Accounting Horizons

A Publication of the
American Accounting Association

American Accounting Association
Thought Leaders in Accounting

Accounting Horizons

V.38 N.4 2024

ACCOUNTING HORIZONS
Vol. 38, No. 4
December 2024
pp. 1–29

American Accounting Association
DOI: 10.2308/HORIZONS-2021-016

Customer Analytics in Performance Measurement and Reporting Systems

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SYNOPSIS: This study examines how firms deploy customer analytics in their performance measurement and reporting systems. Firstly, we synthesize insights from the literature on customer analytics in accounting and marketing and conduct interviews with experts in the field. We then present the results of an online survey conducted among a sample of subscription-based firms known for their early adoption of customer analytics. Our findings reveal that the use of customer analytics varies significantly by metric type, with traditional indicators (e.g., number of customers) showing higher levels of integration compared with more advanced metrics, such as customer lifetime value and customer equity. The extent of adoption in performance measurement and reporting systems appears to depend on the ability of a firm to fit customer analytics into its organizational architecture. We conclude by identifying research avenues reflecting current trends that will likely shape the emerging literature on customer analytics.

Keywords: customer analytics; customer accounting; customer centricity; customer lifetime value; customer equity; organizational architecture.

I. INTRODUCTION

The objective of this study is to examine how firms deploy customer analytics in their performance measurement and reporting systems. Customer analytics is the practice of leveraging data and statistical methods to better understand customer behavior. By collecting and analyzing data about customer interactions, such as purchase history, mobile app usage, or customer service inquiries, firms can identify, attract, and retain the most valuable customers or customer segments. In today's digital economy, the advent of Big Data and artificial intelligence (AI) has enabled customer analytics to reveal patterns and trends in customer preferences that were previously unidentifiable. As a result, customers instead of products are becoming the new fundamental unit of analysis for assessing the future value of a firm (Markey 2020; McCarthy and Fader 2020). In a 2022 Gartner survey of 283 customer service leaders, 84 percent of respondents cited customer analytics as "very or extremely important" for achieving their organizational goals (Gartner 2023). Despite the growing relevance of customer analytics, empirical evidence regarding their usage remains limited, particularly concerning how chief finance officers and management accountants apply customer analytics for the

We would like to thank Margaret H. Christ (editor) and two anonymous reviewers for their constructive comments and guidance during the review process. We also appreciate helpful suggestions from Gary Cokins, Daniel McCarthy, Peter Fader, Massimiliano Pellegrini, Arthur Posch (discussant), and conference participants at the 2019 American Accounting Association Management Accounting Section Midyear Meeting. We are extremely grateful to the eight professionals interviewed for sharing their insights. The authors of this publication have no conflicts of interest related to this research.

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Supplemental material is available online, as linked in the text.

Editor's note: Accepted by Margaret H. Christ, under the Senior Editorship of Ray J. Pfeiffer.

Submitted: February 2021
Accepted: October 2023
Early Access: November 2023

purposes of measuring and valuing customer attraction, conversion, and retention (Rikhardsson and Yigitbasioglu 2018; Matsuoka 2020).

We use a multimethod research approach to identify and address this gap in the literature. First, we review and synthetize the literature on customer analytics. Second, we use this literature review to direct our line of enquiry as we interview eight professionals with expertise in customer analytics. Third, we further explore the insights gained from our interviews through a broad-based survey of 300 respondents recruited via Qualtrics from firms with a subscription-based business model (i.e., early adopters of customer analytics due to the easy availability of customer data).

Our descriptive findings reveal that the diffusion of customer analytics varies significantly, with traditional metrics (e.g., number of customers) exhibiting a higher level of penetration than more advanced analytics like customer lifetime value (CLV) and customer equity (CE). The implementation of a customer-centric strategy appears to be a significant determinant of customer analytics, which is consistent with prior research (e.g., Holm and Ax 2020). Our survey findings, however, are the first to reveal that the pattern of customer analytics adoption in performance measurement and reporting systems are associated with the presence of a Specialized Business Intelligence Unit. Furthermore, the limited integration of CLV and CE as performance targets within compensation and incentive systems weakens the penetration of these analytics in comparison to other metrics (cf. Casas-Arce, Martínez-Jerez, and Narayanan 2017). The current level of ownership of customer analytics by the accounting function is relatively low, which presents an additional potential barrier to the diffusion of these metrics across functional silos.

The paper contributes to advance knowledge on customer analytics in two ways. First, leading professional bodies (Institute of Management Accountants (IMA) 2010; Chartered Institute of Management Accountants (CIMA) 2012; Institute of Management Accountants (IMA) 2014) and practitioner literature (e.g., Kumar and Rajan 2009a, 2009b; Cokins 2015; McKinsey & Company 2016; Beaudin 2017; Aguilar and Ittner 2019; Fader 2020; *Harvard Business Review* 2020; Markey 2020; Srivastava and Rajgopal 2022) noticeably advocate the fundamental role of customer analytics as a source of competitive advantage. To the best of our knowledge, our study is the first to provide detailed insights into the use of customer analytics in performance measurement and reporting systems. Second, our research sheds light on how customer analytics are integrated into performance measurement and reporting systems in response to a customer-centric strategy, with a particular emphasis on subscription-based firms. Although these companies have been at the forefront of adopting customer analytics, our findings have broader implications for other firms that are in the process of transitioning from a product-centric to a customer-centric approach. Third, we provide suggestions for a theory-based research agenda that relies on the organizational architecture (OA) framework (Brickley, Smith, and Zimmerman 1995, 2004; Brickley, Smith, Zimmerman, and Willett 2009) as a robust model to build a cohesive body of knowledge on customer analytics as well as support practitioners' decisions on the implementation of customer analytics in accounting systems.

