Taking measure: the link between metrics and marketing's exploitative and explorative capabilities

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Abstract

Purpose – While metrics are becoming increasingly important for marketing's relevance, there is also a need to understand how they, as enablers of learning, affect marketing's adaptive capabilities that ensure its long-term success. Therefore, this study aims to test the association of marketing and financial metrics use and the metric-based orientations of training and compensation, with two key marketing routines – exploitation, i.e. the perfecting of existing activities while allowing for incremental adaptations and exploration or experimentation accompanied by radical adaptation

Design/methodology/approach – The study gathers data from 205 managers and uses partial least squares structural equation modeling to test the hypothesized relationships.

Findings – Marketing metrics encourage both forms of marketing adaptation. Financial metrics use discourages exploration. Market orientation and long-term orientation strengthen (weaken) the positive (negative) relationship between marketing (financial) metrics use and marketing exploration. Metric-based training is more positively associated with both adaptive capabilities than a metric-based compensation orientation, albeit weakly.

Research limitations/implications – The study's central proposition – that different metrics or metric orientations are associated with distinct types of knowledge, interpretations, mindsets, motivations and cultural contexts – provides a deeper theoretical understanding of the pathways by which a metric emphasis affects marketing adaptation.

Practical implications – Marketing managers should emphasize marketing metrics and training more than compensation, to promote marketing exploitation/exploration, while exercising caution in overstressing financial metrics given their negative association with exploration. This latter negative relationship can be weakened (as can the positive one between marketing metrics and exploration be strengthened) with increased market orientation and long-term orientation.

Originality/value – This study addresses the research gap regarding the relationship between metrics as a configurational element of marketing organization and marketing adaptation.

Keywords Market orientation, Marketing metrics, Financial metrics, Marketing exploitation, Marketing exploration, Training and compensation metric orientation

Paper type Research paper

Introduction

> We have two streams of marketing. One is "ready, aim, fire," which is marketing we know [. . .] the other is "ready, fire, aim." That is, things we don't know but we believe we have to at least try so we stay current and fresh and new in the marketplace. If you hold the new tools to the same standard as the old tools, you actually won't do many new things. ~ Michael Linton, when Chief Marketing Officer of Best Buy.

Organizational theorists and marketing scholars stress the importance of developing the adaptive capabilities of exploitation and exploration (Kim and Atuahene-Gima, 2010;

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Kyriakopoulos and Moorman, 2004; Raisch and Birkinshaw, 2008). As the opening quote indicates, senior marketers are also concerned with these facets of adaptation. Marketing exploitation – through repetition and incremental adaptation – allows for the perfecting of tried and tested marketing tools, i.e. the "marketing we know"; whereas marketing exploration – through experimentation and radical adaptation – takes on the marketing "we do not know but [. . .] have to [. . .] try so we stay current and fresh and new in the marketplace (Colvin, 2006)." Prior research has shown that both these forms of marketing adaptation are important for generating new product success, developing effective marketing capabilities and delivering superior firm performance (Vorhies *et al.*, 2011; Zhang *et al.*, 2015). Yet, there exists a tension in routinizing these respective capabilities that emphasize "old certainties" vs "new possibilities," as they "compete for scarce resources," requiring firms to make "choices [. . .]in rules and practices, in the ways in which targets are set and changed and in incentive systems (March, 1991, p. 71)."

Our study aims to provide insight into this balancing act that firms have to undertake by studying an important component of the systems that marketing organizations have in place to drive these adaptive routines. Specifically, we focus our investigation on metrics, which Moorman and Day (2016) classify as one of the configurational elements of the marketing organization that affects marketing adaptation. Such a focus is theoretically and practically relevant in the backdrop of marketing departments being urged to use metrics and adopt a metric-based mindset, to become accountable and improve their status within the organization (Farris *et al.*, 2014; O'Sullivan and Abela, 2007; Rust *et al.*, 2004; Srinivasan and Hanssens, 2009; Verhoef and Leeflang, 2009). Notably, Moorman and Day (2016), in their review of 25 years of research, find that while there is some empirical work on understanding metrics and marketing adaptation separately, almost no study explores their relationship (Table W5 of their Web Appendix). Our study fills this gap by studying the effects that two aspects of metrics – metrics use and metric orientation (Mintz and Currim, 2015) – have on the outcomes of marketing exploitation and exploration (Figure 1 shows our study's conceptual model).

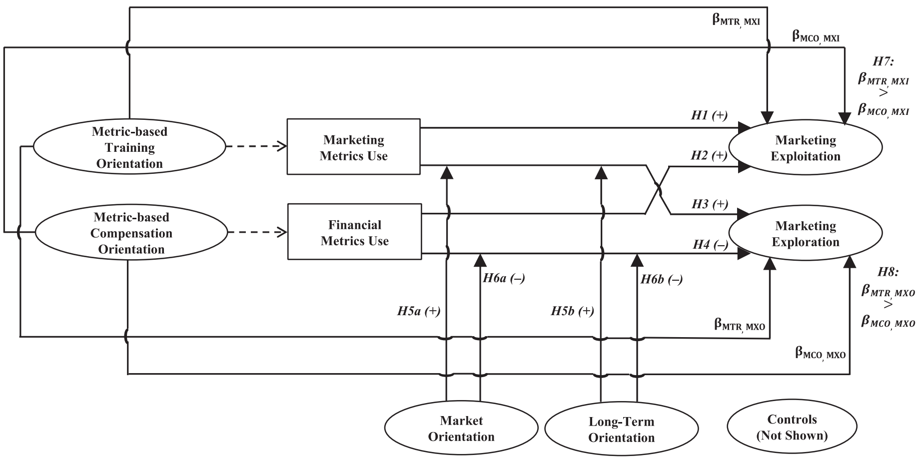

Figure 1.
Conceptual model[a]

Note: [a]Solid arrows represent focal relationships investigated in this research; controls and their paths are not shown for clarity

Theoretically, we argue that metrics use acts as a source of information and creates a mindset (Clark *et al.*, 2006), in the knowledge acquisition and interpretation phases of organizational learning that is embodied in marketing adaptation (Huber, 1991). Similarly, a metric orientation, which encourages metrics use (Mintz and Currim, 2013), creates a cultural context for these adaptive processes (Jaworski, 1988). However, recent work has also found that the benefits of increased metrics use is not universally applicable to all types of metrics or contexts (Frösén *et al.*, 2016; Mintz *et al.*, 2019). Therefore, as shown in our conceptual model, and in line with prior research (Mintz and Currim, 2013, 2015), we separate metrics usage into the use of marketing and financial metrics and metric orientation, which is also an antecedent of metrics use, into metric-based training and compensation – with the expectation of potentially differential effects across them. We also test whether some of the relationships in our model depend on the level of market orientation and long-term orientation. In particular, we expect these moderators to create firm-wide contexts that, respectively, encourage variety in insights and experimentation (Gebhardt *et al.*, 2006; Homburg and Jensen, 2007), affecting the associations between the type of metrics use and marketing exploration.

Our results from testing this model through a survey of 205 marketing and sales managers have important implications for theory and practice. Three key findings, which we briefly describe here, are illustrative in this regard. First, while the use of marketing metrics is linked with increasing both types of marketing adaptation, financial metrics use in comparison, seems to be associated with lower levels of exploration. Second, the positive (negative) association of marketing (financial) metrics use with marketing exploration is strengthened (weakened) as the levels of market orientation and long-term orientation increase. Finally, metric-based training seems to encourage both forms of marketing adaptation slightly more strongly than a metric-based orientation that uses compensation. Theoretically, these results suggest that the role that metrics play in creating knowledge, mindsets and cultural contexts that are central to organizational learning, and therefore to marketing adaptation, can differ depending on the type of metrics emphasis. Practically, marketing departments can use our findings to encourage incremental adaptation through exploitation or radical adaptation through exploration, by emphasizing different metrics, metric orientations and cultural orientations. Thus, we also add to the body of empirical work on the antecedents of exploitation and exploration (Josephson *et al.*, 2016; Marin-Idarraga *et al.*, 2016). As such, our research represents an early effort to fill the gap in our understanding of the association between metrics and marketing adaptation.

Theory and hypotheses

The focus of our research is on the role of metrics in marketing adaptation. We first discuss research related to metrics and make the case for studying two dimensions of importance, namely, metrics use, particularly its classification into marketing and financial metrics use and metric orientation, conceptualized as an emphasis on metrics in compensation and the amount of training received on using metrics. This is followed by a review of the literature on marketing adaptation and its components of exploitation and exploration. Finally, and based on these sections, we present our arguments and related formal hypotheses for the relationships – shown in the conceptual model in Figure 1 – that we investigate.

Metrics use and metric orientation

Metrics are measurement tools that are used to evaluate performance, typically by comparing performance on the metric relative to expectations (Morgan *et al.*, 2002). Marketing scholars also refer to metrics as assessments or measurements of marketing performance, forming part of the formal system of marketing control (Ambler *et al.*, 2004; Jaworski, 1988; O'Sullivan *et al.*, 2009). Understanding the role of metrics in the marketing organization ostensibly requires determining the extent to which metrics are used, while simultaneously exploring the types of metrics used. While early research on metrics has focused on productivity measures, subsequent efforts have included the use of non-financial or non-pecuniary measures (Frösén *et al.*, 2013; Morgan *et al.*, 2002). More recent work has used the classification of marketing vs financial metrics [1]: the former "are based on a customer or marketing mind-set" and include metrics such as likeability, willingness to recommend and market share, and the latter "are monetarily based, based on financial ratios or readily converted to monetary outcomes," and include metrics such as share of wallet and various measures of costs and profits (Mintz and Currim, 2013, p. 17).

Other scholars too, in considering facets such as comprehensiveness of marketing performance measurement systems, recognize this classification, wherein comprehensiveness is greater when both marketing and financial metrics are considered (Frösén *et al.*, 2016; Homburg *et al.*, 2012; O'Sullivan and Abela, 2007). Furthermore, even though marketing accountability presumes that marketing will deliver on financial metrics (Verhoef and Leeflang, 2009), there is a strong recognition of the need for non-financial or marketing metrics to evaluate marketing activities (Barwise and Farley, 2003; Rust *et al.*, 2004).

