ^2 (175) = 243; CFI = .97; RMSEA = .04; 90% C.I. = [.03; .06]), and the paths are very similar to those of the moderated model. Based on these results, we conclude that the "un-moderated" model fits the data well and that the moderated model enhances the model fit.

Table 3
Sample firm profiles.

Industry groups	#	%
Services	88	41.5
Manufacturing	65	30.7
Trade	22	10.4
Construction and Mining	7	3.3
Finance and Insurance	30	14.1
Total	212	100
Sales	#	%
<$1 Million	5	2.4
$1 Million to $10 Million	14	6.6
$10 Million to $100 Million	23	10.8
$100 Million to $1 Billion	57	26.9
$1 Billion to $5 Billion	74	34.9
>$5 Billion	39	18.4
Total	**212**	**100**
Number of employees	#	%
0–100	20	9.4
101–1000	37	17.5
1001–10,000	39	18.4
10,001–100,000	60	28.3
100,001–200,000	32	15.1
>200,000	24	11.3
Total	212	100

Note: The profiles pertain to either the strategic business unit (SBU) or the overall company associated with our respondents, depending on which UNIT the respondents selected when completing the survey.

Table 4
Sample firms (partial list).

• IBM	• Kraft Foods
• Honeywell	• FedEx
• American Express	• Sears Holdings
• Marriott International	• JP Morgan Chase
• Raytheon	• UPS
• Capital One	• Deere & Company
• DuPont	• Alcoa
• Hewlett-Packard	• Aramark
• Ford Motor Co	• Citigroup
• Pfizer	• Baxter International
• AT&T	• General Mills
• Xerox	• 3 M
• Johnson & Johnson	• Motorola
• Progressive	• Starbucks
• Boeing	• Verizon
• Amazon.com	• Charles Schwab
• ConAgra Foods	• Dick's Sporting Goods
• Apple	• Harley-Davidson
• Oracle	• Hershey

4.2. Specific model paths and hypothesis test results

All of the paths from TMT advocacy to the respective subsequent latent constructs are positive and significant, suggesting that the TMT plays a key role in establishing an organizational setting in which marketing analytics can be deployed effectively. Additionally, as predicted, an analytics-oriented culture has a positive and significant effect on the deployment of analytics ($\beta = .317$, $p<.01$), in line with our proposition that strengthening a firm's analytics-oriented culture leads to an actual increase in the deployment of marketing analytics. In addition, we find that enhancements to a firm's marketing analytics skills have both a direct and positive impact on the deployment of analytics ($\beta = .427$, $p<.001$) and a positive, indirect effect through analytics culture ($\beta = .120$, $p<.05$). That is, employees' marketing analytics skills directly influence the degree to which the firm uses analytics-based findings in marketing decision making; they also exert an indirect influence by enhancing the organization's analytics-oriented culture. We also find that the presence of a strong data and IT infrastructure promotes marketing analytics skills within the firm ($\beta = .621$, $p<.001$).[9]

As hypothesized in H_1, higher levels of deployment of marketing analytics leads to an increase in firm performance ($\beta = .106$, $p<.01$). Moreover, as hypothesized in H_2, we find a positive and significant deployment of analytics × competition interaction ($\beta = .081$, $p<.05$), which shows that the use of analytics is more effective in more competitive environments than in less competitive environments.[10] Similarly, in support of H_3, the use of analytics is more effective in environments in which customers' needs and wants change frequently ($\beta = .060$, $p<.01$). However, we do not find support for H_4 concerning the analytics × prevalence interaction ($\beta = -.034$, ns).

4.3. Robustness checks

4.3.1. Validity of the performance measure/monomethod bias

Because our independent and dependent measures originate from the same respondents, leading to the possibility of monomethod bias (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003), we collected performance data from independent sources to validate our performance measure. We obtained information on firm-specific net income and total assets for as many firms as possible by retrieving their 10 K and other filings with the U.S. Securities and Exchange Commission

[9] Because data and IT go hand in hand, this may imply an interaction effect between the two in our model. As a robustness check, we added a fourth item to the "Data and IT" construct that captured the interaction between the data and IT items and then reran our model. The results did not change in any substantive way.

[10] The competition variable was skewed to the left. As a robustness check, we reran our analysis, substituting the competition variable with a dummy variable (1 = high competition [survey score of 6 or 7]; 0 = low competition [survey score between 1 and 5]). The results did not change in any substantive way.

Table 5
Correlations and summary statistics.

Variables	Correlations									
	1	2	3	4	5	6	7	8	9	10
1. TMT attitude toward marketing analytics	1.000									
2. Annual reports highlight use of marketing analytics	0.579	1.000								
3. TMT expects quantitative analyses	0.578	0.778	1.000							
4. If we reduce marketing analytics use, profits will suffer	0.379	0.558	0.601	1.000						
5. Confident that use of marketing analytics improves customer satisfaction	0.492	0.641	0.635	0.697	1.000					
6. Most people are skeptical of any kind of analytics-based results (R)	0.401	0.552	0.581	0.676	0.713	1.000				
7. Appropriate marketing analytics tool use	0.497	0.546	0.600	0.630	0.637	0.561	1.000			
8. Master many different marketing analysis tools and techniques	0.466	0.569	0.591	0.648	0.615	0.558	0.837	1.000		
9. Our people can be considered experts in marketing analytics	0.572	0.599	0.642	0.621	0.648	0.637	0.736	0.738	1.000	
10. We have a state-of-art IT infrastructure	0.283	0.281	0.264	0.300	0.331	0.283	0.431	0.343	0.361	1.000
11. We use IT to gain a competitive advantage	0.190	0.230	0.285	0.220	0.180	0.103	0.315	0.312	0.320	0.344
12. In general, we collect more data than our primary competitors	0.269	0.268	0.349	0.326	0.319	0.253	0.432	0.422	0.420	0.392
13. Everyone in our UNIT uses analytics insights to support decisions	0.459	0.537	0.586	0.577	0.624	0.560	0.649	0.639	0.645	0.312
14. We back arguments with analytics based facts	0.404	0.436	0.516	0.460	0.498	0.444	0.586	0.598	0.562	0.234
15. We regularly use analytics in the following areas	0.335	0.550	0.502	0.442	0.598	0.460	0.489	0.517	0.509	0.310
16. Firm performance - total sales growth	0.077	0.007	0.006	0.089	0.124	0.062	0.100	0.149	0.147	0.207
17. Firm performance - profits	0.293	0.150	0.186	0.106	0.113	0.167	0.193	0.203	0.230	0.343
18. Firm performance - return on investment	0.276	0.158	0.182	0.134	0.136	0.216	0.204	0.197	0.236	0.313
19. We face intense competition	−0.060	−0.115	−0.060	−0.058	−0.078	−0.082	−0.050	−0.058	−0.113	−0.042
20. Our customers' needs and wants change frequently	−0.090	−0.083	−0.103	−0.130	−0.172	−0.084	−0.040	−0.057	−0.042	0.051
21. Marketing analytics are used extensively in our industry	−0.052	0.126	0.101	0.069	0.061	0.069	0.014	0.032	0.049	−0.063
22. Size	−0.005	0.017	0.057	0.081	0.084	0.043	0.069	0.067	0.091	0.044
23. Objective ROA (Time 1)	0.278	0.276	0.334	0.168	0.288	0.287	0.320	0.283	0.294	0.056
24. Objective ROA (Time 2)	0.276	0.300	0.270	0.151	0.229	0.244	0.219	0.187	0.258	0.060
Summary statistics										
Mean	3.571	5.029	5.014	4.699	4.714	4.455	3.596	3.790	3.720	4.696
Standard Deviation	1.705	1.506	1.419	1.589	1.511	1.618	1.860	1.704	1.771	1.576

from the EDGAR database. We also consulted COMPUSTAT, Mergent Online and the firms' websites. With these financial data, we computed the respective firm's return on assets (ROA). These procedures yielded financial performance data for 68 of the 212 responses. After matching the time horizon of the performance measures, we computed a 2-year average ROA for the 2 years preceding our primary data collection (see, for example, Boulding, Lee, & Staelin, 1994). We also standardized the ROA measure with respect to each firm's competitors (from Mergent Online).