The remainder of this paper is structured as follows. We start with a literature review on customer analytics organized around the OA framework. We further present descriptive evidence derived from an online survey on the use of customer analytics, supplemented with insights from interviews with experts in the field. We then conclude with limitations of our study and avenues for future research.

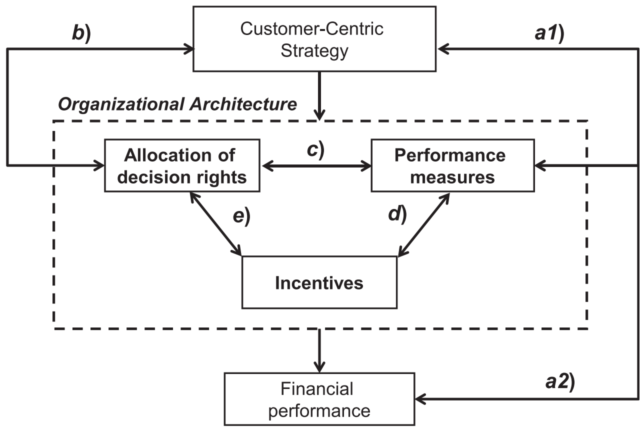
II. LITERATURE REVIEW AND RESEARCH OBJECTIVES

Customer Analytics and Customer-Centric Strategy in the Organizational Architecture

Both marketing and accounting scholars are increasingly interested in gaining insights on how to measure and manage customer data to improve a firm's competitive advantage. Marketing researchers employ the labels *customer analytics* and *marketing analytics* interchangeably to denote metrics and analytical models that leverage customer and market data to enhance marketing decision making (Wedel and Kannan 2016; Lilien 2011; Germann, Lilien, Moorman, Fiedler, and Großmaß 2020). Accounting researchers use instead the label *customer accounting* as an umbrella term defined as "all accounting practices directed toward appraising profit, sales, or present value of earnings relating to a customer or group of customers" (Guilding and McManus 2002, 48). Despite distinctive elements in terminology and emphasis that emerge from the literature on marketing/customer analytics and customer accounting (McManus and Guilding 2008), the tools and organizational processes object of study in both disciplines substantially overlap (Matsuoka 2020; Hossain, Akter, and Yanamandram 2020). We accordingly adopt a broad notion of *customer analytics* in delimiting the scope of our literature review to embrace an emergent area of research at the interface of marketing and accounting. As to the depth of the literature review, we apply a selective approach that focuses on representative papers, mostly published in the *Financial Times*'s 50 journals list. Our aim is not to provide a systematic review of the customer analytics literature; this endeavor was previously fulfilled by others (e.g., McManus and Guilding 2008;

FIGURE 1

Conceptual Framework: Organizational Architecture



Adapted from Brickley et al. (2009) and Bonacchi and Perego (2019).
The arrows refer to the linkages among the variables we use to organize our literature review.

Kraus, Håkansson, and Lind 2015; Rikhardsson and Yigitbasioglu 2018; Matsuoka 2020; Hossain et al. 2020). Instead, we follow an approach similar to that of Ittner and Larcker (2001) and organize our review drawing on the OA theoretical framework, an integrated model that captures linkages embedded in contingency theory, principal agent, and economics-based organizational design models (Brickley et al. 2004; Brickley et al. 2009).

The underlying principle of the OA is that the creation of value is dependent on the fit between a business strategy and three interdependent organizational components, as illustrated in Figure 1. The first component is the *performance measurement system* that encompasses the selection of specific metrics for coordinating decision making processes, monitoring progress toward strategic objectives, and providing feedback to employees for learning purposes. The second component is the *allocation of decision rights* (i.e., who is given the authority to make decisions), which recognizes the importance of delegation to individuals and organizational units with specific knowledge as a crucial determinant of accountability. The third component is the *incentive and compensation systems*, which aim to align the efforts of managers and employees with strategic objectives. The optimal combination of these three formal organizational arrangements should result in effective alignment with a firm's strategy and lead to higher value creation (cf. Chenhall 2003; Abernethy, Bouwens, and van Lent 2004; Widener, Shackell, and Demers 2008; Lee and Yang 2011).

Starting from the top of Figure 1, the business strategy investigated in the customer analytics literature develops around the notion of customer centricity (Lee, Sridhar, Henderson, and Palmatier 2015; Palmatier, Moorman, and Lee 2019), "a carefully defined and quantified customer segmentation strategy in which firm's operations aim at delivering the greatest value to the best customers for the least cost" (Sheth, Sisodia, and Sharma 2000; Shah, Rust, Parasuraman, Staelin, and Day 2006; Ramani and Kumar 2008). Customer-centric firms are relationship oriented in their customer-focused value proposition and tend to highlight products' benefits in terms of customer experience (Shah et al. 2006). Conversely, product-centric firms have a transaction-oriented business orientation, with a product positioning that emphasizes product features. Customer centricity principles can be partially or incrementally adopted; thus, a firm may transition along a continuum that moves from product centricity to customer centricity depending on its contingent capabilities to address strategic issues. These issues include questions such as whether to prioritize volume or margin for a particular customer, how many products to sell to a specific customer, and how to develop profitable customer relationships over the long term (Sheth et al. 2000; Shah et al. 2006; Kumar and Rajan 2012; Cokins 2015; Bonacchi and Perego 2019). Apple, Dyson, and Ikea are among the firms that are currently shifting from a product-centric business model to a customer-centric one. As a result of the dynamic adaptation of the OA to a business strategy, firms may exhibit a range of heterogeneous configurations. Firms that have a high degree of alignment between the three OA components and a customer-centric strategy are more likely to achieve superior performance compared with those that deviate from this alignment.