Besides metrics use, we also consider metric orientation in exploring the link between metrics and marketing adaptation. Mintz and Currim (2013) propose this construct to capture the firm's approach in motivating the use of metrics. A more formal treatment of this concept is that of control systems, which "influence the behavior and activities of marketing personnel to achieve desired outcomes" and are typically discussed at the level of inputs or outputs or behavior or outcome (Jaworski, 1988, p. 24). While Mintz and Currim's (2013) main concern was with how metric orientation influences metrics use, control systems that make up such an orientation are part of the configurational element of marketing organization that affects marketing adaptation (Kohli *et al.*, 1998; Moorman and Day, 2016).

Two such important input and output control systems are training and compensation, respectively (Kohli *et al.*, 1998). Much like the use of these management tools in monitoring selling behavior in a sales management system, their use in controlling or at the very least encouraging the use of metrics represents part of the formal system of measurement (Kumar *et al.*, 2014). Training provides general and task-related knowledge, skills and capabilities (Cron *et al.*, 2005), which in the context of metrics might include the use of dashboards, quantitative analysis or other such means that intrinsically motivate the use of metrics (Germann *et al.*, 2013; O'Sullivan and Abela, 2007). Metric-based compensation, on the other hand, incentivizes the use of metrics through extrinsic motivation or the expectation of a reward (Segalla *et al.*, 2006).

Marketing adaptation

Theory in marketing has long recognized the need for marketing capabilities that create a sustainable competitive advantage (Day, 1994; Hunt and Morgan, 1995; Vargo and Lusch, 2000). Prior research has shown how market orientation allows firms to build sense-and-respond capabilities (Kumar *et al.*, 2011). However, scholars have also recognized the need for learning-oriented capabilities that increase the stock of marketing knowledge and help firms adapt to dynamically changing environments (Vorhies *et al.*, 2011). Most research in this area has drawn on the distinction in organizational theory between the routines of exploitation and exploration (March, 1991). As mentioned in the introduction section, exploitation allows firms to identify and correct errors in existing or known contexts, and, in combination with repetition, improve existing behavioral routines. Exploration, on the other hand, causes firms to develop new, cognitive frames of reference that are suitable to dynamic and changing contexts and often requires the unlearning of existing behavioral routines.

Within marketing, studies have primarily focused on these learning capabilities in the context of new product development projects and have found that both marketing exploitation and exploration can lead to superior outcomes (Atuahene-Gima, 2005; Kim and Atuahene-Gima, 2010; Zhang *et al.*, 2015). Given the context of new product development, these adaptive marketing capabilities have been typically captured in the form of routines that involve the product or the market. For example, Kim and Atuahene-Gima (2010) posit and find that exploitative learning with its focus on existing knowledge of current markets and products and on continuous improvement, leads to cost efficiency gains in new product development; on the other hand, exploratory market learning allows firms to learn about new market opportunities, leading to greater product differentiation.

However, marketing scholars have also proposed that marketing exploitation and exploration are relevant beyond the context of new product development routines, to the entire range of marketing activities (Aspara *et al.*, 2011; Kyriakopoulos and Moorman, 2004; Vorhies *et al.*, 2011). For example, Kyriakopoulos and Moorman (2004, p. 221) propose that marketing exploitation involves "improving and refining current skills and procedures associated with existing marketing strategies, including current market segments, positioning, distribution and other marketing mix" activities, while marketing exploration entails "challenging prior approaches to interfacing with the market [through] new segmentation, new positioning, new products, new channels and other marketing mix" activities. Vorhies *et al.* (2011) further reinforce this broader conceptualization of marketing exploitation and exploration by defining them as adaptive capabilities, which implies that they embody these (marketing) activities in an ongoing and continual manner. This approach ties in with the view that marketing capabilities reside in these key activities that the marketing function/organization performs (Vorhies and Morgan, 2005). These activities refer to segmentation, targeting, positioning, branding, and those in the marketing mix or 4 P's of product, price, place and promotion. Thus, marketing exploitation (exploration) refers to the adaptive capabilities that enable firms to improve their existing (develop new) knowledge and skills across these marketing activities.

The relationship between metrics and marketing adaptation

As discussed in the previous section, marketing adaptation involves changing marketing processes, either incrementally, by exploiting tried and tested marketing routines that work or radically, by experimenting with fundamentally new ways of carrying out marketing activities. Organizations exhibiting such change are said to be experiencing the process of learning. Such learning can occur either intentionally or unintentionally, but it is primarily caused by the processing of information or knowledge (Sinkula *et al.*, 1997; Vorhies *et al.*, 2011; Yalcinkaya *et al.*, 2007). We first make the general case that metrics use and a metric orientation discussed previously, can play important roles in such information processing; subsequently, we provide specific arguments for differential effects across the type of metric or metric orientation.

Huber (1991) identifies several constructs that make up information processing. Germane to our discussion here are knowledge acquisition and information interpretation. While firms acquire knowledge from various sources throughout their existence, the use of metrics or the monitoring of performance of firms' activities, is arguably one of the most prevalent means of doing so (Clark *et al.*, 2006; Krush *et al.*, 2016). A comparison of how a firm does against a standard or expectation becomes a relatively objective source of information that can be consistently and easily interpreted (Vorhies and Morgan, 2005). Such comparisons directly articulate causal links between action and performance (De Luca and Atuahene-Gima, 2007; Moorman, 1995), creating knowledge of what works and what does not and laying the foundation for future adaptations (Atuahene-Gima, 2005). Thus, it is not surprising that metrics are used in firms both formally and informally, to understand the need for, and to carry out, adaptation, with the ultimate goal of improving performance (Homburg *et al.*, 2012). In addition to enabling knowledge acquisition and interpretation, the use of metrics also creates a mindset that becomes a context in which new knowledge is interpreted and acted upon (Day and Nedungadi, 1994; Gibson and Birkinshaw, 2004). Consequently, such mindsets, in turn, can also affect the extent to which adaptation is pursued (Slater and Narver, 1995).

The preceding discussion and Mintz and Currim's (2013) finding that a metric orientation drives metrics use, suggest that such an orientation should indirectly, through metrics use, impact marketing adaptation. However, a metric orientation that emphasizes the use of metrics with pervasive management tools such as training and compensation is also bound to create a cultural context (Jaworski, 1988), which can enable or dampen the adoption of adaptive marketing activities. Thus, arguably, a metric orientation would also have a direct effect on marketing adaptation. In essence, we are proposing that, while the intention with control systems embodied in a metric orientation may be their impact on metrics use, they also have unintentional, direct effects on the learning capability of the firm (Kohli *et al.*, 1998; Moorman and Day, 2016).

While we expect metrics use through knowledge acquisition and interpretation and the creation of mindsets and metric orientation through the creation of a cultural context, to affect marketing adaptation, it is important to note that the requirements for carrying out such adaptation might differ depending on whether it is exploitative and explorative (Aspara *et al.*, 2011). As Mom *et al.* (2007, p. 913), note, the essence of exploitation is "creating reliability in experience," whereas that of exploration is "creating variety in experience" (p. 912), suggesting a difference in the "kind of knowledge" required for each (March, 1991, p. 84). The knowledge needed for marketing exploitation identifies direct cause-and-effect linkages of marketing activities and any inefficiencies that prevent replicability. On the other hand, marketing exploration requires knowledge that generates a variety of potential cause-and-effect linkages, which can then lead to a diverse range of possible marketing actions, even if some of them may be radical or risky (Benner and Tushman, 2003). However, to the extent that both are adaptive activities that change the *status quo* (Atuahene-Gima, 2005), the cultural contexts that encourage them may be similar to the extent that the motivations that drive each of these activities overlap.

Metrics use and marketing adaptation

In the previous section, we made a general case for why metrics can affect marketing adaptation while highlighting differences and similarities in the requirements for exploitative vs explorative adaptation. Here, we argue for and hypothesize specific relationships between marketing and financial metrics use and exploitative and explorative marketing adaptation.

Marketing metrics, with their focus on customers, provide knowledge on causal linkages between marketing actions and customer-level outcomes, whereas financial metrics, with their focus on monetary measures, similarly supply information on possible relationships between marketing actions and financial-level outcomes, especially in terms of inefficiencies (Mintz and Currim, 2015). Thus, both types of knowledge should enable exploitation in the form of incremental refinements and/or replication of current marketing activities, as they identify areas where firms may not be delivering against benchmarks. We therefore hypothesize that:

H1. Marketing metrics use is positively related to marketing exploitation.

H2. Financial metrics use is positively related to marketing exploitation.

However, the efficiency focus of financial measures makes them inherently variance-reducing (Benner and Tushman, 2003), which can hinder exploration. Conversely, a customer or marketing mindset that is reflected in the use of marketing metrics provides a diverse range of potential actions (Kyriakopoulos and Moorman, 2004), which is required for exploration.

Furthermore, in the chain of marketing productivity, customer-level outcomes are a more direct result of marketing actions than financial-level outcomes (Rust *et al.*, 2004). Consequently, the causal linkages that are revealed with marketing metrics are more informative than those revealed by financial metrics, which we expect to result in giving marketing managers greater confidence to make challenging, radical changes.

Conceptual arguments and findings from prior research on innovation outcomes lend credence to these aforementioned logics. For example, Morgan *et al.* (2002) are concerned that a greater reliance on metrics "that emphasize short-term assessments of tangible inputs and outputs" can result in the slashing of inputs that contribute to capabilities such as marketing exploration (p. 371). Empirical work on innovation also finds that a short-term, risk-averse mindset can result from an overemphasis on financial metrics (Atuahene-Gima, 2005). On the other hand, marketing metrics, by generating a customer-level mindset, provide a frame of reference that allows for the pursuit of exploration (Kyriakopoulos and Moorman, 2004). Metrics such as loyalty, share of voice and brand equity encourage a long-term view that accommodates making risky or radical changes. Overall, these arguments imply that these metrics will have opposite impacts on marketing exploration, leading us to formally hypothesize that:

H3. Marketing metrics use is positively related to marketing exploration.