To address same-source bias, we used the objective performance data (i.e., ROA) to reanalyze our conceptual framework. Given the small sample size and the consequent lack of statistical power ($n=68$), it was not feasible to simultaneously test all of the hypothesized effects of our framework in a single SEM model. Instead, we conducted two separate analyses: first, we used a SEM to estimate the direct (un-moderated) effects in our conceptual framework. Second, we used an ordinary least squares (OLS) regression model to (re) examine the link between deployment of analytics and firm performance and to (re)test H_1–H_4. We substituted the ROA objective performance measure for the perceptual performance measure in both analyses.

The SEM results remain consistent regardless of the use of objective or subjective data; in fact, the link from deployment to performance is even stronger with objective data than with subjective data. We provide the SEM results with objective data in Fig. 3.

We report the regression results with objective data in Table 8 (model 1). We used a simple average of the items measuring deployment of analytics as our deployment construct in that analysis. We repeated the analyses using the factor scores from our SEM for our deployment construct. These two measures were highly correlated (correlation > .94), and none of our inferences were affected by the choice of deployment construct. Overall, the regression model is significant, and our inferences did not change.

In summary, the signs of the SEM and regression model coefficients using objective data are consistent with those obtained using the survey-based data. However, the deployment of analytics × competition interaction did not reach significance in the regression model ($t=1.60$), a result that could be due to the small sample size for the objective data ($n=68$).

4.3.2. Multiple respondents for some firms

As noted, we obtained data from multiple respondents from 35 organizational units. To address potential issues of non-independence among these observations in our data, we averaged the responses of multiple respondents[11] from each firm (e.g., Homburg, Grozdanovic, & Klarmann, 2007) and then re-estimated the SEM using individual responses as if we had only obtained single responses (i.e., the average responses for those organizational units for which we obtained multiple responses). The results remain virtually the same, and our inferences do not change.

4.3.3. Multigroup analysis — B2B vs. B2C

There are many differences between business-to-business (B2B) and business-to-consumer (B2C) firms (see Grewal & Lilien, 2012) that might lead one to expect that there would be differences in the role and impact of marketing analytics within B2B and B2C firms. To assess this possibility, we performed a multigroup confirmatory factor analysis to compare the factor loadings of B2B with B2C firms. To test for partial measurement invariance across groups, we compared a model in which all parameters could be unequal across the two groups with one in which we constrained the factor loadings to be equal. The model with all parameters freely estimated fit the data well (χ^2 (252) = 321.541; CFI = .97; RMSEA = .05), as did the partial invariance model with factor loadings constrained to be equal (χ^2 (270) = 336.227; CFI = .97; RMSEA = .05). Furthermore, the χ^2 difference test indicated that the two models were not statistically significantly different (χ^2 (18) = 14.7, $p=.68$), thereby suggesting that our findings hold across different types of firms.

[11] The t-tests of the key variables across these respondents' reports indicated that the respective means were not statistically different.

11	12	13	14	15	16	17	18	19	20	21	22	23	24
1.000													
0.637	1.000												
0.248	0.352	1.000											
0.205	0.314	0.813	1.000										
0.205	0.354	0.542	0.479	1.000									
0.156	0.206	0.172	0.148	0.174	1.000								
0.218	0.242	0.197	0.172	0.222	0.451	1.000							
0.204	0.193	0.208	0.188	0.181	0.496	0.832	1.000						
−0.034	−0.017	−0.118	−0.154	−0.117	0.018	−0.068	−0.097	1.000					
0.013	0.005	−0.092	−0.060	0.022	0.031	0.020	0.005	0.167	1.000				
0.033	0.117	0.079	0.097	0.115	−0.032	−0.023	−0.011	0.007	0.052	1.000			
0.012	0.007	−0.006	−0.030	−0.024	−0.012	−0.157	−0.162	0.146	0.177	−0.070	1.000		
0.291	0.279	0.342	0.397	0.444	0.275	0.318	0.375	0.061	−0.037	0.177	0.048	1.000	
0.204	0.145	0.347	0.323	0.362	0.217	0.341	0.371	0.082	−0.003	0.230	0.001	0.508	1.000
4.219	4.505	5.241	4.580	5.189	4.839	5.196	5.006	5.422	3.743	3.408	3.561	4.962	4.674
1.755	1.744	1.422	1.383	1.435	1.208	1.268	1.262	1.635	1.966	1.638	1.467	1.541	1.234

4.3.4. Robustness of the deployment to performance link

Our study reveals a statistically significant positive relationship between the deployment of marketing analytics and firm performance (both subjective and objective). This result is of great managerial importance, and, therefore, we subjected this relationship to additional scrutiny via (1) testing for the linearity of this relationship, (2) assessing the effects of various controls, (3) subjecting it to a reverse-causality test, (4) assessing the contemporary vs. carryover effects of deployment on performance, (5) testing for the effects of unobserved heterogeneity, and (6) assessing the unidimensionality of our performance construct. We elaborate on these robustness tests below.

First, we ran an OLS regression model similar to that reported in Table 8 and included a quadratic term to check for curvilinear effects of the deployment of analytics. The squared term was not statistically significant, suggesting the absence of a curvilinear effect, at least within the range of our data.

Second, we included organization size (number of employees) and industry dummy variables as controls in the regression model. Firm size would account for the fact that larger firms could benefit from economies of scale and scope, rendering their use of analytics more effective. Industry dummies would account for differences in industry segments. We used standard industrial classifications to group the sample firms into five categories (see Table 3): services, manufacturing, finance/insurance, trade, and construction/mining. The size and industry dummy variables had neither a main nor a moderating effect on the relationship between deployment of analytics and firm performance, and our inferences did not change. Thus, our results appear robust to firm size and industry segments.

Third, it might be that firms that perform well have more leeway and, hence, more resources to deploy marketing analytics than do those that perform poorly, implying that firm performance may affect the deployment of marketing analytics, and not vice versa. To (at least partially) assess this potential reverse-causality issue, we collected additional objective performance data for the year following our survey. We followed the same procedure as outlined earlier to collect the objective performance data and then calculated the 2-year average ROA using the newly collected data, as well as the data for the year preceding our primary data collection. We then used this new objective performance data to reanalyze our conceptual model. As before, we relied on SEM to estimate the direct (un-moderated) effects in our conceptual model and used OLS regression to examine the link between deployment of marketing analytics and firm performance. We report the SEM results in Fig. 4 and include the regression results in Table 8 (model 2). As the results show, the outcomes did not change in any substantive manner, providing support for the notion that the deployment of marketing analytics is an antecedent of firm performance, not vice versa.