In our literature search, we include representative studies that examined the role of customer analytics in the interplay among OA elements observed in firms that embark on a customer-centric continuum journey (refer to the links *a–e* in Figure 1). For each relationship, Table 1 outlines independent/dependent variables investigated and summarizes

TABLE 1

Overview of the Literature on Customer Analytics

Organizational Architecture Relationship (Link)	Independent Variables	Dependent Variables	Representative Studies in Accounting and Marketing	Key Research Questions	Practical Implications
Customer-centric strategy → performance measurement systems (PMS) (link *a1*)	• Customer-centric strategy	• Customer analytics/customer accounting (CA) • PMS	Guilding and McManus (2002); McManus and Guilding (2009); Holm et al. (2012); Mintz and Currim (2013); Germann et al. 2013, 2020); Holm and Ax (2020)	• How does a customer-centric strategy affect the design and use of a PMS? • What is the relationship between competition intensity and customer analytics/CA sophistication? • What is the relationship between customer behavioral complexity and customer analytics/CA sophistication? • How do customer-centric strategy and customer service competition interact on customer analytics/CA sophistication?	• Understand how to implement customer analytics/PMS that suits to customer-centric strategies, in response to varying levels of competition intensity, and *vice versa* • Align the long-term strategy of the firm to the type and behavioral complexity of the customers served • Benchmark and prioritize customer analytics/PMS with different degrees of sophistication depending on both competitive contexts and strategic orientation
Customer-centric strategy → allocation of decision rights (link *b*) Allocation of decision rights→ PMS (link *c*)	• Customer-centric strategy • Allocation of decision rights	• Allocation of decision rights • Customer analytics/CA • PMS	Lee et al. (2015); Lee and Day (2019)	• How does a customer-centric strategy affect the formal organizational structures in charge of marketing-related decisions? • What is the level of coordination and interaction among marketing and accounting functions in customer-centric firms? • How does a customer-centric strategy influence the	• Assess the fit between a customer-centric strategy and the level of decentralization of marketing-related decisions • Understand how to define responsibility to implement a customer-centric strategy among functions, including marketing and accounting • Consider the adoption of a specialized unit in charge of customer analytics/CA deployment (e.g., Business Intelligence Unit), separate from other functions

(*continued on next page*)

TABLE 1 (continued)

Organizational Architecture Relationship (Link)	Independent Variables	Dependent Variables	Representative Studies in Accounting and Marketing	Key Research Questions	Practical Implications
				ownership of customer analytics/CA in marketing or accounting functions?	
Allocation of decision rights → incentives (link *e*) PMS → incentives (link *d*)	• Allocation of decision rights • Customer analytics/ CA/PMS	• Incentives	Mintz and Currim (2013); Casas-Arce et al. (2017)	• How are customer analytics/PMS design and sophistication related to the use of customer analytics in incentive and compensation schemes? • Which customer analytics are used in incentive and compensation schemes at different organizational levels? • How do firms define the difficulty of customer analytics targets and the frequency of revision?	• Examine whether and how customer analytics' accuracy and sophistication affect managerial performance evaluation • Understand how to calibrate the use of customer analytics in incentive schemes in different functions/tasks and different organizational levels
PMS → financial performance/firm value (link *a2*)	• PMS/customer analytics/CA sophistication and usage • Customer analytics in corporate disclosure	• Firm financial performance • Firm value	Abramson et al. (2005); Schulze et al. (2012); Homburg et al. (2012); Germann et al. (2013, 2020); Bonacchi et al. (2015); Bayer et al. (2017); McCarthy et al. (2017); Holm, Kumar, and Plenborg (2016); McCarthy and Fader (2018)	• What is the impact of PMS/ customer analytics/CA sophistication and usage on financial performance? • What is the role of customer equity in determining the value of the firm? • How do the capital markets react to the disclosure of different types of customer analytics?	• Understand and predict how to effectively measure and manage the creation of value from the customer base • Execute a firm's valuation for IPOs or for internal purposes • Benchmark with competitors the disclosure of customer analytics and calibrate the communication with financial analysts and other financial markets key players

research questions and main implications for practitioners. We depict the links shown in Figure 1 using two-headed arrows between variables, suggesting the presence of reciprocal/recursive causal relationships that were either empirically examined or conceptualized as a potential alternative to unidirectional effects.

Customer-Centric Strategy and Performance Measurement (Link *a1*)

Regarding the link between customer-centric strategy and performance measurement systems (represented by link *a1*), firms should tailor metrics that enable managers to assess the execution of a firm's strategy. The marketing and accounting literature comprises a variety of constructs categorized into observable/behavioral (e.g., customer retention) and unobservable/perceptual metrics (e.g., customer satisfaction and loyalty intentions; Gupta and Zeithaml 2006; Petersen, Kumar, Polo, and Sese 2018). With the advent of Big Data and AI, firms can bypass unobservable metrics, directly link a firm's actions to observable customer behavior, and track their impact on financial performance. Internet-based firms (such as Amazon and Netflix) are adopting machine-learning techniques to track online interaction patterns. Even traditional brick-and-mortar firms are rapidly adopting AI technologies to collect massive amounts of data on their operations and supply chains. Walmart, for instance, leverages Big Data and customer analytics to provide personalized product recommendations, optimize inventory management, and streamline their distribution networks. A decade ago, none of these disruptive digital technologies was close to becoming a daily practice. Therefore, in this review, we explicitly concentrate on observable customer analytics.