H4. Financial metrics use is negatively related to marketing exploration.

Moderation by market orientation and long-term orientation. We expect the preceding logics related to the variance of knowledge and the temporal nature of mindsets generated by marketing and financial metrics use, to be affected by the levels of market orientation and long-term orientation. A market orientation institutes a firm-wide cultural context that values the generation and dissemination of a range of market insights, i.e. variance in knowledge (Gebhardt *et al.*, 2006; Kohli and Jaworski, 1990; Narver and Slater, 1990). Similarly, a long- term orientation supports experimentation while allowing for failures, i.e. it encourages a temporal view that stretches over a relatively longer time horizon (Homburg and Jensen, 2007; Verhoef and Leeflang, 2009). Consequently, the positive effect of marketing metrics use should be amplified in market-oriented and long-term oriented firms as managers are emboldened in translating their use of these metrics into greater marketing exploration. By the same logic, the negative effect of financial metrics use on marketing exploration should be dampened when market orientation and long-term orientation are high, as these cultural contexts, respectively, deemphasize the lack of variety in knowledge and the short-term view that such metrics engender. We therefore hypothesize the following moderating relationships:

H5. The positive relationship between marketing metrics use and marketing exploration (hypothesized in H3) is strengthened at relatively high levels of market orientation and long-term orientation.

H6. The negative relationship between financial metrics use and marketing exploration (hypothesized in H4) is weakened at relatively high levels of market orientation and long-term orientation.

Metric orientation and marketing adaptation

A metric orientation creates a cultural context that encourages the use of both marketing and financial metrics (Mintz and Currim, 2013). However, the pathways that are responsible for this relationship differ with the type of orientation or control system that is used. Training, an input-level control system, acts primarily through the increase of knowledge, skills and ability in the use of metrics, and is, therefore, an intrinsic driver, while compensation, which creates incentives of remuneration and is, therefore, outcome-based, generates an extrinsic impetus (Miao *et al.*, 2007; Oliver and Anderson, 1994). A range of studies in the field of psychology that broadly fall under the rubric of self-determination theory have shown that intrinsic motivators better satisfy needs of competence and autonomy, leading to higher self-motivation and outcomes such as better learning (Ryan and Deci, 2000). Thus, in the context of adaptive activities, we can expect that differences in the motivations that are operational across the types of metric orientation cause them to differentially impact how such activities are pursued (Kohli *et al.*, 1998).

An intrinsic motivation creates an innate and natural desire to seek improvements as marketers look to apply their knowledge, skills and ability in the use of metrics, to the range of marketing activities (Gibson and Birkinshaw, 2004). Conversely, an extrinsic motivation is likely to create a relatively superficial and fleeting pursuit of adaptation (Stathakopoulos, 1998).

Additionally, in the face of uncertainty, it is likely that the change pursued will be minimal when a potential consequence is the loss of remuneration (Segalla *et al.*, 2006). Consequently, among metric orientations, metric-based training is likely to lead to greater levels of both type of marketing adaptation than metric-based compensation. We therefore hypothesize that:

H7. Metric-based training as a type of metric orientation is more positively related to marketing exploitation than metric-based compensation.

H8. Metric-based training as a type of metric orientation is more positively related to marketing exploration than metric-based compensation.

Methodology

Sample

We tested our model by surveying mid to high-level managers with primary functional responsibility in marketing or sales. The data was collected using an online survey through Survey Monkey, a professional data collection firm, using their audience panel. This form of primary data collection through contracting with reputed firms such as Survey Monkey and Qualtrics has been used in prior research in the marketing discipline (Bendle and Wang, 2017). We note that we also carried out three in-depth qualitative interviews with mid- and top-level marketing executives in a consumer goods firm, a marketing services firm and a retail firm, and six pilot surveys, before finalizing the online questionnaire.

For generalizability, we ensured that our sample of respondents represented a range of possible firm sizes (excluding small firms with less than 20 employees) and industries (excluding the utilities and legal industries). Initial e-mails inviting participation in the survey were sent out to 4,625 respondents in Survey Monkey's panel, of which 1,993 started taking the survey [2]. Filter questions on firm size, functional responsibility, level and industry, resulted in a final sample of 205 complete responses in the eight weeks that the survey was open. We provide our sample's characteristics on the variables associated with these filter questions and other relevant dimensions, in Table 1. As shown in this table, our sample represents a fairly broad profile of firms, industries and respondents. As we are

Firm profile	% of total
Number of employees	
20-499	24.9
500-999	20.5
1,000 and above	54.6
Primary industry	
Marketing services (e.g. advertising)	14.6
Goods	21.0
Retail	20.5
Business/consumer services	43.9
B2B sales	
0%	13.2
Greater than 0% and less than 49%	34.6
Greater than 49% and less than 100%	33.7
100%	18.5
Services sales	
0%	16.1
Greater than 0% and less than 49%	37.6
Greater than 49% and less than 100%	25.3
100%	21.0
Respondent profile	
Level in firm	
Middle management	73.7
Top management	21.9
Owner or CEO	4.4
Years with firm	
1-3	31.2
4-8	33.7
9-15	23.9
Greater than 15	11.2
Years of work experience	
1-9	20.0
10-15	36.6
16-25	25.8
Greater than 25	17.6

Table 1. Sample characteristics

unable to provide a test of non-response bias given the unavailability of any meaningful measures on non-respondents, we carry out an early-late respondent analysis as a close proxy of this test [3] (Armstrong and Overton, 1977). We find that out of the more than 50 items or measures on which we collect data, only three have significantly different means at $p < 0.05$, between either the first and third tercile and/or the first and fourth quartile. However, at the construct level, none of the factors differ in their means across these terciles or quartiles, suggesting that there is no response bias that is temporal.

Constructs and measures

The item measures or indicators used for the constructs in our research were primarily drawn or adapted from prior research and are detailed in Appendix 1. Given our similarity to Vorhies *et al.*'s (2011) conceptualization of marketing exploitation and exploration, the items we use are primarily drawn from the four that they have for each of these reflective constructs, with the focus being on incremental adaptation for the former and radical for the latter construct. Each of these items refers to "marketing processes" to capture marketing adaptation at the general level of all marketing activities. Respondents were reminded of this through the following statement that appeared at the introduction of the questions related to these constructs: "Marketing processes refer to the way that marketing activities are carried out." Respondents were also cued to think about a wide range of marketing activities before these questions by being asked to indicate their level of involvement – on a three-point scale (i.e. low, moderate and high) – with each of the following activities: new product/service development, pricing, distribution/channel or location management, marketing communication (e.g. advertising), sales/selling, market research, segmentation-targeting-positioning, customer service/satisfaction/loyalty/relationship management and marketing strategy formulation/implementation.

We conceptualize the marketing metrics use construct as being *composed of* or *formed by* the use of metrics that are based on a customer or marketing mindset; similarly, financial metrics use is formed by the use of metrics that are monetarily based, based on financial ratios or readily converted to monetary outcomes (Mintz and Currim, 2013). We therefore treat these constructs as formative as (Diamantopoulos *et al.*, 2008):

- The direction of causality is from the use of these specific marketing or financial metrics, i.e. from the indicators/items, to the respective construct of marketing or financial metrics use.
- The indicators are not interchangeable because the use of each metric makes a distinct contribution to each respective construct of metrics use.

Our list of metrics for each construct is primarily derived from Mintz and Currim (2013), who go through an exhaustive qualitative procedure in their research, to arrive at a set of general, marketing and financial metrics that are applicable across a range of marketing activities and decisions [4]. We note that in summing the scores of these metrics to create their measures of marketing and financial metrics use, Mintz and Currim (2013) also consider these constructs as formative; however, their treatment does not allow for each of the metrics to have different weights, which is what we do [5].

We split the presentation of each set of metrics into customer- and firm-level metrics so as to reduce fatigue and tedium. Our qualitative interviews suggested that such a sub-classification was related to the way marketing managers thought about these metrics. Moreover, this also allowed us to follow Mintz and Currim (2013) in measuring the metric-based orientation constructs of training and compensation as being reflected in items measured at the level of each of these general sets of metrics, i.e. as reflective constructs. Thus, in terms of survey flow, the presentation of each of the four sub-classifications of metrics – customer-level marketing metrics, firm-level marketing metrics, customer-level financial metrics and firm-level financial metrics – was followed by the items reflecting metric-based training and compensation orientations with respect to that set of metrics (Appendix 1).

Given the length of our survey, the moderator of market orientation was operationalized as a reflective construct measured using a reduced scale of five items that were drawn from a similar, smaller scale that Verhoef and Leeflang (2009) use. Notably, these items capture key aspects of market orientation, such as being market-driven – by generating insights on customers and competitors – and firm-wide, by disseminating these insights to all functions and responding to them at the business level. Our second moderator of long-term orientation is also a reflective construct made up of items derived from prior research (Homburg and Jensen, 2007).

We also include firm and market-level controls to control for different levels of metrics use and marketing adaptation (Appendix 1 also lists the controls' and moderators' items). Firm size is measured as the log of the number of employees reported by respondents as a single item and is used as a control for both adaptive capabilities. A firm's strategic orientation is captured by asking respondents to pick one of four statements that correspond to prospectors, analyzers, low-cost defenders and differentiated defenders (Mintz and Currim, 2013). We combined the former two and the latter two statements into categories to create a dummy variable for defenders that is also used as a control for both adaptive capabilities. Market turbulence is a reflective construct that acts as a control for both metrics use and marketing adaptation (Atuahene-Gima, 2005; Mintz and Currim, 2013). Finally, market orientation, besides being a moderator, is also included as a control for the metrics use constructs following Mintz and Currim (2013).

Analysis

We estimate our conceptual model in Figure 1 with partial least squares (PLS) structural equation modeling (SEM), using SmartPLS 3 (Ringle *et al.*, 2015). A key reason for using PLS-SEM is that it allows for the estimation of formative constructs – two of our focal constructs related to metrics use are formative – without any identification issues, unlike covariance-based (CB) SEM. This advantage of PLS-SEM stems from its variance-based approach, which treats constructs as weighted composites of their indicators or item measures; CB-SEM, on the other hand, considers constructs as common factors that explain the covariances between its associated indicators. Hair *et al.* (2017b) also find that PLS-SEM has greater statistical power, producing lower Type II errors (or false negatives) particularly with smaller sample sizes, while being as good as, if not better than CB-SEM in avoiding Type I errors (or false positives).