Fourth, to assess the timing of the performance effects of deployment of marketing analytics, we combined the objective performance measures as follows:

$$(\lambda \times \text{Performance}_{\text{Time }1}) + ([1\text{–}\lambda] \times \text{Performance}_{\text{Time }2}),$$

where λ can range from 0 to 1, $\text{Performance}_{\text{Time }1}$ is our initial objective ROA measure and $\text{Performance}_{\text{Time }2}$ is the ROA measure with a 1-year lag. We then re-estimated our OLS regression model, with the resulting linear combination values as the dependent variable (with λ varying in increments of 0.1 from 0 to 1), and assessed which linear combination yields the best fitting model as determined by Adj. R^2. Fig. 5 provides the results of our analyses.

The results reveal that the highest Adj. R^2 occurs when $\lambda = .4$ (this is the maximum likelihood estimate for λ assuming Normal distribution of the error terms of the OLS regression), suggesting that the performance effects of the deployment of analytics appear to be observed both immediately and with a slightly stronger carryover. This finding further discounts the possibility of a reverse-causality effect, with the effects being slightly stronger in *Time 2* than in *Time 1* (A value of $\lambda = .5$ would indicate that the short-term and longer-term effects are the same).

Fifth, we estimated a mixture regression model (DeSarbo & Cron, 1988) to explore the possibility of unobserved heterogeneity among firms. The lowest Bayesian Information Criterion (BIC) emerged for a one-class model (consistent with our multi-group analysis above), which suggests that unobserved heterogeneity was not relevant for our model. Thus, our findings appear to be generalizable to all types of *Fortune* 1000 firms.

Sixth, the correlations among the subjective performance measures (items 16–18 in Table 5) suggest that our performance construct may not be unidimensional: the correlation between profits and return on investment (ROI) is quite high ($r=.832$), whereas the correlations between sales growth and profits ($r=.451$) and sales growth and ROI ($r=.496$) are significantly lower. Therefore, we analyzed the effect of the deployment of analytics on performance with regard to sales growth and profits/ROI separately. In the SEM model, the main effect of the deployment of analytics on performance increased in both instances, i.e., when using only the single-item sales growth measure ($\beta=.171$ vs. .106) and when using the construct comprised of the profits and ROI items ($\beta=.198$ vs. .106). Furthermore, when employing sales growth as the outcome measure, competition no longer emerges as a significant moderator of analytics deployments' effect on performance ($\beta_{\text{deployment} \times \text{competition}}=.063$ vs. .081; the interaction between needs and wants change and deployment of analytics remains marginally significant: $\beta_{\text{deployment} \times \text{needs and wants change}}=.076$ vs. .06). In contrast, both interactions, i.e., competition × deployment of analytics and needs and wants change × deployment of analytics become stronger when including the profits/ROI performance variables in the SEM ($\beta_{\text{deployment x competition}}=.149$ vs. .081 and $\beta_{\text{deployment x needs and wants change}}=.113$ vs. .06). All other paths remain virtually the same in the respective models.

Thus, although the use of marketing analytics appears to positively affect sales growth, profits and ROI, our analysis suggests that the deployment of analytics may have a somewhat stronger effect on profits/ROI than on sales growth. We offer the following possible explanations for this finding: First, many marketing analytics applications are geared toward identifying the most profitable customer segment(s) (e.g., Reinartz & Kumar, 2000), applications designed to improve profits and ROI, as opposed to sales. Second, our sample is drawn from *Fortune* 1000 firms — all large firms — and their scale may prevent them from growing as quickly as smaller firms. Thus, this finding may be specific to our sample and should be explored more broadly.

Table 9 summarizes our robustness checks of the deployment to performance link.

4.3.5. Deployment of analytics as mediator

Our conceptual model assumes that the deployment of analytics mediates the effect of analytics culture and analytics skills on firm performance. To test this assumption, we conducted a formal test of mediation, following the procedure recommended by Baron and Kenny (1986). We used both of the objective performance measures as the respective dependent variables, deployment of analytics as the mediator, and analytics skills or analytics culture as the respective independent variables. Deployment of analytics emerges as a mediator for both independent variables irrespective of the objective performance measure used.

5. Discussion and conclusions

Our research objective was to determine whether the deployment of marketing analytics leads to improved firm performance and to identify the factors that lead firms to deploy marketing analytics. Our findings address these two research objectives and provide insights of value for both marketing theory and practice.

5.1. Theoretical implications

Our study helps explain what drives the adoption of marketing analytics by firms and why that adoption leads to improved firm performance.

We find support for our hypotheses that the positive effect of marketing analytics deployment on firm performance is moderated by the level of competition that a firm faces, as well as by the degree to which the needs and wants of its customers change over time. However, contrary to our hypothesis, the prevalence of marketing analytics use in a given industry does not moderate the effect of marketing analytics on firm performance. We suggest a possible explanation for this (non)result: consistent with McKinsey & Co.'s (2009) findings, the prevalence of marketing analytics use in the industries that we examined is relatively low. That is, the average response of executives who participated in our survey to the statement "marketing analytics are used extensively in our industry" was a 3.4 on a 7-point scale (SD = 1.6). Perhaps the moderating effect of marketing analytics' prevalence does not emerge until the industry-wide use of marketing analytics reaches a higher level than evidenced in our sample. Our data simply may not provide the necessary range to manifest such an effect,[12] an issue we plan to examine in more detail in the future. An alternative explanation for the non-significant interaction could be that competitors cannot compete away a firm's marketing analytics capability that is implemented properly.

We posit and show empirically that a firm's TMT must ensure that the firm (1) employs people with requisite analytics skills, (2) deploys sophisticated IT infrastructure and data, and (3) develops a culture that supports marketing analytics so that the insights gained from marketing analytics can be deployed effectively within the firm.

The people who perform marketing analytics (e.g., marketing analysts) are frequently not those who implement the insights gained from marketing analytics (e.g., marketing executives), but both groups should support the use of marketing analytics if the firm is to possess a strong marketing analytics-oriented culture (Deshpande et al., 1993). Therefore, a suitable analytics culture that promotes the use of marketing analytics is a critical component of our framework. Additionally, the centrality of an analytics culture, which is sticky and difficult to change or replicate, suggests that the deployment of marketing analytics may provide the necessary firm capability properties that can lead to a sustainable competitive advantage (Barney, 1991).