Kumar and George (2007), Villanueva and Hanssens (2007), Kumar (2008), and Petersen et al. (2009) indicate three core customer analytics crucial to the shift toward a customer-centric strategy. First, *customer profitability* is defined as the difference between the revenue earned from a customer relationship and the associated costs during a specified period (Smith 1993; Smith and Dikolli 1995; Foster, Gupta, and Sjoblon 1996). Second, *customer lifetime value* (CLV) is the discounted value of future cash flows attributed to a single customer or group of customers. CLV provides a model for valuing a customer base, allowing the firm to understand the mechanisms by which three main components—the cost of customer acquisition, margin per customer (i.e., average revenue per user or ARPU minus cost of serving the customer; ARPU is increasingly used to monetize a single customer in a given period), and retention rate—affect a firm's profitability, Third, *customer equity* (CE) is defined as the sum of CLV among all of a firm's existing and potential customers (Gupta, Lehmann, and Stuart 2004; Villanueva and Hanssens 2007; Kumar and Shah 2009). CE represents an intangible firm-level asset that is positively correlated with a firm's stock return (Bonacchi, Kolev, and Lev 2015; McCarthy and Fader 2020).

From our literature search, a stream of emergent research applied heterogeneous approaches to investigate customer-centric strategies and measure the degree of sophistication of customer analytics. Survey-based studies examined the link between the position of a firm along the customer-centric strategy continuum and the type of customer analytics deployed (e.g., Guilding and McManus 2002; Holm, Kumar, and Rohde 2012; Germann, Lilien, and Rangaswamy 2013; Mintz and Currim 2013; Germann et al. 2020; Holm and Ax 2020). Case-based research revealed the beneficial consequences of CLV and CE as informative, forward-looking customer analytics, despite accountants having been initially reluctant to integrate them in traditional performance measurement systems (Roslender and Hart 2003; McManus and Guilding 2009). For instance, Capital One, an online bank, segments its customers to calculate their CLV and identifies the most effective use of its resources in marketing campaigns and investments (Anand, Rukstad, and Paige 2000; Lattin 2007). Likewise, Harrah's hotel and casino increasingly operates its business by utilizing observable customer metrics (Loveman 2003).

These examples show that customer analytics are gaining traction by both contractual and noncontractual business models. The defining characteristic of contractual or subscription-based companies (SBCs) (e.g., insurance, banking, internet services, and online gaming) is that the customer acquisition and departure can be straightforwardly observed and the vendor can track the number of currently active customers at any point in time. In contrast, noncontractual businesses (e.g., hotel, retail, and leisure) have more complex transactional patterns because customer purchase timing and spending amounts are irregular. The number of SBCs skyrocketed by almost 435 percent between 2012 and 2020. Moreover, the usage of customer analytics contributed to the growth of the Subscription Economy Index 4.6 times faster than the S&P 500, which represents more traditional, product-based businesses (Zuora 2022). As a result, leading manufacturers in automotive, like Hyundai or Porsche (Forbes 2022), as well as retailers like Home Depot (Gupta and Ramachandran 2021) are increasingly using customer analytics to build brand loyalty and cultivate lifetime customers.

Customer-Centric Strategy and the Allocation of Decision Rights (Link *b*)

With regards to the allocation of decision rights (links *b* and *c*), marketing research indicates that firms aiming to enhance customer centricity should avoid organizing themselves around functional silos defined by product/service types. Such a product-centric approach may lead each sales manager to push the same product or service offering to each customer without considering the purchasing power or individualized needs for bundles of product/service bundles (Shah et al. 2006). To achieve customer centricity, an organizational realignment through integrated functional activities and lateral coordination is necessary, and decision rights should be allocated by setting up a horizontal structure that allows for useful information flows between marketing and accounting functions. Some Fortune 1000 firms, such as Coca-Cola, Intel, HP, and JD Edwards, have created specialized functions, including a "chief customer officer" or "head of digital metrics," which acknowledge the importance of customer centricity in the boardroom. Wells Fargo, for example, has successfully realigned its decision rights by creating a two-tiered sales structure, with a product specialist providing technical input for product development with an internal focus and a relationship manager ensuring an interaction orientation with an external focus (Shah et al. 2006; Rust, Moorman, and Bhalla 2010).

The allocation of responsibility and ownership of customer analytics within a firm's OA is an area that has been largely unexplored. Lee et al. (2015) have conducted research in this area and found that firms must carefully weigh the benefits and costs of adopting a customer-centric approach before realigning their organizational structure. Lee and Day (2019) further theorize on how different organizational customer-centric configurations and structural changes can develop dynamic capabilities, with a potential (and varying) impact on internal complexity and coordinating costs depending upon contingent factors and market changes. Overall, despite their potential implications in practice, such arguments remain empirically untested and remain a research priority.

Allocation of Decision Rights/Performance Measurement and Incentives (Links *c–e*)

Another research area that appears underdeveloped relates to the role of incentive systems (links *d* and *e*). Encouraging the use of customer metrics through incentive systems likely modifies decision making and decision control processes and ultimately serves the purpose of internalizing customer centricity within the firm culture (Kumar and Rajan 2009a, 2009b). Texas Instruments, for instance, successfully applies a reward system with customer metrics that monitor marketing gains over the three previous years and efficient and timely services; these initiatives have led to a better understanding of its customers (Kumar 2008). Mintz and Currim (2013) find evidence that a higher reliance on metric-based compensation is associated with a more extensive use of customer metrics in marketing decisions. Casas-Arce et al. (2017) document how two banks started providing its employees with CLV data. Although the employees' decision making benefited from an enlarged information set of customer-related metrics, the managerial bonus scheme remained linked to short-term accounting profits. Interestingly, shorter tenure branch managers demonstrated a stronger response after the firms started to include CLV in the performance evaluation system, suggesting a potential (and as-yet unresearched) substitute mechanism between sophistication of customer analytics and work experience.