As PLS-SEM does not make any distributional assumptions, statistical significance is determined through the calculation of confidence intervals (CIs) at the 0.05 (0.10) level for strong (weak) support] using bootstrapping; we use 5,000 replications. Unlike CB-SEM, there are no global measures of fit that allow for model comparisons in PLS-SEM (Henseler and Sarstedt, 2013). However, we closely follow Hair *et al.*'s (2017a) recommendations, in using diagnostics reported for the measurement and structural models by Smart PLS 3 as discussed next, to evaluate and justify our final model specification.

Results

Measurement model

We first evaluate the measurement model to check whether the items or indicators of the constructs in our model require purification. For the formative constructs, we check whether the indicators contribute to the constructs as intended, i.e. are relevant and whether they do so independently. Regarding relevance, Hair *et al.* (2017a) recommend dropping indicators if their outer model coefficients (or weights) are non-significant *and* their loadings have low values, in particular, if they are below 0.10 and non-significant. We find that none of our metrics meet these criteria (we retain the two that have loadings slightly below the less conservative cut-off of 0.50 at this stage; in any case, they get dropped subsequently for other reasons). Appendix 1 lists the weights and loadings of the indicators retained in the final model.

For independence, these authors recommend retaining formative indicators only if their variance inflation factors (VIFs) are below five, which we find to be the case for all the metrics. However, we also find that some of the weights are negative. Hair *et al.* (2017a) suggest that such negative weights indicate collinearity issues when the indicators are supposed to directionally increase the formative construct, i.e. have a positively valenced coefficient, as is the case with all our metrics derived from Mintz and Currim (2013). We, therefore, drop the following nine metrics because they have negative weights – awareness, satisfaction, perceived quality, customer acquisitions and sales in units or dollars under marketing metrics and customer revenue, net profit, return on investment and total costs under financial metrics – still leaving a total of 18 from our original list of 27, with 9 under each type of metric.

While some of these metrics (e.g. awareness and net profit) are used with relatively high frequency in Mintz and Currim's (2013) study, we note that they do not formally treat the metrics use constructs as formative in the manner that we do, i.e. by allowing each indicator to have different weights. Thus, we posit that the reason some indicators/metrics get dropped during purification is because they overlap with the retained metrics. For example, the correlations of satisfaction, which is dropped, with the retained marketing metrics of loyalty and willingness to recommend are 0.729 and 0.655, respectively (Appendix 2 lists all the inter-metrics correlations). Similarly, the dropped financial metrics of net profit and return on investment, have fairly high correlations (0.638 and 0.651, respectively) with the retained metric of return on sales. However, we also caution future researchers from generalizing the composition of these formative constructs observed in our model because "they can have different contents and meanings depending on the endogenous constructs used as outcomes," as "the values of the formative indicator weights are influenced by other relationships in the model" (Hair *et al.*, 2017a, p. 147).

We also assess if our treatment of marketing and financial metrics use as formative constructs is valid as measurement model misspecification can lead to biased outcomes. We do so using the confirmatory tetrad analysis (CTA) test proposed by Bollen and Ting (2000) and adapted for PLS by Gudergan *et al.* (2008). The null hypothesis of this test is that of a reflective construct where all indicators of a construct represent its domain equally well. To perform this test, CTA-PLS in Smart PLS 3 identifies non-redundant pairs of covariances among indicators of a construct, and confirms if the differences of all such pairs (or tetrads) are not significantly different from zero (i.e. vanishing). Significance is determined using bootstrapped CIs that are adjusted for the multiple testing problem. Rejection of the null of vanishing tetrads – implied by the presence of even one significantly different pair of covariances – suggests that a formative construct is more appropriate. We find this to be the case for both the metrics use constructs (a CTA-PLS before purification also supported formative treatment). For example, the difference in the covariances between the pairs of marketing metrics formed by likeability and preference and market share and share of voice, is significantly different from zero based on the 95% CIs (i.e. the CIs do not include zero). We find similar examples of non-vanishing tetrads – implying a rejection of the null of a reflective construct – for financial metrics use. We note, however, that determining a formative or reflective specification cannot rely on the results of this test alone and must be conceptually supported, which we have done when discussing these constructs and their measures (Hair *et al.*, 2017a).

The criteria for measure purification of the reflective constructs are reliability and validity. All the Cronbach's coefficient alphas and construct reliabilities, which we report in Table 2, exceed the 0.7 threshold, indicating that the measures are reliable. Table 2 also reports the inter-construct correlations and the average variance extracted (AVE) for each reflective construct. All the AVEs exceed the threshold of 0.5 providing evidence of convergent validity of these constructs (Bagozzi and Yi, 1988). We also find that the square root of each construct's AVE exceeds the value of its correlation with any other construct, as proof of discriminant validity (Fornell and Larker, 1981). Finally, all outer loadings (reported in Appendix 1) are significantly greater than 0, with values of most exceeding or close to 0.7. We therefore retain all the items or indicators for the reflective constructs.

Notably, we cannot conduct a similar test of discriminant validity for the formative constructs of marketing and financial metrics use. Diamantopoulos *et al.* (2008) point out there are two views on the matter. One is that "discriminant validity [is] not meaningful when indexes are formed as linear sums of measurement," while another is that "standard procedures for assessing discriminant validity are equally applicable to formative indexes" (p. 1,216). Thus, per the former view, discriminant validity between these constructs is not a problem. Further, per the latter view, which recommends a cut-off of 0.71 for construct intercorrelations, again, the correlation between them, which is 0.72 (i.e. very close to 0.71), is not a serious problem [6]. In this regard, we note that Henri (2006) also finds a correlation of 0.64 between diagnostic and interactive metrics use, two facets of performance measurement systems, which likely indicates a wider analytics culture underlying the use of different types of metrics (Germann *et al.*, 2013).

Structural model

Unlike CB-SEM, where model fit criteria are related to its goal of minimizing the discrepancy between observed and estimated correlations, PLS-SEM aims to maximize the variance of the endogenous constructs, making this same discrepancy and the related fit criteria, less relevant. Nevertheless, Smart PLS 3 reports one such measure, namely, the standardized root mean square residual (SRMR), which if below 0.08, is indicative of good fit in the context of CB-SEM (Hu and Bentler, 1999), although Hair *et al.* (2017a) consider this threshold to be too low for PLS-SEM. We find that the SRMR for our model is 0.071, which suggests a good fit. In addition, we find that none of the VIFs of the structural model exceed 3, well below the threshold of 5 that indicates multicollinearity between predictor constructs and below the threshold of 3.3 that is indicative of common method bias (Kock, 2015). Furthermore, the R^2 values for each of our endogenous constructs reported in Table 2, shows that our model explains substantial variation in them as a function of the exogenous constructs linked to each.

A final evaluation of the structural model is its out-of-sample predictive power or predictive relevance as captured by the Stone-Geisser's Q^2 value that is reported by Smart PLS 3 (Ringle *et al.*, 2015). We specify an omission distance of seven, which results in seven rounds of estimation being run, such that across all these runs, every data point across all

Table 2. Correlations and summary statistics

Constructs and summary statistics	1	2	3	4	5	6	7	8	9	10	11
1. Marketing exploitation	0.638										
2. Marketing exploration	0.385	0.651									
3. Marketing metrics use	0.481	0.454	NA								
4. Financial metrics use	0.466	0.378	0.720	NA							
5. Metric-based training orientation	0.429	0.552	0.574	0.631	0.777						
6. Metric-based compensation orientation	0.314	0.463	0.578	0.625	0.669	0.691					
7. Market orientation	0.406	0.375	0.482	0.563	0.510	0.424	0.520				
8. Long-term orientation	0.405	0.419	0.417	0.415	0.458	0.402	0.530	0.637			
9. Firm size	0.077	0.099	0.075	0.086	0.057	0.123	0.115	0.076	NA		
10. Defender strategic orientation	−0.215	−0.323	−0.193	−0.211	−0.220	−0.222	−0.156	−0.209	0.074	NA	
11. Market turbulence	0.375	0.403	0.282	0.413	0.369	0.320	0.316	0.341	0.087	−0.187	0.658
Mean	3.720	3.345	3.522	3.399	3.046	3.038	3.675	3.475	2.775	0.337	3.306
Standard deviation	0.945	0.993	1.069	1.113	1.142	1.158	0.972	0.971	0.979	0.474	1.082
Cronbach's alpha	0.809	0.821	NA	NA	0.904	0.851	0.768	0.718	NA	NA	0.741
Composite reliability	0.875	0.882	NA	NA	0.933	0.900	0.844	0.840	NA	NA	0.852
R^2	0.352	0.438	0.433	0.551	NA	NA	NA	NA	NA	NA	NA

Notes: Correlations are shown on the off-diagonals and the average variance extracted (AVE) for each reflective latent construct is shown on the diagonal. As PLS-SEM does not make any distributional assumptions, statistical significance is determined through the calculation of CIs using bootstrapping (with 5,000 replications). Correlations reported in the table are significant at the $p < 0.05$ level, i.e. the 95% confidence interval does not include 0.000, if they are equal to or above the absolute value of 0.156. Means and standard deviations are computed across all items and observations for the latent constructs indicators of the reflective endogenous constructs of marketing exploitation and exploration, is omitted and predicted once. These runs or blindfolding rounds use the estimated paths and scores of all other constructs and variables in the model, along with a missing value function for the omitted data, to first predict the score of these endogenous constructs, and then predict the omitted data points. The Q^2 value is computed as a prediction error, namely, the difference between predicted and original values of the omitted data points. We find this value to be 0.19 and 0.25 for marketing exploitation and exploration, well above the threshold of 0, which suggests that our model has high predictive relevance for the marketing adaptation constructs (Hair *et al.*, 2017a).