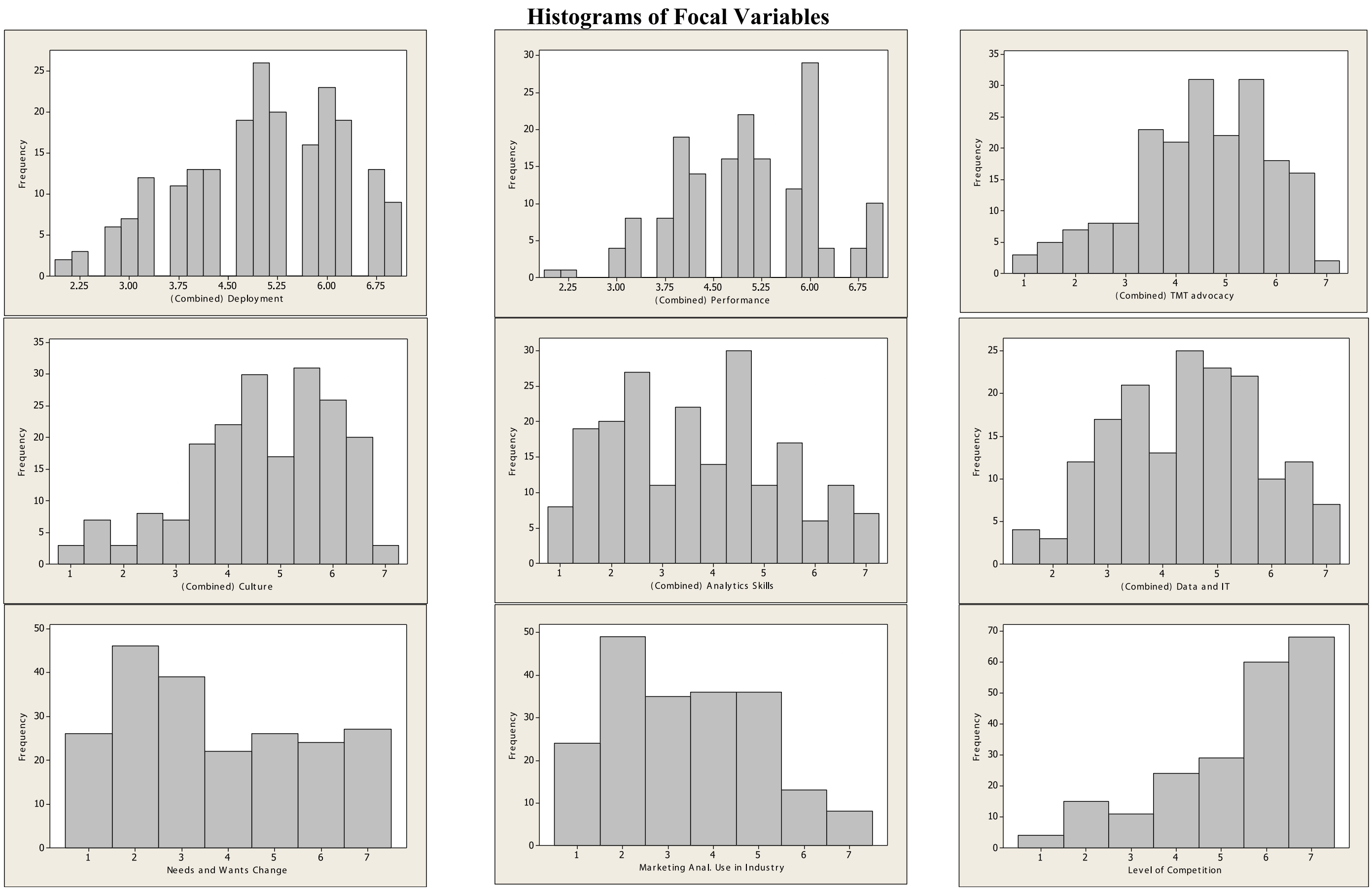
5.2. Managerial implications

Our findings offer several useful implications for managerial practice. First, the low prevalence of marketing analytics use indicates that few managers are convinced of the benefits of marketing analytics. However, our results suggest that most firms can expect favorable performance outcomes from deploying marketing analytics. Moreover, these favorable performance outcomes should be even greater in industries in which competition is high and in which customers change their needs and wants frequently.

The use of objective performance data as the dependent variable in our regression model enables us to quantify the actual performance implications of, for instance, a one-unit increase (on a scale of 1 to 7) in marketing analytics deployment. Consider Firm A in our sample, which is at the median (50th percentile) in deployment of marketing analytics and operates in an industry characterized by *average* competition and *average* changes in customer needs and wants. For Firm A, a one-unit increase in the deployment of marketing analytics is associated with an 8% increase in ROA. Now, consider Firm B in our sample, which is also at the median (50th percentile) deployment of marketing analytics but which operates in *highly competitive* industries with *frequently* changing customer needs and wants. For Firm B, a one-unit increase is associated with a 21% average increase

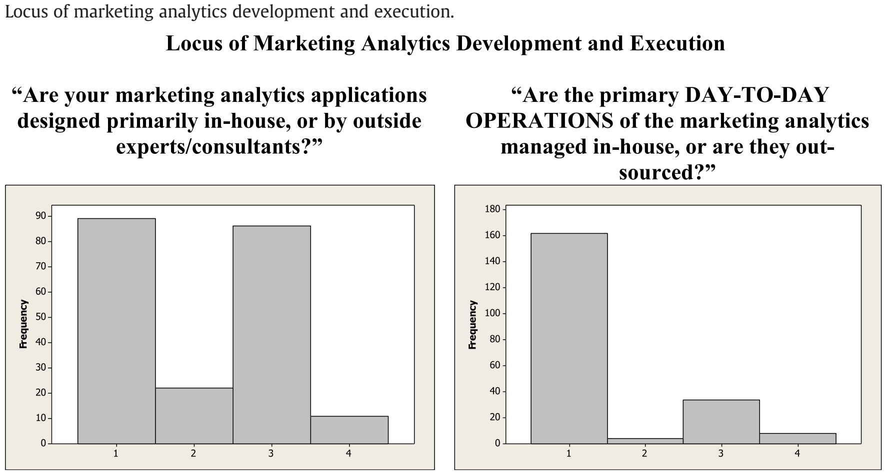
[12] We also examined potential curvilinear effects of marketing analytics prevalence but did not find any such effects.

Table 6
Histograms of focal variables.



Note: (Combined) signifies that the graph reports the average scores of the variables that form the respective latent variables. As the histograms illustrate, the firms in the sample display a wide range of values for our focal variables.

Table 7
Locus of marketing analytics development and execution.



1 = Primarily in-house; 2 = Primarily external; 3 = Combination of in-house and external; 4 = Don't know.

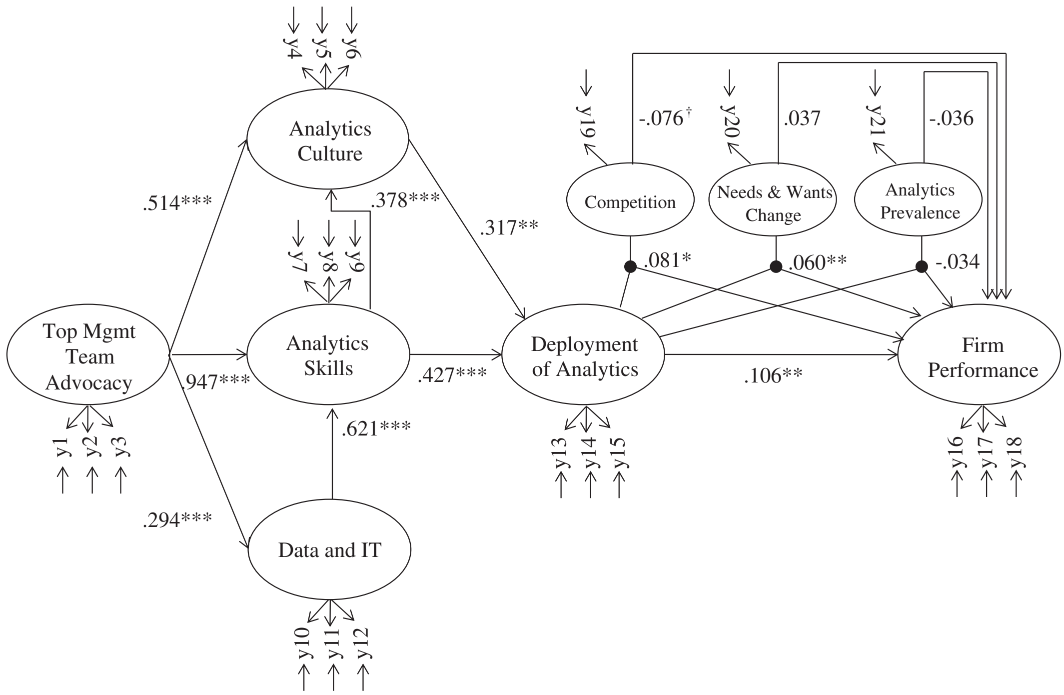


Fig. 2. Structural equation model results. We used full information maximum likelihood to estimate the model; $^{***}t \geq 3.291$, $p < .001$; $^{**}t \geq 2.576$, $p < .01$; $^{*}t \geq 1.96$, $p < .05$; $^{\dagger}t \geq 1.645$, $p < .10$.