Performance Measurement and Financial Performance (Link *a2*)

The more consolidated stream of accounting and marketing literature examines customer analytics as leading indicators of financial performance (Gupta and Zeithaml 2006; Verhoef and Lemon 2013; Ascarza, Fader, and Hardie 2017). These studies (link *a2*) document that the provision of customer analytics affects both firm profits (e.g., Homburg, Artz, and Wieseke 2012; Abramson, Currim, and Sarin 2005) and shareholder value (e.g., Schulze, Skiera, and Wiesel 2012). Bayer, Tuli, and Skiera (2017) examined the prevalence and consequences of the backward- and forward-looking disclosures inherent in 34 customer metrics by manually coding the annual reports of firms in a subscription-based (telecommunications) and a noncontractual (airlines) industry. Forward-looking disclosures of customer metrics reduce the information asymmetry that investors in both industries otherwise face. CE was disclosed by 16.99 percent of telecommunication firms against 2.19 percent of airlines. Such evidence indicates that firms tend not to deliberately disclose proprietary customer analytics, especially in nonsubscription-based industries (cf. Srivastava and Rajgopal 2022).

An adjacent body of literature focuses on customer valuation (see exhaustive reviews in Ascarza et al. 2017 and Kumar 2018), building on a wide range of CLV modeling that reflects a variety of business models (broadly categorized in terms of contractual or noncontractual settings), markets (business-to-business versus business-to-consumer), customer data, and demographic typologies (e.g., Bonacchi et al. 2015; McCarthy, Fader, and Hardie 2017; McCarthy and Fader 2018). McCarthy and Pereda (2020) emphasize a lack of agreement about CLV and CE definition and operationalization; this hinders their implementation by financial analysts and company executives. To cope with the challenge, McCarthy and Fader (2018, 2020) propose a novel tool, called customer-based corporate valuation, that relies on cohort analysis from publicly available data to provide investors a powerful tool for gauging what a company is really worth for both contractual and noncontractual industries.

Evaluation of the Literature and Research Objectives of This Study

In summary, from our review, we conclude that the limited literature on customer analytics mainly focused on testing contingency-based relationships of their adoption through survey-based or case-based evidence due to a lack of publicly disclosed data on customer analytics, such as CLV and CE (Holm and Ax 2020; Matsuoka 2020). Relatively more attention has been devoted to examining antecedents and economic consequences of perceptual customer metrics—such as customer satisfaction and customer loyalty—as the most commonly used and retrievable proxy of customer performance. In contrast, there is little granular evidence with regards to the actual use of customer analytics for internal decision making (e.g., budgeting and executive compensation) and external (e.g., financial reporting and valuation) purposes (Foster and Gupta 1994; Guilding and McManus 2002; McManus and Guilding 2008, 2009; Wiesel, Skiera, and Villanueva 2008).

The empirical part of this study addresses this gap with the objective of examining the following overarching research questions: "What is the current state of customer analytics adoption? Which OA dimensions are more frequently associated with the utilization of customer analytics? For which specific purposes and organizational functions is the deployment of customer analytics more prevalent?" Given the dearth of academic literature available, our expectations about the integration of customer analytics within an OA remained restrained. Specifically, we anticipated this integration to be more pronounced when coupled with an advanced customer-centric strategy and in the presence of advanced metrics, such as CLV and/or CE. Our broader goal is to explore the depth to which customer analytics permeate performance measurement and reporting systems. This research endeavor seeks to ascertain whether their claimed pivotal role in ensuring a company's profitability (e.g., Kumar and Rajan 2009a, 2009b; IMA 2014; Beaudin 2017; Aguilar and Ittner 2019; *Harvard Business Review* 2020; Markey 2020) is substantiated through practical evidence.

III. RESEARCH METHODOLOGY

Interviews

To better grasp current developments in customer analytics, we conducted a series of in-depth interviews with eight professionals (six men and two women) with ten or more years of experience in this area across a variety of sectors (see Online Appendix A for a list of interviewees). The interviews (average length: approximately 52 min) were conducted face to face whenever possible or by Skype, with the agreement that firms and interview subjects alike would remain anonymous. The format of the interviews was semistructured and followed a general script, with questions and topics related to the utilization of customer analytics stemming from the literature review. With each interviewee's permission, the interview was recorded and transcribed. We provided all interviewees with their respective transcripts, and no substantive changes were required after their feedback. Like prior accounting studies that used mixed methods-survey data with field interviews (e.g., Dichev, Graham, Harvey, and Rajgopal 2013), our interview evidence served primarily to supplement *ex ante* the literature review to identify unresearched topics, elicit input from professional experts, and guide us in the operationalization of the survey questions. We additionally rely on selected quotes from our interviewees to integrate or problematize *ex post* the interpretation of our survey findings.

Survey Variables, Sampling Approach, and Survey Administration

We designed an online survey following Dillman (2011), developed with the help of faculty colleagues and experts who had participated in our interviews. We pretested the questionnaire without geographical restrictions among a sample of professionals who mentioned the keywords "ARPU" and "Churn" in their LinkedIn profile. We obtained 51 responses (10 percent response rate), with half of respondents employed at firms headquartered in The Netherlands (likely due to the proximity to one of this paper's author) and one-third from the telecommunication industry. The pilot findings are reported in Bonacchi and Perego (2019). We then slightly revised the questionnaire based on the pilot's feedback. Table 2 presents the list of variables investigated.

The survey invitation and the complete online questionnaire are reproduced in Online Appendix B. The questionnaire elicited information regarding the availability of customer analytics by providing a list of the ten most common customer analytics retrievable from the literature, such as number of customers, customer addition, churn rate, CLV, and CE (Q6). Further, we inquired into the use of customer analytics for internal purposes (i.e., decision making and performance evaluation) at different occupational levels (i.e., top management, middle management, and sales employees) (Q7–Q9). We additionally included a series of questions about the use of customer analytics for external purposes (i.e., financial reporting and valuation), with the goal of assessing the adoption of these metrics for objectives other than