Tests of hypothesized relationships

The results of testing the hypothesis *H1* to *H4* and *H7* to *H8*, related to the main effects, appear in Table 3; those for *H5* to *H6*, the moderation hypotheses, are presented in Table 4 and discussed subsequently. As mentioned previously, as PLS-SEM is distribution-free, we use the reported CIs from bootstrapping – we use 5,000 replications – to determine significance, i.e. we infer strong (weak) support if the 95% (90%) CI does not include the value of 0.000 (Table 3 shows the lower and upper bounds of each interval under the columns labeled CI_{LB} and CI_{UB}, respectively). As shown in Table 3, we find that *H1* (β = 0.261), which hypothesized that marketing metrics use is positively associated with marketing exploitation, is strongly supported as the 95% CI of this path's estimate does not include 0.000. However, *H2* (β = 0.098), which similarly hypothesized a positive effect for financial metrics use, is not supported as even the weaker 90% CI includes the value of 0.000. Still, *H3* (β = 0.229) and *H4* (β = –0.243), which, respectively, hypothesized a positive and negative relationship between marketing and financial metrics use and marketing exploration, are both strongly supported as the 95% CIs for these paths' estimates do not include 0.000.

For testing the hypothesized effects associated with the types of metric orientation, we need to compare their direct paths to each type of marketing adaptation. To do so, we first compute the difference between the estimated paths of metric-based training and metric-based compensation, for each of the 5,000 bootstrapped samples, as reported by Smart PLS 3. The averages of these differences are reported as the estimates testing *H7* (β = 0.287) and *H8* (β = 0.230) in Table 3. We then sort these differences and record the lower and upper bounds of the CIs (e.g. the difference of the 125th (5000 $\times$ 0.025) sample after sorting on the difference represents the lower bound of the 95% CI). If the CI of the estimated average difference between training and compensation includes 0.000, then the effect of training is not significantly greater than that of compensation at that level of significance. As shown in Table 3, we can therefore only infer weak support for both these hypothesized relationships, namely, that, the metric-based orientation of training is more positively associated than compensation, with both marketing exploitation and exploration, as only the 90% CIs do not include 0.000.

Table 4 reports the results of the tests of our four moderation hypotheses. Each effect is tested by specifying a path from the interaction of the respective pair of related latent constructs (direct paths from each construct are already present in the main effects model). We estimate each interaction separately by specifying in each case, a two-stage bootstrapped estimation (with 5,000 replications) in Smart PLS 3, which essentially uses the scores from the 1st-stage PLS-SEM main effects model to compute the interaction term (Hair *et al.*, 2017a). As shown in Table 4, we find strong support for the strengthening of the positive relationship between marketing metrics use and marketing exploration by market

Table 3. Structural model results – main effects[a]

Predictors and outcomes	Estimate	95% CI_{LB}^{b}	95% CI_{UB}^{b}	90% CI_{LB}^{b}	90% CI_{UB}^{b}	Support
Direct paths to marketing exploitation						
H1: Marketing metrics use (+)	0.261	0.050	0.464	0.085	0.425	Strong
H2: Financial metrics use (+)	0.098	−0.154	0.291	−0.114	0.260	None
Metric-based training orientation ($\beta_{MTR,MXI}$)	0.135	−0.046	0.323	−0.016	0.302	
Metric-based compensation orientation ($\beta_{MCO,MXI}$)	−0.152	−0.303	0.024	−0.278	−0.005	
H7: ($\beta_{MTR,MXI} - \beta_{MCO,MXI}$) (+)	0.287	−0.051	0.574	0.010	0.529	Weak
Market orientation	0.079	−0.069	0.245	−0.040	0.224	
Long-term orientation	0.136	−0.013	0.276	0.008	0.252	
Firm size	0.032	−0.083	0.138	−0.062	0.123	
Defender strategic orientation	−0.078	−0.212	0.049	−0.190	0.029	
Market turbulence	0.171	0.047	0.304	0.075	0.291	
Direct paths to marketing exploration						
H3: Marketing metrics use (+)	0.229	0.026	0.413	0.058	0.389	Strong
H4: Financial metrics use (−)	−0.243	−0.481	−0.063	−0.442	−0.102	Strong
Metric-based training orientation ($\beta_{MTR,MXO}$)	0.325	0.161	0.525	0.184	0.481	
Metric-based compensation orientation ($\beta_{MCO,MXO}$)	0.095	−0.067	0.268	−0.038	0.235	
H8: ($\beta_{MTR,MXI} - \beta_{MCO,MXI}$) (+)	0.230	−0.042	0.537	0.001	0.491	Weak
Market orientation	0.042	−0.126	0.235	−0.094	0.197	
Long-term orientation	0.106	−0.051	0.242	−0.031	0.217	
Firm size	0.055	−0.065	0.175	−0.049	0.157	
Defender strategic orientation	−0.175	−0.301	−0.057	−0.280	−0.073	
Market turbulence	0.202	0.078	0.327	0.099	0.304	
Direct paths to marketing metrics use						
Metric-based training orientation	0.243	0.064	0.411	0.095	0.382	
Metric-based compensation orientation	0.317	0.165	0.501	0.189	0.468	
Market orientation	0.217	0.002	0.407	0.029	0.370	
Market turbulence	0.023	−0.142	0.153	−0.114	0.132	
Direct paths to financial metrics use						
Metric-based training orientation	0.236	0.079	0.377	0.102	0.361	
Metric-based compensation orientation	0.308	0.169	0.464	0.194	0.446	
Market orientation	0.267	0.104	0.401	0.132	0.378	
Market turbulence	0.142	0.010	0.265	0.033	0.242	

Notes: [a]Results based on PLS-SEM estimation; tests of the moderation effects (*H5a*, *H5b*, *H6a* and *H6b*) presented in Table 4. [b]Lower bound (LB) and upper bound (UB) of confidence intervals (CI) obtained from bootstrapping with 5,000 replications

orientation (*H5a*: β = 0.129) and long-term orientation (*H5b*: β = 0.131), as the 95% CIs for the related interactions do not include 0.000.

We similarly find strong support for the weakening of the negative relationship between financial metrics use and marketing exploration by long-term orientation (*H6b*: β = 0.145).

However, the analogous moderation by market orientation (*H6a*: β = 0.112) is only weakly supported as only the 90% CI does not include 0.000 (we do not show its 95% CI in the interest of space). We plot each of these four moderations in Panels A to D of Figure 2,

Table 4. Structural model results – moderation effects[a]

Predictors and outcomes	Est.	95% CI_{LB}[b]	95% CI_{UB}[b]	Est.	95% CI_{LB}[b]	95% CI_{UB}[b]	Est.	90% CI_{LB}[b,c]	90% CI_{UB}[b,c]	Est.	95% CI_{LB}[b]	95% CI_{UB}[b]	Support
Interaction paths to marketing exploration													
H5a: Marketing metrics use × market orientation	0.129	0.024	0.230										Strong
H5b: Marketing metrics use × long-term orientation				0.131	0.016	0.242							Strong
H6a: Financial metrics use × market orientation							0.112	0.006	0.205				Weak[c]
H6b: Financial metrics use × long-term orientation										0.145	0.037	0.248	Strong
Direct paths to marketing exploitation													
Marketing metrics use	0.261	0.041	0.453	0.261	0.045	0.459	0.261	0.068	0.415	0.261	0.041	0.454	
Financial metrics use	0.098	−0.142	0.295	0.098	−0.152	0.290	0.098	−0.117	0.261	0.098	−0.147	0.288	
Metric-based training orientation	0.135	−0.047	0.335	0.135	−0.049	0.330	0.135	−0.015	0.298	0.135	−0.042	0.340	
Metric-based compensation orientation	−0.152	−0.308	0.026	−0.152	−0.301	0.028	−0.152	−0.279	−0.003	−0.152	−0.307	0.020	
Market orientation	0.079	−0.068	0.250	0.079	−0.065	0.244	0.079	−0.038	0.224	0.079	−0.069	0.253	
Long-term orientation	0.136	−0.015	0.268	0.136	−0.014	0.272	0.136	0.011	0.252	0.136	−0.014	0.274	
Firm size	0.032	−0.077	0.141	0.032	−0.077	0.139	0.032	−0.064	0.120	0.032	−0.080	0.141	
Defender strategic orientation	−0.078	−0.213	0.051	−0.078	−0.213	0.047	−0.078	−0.187	0.033	−0.078	−0.208	0.053	
Market turbulence	0.171	0.049	0.308	0.171	0.048	0.308	0.171	0.070	0.285	0.171	0.050	0.298	
Direct paths to marketing exploration													
Marketing metrics use	0.205	0.016	0.382	0.236	0.046	0.418	0.249	0.082	0.410	0.261	0.071	0.449	
Financial metrics use	−0.205	−0.447	−0.029	−0.226	−0.465	−0.047	−0.246	−0.463	−0.110	−0.249	−0.491	−0.075	
Metric-based training orientation	0.305	0.148	0.484	0.311	0.146	0.504	0.305	0.173	0.460	0.306	0.135	0.484	
Metric-based compensation orientation	0.090	−0.061	0.265	0.073	−0.093	0.244	0.099	−0.021	0.242	0.071	−0.086	0.250	
Market orientation	0.060	−0.109	0.260	0.075	−0.088	0.263	0.066	−0.077	0.230	0.072	−0.081	0.253	
Long-term orientation	0.130	−0.019	0.268	0.114	−0.043	0.250	0.116	−0.008	0.238	0.124	−0.031	0.257	
Firm size	0.052	−0.067	0.170	0.032	−0.087	0.155	0.046	−0.055	0.148	0.047	−0.074	0.161	
Defender strategic orientation	−0.174	−0.296	−0.056	−0.168	−0.286	−0.049	−0.174	−0.276	−0.065	−0.166	−0.292	−0.053	
Market turbulence	0.199	0.077	0.317	0.197	0.075	0.319	0.189	0.077	0.290	0.181	0.060	0.307	
Direct paths to marketing metrics use													
Metric-based training orientation	0.243	0.062	0.413	0.243	0.059	0.420	0.243	0.093	0.383	0.243	0.067	0.418	
Metric-based compensation orientation	0.317	0.161	0.490	0.317	0.164	0.496	0.317	0.191	0.463	0.317	0.166	0.500	
Market orientation	0.217	0.001	0.401	0.217	−0.003	0.396	0.217	0.019	0.374	0.217	−0.004	0.397	
Market turbulence	0.023	−0.135	0.154	0.023	−0.138	0.154	0.023	−0.113	0.130	0.023	−0.136	0.151	

(*continued*)

Table 4.