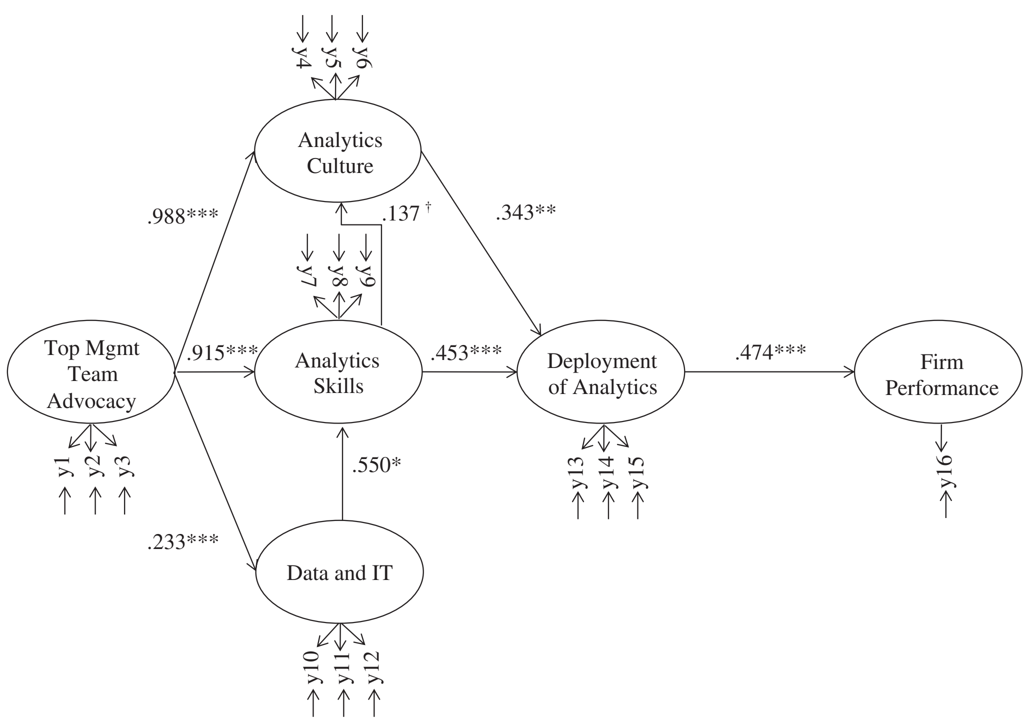


Fig. 3. Structural equation model results using objective ROA (Time 1) as performance measure. Overall, the model fits the data reasonably well; $\chi^2 = 158.153$; CFI = .922; RMSEA = .096, 90% confidence interval of RMSEA = [.068; .123]. $^{***}t \geq 3.291$, $p < .001$; $^{**}t \geq 2.576$, $p < .01$; $^{*}t \geq 1.96$, $p < .05$; $^{\dagger}t \geq 1.645$, $p < .10$.

in ROA.[13] The 8% increase in ROA translates to an expected increase of approximately $70 million in net income for the firms in our sample; the 21% increase indicates an increase of $180 million in net income.[14]

Second, if implemented properly, the use of marketing analytics could be a source of a sustainable competitive advantage for a firm. Our study should aid managers in avoiding what appears to be a common misconception, i.e., that simply hiring marketing analysts who know how to perform marketing analytics will be sufficient for a firm to benefit from marketing analytics. Instead, we find that TMT involvement and a suitable analytics culture that supports the use of marketing analytics (along with the appropriate IT and data infrastructure) are necessary for the firm to see the benefits of greater deployment.

13 Assuming Firm B's ROA is 0.05, a one-unit increase in deployment of analytics should, on average, be associated with an increase in ROA of about 0.01 (i.e., $0.05 \times 1.21 \approx 0.06$).

14 We used our first objective performance measure in this analysis (i.e., the performance measure used in regression 1 in Table 8). The average net income of the firms in our sample was $922 million. We note that we repeated the analysis using our second objective performance measure, and our conclusions did not change in any significant way.

Table 8
The effect of analytics deployment on (objective) firm performance (=DV).

Predictor Variable	Model 1: Objective ROA (Time 1)		Model 2: Objective ROA (Time 2)	
	Parameter estimate	*t*-Value	Parameter estimate	*t*-Value
Main Effects				
Deployment of Analytics	.45**	3.06	.24*	2.08
Needs & Wants Change	.04	.46	.06	.83
Competition	.11	1.09	.10	1.26
Analytics Prevalence	.08	.87	.11	1.43
Interactions				
Depl × Competition	.12	1.60	.11†	1.79
Depl × Needs & Wants Change	.13*	2.15	.13**	2.68
Depl × Prevalence	.03	.46	−0.04	−0.63
Other				
Constant	5.00	29.14	4.75	35.58
R^2	32.5%		36.3%	
Adjusted R^2	24.7%		28.9%	
F-value (7,60)	4.14		4.89	
F-probability	<.001		<.001	

Note: For ease of interpretation, we mean-centered the focal variables (i.e., deployment of analytics, needs and wants change, competition, and analytics prevalence) before creating the interaction terms (Echambadi & Hess, 2007). **$t \geq 2.576$, $p<.01$; *$t \geq 1.96$, $p<.05$; †$t \geq 1.645$, $p<.10$.

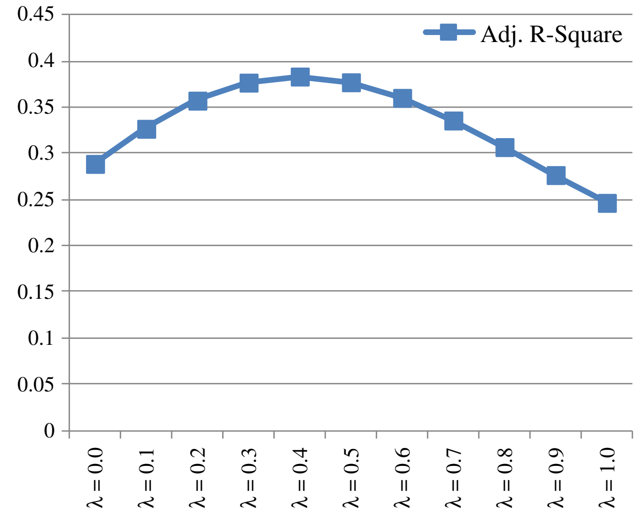


Fig. 5. Contemporary vs. carryover effects on firm performance. This linear combination analysis shows that the highest Adj. R^2 occurs for $\lambda = .4$. This result suggests that the deployment to performance link is strongest with an objective performance variable that gives 40% of the weight ($\lambda = .4$) to contemporary effects on firm performance and 60% to carryover effects.

5.3. Limitations and further research

Although we believe that we have broken new ground with this work, there are clear limitations, several of which provide avenues for future research. First, while our robustness analysis shows that the effects that we report are associated with financial returns, our main measures are attitudinal, not objective. In addition, we do not examine the actual return that a firm could expect from its investments in marketing analytics. Thus, obtaining objective data on the costs and benefits that we measure subjectively in this research would be useful.