TABLE 2

List of Variables Measured in the Survey

Acronym and Variable Description	Question No. (Online Appendix B)	Source
Availability of customer analytics:	Q6	Literature review, various sources
Number of customers (*NuCust*)		
Usage or traffic (*Usage*)		
Gross customer additions (*GCA*)		
Net customer additions (*NCA*)		
Average revenue per user (*ARPU*)		
Churn or retention rate (*Churn*)		
Cost of service (*CoS*)		
Cost of customer acquisition (*CoA*)		
Customer lifetime value (*CLV*)		
Customer equity (*CE*)		
Usage of customer analytics:		
Use for planning and control	Q7–Q8	Literature review, various sources
Use for compensation	Q9	Literature review, various sources
Use for external reporting	Q10	Literature review, various sources
Use for valuation	Q11	Literature review, various sources
Organizational structure:		
Function in charge of customer data	Q12	Literature review, various sources
Ownership of customer data	Q13a	Barker (2008); Song and Thieme (2006)
Assurance of customer data	Q13c	Literature review, various sources
Strategic customer-centricity orientation	Q15	Ramani and Kumar (2008)

This table exhibits the variables measured by the survey items reproduced in Online Appendix B.

internal managerial accounting (Q10–Q11). Finally, we asked about the organizational structure (Q12–Q13) and the strategic orientation of firms in their journey toward customer centricity (Q15).

We used Qualtrics Panels, an online service that delivers commercial research instruments, to recruit participants for our web-based survey.[1] Qualtrics works with over 20 online panel providers to build both broad and targeted participant panels (Brandon, Long, Loraas, Mueller-Phillips, and Vansant 2014; Leiby, Rennekamp, and Trotman 2021). Using a traditional convenience sampling approach, Qualtrics partners randomly select panel participants who are likely to qualify, based on the sample requested. We contracted with Qualtrics to gain access to 300 fully completed online surveys that met certain demographic constraints from a panel of potential respondents working in SBCs. We focus on SBCs because they can be considered as early adopters of customer analytics. We contend that this research design allows generalizable findings to other settings, since technological advances increasingly facilitate tracking and inference of consumer behavior in non-SBCs, for instance, with regards to the timing and size of each individual purchase and service interaction in traditional retail or manufacturing firms (McCarthy and Fader 2020; Gupta and Ramachandran 2021; Zuora 2022). Furthermore, we decided to collect data solely from U.S. firms to mitigate potential confounding effects of customer analytics adoption due to different institutional and technological factors. We also specified to Qualtrics that each firm need to have a minimum size of 1,000 employees to prevent eliciting information about small firms unlikely to have adopted a minimally sophisticated system of customer analytics. Finally, each potential participant was to have a job function in accounting, finance, or marketing, to maximize the possibility of collecting data on the survey topic solely from informed participants.

The survey opened with a short text that aimed to broadly introduce the potential respondent to the survey's objectives and mention the time required to complete the questionnaire (refer to Online Appendix B). Question 1 of the survey served as an attention check: we explicitly asked the extent to which the potential participant's firm operated under a subscription-based model. Individuals whose answer was "no extent" or "little extent" were immediately excluded from further involvement in the survey. Given the conditions that we imposed on our target subject pool, we paid Qualtrics

[1] This study received an Institutional Review Board exemption by the university's dean.

TABLE 3

Demographic Characteristics of Survey Participants

	Frequency	Percent
Industry		
Banking	97	32.3
Wholesale	43	14.3
Manufacturing	40	13.3
Telecom	33	11.0
Insurance	30	10.0
Media	23	7.7
Energy	18	6.0
Hospitality	16	5.3
Revenues		
100M–499M	24	8.0
500M–999M	48	16.0
1B–4.9B	76	25.3
5B–9.9B	45	15.0
10B–19.9B	49	16.3
>20B	58	19.3
Number of Employees		
1,001–5,000	67	22.3
5,001–10,000	55	18.3
5,001–20,000	34	11.3
20,001–50,000	46	15.3
50,001–100,000	40	13.3
>100.000	58	19.3
Function		
Finance	156	52.0
Accounting	44	14.7
Marketing	100	33.3

n = 300.

an average of USD $30 per participant who completed the questionnaire. Qualtrics ensured that individuals recruited from their panels were prevented from repeatedly taking the survey; this restriction also prevented those who did not qualify from resubmitting answers. We obtained from Qualtrics only the questionnaire data collected through its survey management system; hence, we do not have access to further details or log files generated during the survey administration.

The descriptive statistics in Table 3 indicate a wide coverage of SBCs from the 300 respondents. Banking (32.3 percent), wholesale (14.3 percent), and manufacturing (13.3 percent) are the industries most represented. In terms of firm size, the firms surveyed comprise a balanced distribution between large and very large companies: almost 20 percent of the participants are employed by firms with more than 100,000 employees. The average respondent was on average 37 years old and two-thirds of all respondents identified as male. The participants have positions relating to finance (52 percent), marketing (33 percent), or accounting (15 percent) functions. Two-thirds of the sample work at the corporate level, whereas the rest are employed at the business unit level.

IV. RESULTS AND DISCUSSION

Availability and Use of Customer Analytics in Performance Measurement Systems

As Table 4 reports, whereas basic customer metrics, such as number of customers, usage, and gross and net customer addition, appear to be widely adopted, our findings reveal that 40.7 percent of the companies surveyed make CLV available in their performance measurement system (column (1)). Similarly, CE appears to have the lowest