Predictors and outcomes	Est.	95% CI_{LB}[b]	95% CI_{UB}[b]	Est.	95% CI_{LB}[b]	95% CI_{UB}[b]	Est.	90% CI_{LB}[b,c]	90% CI_{UB}[b,c]	Est.	95% CI_{LB}[b]	95% CI_{UB}[b]	Support
Direct paths to financial metrics use													
Metric-based training orientation	0.236	0.076	0.385	0.236	0.071	0.377	0.236	0.097	0.356	0.236	0.072	0.382	
Metric-based compensation orientation	0.308	0.162	0.466	0.308	0.166	0.469	0.308	0.193	0.443	0.308	0.164	0.462	
Market orientation	0.267	0.105	0.403	0.267	0.105	0.397	0.267	0.129	0.383	0.267	0.110	0.400	
Market turbulence	0.142	0.015	0.265	0.142	0.013	0.265	0.142	0.033	0.246	0.142	0.013	0.268	

Notes: [a]Results based on PLS-SEM estimation; tests of the main effects (*H1* to *H4* and *H7* to *H8*) presented in Table 3. [b]Lower bound (LB) and upper bound (UB) of confidence intervals (CI) obtained from bootstrapping with 5,000 replications. [c]The 95% CIs for the estimate of the interaction term testing *H6a* contained the value of 0.000, suggesting no support for it at this strong level of significance, and is therefore not shown

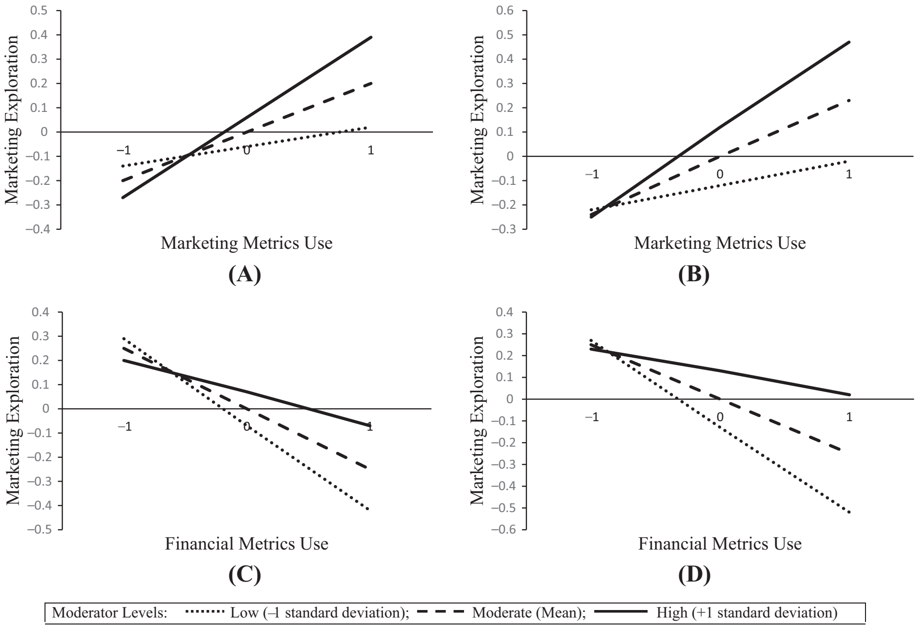

Figure 2. Moderation of the relationships between metrics use and marketing exploration by market orientation and long-term orientation

Notes: Panel A: Moderation by Market Orientation (H5a); Panel B: Moderation by Long-Term Orientation (H5b); Panel C: Moderation by Market Orientation (H6a); Panel D: Moderation by Long-Term Orientation (H6b)

using standardized values, with moderate and low (high) values of the moderators being represented by their mean, and their values at 1 standard deviation below (above) the mean, respectively. The four plots demonstrate the moderation effects in line with the directionalities hypothesized.

Mediation effects, comparisons with non-mediated effects and controls

We also test *H7* and *H8* using indirect or mediated effects that the metric orientations have on marketing adaptation through metrics use (reported in Table 5, which also shows select estimates from a non-mediated model that we discuss subsequently, and does not report CIs, but shows significance levels based on them for ease of presentation). Indirect support for these hypotheses requires the total mediated effect on each type of marketing adaptation to be significantly greater for metric-based training than for compensation. However, the 90% CIs of the sorted differences of these total mediated effects – β = 0.086 – 0.113 = –0.027 and β = –0.002 – (–0.003) = 0.001 for marketing exploitation and exploration, respectively – for the 5,000 bootstrapped samples includes 0.000, i.e. they are not significantly different. Thus, *H7* and *H8*, which were weakly supported with the direct effects, become non-significant with mediation, although notably, our arguments were for the direct paths from these orientations to marketing adaptation.

Table 5 also reports select estimates from a model that drops the metrics use constructs. In comparing these estimates with those from the focal model with mediation by metrics use

Table 5. Comparison of select non-mediated and mediated model effects[a]

Predictor	Outcome	Non-mediated model estimates[b]	Mediated model estimates and type of effect/mediator/mediation: Estimates[b]	Direct effect/specific mediator/total mediation
Metric-based training orientation	Marketing exploitation	0.222[c]	0.135	Direct effect
			0.063[d]	Marketing metrics use
			0.023	Financial metrics use
			0.086[c]	Total mediation
Metric-based training orientation	Marketing exploration	0.314[c]	0.325[c]	Direct effect
			0.055[d]	Marketing metrics use
			−0.057[d]	Financial metrics use
			−0.002	Total mediation
Metric-based compensation orientation	Marketing exploitation	−0.048	−0.152[d]	Direct effect
			0.083[c]	Marketing metrics use
			0.030	Financial metrics use
			0.113[c]	Total mediation
Metric-based compensation orientation	Marketing exploration	0.093	0.095	Direct effect
			0.072[d]	Marketing metrics use
			−0.075[c]	Financial metrics use
			−0.003	Total mediation
Market orientation	Marketing exploitation	0.157[d]	0.079	Direct effect
			0.057	Marketing metrics use
			0.026	Financial metrics use
			0.083[d]	Total mediation
Market orientation	Marketing exploration	0.034	0.042	Direct effect
			0.050	Marketing metrics use
			−0.065[d]	Financial metrics use
			−0.015	Total mediation
Market turbulence	Marketing exploitation	0.190[c]	0.171[c]	Direct effect
			0.006	Marketing metrics use
			0.014	Financial metrics use
			0.020	Total mediation
Market turbulence	Marketing exploration	0.171[c]	0.202[c]	Direct effect
			0.005	Marketing metrics use
			−0.035	Financial metrics use
			−0.029	Total mediation

Notes: [a]Table 5 compares only those effects that are mediated in the study's focal model estimated in Table 3 with the corresponding effects from a non-mediated model that excludes the metrics use constructs (we therefore do not report this model's estimates of long-term orientation, firm size and strategic orientation). [b]90% bootstrapped confidence interval of estimates without any superscripted letter include 0. [c]95% bootstrapped confidence interval of estimate does not include 0. [d]90% bootstrapped confidence interval of estimate does not include 0

(also reported in Table 5), we see that that the positive, direct effect of a metric-based training orientation on marketing exploitation loses significance in the mediated model. In addition, the mediation is significant. Thus, we see evidence of metrics use mediating the effect of a metric-based orientation on marketing adaptation (we only claim partial mediation given the estimates' values). Interestingly, a similar inference can be made for market orientation, albeit a weaker one given the significance of its non-mediated effect on exploitation. However, we do not observe such a mediation for metric-based training on marketing exploration; in fact, its significantly positive, direct effect increases in the mediated model as a negative mediation occurs through financial metrics use that is negatively related to exploration. Overall, these effects support our theorizing that metric orientations can have direct and indirect effects – through metrics use – on marketing adaptation. Yet, metric-based compensation orientation has non-significant, non-mediated effects. Thus, our theorizing that metric-based orientations create cultural contexts that enable adaptation seems more relevant when the motivations they enable are intrinsic.

Finally, we briefly comment on our control variables, many of which have significant direct paths with expected directionalities, indicating the relevance of their inclusion (Table 3). For example, a defender strategic orientation is negatively related to marketing exploration, market turbulence is positively related to both types of marketing adaptation, and in line with Mintz and Currim (2013), market orientation is positively related to both types of metrics use.

Discussion

A key aspect of organizing for marketing excellence is ensuring that the marketing organization actively engages in learning, through its adaptive capabilities of exploitation and exploration (Moorman and Day, 2016). Scholars acknowledge that knowledge plays an important role in encouraging these capabilities (Vorhies *et al.*, 2011). Yet, how metrics – part of the organization's formal control mechanism used to generate such knowledge – contribute to this effort is not well understood. Our study addresses this gap by testing a conceptual model (Figure 1) where two aspects of metrics, namely, metrics use – broken down into marketing and financial metrics use – and metric orientations driven by training and compensation, are posited to be differentially associated with marketing exploitation and exploration. Results from a survey of managers show support for many of our predictions (Table 3). The theoretical and practical implications of these results and those related to our hypothesized moderation effects (Table 4 and Figure 2) shown in Figure 1, as well as limitations of our study and suggestions for future research, are discussed in the sections that follow.