Second, our findings are correlational, not causal. For example, we find that a higher level of analytics skills and culture *ceteris paribus* is associated with the deployment of analytics, which in turn, is associated with higher firm performance. However, we cannot make causal claims regarding these relationships. Future research could be based on longitudinal data for a sample of firms to track changes in the precursors of the deployment of marketing

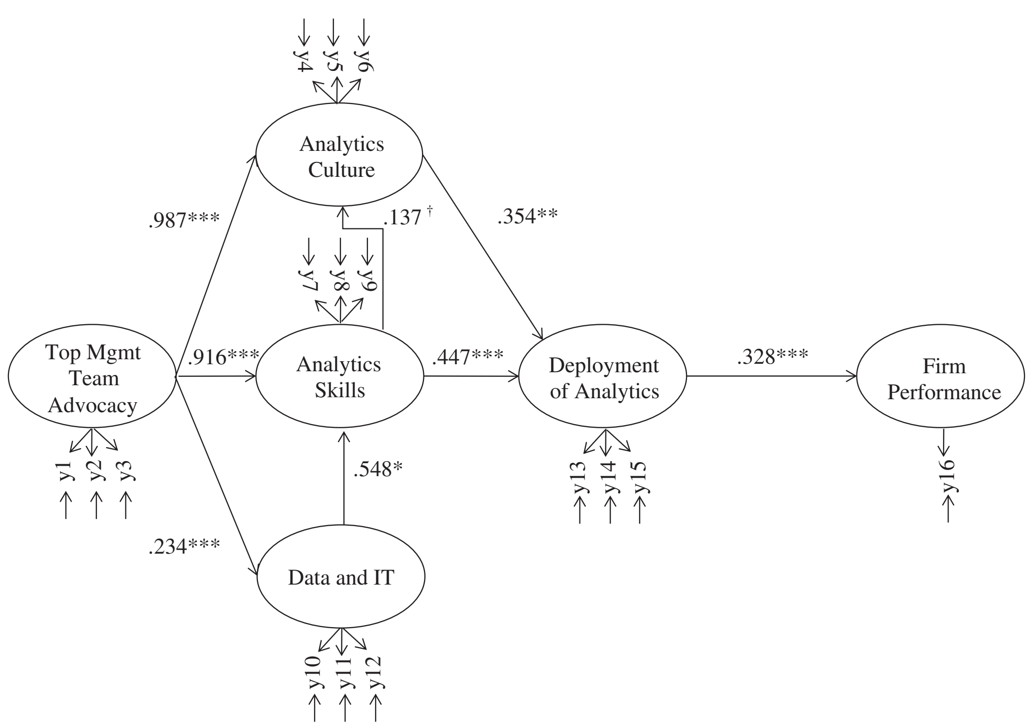


Fig. 4. Structural equation model results using objective ROA (Time 2) as performance measure. Overall, the model fits the data reasonably well; $\chi^2 = 149.744$; CFI = .932; RMSEA = .089, 90% confidence interval of RMSEA = [.060; .117]. ***$t \geq 3.291$, $p<.001$; **$t \geq 2.576$, $p<.01$; *$t \geq 1.96$, $p<.05$; †$t \geq 1.645$, $p<.10$.

Table 9
Robustness of the deployment to performance link.

Model	Parameter estimates and significance levels (two-sided)	Conclusion			
		H1: Deployment of analytics is positively correlated with performance measure (*p*<.05)	H2: The interaction between deployment of analytics and competition is significant (*p*<.05)	H3: The interaction between deployment of analytics and needs and wants change is significant (*p*<.05)	H4: The interaction between deployment of analytics and analytics prevalence is significant (*p*<.05)
OLS regression using objective performance measure (ROA) at Time 1	βDepl. of analytics = .45; *p* = .003 βDepl. of analytics × competition = .12; *p* = .114 βDepl. of analytics × needs and wants change = .13; *p* = .036 βDepl. of analytics × prevalence = .03; *p* = .645	✓		✓	
SEM in which we averaged the responses of multiple respondents of each firm	βDepl. of analytics = .093.; p = .018. βDepl. of analytics × competition = .07; *p* = .033 βDepl. of analytics × needs and wants change = .06; *p* = .012 βDepl. of analytics × prevalance = −.02; *p* = .352	✓	✓	✓	
OLS regression using objective performance measure (ROA) at Time 1 and including quadratic term of deployment of analytics	βDepl. of analytics = .38.; *p* = .016 βDepl. of analytics2 = −.16; *p* = .149 βDepl. of analytics × competition = .08; *p* = .308 βDepl. of analytics × needs and wants change = .14; *p* = .027 βDepl. of analytics × prevalence = .07; *p* = .404	✓		✓	
OLS regression using objective performance measure (ROA) at Time 1 and including control variables	βDepl. of analytics = .42; *p* = .008 βDepl. of analytics × competition = .13; *p* = .113 βDepl. of analytics × needs and wants change = .14; *p* = .040 βDepl. of analytics × prevalence = .02; *p* = .835	✓		✓	
OLS regression using objective performance measure (ROA) at Time 2	βDepl. of analytics = .24; *p* = .042 βDepl. of analytics × competition = .11; *p* = .078 βDepl. of analytics × needs and wants change = .13; *p* = .009 βDepl. of analytics × prevalence = −.04; *p* = .534	✓		✓	
Mixture regression model (one-class model)	βDepl. of analytics = .17; *p* = .011 βDepl. of analytics × competition = .09; *p* = .031 βDepl. of analytics × needs and wants change = .10; *p* = .002 βDepl. of analytics × prevalence = −.03; *p* = .476	✓	✓	✓	
SEM using single-item sales growth measure from survey instrument	βDepl. of analytics = .171; *p* = .016 βDepl. of analytics × competition = .063; *p* = .408 βDepl. of analytics × needs and wants change = .076; *p* = .095 βDepl. of analytics × prevalence = −.032; *p* = .629	✓			
SEM using profit and ROI measures from survey instrument	βDepl. of analytics = .198; *p* = .004 βDepl. of analytics × competition = .149; *p* = .013 βDepl. of analytics × needs and wants change = .113; *p* = .008 βDepl. of analytics × prevalence = −.060.; *p* = .296	✓	✓	✓	

analytics to determine how they affect deployment and how changes in deployment affect firm performance. Such research should be feasible because many firms are still in the early stages of deploying marketing analytics.

Third, our results are based on the overall deployment and impact of marketing analytics. Additional research is needed to understand the performance implications associated with different types of analytics (e.g., embedded automated models vs. interactive decision support), as well as from various aspects of analytics implementation, such as the nature of the decisions/actions supported by analytics (e.g., segmentation, targeting, forecasting, pricing, sales), and the penetration of marketing analytics into non-marketing decisions and actions.

Fourth, our results are based on and limited to very large U.S. firms. Extending this work to other geographies and to the much larger universe of medium-sized and small firms would be useful.

Despite these limitations, we believe that beyond their theoretical interest, our framework and findings should prove useful for managers who are seeking a framework that will aid them in deploying their marketing analytics investments most effectively. Our results also provide a bit of a cautionary tale: Without TMT advocacy and support, the necessary investments in data, analytic skills, and a supportive analytics culture are unlikely to occur. We hope that the modest step we have taken here to address the performance implications of marketing analytics will prove provocative and spawn additional research in this important area.