TABLE 4

Availability of Customer Analytics in Performance Measurement Systems

	Complete Sample		Size			Customer-Centric Strategy			Specialized BI Unit			Ownership Customer Data		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	(%)	Significantly Different	<$1B Revenues (%)	>$1B Revenues (%)	Diff (3) − (4)[a]	Low (%)	High (%)	Diff (6) − (7)[a]	Not Present (%)	Present (%)	Diff (9) − (10)[a]	Other Than A&F (%)	A&F (%)	Diff (12) − (13)[a]
NuCust	77.7	2–10	80.6	76.8		72.3	82.2	0.039	75.3	81.6		78.7	74.7	
Usage	57.7	1, 6, 9–10	62.5	56.1		53.3	61.3		50.5	69.3	0.001	57.3	58.7	
GCA	55.7	1, 7, 9–10	59.7	54.4		58.4	53.4		48.9	66.7	0.003	54.7	58.7	
NCA	60.0	1, 6, 9–10	61.1	59.6		56.9	62.6		52.2	72.8	0.000	62.7	52.0	
ARPU	58.7	1, 6, 9–10	72.2	54.4	0.007	55.5	61.3		52.7	68.4	0.007	58.2	60.0	
Churn	44.7	1, 2–5, 7–8, 10	43.1	45.2		37.2	50.9	0.017	37.6	56.1	0.002	44.4	45.3	
CoS	65.0	1–3, 5–6, 8–10	69.4	63.6		66.4	63.8		59.7	73.7	0.014	61.8	74.7	0.043
CoA	53.0	1, 4–7, 9–10	56.9	51.8		55.5	50.9		48.9	59.6		50.2	61.3	
CLV	40.7	1–8	44.4	40.4		37.2	44.8		33.9	53.5	0.001	35.6	48.7	0.000
CE	37.7	1–8	41.7	36.4		32.1	42.3		29.0	51.8	0.000	34.2	48.0	0.033

This table reports survey responses to Q6: Which customer metrics are available in your firm′s information system? Column (1) exhibits the percentage of respondents (n = 300), indicating the availability of customer analytics among the ten metrics listed in each row. Column (2) shows the results of a t-statistic of the null hypothesis that the percentage for a given row is equal to the percentage of the other rows. For example, for response 1 about *NuCust*, "2–10" in column (2) means that the percentage for the response in row 1 is significantly different from the percentages for the responses in rows 2–10. Columns (3) and (4) report the percentages for respondents employed in firms with revenues lower than $1B and higher than $1B, respectively. Column (5) reports the result of a test of the null hypothesis that the percentages in column (3) and (4) are equal. Columns (6) and (7) report the percentages for respondents employed in firms with scores for customer-centric strategy above and below the mean, respectively. Column (8) reports the result of a test of the null hypothesis that the percentages in columns (6) and (7) are equal. Columns (9) and (10) report the percentages for respondents employed in firms without and with a Specialized Business Intelligence Unit, respectively. Column (11) reports the result of a test of the null hypothesis that the percentages in columns (9) and (10) are equal. Columns (12) and (13) report the percentages for respondents employed in firms where the ownership of customer data belongs to either a function other than Accounting and Finance (A&F) or to A&F, respectively. Column (14) reports the result of a test of the null hypothesis that the percentages in columns (12) and (13) are equal.

[a] We report only p-values lower than 0.05.

Variables Definitions:
NuCust = number of customers;
Usage = usage or traffic;
GCA = gross customer additions;
NCA = net customer additions;
ARPU = average revenue per user;
Churn = churn or retention rate;
CoS = cost of service;
CoA = cost of customer acquisition;
CLV = customer lifetime value; and
CE = customer equity.

penetration (37.7 percent). We then analyzed the distribution of responses to detect possible cross-sectional patterns of customer analytics adoption. We condition the results based on the median of firm size (large versus small, columns (3) and (4)), the adoption of a customer-metric strategy (columns (6) and (7)), the presence of a Specialized Business Intelligence (BI) Unit (columns (9) and (10)), and the ownership of customer data by the accounting and finance (A&F) function (columns (12) and (13)). Except for ARPU, the results reveal no statistically significant difference between large and small firms (column (5)), meaning that the deployment of customer analytics occurs independently of firm size. Only number of customers and churn rate are significantly associated with firms that score higher in terms of customer-centric strategy (column (8)), coherently with prior research evidence drawing on the OA that focused on link *a1* (e.g., Guilding and McManus 2002; Holm and Ax 2020). In contrast, the presence of a specialized BI function corresponds with statistically significant higher frequencies of usage for all metrics, except for number of customers and cost of acquisition (column (11)). With regards to link *b*, firms in which customer data are formally owned by the A&F function rely more on analytics like cost of service, CLV, and CE (column (14)). These results confirm the expectations stemming from practitioner′s literature (e.g., Kumar and Rajan 2009a, 2009b; IMA 2014; Cokins 2015) that Chief Financial Officers (CFOs) and management accountants are increasingly incorporating advanced customer analytics into their performance measurement system as accounting and finance functions have more decision rights about customer data.

Table 5 presents results on the frequency with which firms internally report customer analytics and use them for target-setting purposes at three occupational levels. The sample size of the responses varies depending on the availability of each metric from n = 232 (number of customers) to n = 113 (CE). The analysis is run per occupation level (by column) and type of metrics/frequency (by row). Table 5, Panel A displays statistics for customer analytics for internal reporting. In particular, the metrics with higher reporting frequency are net customer additions (51.7 percent) for top management (column (1)) and number of customers (51.9 percent and 52.8 percent) for middle management (column (2)) and sales employees (column (3)), respectively, all on a monthly level.

Table 5, Panel B shows that the use of customer analytics for target-setting purposes is on average less frequent compared with internal reporting. Among the metrics that are the most used for target setting, gross customer additions has a higher frequency among top management (44.3 percent) on a monthly level (column (4)). For sales employees (column (5)) and middle management (column (6)), number of customers score the highest frequencies at 43.3 percent and 45.1 percent on a monthly level, respectively. Overall, CLV and CE appear less widespread at lower organizational levels for both internal reporting and target setting purposes. Moreover, in 70 percent of internally reported customer analytics, the highest frequency observed is on a monthly basis. This finding suggests that the majority of firms deploying these analytics possess the capabilities to frequently update them. From the qualitative comments from the interview, customer-centric firms seem to be more adept at reporting customer analytics internally across organizational functions. This trend is exemplified by Interviewee C:

> In our company there is a visibility of metrics at every level. It is something quite different from other companies I worked for. A fairly democratic visibility of metrics is a positive principle for a learning organization. If there is maybe some number that is not good, you know it immediately.