Theoretical implications

The relationships between types of metrics used and forms of marketing adaptation. Metrics play an important role in the acquisition and interpretation of knowledge, which, in turn, becomes the basis for the firm and functions within the firm, to continually adapt themselves to dynamic business environments (Morgan *et al.*, 2002). Two sets of metrics used by the marketing function are marketing and financial metrics (O'Sullivan and Abela, 2007). We argued that each set of metrics provides information on the respective inefficiencies in achieving marketing-level and financial-level outcomes from marketing actions and should therefore drive marketing exploitation. However, our results show that only marketing metrics use is positively associated with this form of adaptation (see results for *H1* and *H2* in Table 3). Further, we made the case that marketing metrics allow for diverse interpretations and encourage a customer mindset with a long-term view, while financial metrics are variance-reducing and induce a short-term mindset (Benner and Tushman, 2003; Kyriakopoulos and Moorman, 2004). Moreover, as marketing metrics are a more direct measure of marketing actions compared to financial metrics (Rust *et al.*, 2004), they instill a greater sense of confidence in the interpretations they engender, enabling marketing managers to pursue riskier, exploratory adaptations. Our results support the positive (negative) association of marketing (financial) metrics use with marketing exploration in line with these arguments (see results for *H3* and *H4*).

Theoretically, we connect the use of metrics to marketing adaptation through the rationales of knowledge acquisition and interpretation and the creation of mindsets. Our results support the theorizing based on these rationales, as in line with our expectations, we find that marketing and financial metrics have differential impacts on marketing exploitation and exploration. These findings are noteworthy in light of research by Mintz *et al.* (2019) who find marketing metrics to be superior compared to financial metrics for many marketing mix decision outcomes. As such, this study addresses the gap in our understanding of the relationship between metrics use and marketing adaptation [7]. In doing so, we build on and add to prior research that demonstrates how firms can develop exploitative and explorative capabilities (Atuahene-Gima, 2005; Vorhies *et al.*, 2011), but how the resources needed for doing so may not be the same for each (Jansen *et al.*, 2006; Josephson *et al.*, 2016; Yalcinkaya *et al.*, 2007). Our moderation results (Table 4 and Figure 2) underscore this contribution as we show that market orientation (*H5a* and *H6a*) and long-term orientation (*H5b* and *H6b*) can create contexts that, respectively, encourage variety in knowledge and experimentation (Gebhardt *et al.*, 2006; Homburg and Jensen, 2007), strengthening (weakening) the positive (negative) effects of marketing (financial) metrics on marketing exploration.

The relationships between types of metric orientation and marketing adaptation. Our conceptual model also explores the impact that a metric orientation has on marketing adaptation. We test two facets of such an orientation that have been proposed as part of the formal marketing control system, namely, training and compensation (Mintz and Currim, 2013). While these management tools encourage the use of marketing and financial metrics, we proposed that the cultural context they create (Jaworski, 1988), can have unintended yet direct consequences on the adaptive capabilities of the marketing organization. Specifically, our argument was that as training operates by creating an intrinsic motivation (Oliver and Anderson, 1994), it should create an innate desire to pursue both exploitation and exploration, as marketers look to apply their knowledge across various marketing activities. On the other hand, given compensation's role as an extrinsic motivator, we posited that it creates a cultural context where adaptations are not pursued unless absolutely necessary, as marketers may not want to risk any loss in remuneration (Segalla *et al.*, 2006). Our focal results support these arguments, in that the effects for training are stronger than those for compensation, albeit at low levels of significance (see results for *H7* and *H8* in Table 3). In fact, compensation has no direct effect on either forms of adaptation, whereas training increases both marketing exploitation and exploration, with the former of these two significant effects being partially mediated by the use of metrics (Table 5). These findings, which are in line with those from the sales management literature (Miao *et al.*, 2007), highlight the important and nuanced role that management tools such as training and compensation can play in creating, either directly or indirectly through the use of metrics, an adaptive mindset and a culture that enables continuous learning.

Managerial implications

Frösén *et al.* (2016) note that "measuring the wrong things can be costly not only in terms of wasted resources but also in distracting managerial attention" (p. 75). In that regard, our results show that an emphasis on the use of marketing metrics allows firms to pursue both forms of marketing adaptation. Where marketing managers need to exercise caution is with financial metrics, as their use may result in a marketing organization that loses its competitive edge as a radically adaptive entity, given the significant negative effect that the use of these metrics have on marketing exploration. However, prior research has demonstrated the importance of these metrics for marketing influence (Verhoef and Leeflang, 2009). Moreover, we also find that firms tend to use both types of metrics, given the correlation of 0.72 between them. Attenuations by market orientation and long-term orientation of the negative effect that financial metrics use has on market exploration (Panels C and D of Figure 2), suggest that encouraging these orientations can address this dilemma. Marketing managers may also use the weights or importances of formative items reported in Appendix 1 to determine which metric needs to be emphasized (de-emphasized) to have the greatest impact in increasing marketing (decreasing financial) metrics use. Finally, our study provides guidelines for marketing managers with regards to emphasizing training more than compensation as a control mechanism to sustain adaptation within the marketing function. Notably, both these tools have nuanced indirect effects on marketing adaptation through metrics use, broadly favoring having both in place. However, a metric-based training orientation directly increases exploration further reinforcing its relative advantage.

Limitations and suggestions for future research

Future research could extend our conceptual model to understand the impact of marketing and financial metrics on adaptation at the level of each marketing activity, such as the 4P's, by using specific metrics associated with them (Mintz and Currim, 2013). Studies could also identify configurations of firms defined by, for example, metrics use, based on how well they achieve outcomes such as adaptation (Frösén *et al.*, 2016, se fuzzy-set qualitative comparative analysis for this purpose). Research should also extend our study by exploring additional moderators with respect to the focal main effects of our conceptual model. Given that these main effects are hypothesized under the assumption that the knowledge, mindsets and cultural contexts created, differ with the type of metric emphasis, it is likely that facets such as leadership style, managerial capital and organizational and national culture, affect these relationships (Atuahene-Gima, 2005; Broekhuizen *et al.*, 2017; Germann *et al.*, 2013; Homburg *et al.*, 2012; Moorman, 1995; Raisch and Birkinshaw, 2008; Stathakopoulos, 1998). Such findings would further deepen our understanding of the chain of productivity with respect to metrics, while providing marketing managers practical recommendations for making their emphasis beneficial. In this regard, researchers could also conceptualize marketing and financial metrics use as reflective constructs, with indicators that measure the distinct knowledge and mindsets engendered by their use, thereby, more directly capturing the rationales that we proposed for their differential effects.

Notes

1. We discuss the specific measures we use for each type of metric in our methodology but note here that we closely follow Mintz and Currim's (2013) classification of general metrics into marketing and financial metrics (see their Table 1 for their measures, as well as their three-step procedure used to generate them, on p. 20 and pp. 25-26 of their paper, respectively).

2. Survey Monkey builds their audience panels by recruiting from "2.5 million people who complete [their] surveys daily" (www.surveymonkey.com/mp/audience/our-survey-respondents). For competitive reasons, they do not provide details about their panel, which prevents us from either commenting on their choice of 4,625 as a starting sample or providing any comparison of these 4,625 respondents with their panel.

3. We do not have any demographic details on the (4,625 minus 1,993) respondents not starting the survey. Further, the only data we have on those not in our final sample, from the 1993 that started the survey, is the answers on the filter questions that are in multiple choice format. Thus, as a non-response bias analysis is not possible or meaningful for our sample, we carry out an early-late respondent analysis as reported subsequently in the paper. We thank an anonymous reviewer for making this suggestion.

4. While our list (Appendix 1) is very close to Mintz and Currim's (2013) set of general metrics (Table 1 on p. 20 of their paper), there are a few differences, driven by our in-depth interviews and with a view to being parsimonious in the metrics we present to respondents in our study. We report these differences in footnote b of our Appendix 1.
5. We thank the associate editor for emphasizing that indicator or item weights need to be modeled or estimated with formative constructs.
6. We also ran a PLS-SEM model combining the indicators for marketing and financial metrics use into a single formative construct. We find that the combined construct of metrics use in this more parsimonious model is positively and significantly related to marketing exploitation and negatively but non-significantly related to exploration. In comparison, separating these two constructs gives similar but more nuanced results, which as reported subsequently in the paper, show that marketing metrics use is positively related to both types of marketing adaptation, while financial metrics use is negatively related to marketing exploration. Empirically, there is no clear winner between these two models as various fit statistics such as R^2 and BIC show that exploration (exploitation) is better explained with the less (more) parsimonious model. Notably, however, the less parsimonious model's fine-grained results are in line with our theorizing, suggesting that the results with these constructs being separated, even though they share a correlation of 0.72, are more meaningful.
7. We also ran a PLS-SEM model where we operationalized metrics use as two formative constructs, one composed of all customer-level metrics and the other formed by all the firm-level metrics (Appendix 1 shows the metrics under each of these sub-classifications). Customer-level metrics use was not significantly related to either marketing exploitation or exploration (the latter effect was the only one that was negative in sign). Firm-level metrics use was only weakly (and positively) related to exploitation and not significantly related to exploration. These largely non-significant results underscore the theoretical and empirical case for conceptualizing and distinguishing metrics use as we do in the paper, namely, as being made up of the use of marketing and financial metrics, rather than on the basis of customer-level and firm-level metrics use.