Appendix A. Scale Items

Measure	Items
Top management team advocacy	1. Our top management has a favorable attitude towards marketing analytics.
$\alpha = .84$	2. Our annual reports and other publications highlight our use of analytics as a core competitive advantage.
Average variance extracted (AVE) = 0.659	3. Our top management expects quantitative analysis to support important marketing decisions.
Analytics culture	4. If we reduce our marketing analytics activities, our UNIT's profits will suffer.
$\alpha = .87$	5. We are confident that the use of marketing analytics improves our ability to satisfy our customers.
AVE = 0.692	6. Most people in my unit are skeptical of any kind of analytics-based results (R).
Marketing analytics skills	7. Our people are very good at identifying and employing the appropriate marketing analysis tool given the problem at hand.
$\alpha = .90$	
AVE = 0.777	8. Our people master many different quantitative marketing analysis tools and techniques.
	9. Our people can be considered as experts in marketing analytics.
Data and IT	10. We have a state-of-art IT infrastructure.
$\alpha = 0.72$	11. We use IT to gain a competitive advantage.
AVE = 0.503	12. In general, we collect more data than our primary competitors.
Deployment of analytics	13. Virtually everyone in our UNIT uses analytics based insights to support decisions.
$\alpha = .82$	14. In our strategy meetings, we back arguments with analytics based facts.
AVE = 0.657	15. We regularly use analytics to support decisions in the following areas (average score across 12 areas to choose from [pricing, promotion and discount management, sales-force planning, segmentation, targeting, product positioning, developing annual budgets, advertising, marketing mix allocation, new product development, long-term strategic planning, sales forecasting] + 2 open ended areas).
Firm performance	Please circle the number that most accurately describes the performance of your UNIT in the following areas relative to your average competitor (1 = well below our competition; 7 = well above our competition) Please consider the immediate past year in responding to these items.
$\alpha = .81$	
AVE = 0.639	
	16. Total Sales Growth.
	17. Profit.
	18. Return on Investment.
Competition	19. We face intense competition.
Needs and wants change	20. Our customers are fickle—their needs and wants change frequently
Industry prevalence	21. Marketing analytics are used extensively in our industry.

References

Amit, R., & Schoemaker, P. (1993). Strategic assets and organizational rent. *Strategic Management Journal*, *14*(1), 33–46.

Anderson, E. W., & Sullivan, M. W. (1993). The antecedents and consequences of customer satisfaction for firms. *Marketing Science*, *12*(2), 125–143.

Armstrong, J. S., & Overton, T. S. (1977). Estimating non-response bias in mail surveys. *Journal of Marketing Research*, *14*(3), 396–402.

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science*, *16*(1), 74–94.

Bagozzi, R. P., Yi, Y., & Phillips, L. W. (1991). Assessing construct validity in organizational research. *Administrative Science Quarterly*, *36*(3), 421–458.

Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99–120.

Baron, R. M., & Kenny, D. A. (1986). Moderator–mediator variables distinction in social psychological research: conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *51*(6), 1173–1182.

Bergkvist, L., & Rossiter, J. R. (2007). The predictive validity of multiple-item versus single-item measures of the same constructs. *Journal of Marketing Research*, *44*(3), 175–184.

Boulding, W., Lee, E., & Staelin, R. (1994). Mastering the mix: Do advertising promotion, and sales force activities lead to differentiation? *Journal of Marketing Research*, *31*(2), 159–172.

Carlsson, C., & Turban, E. (2002). DSS: Directions for the next decade. *Decision Support Systems*, *33*(2), 105–110.

Chen, M. J., Su, K. H., & Tsai, W. (2007). Competitive tension: The awareness-motivation-capability perspective. *Academy of Management Journal*, *50*(1), 101–118.

Churchill, G. A., Jr. (1979). A paradigm for developing better measures of marketing constructs. *Journal of Marketing Research*, *16*(1), 64–73.

D'Aveni, R. (1994). *Hypercompetition: Managing the dynamics of strategic maneuvering.* New York: The Free Press.

Daft, R. L., & Weick, K. E. (1984). Toward a model of organizations as interpretation systems. *Academy of Management Review*, *9*(2), 284–295.

Debruyne, M., & Reibstein, D. J. (2005). Competitor see, competitor do: Incumbent entry in new market niches. *Marketing Science*, *24*(1), 55–66.

DeSarbo, W., & Cron, W. L. (1988). A maximum likelihood methodology for clusterwise linear regression. *Journal of Classification*, *5*(2), 249–282.

DeSarbo, W., Grewal, R., & Wind, J. (2006). Who competes with whom? A demand-based perspective for identifying and representing asymmetric competition. *Strategic Management Journal*, *27*(2), 101–129.

Deshpande, R., Farley, J. U., & Webster, F. E. (1993). Corporate culture, customer orientation, and innovativeness in Japanese firms: A quadrad analysis. *Journal of Marketing*, *57*(1), 23–37.

Deshpande, R., & Webster, F. E., Jr. (1989). Organizational culture and marketing: Defining the research agenda. *Journal of Marketing*, *53*(1), 3–15.

Drolet, A. L., & Morrison, D. G. (2001). Do we really need multiple-item measures in service research? *Journal of Service Research*, *3*(3), 196–204.

Echambadi, R., & Hess, J. D. (2007). Mean-centering does not alleviate collinearity problems in moderated multiple regression models. *Marketing Science*, *26*(3), 438–445.

Elsner, R., Krafft, M., & Huchzermeier, A. (2004). Optimizing Rhenania's direct marketing business through dynamic multilevel modeling (DMLM) in a multicatalog-brand environment. *Marketing Science*, *23*(2), 192–206.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50.

Gerbing, D. W., & Anderson, J. C. (1988). An updated paradigm for scale development incorporating unidimensionality and its assessment. *Journal of Marketing Research*, *25*(2), 186–192.

Grant, R. M. (1991). The resource-based theory of competitive advantage. *California Management Review*, *33*(3), 114–135.

Grewal, R., & Lilien, G. L. (2012). Business-to-business marketing: Looking back, looking forward. In G. L. Lilien, & R. Grewal (Eds.), *Handbook of business-to-business marketing* (pp. 3–14). Northhampton: Edward Elgar Press.

Hambrick, D. C. (2005). Upper echelons theory: Origins, twists and turns, and lessons learned. In K. G. Smith, & M. A. Hitt (Eds.), *Great minds in management: The process of theory development*. New York: Oxford University Press.

Hambrick, D. C., & Mason, P. A. (1984). Upper echelons: The organization as a reflection of its top managers. *Academy of Management Review*, *9*(2), 193–206.

Harari, O. (1996). Quotations from Chairman Powell: A leadership primer. *Management Review*, *84*(12), 34–37.

Hoch, S. J., & Schkade, D. A. (1996). A psychological approach to decision support systems. *Management Science*, *42*(1), 51–65.

Hoekstra, J. C., & Verhoef, P. C. (2011). *The customer intelligence — Marketing interface: Its effect on firm performance. working draft.*

Homburg, C., Grozdanovic, M., & Klarmann, M. (2007). Responsiveness to customers and competitors: The role of affective and cognitive organizational systems. *Journal of Marketing*, *71*(3), 18–38.

Kannan, P. K., Kline Pope, B., & Jain, S. (2009). Pricing digital content product lines: A model and application for the National Academies Press. *Marketing Science*, *28*(4), 620–638.

Klein, A., & Moosbrugger, H. (2000). Maximum likelihood estimation of latent interaction effects with the LMS method. *Psychometrika*, *65*(4), 457–474.