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Appendix 1

Table A1

Construct items or indicators [Source; scale]	Loadings[a]	Weights[a]
Marketing exploitation		
(Vorhies *et al.*, 2011; 1-strongly disagree, 5-strongly agree)		
1. We routinely fine-tune our existing marketing processes	0.825	0.328
2. The changes we make in our marketing processes are usually focused on improving their efficiency	0.840	0.309
3. We frequently refine our marketing processes by studying and correcting existing problems with them	0.851	0.371
Marketing exploration		
(Vorhies *et al.*, 2011; 1-strongly disagree, 5-strongly agree)		
1. We continually develop new marketing processes that are very different from others developed in the past	0.797	0.298
2. We consistently develop new marketing processes which deliver different outputs from existing processes	0.828	0.312
3. We often experiment or "break the mold" and create new marketing processes not used before	0.819	0.326
4. We frequently challenge and/or change our thinking with respect to our marketing processes	0.783	0.304
Marketing metrics use[b] (presented as sets of customer and firm-level metrics)		
(Mintz and Currim, 2013; 1-very infrequently, 5-very frequently)		
Customer-level marketing metrics		
1. Awareness	Dropped[a]	Dropped[a]
2. Likeability	0.675	0.106
3. Preference	0.712	0.200
4. Satisfaction	Dropped[a]	Dropped[a]
5. Loyalty	0.674	0.120
6. Willingness to recommend	0.652	0.074
7. Perceived quality	Dropped[a]	Dropped[a]
Firm-level marketing metrics		
8. Market share in units or dollars	0.652	0.125
9. Sales in units or dollars	Dropped[a]	Dropped[a]
10. Customer acquisitions	Dropped[a]	Dropped[a]
11. Customer retentions or churn	0.672	0.145
12. Price premium	0.646	0.153
13. Share of voice	0.813	0.337
14. Brand equity	0.744	0.141
Financial metrics use[b] (presented as sets of customer and firm-level metrics)		
(Mintz and Currim, 2013; 1-very infrequently, 5-very frequently)		
1. Customer-level financial metrics		
2. Customer acquisition costs	0.735	0.263
3. Customer retention costs	0.777	0.147
4. Customer revenue	Dropped[a]	Dropped[a]
5. Customer lifetime value	0.662	0.092
6. Customer segment profitability	0.716	0.057
Share of customer wallet	0.725	0.157
Firm-level financial metrics		
7. Net profit	Dropped[a]	Dropped[a]
8. Return on investment	Dropped[a]	Dropped[a]

(continued)

Construct items or indicators [Source; scale]	Loadings[a]	Weights[a]
9. Return on sales	0.727	0.225
10. Net present value	0.734	0.112
11. Total costs	Dropped[a]	Dropped[a]
12. Cash flow	0.686	0.185
13. Total shareholder return	0.630	0.166
Metric-based training orientation (items below presented after each set of respective customer/firm-level marketing/financial metrics): *Marketing personnel in my firm receive a lot of training on the use of these . . . metrics* (Mintz and Currim, 2013; 1-strongly disagree, 5-strongly agree)		
1. [customer-level marketing]	0.866	0.294
2. [firm-level marketing]	0.897	0.287
3. [customer-level financial]	0.895	0.281
4. [firm-level financial]	0.866	0.273
Metric-based compensation orientation (items below presented after each set of respective customer/firm-level marketing/financial metric): Such . . . metrics are an important part of how marketing personnel are compensated in my firm (Mintz and Currim, 2013; 1-strongly disagree, 5-strongly agree)		
1. [customer-level marketing]	0.824	0.296
2. [firm-level marketing]	0.870	0.288
3. [customer-level financial]	0.841	0.307
4. [firm-level financial]	0.789	0.314
Market orientation (Verhoef and Leeflang, 2009; 1-strongly disagree, 5-strongly agree)		
1. Our business objectives are driven primarily by customer satisfaction	0.676	0.243
2. We have routine or regular measures for customer service	0.721	0.272
3. We freely communicate information about our successful and unsuccessful customer through all business functions experiences	0.764	0.292
4. Our strategy for competitive advantage is based on our understanding of customer needs	0.770	0.277
5. We regularly discuss competitors' strengths and strategies to respond to competitive actions	0.668	0.303
Long-term orientation (Homburg and Jensen, 2007; 1-strongly disagree, 5-strongly agree)		
1. My firm or business unit takes the long view in evaluating the success of its marketing activities and processes	0.826	0.474
2. My firm or business unit does not make quick judgments regarding marketing successes or failures	0.720	0.323
3. Marketing personnel in my firm or business unit are encouraged to think and act in line with a longer time horizon, rather than a short one	0.843	0.446
Market turbulence (Mintz and Currim, 2013; 1-strongly disagree, 5-strongly agree)		
1. Customer preferences and demand are very hard to forecast in our business	0.826	0.416
2. We need to constantly change our production/service technology to keep up with competitors and/or customer preferences	0.792	0.434
Firm size (log of the number of employees)	NA	
Strategic orientation (= 10 if 1/2[3/4] chosen; respondents pick one that characterizes their firm)		

Table A1

(*continued*)

Construct items or indicators [Source; scale]	Loadings[a]	Weights[a]
(Mintz and Currim, 2013) 1. Prospectors: Tend to be first to market with new products/services that offer either a substantial performance/quality improvement or cost reduction. They do not hesitate to enter new markets with emerging opportunities 2. Analyzers: Monitor market activity and tend to be early followers with a better targeting strategy, increased customer benefits or lower costs. They are seldom first to market or first to enter an emerging market 3. Low-cost defenders: Prefer to maintain stability and are rarely at the forefront of new product/service development. They protect their market position by focusing on efficiency or low prices 4. Differentiated defenders: Prefer to maintain stability and are rarely at the forefront of new product/service development. They protect their market position through high prices that are enabled by a focus on delivering superior product/quality 5. NA		

Notes: [a]As PLS-SEM does not make any distributional assumptions, statistical significance is determined through the calculation of CIs using bootstrapping (with 5,000 replications). All item loadings, which are used to score reflective constructs, are significant at the $p < 0.01$ level, i.e. the 99% confidence interval does not include 0.000. As described in the body of the paper, significance of item weights, which are used to score formative constructs, is not required for their inclusion. Dropped formative indicators are those that have negative weights or those that have loadings below 0.5. [b]As mentioned in the body of the paper, our list of marketing and financial metrics closely follows Mintz and Currim's (2013) set of general metrics. The few key differences, driven by our in-depth interviews, and with a view to being parsimonious, are as follows: we dropped the metrics of consideration set and economic value added (both had less than 5% reported usage in their study); combined Tobin's Q and stock price into total shareholder return; added a pricing and a brand-related marketing metric; split their total customers marketing metric into acquisitions and retentions and added costs of acquiring and retaining customers under financial metrics. Notably, Mintz and Currim (2013), also incorporate or consider many of these modifications, as metrics at the specific marketing mix-level (Table 1 on p. 20 of their paper).

Table A1

Appendix 2

Table A2.
Correlations among metrics use items

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
1. Awareness																										
2. Likeability	0.618																									
3. Preference	0.645	0.640																								
4. Satisfaction	0.528	0.591	0.662																							
5. Loyalty	0.573	0.575	0.597	0.729																						
6. Willingness to recommend	0.600	0.577	0.554	0.611	0.655																					
7. Perceived quality	0.510	0.560	0.597	0.681	0.595	0.599																				
8. Market share in units or dollars	0.304	0.306	0.323	0.256	0.301	0.329	0.260																			
9. Sales in units or dollars	0.232	0.298	0.319	0.437	0.391	0.257	0.350	0.475																		
10. Customer acquisitions	0.248	0.264	0.317	0.272	0.263	0.290	0.307	0.343	0.426																	
11. Customer retentions or churn	0.305	0.308	0.388	0.400	0.410	0.329	0.382	0.439	0.475	0.581																
12. Price premium	0.203	0.310	0.299	0.377	0.363	0.375	0.372	0.426	0.536	0.366	0.464															
13. Share of voice	0.399	0.400	0.393	0.335	0.349	0.390	0.362	0.524	0.440	0.337	0.442	0.437														
14. Brand equity	0.397	0.454	0.403	0.341	0.386	0.356	0.414	0.452	0.490	0.317	0.482	0.433	0.619													
15. Customer acquisition costs	0.334	0.377	0.355	0.252	0.336	0.316	0.257	0.469	0.329	0.478	0.457	0.338	0.467	0.315												
16. Customer retention costs	0.292	0.351	0.355	0.289	0.367	0.342	0.312	0.445	0.291	0.388	0.600	0.425	0.414	0.355	0.735											
17. Customer revenue	0.239	0.259	0.392	0.480	0.392	0.259	0.361	0.362	0.550	0.393	0.425	0.376	0.250	0.269	0.526	0.476										
18. Customer lifetime value	0.333	0.422	0.386	0.379	0.376	0.349	0.373	0.250	0.308	0.395	0.453	0.339	0.333	0.373	0.554	0.577	0.461									
19. Customer segment profitability	0.395	0.384	0.380	0.371	0.401	0.324	0.324	0.428	0.385	0.359	0.517	0.459	0.396	0.381	0.549	0.581	0.550	0.660								
20. Share of customer wallet	0.299	0.348	0.289	0.298	0.325	0.347	0.292	0.478	0.363	0.287	0.411	0.425	0.476	0.435	0.478	0.518	0.430	0.501	0.633							
21. Net profit	0.240	0.295	0.265	0.334	0.346	0.271	0.325	0.437	0.602	0.247	0.359	0.411	0.300	0.322	0.375	0.397	0.482	0.268	0.409	0.410						
22.Return on investment	0.294	0.229	0.307	0.263	0.295	0.225	0.281	0.377	0.401	0.345	0.398	0.381	0.269	0.337	0.428	0.474	0.441	0.482	0.452	0.429	0.621					
23. Return on sales	0.187	0.276	0.230	0.286	0.280	0.259	0.391	0.343	0.478	0.346	0.404	0.460	0.312	0.401	0.337	0.449	0.357	0.405	0.374	0.393	0.638	0.651				
24. Net present value	0.273	0.300	0.248	0.304	0.350	0.398	0.380	0.418	0.392	0.255	0.346	0.475	0.381	0.380	0.332	0.460	0.298	0.367	0.439	0.453	0.643	0.474	0.653			
25. Total costs	0.225	0.152	0.218	0.318	0.303	0.204	0.356	0.359	0.444	0.292	0.412	0.394	0.324	0.288	0.287	0.373	0.336	0.221	0.294	0.287	0.646	0.595	0.594	0.491		
26. Cash flow	0.272	0.318	0.351	0.400	0.337	0.317	0.384	0.306	0.443	0.190	0.352	0.434	0.328	0.334	0.286	0.331	0.369	0.279	0.424	0.380	0.607	0.440	0.501	0.587	0.478	
27. Total shareholder return	0.229	0.241	0.231	0.244	0.218	0.245	0.189	0.425	0.262	0.126	0.308	0.317	0.352	0.359	0.247	0.334	0.186	0.235	0.348	0.450	0.419	0.330	0.370	0.493	0.377	0.540