Kotler, P., & Keller, K. L. (2006). *Marketing management* (12th ed.). Upper Saddle River: Pearson Prentice Hall.

Kucera, T., & White, D. (2012). *Predictive analytics for sales and marketing: Seeing around corners.* Aberdeen Group Research Brief (www.aberdeen.com)

Kumar, N., Stern, L. W., & Anderson, J. C. (1993). Conducting interorganizational research using key informants. *Academy of Management Journal*, *36*(6), 1633–1651.

Lamb, C., Hair, J. F., Jr., & McDaniel, C. (2009). *Marketing 3.0.* Mason: Thomson/South-Western.

Lilien, G. L. (2011). Bridging the academic–practitioner divide in marketing decision models. *Journal of Marketing*, *75*(4), 196–210.

Lilien, G. L., & Rangaswamy, A. (2008). Marketing engineering: Connecting models with practice. In Berend Wierenga (Ed.), *Handbook of marketing decision models* (pp. 527–560). New York: Elsevier.

Little, J. D. (1970). Models and managers: The concept of a decision calculus. *Management Science*, *16*(8), B466–B486.

Little, J. D. (2004). Comments on models and managers: The concept of a decision calculus. *Management Science*, *50*(12), 1841–1861.

Lodish, L. M., Curtis, E., Ness, M., & Simpson, M. K. (1988). Sales force sizing and deployment using a decision calculus model at Syntex Laboratories. *Interfaces*, *18*(1), 5–20.

Lounsbury, M. (2001). Institutional sources of practice variation: Staffing college and university recycling programs. *Administrative Science Quarterly*, *46*(1), 29–56.

MacMillan, I. C., McCaffery, M. L., & Van Wijk, G. (1985). Competitors' responses to easily imitated new products—Exploring commercial banking product introductions. *Strategic Management Journal*, *6*(1), 75–86.

Marsh, H. W., Wen, Z., & Hau, K. -T. (2004). Structural equation models of latent interactions: Evaluation of alternative estimation strategies and indicator construction. *Psychological Methods*, *9*(3), 275–300.

McIntyre, S. H. (1982). An experimental study of the impact of judgment-based marketing models. *Management Science*, *28*(1), 17–33.

McKinsey & Co. (2009). McKinsey global survey results: Measuring marketing. *McKinsey Quarterly*, 1–8.

Muthén, B. O. (2010). Mplus discussion — Comment on how to evaluate the fit of a SEM with interaction, posted October 26, 2010 (accessed July 2011). available at http://www.statmodel.com/discussion/messages/11/385.html?1309276920

Muthén, B. O., & Asparouhov, T. (2003). *Modeling interactions between latent and observed continuous variables using maximum-likelihood estimation in Mplus.* Mplus web notes: No. 6.

Muthén, L. K., & Muthén, B. O. (2010). *Mplus user's guide* (6th ed.). Los Angeles: Muthén & Muthén.

Muthén, L. K., & Muthén, B. O. (2011). Chi-square difference testing using the Satorra-Bentler scaled chi-square. (Accessed July 2011). available at http://www.statmodel.com/chidiff.shtml

Natter, M., Mild, A., Wagner, U., & Taudes, A. (2008). Planning new tariffs at tele.ring: The application and impact of an integrated segmentation targeting, and positioning tool. *Marketing Science*, *27*(4), 600–611.

Ouchi, W. G. (1981). *Theory Z.* Reading: Addison-Wesley Publishing Company.

Peters, T. J., & Waterman, R. H. (1982). *In Search of Excellence.* New York: Harper & Row.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. -Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903.

Porter, M. E. (1996). What Is Strategy? *Harvard Business Review*, 61–78.

Reinartz, W., & Kumar, V. (2000). On the profitability of long lifetime customers: An empirical investigation and implications for marketing. *Journal of Marketing*, *64*(3), 17–32.

Roberts, J., Morrison, P., & Nelson, C. (2004). Implementing a pre-launch diffusion model: Measurement and management challenges of the Telstra switching study. *Marketing Science*, *23*(2), 180–191.

Robins, R. W., Hendin, H. M., & Trzesniewski, K. H. (2001). Measuring global self-esteem: Construct validation of a single-item measure and the Rosenberg self-esteem scale. *Personality and Social Psychology Bulletin*, *27*(2), 151–161.

Ross, J. W., Beath, C. M., & Goodhue, D. L. (1996). Develop long-term competitiveness through IT assets. *Sloan Management Review*, *38*(1), 31–45.

Rumelt, R. P. (1984). Towards a strategic theory of the firm. In R. Lamb (Ed.), *Competitive strategic management*. Englewood Cliffs: Prentice-Hall.

Russo, J. E., & Schoemaker, P. J. H. (1989). *Decision traps.* New York: Doubleday and Company.

Satorra, A., & Bentler, P. M. (1999). A scaled difference chi-square test statistic for moment structure analysis. *Psychometrika*, *66*(4), 507–514.

Schein, E. H. (2004). *Organizational culture and leadership* (3rd ed.). San Francisco: Jossey-Bass.

Schimmack, U., & Oishi, S. (2005). The influence of chronically and temporarily accessible information on life satisfaction judgments. *Journal of Personality and Social Psychology*, *89*(3), 395–406.

Silk, A. J., & Urban, G. (1978). Pre-test-market evaluation of new packaged goods: A model and measurement methodology. *Journal of Marketing Research*, *15*(2), 171–191.

Silva-Risso, J. M., Bucklin, R. E., & Morrison, D. G. (1999). A decision support system for planning manufacturers' sales promotion calendars. *Marketing Science*, *18*(3), 274–300.

Sinha, P., & Zoltners, A. A. (2001). Sales-force decision models: Insights from 25 years of implementation. *Interfaces*, *31*(3), S8–S44.

Smart, C., & Vertinsky, I. (1984). Strategy and environment: A study of corporate responses to crises. *Strategic Management Journal*, *5*(3), 199–213.

Srinivasan, R., Lilien, G. L., & Rangaswamy, A. (2002). Technological opportunism and radical technology adoption: An application to E-business. *Journal of Marketing*, *66*(3), 47–60.

Van Bruggen, G. H., & Wierenga, B. (2010). *Marketing decision making and decision support: Challenges and perspectives for successful marketing management support systems. Foundations and trends in marketing*, *Vol. 4*, Boston: Now Publishing.

Wanous, J. P., Reichers, A. E., & Hudy, M. J. (1997). Overall job satisfaction: How good are single-item measures? *Journal of Applied Psychology*, *82*(2), 247–252.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal*, *5*(2), 171–180.

Westphal, J. D., Gulati, R., & Shortell, S. M. (1997). Customization or conformity? An institutional and network perspective on the content and consequences of TQM adoption. *Administrative Science Quarterly*, *42*(2), 366–394.

Wierenga, B., & van Bruggen, G. H. (1997). The integration of marketing-problem-solving modes and marketing management support systems. *Journal of Marketing*, *61*(3), 21–37.

Wind, J., Green, P. E., Shifflet, D., & Scarbrough, M. (1989). Courtyard by Marriott: Designing a hotel facility with consumer-based marketing models. *Interfaces*, *19*(1), 25–47.

Winer, R. S. (2000). Comment on Leeflang and Wittink. *International Journal of Research in Marketing*, *17*(2–3), 141–145.

Zoltners, A. A., & Sinha, P. (2005). The 2004 ISMS practice prize winner: Sales territory design: Thirty years of modeling and implementation. *Marketing Science*, *24*(3), 313–332.