Similarly, Interviewee G confirmed a staggered adoption across organizational hierarchy, as this quote illustrates:

> CLV is a measure for the top management who want to make sure customers generate positive value over the next 12 months; what comes next is an extra.

Interviewee G also emphasizes the need to further explore the level of granularity at which specific, customized customer analytics are deployed:

> The main key performance indicator for us is called expected added value or EAV, computed as the difference between lifetime value and acquisition cost multiplied by number of customers. That is the margin that users acquired in the last week will generate in the next 12 months. We calculate about 5,000 EAVs per week and we calculate them with high granularity, because in the end, if you don't get to cluster a lot, you can't anticipate certain problems. At this moment, we calculate EAV by country, product [e.g., type of games], telephone operator, and advertiser [e.g., Facebook, Google].

Allocation of Decision Rights and Ownership of Customer Analytics

Our findings in Table 6 highlight that 38 percent (114 responses out of 300) of the companies surveyed have formally appointed an *ad hoc* unit or organizational function in charge of collecting and distributing customer-related data ("Business Intelligence" and "Customer Lifetime Management" are the unit names most frequently cited by the survey

TABLE 5

Frequencies with Which Firms Report and Set Targets per Customer Analytics at Different Occupation Levels

Panel A: Internal Reporting

		Top Management (%) (1)	Middle Management (%) (2)	Sales Employees (%) (3)
Number of customers (n = 232)	Not used	6.9	9.0	16.7
	Monthly	**47.2**	**51.9**	**52.8**
	Quarterly	38.6	33.0	22.3
	Yearly	7.3	6.0	8.2
Usage or traffic (n = 173)	Not used	6.9	8.1	17.3
	Monthly	**44.5**	**48.6**	**48.6**
	Quarterly	39.9	40.5	27.2
	Yearly	8.7	2.9	6.9
Gross customer additions (n = 167)	Not used	6.0	7.8	15.6
	Monthly	41.9	45.5	46.1
	Quarterly	**44.3**	**41.3**	**27.5**
	Yearly	7.8	5.4	10.8
Net customer additions (n = 180)	Not used	7.8	8.3	18.9
	Monthly	**51.7**	**51.7**	**48.3**
	Quarterly	33.3	32.2	24.4
	Yearly	7.2	7.8	8.3
Average revenue per user (n = 176)	Not used	8.0	8.5	20.5
	Monthly	**40.3**	**48.3**	**42.6**
	Quarterly	39.8	31.3	28.4
	Yearly	11.9	11.9	8.5
Churn/retention rate (n = 134)	Not used	9.7	11.9	21.6
	Monthly	**39.6**	**44.0**	**38.8**
	Quarterly	38.1	31.3	29.1
	Yearly	12.7	12.7	10.4
Cost of service (n = 195)	Not used	11.8	9.7	21.0
	Monthly	**38.5**	**42.6**	**39.5**
	Quarterly	35.4	35.9	29.7
	Yearly	14.4	11.8	9.7
Cost of customer acquisition (n = 159)	Not used	8.2	11.4	22.6
	Monthly	**37.1**	**41.1**	**40.9**
	Quarterly	35.8	39.2	25.8
	Yearly	18.9	8.2	10.7
Customer lifetime value (n = 124)	Not used	9.7	12.1	26.6
	Monthly	**31.5**	30.6	26.6
	Quarterly	27.4	**34.7**	**31.5**
	Yearly	31.5	22.6	15.3
Customer equity (n = 113)	Not used	10.6	14.2	25.7
	Monthly	34.5	35.4	**38.9**
	Quarterly	**35.4**	**37.2**	22.1
	Yearly	19.5	13.3	13.3

(continued on next page)

respondents). Among these units, 93 percent are in staff to corporate functions, whereas 87 percent are in line to the A&F function.

Our results in Table 7 indicate further that the ownership of customer metrics rests mostly with corporate management, with approximately one-quarter of respondents reporting that the responsibility for collecting, distributing, and

TABLE 5 (continued)

Panel B: Target Setting

		Top Management (%) (4)	Middle Management (%) (5)	Sales Employees (%) (6)
Number of customers (n = 232)	Not used	8.2	16.3	24.5
	Monthly	**41.8**	**43.3**	**45.1**
	Quarterly	40.1	34.8	23.6
	Yearly	9.9	5.6	6.9
Usage or traffic (n = 173)	Not used	8.7	13.3	24.9
	Monthly	**41.6**	**38.2**	**43.4**
	Quarterly	37.6	39.9	24.9
	Yearly	12.1	8.7	6.9
Gross customer additions (n = 167)	Not used	7.8	12.6	17.4
	Monthly	34.7	38.9	43.1
	Quarterly	**44.3**	**40.1**	**29.3**
	Yearly	13.2	8.4	10.2
Net customer additions (n = 180)	Not used	7.2	15.0	22.8
	Monthly	**40.0**	**38.9**	**39.4**
	Quarterly	37.8	37.8	26.1
	Yearly	15.0	8.3	11.7
Average revenue per user (n = 176)	Not used	10.8	14.2	26.7
	Monthly	**29.5**	**41.5**	**34.7**
	Quarterly	39.8	32.4	28.4
	Yearly	19.9	11.9	10.2
Churn/retention rate (n = 134)	Not used	14.9	16.4	26.1
	Monthly	30.6	34.3	**35.8**
	Quarterly	**39.6**	**36.6**	28.4
	Yearly	14.9	12.7	9.7
Cost of service (n = 195)	Not used	10.3	19.0	28.2
	Monthly	32.3	29.2	**32.3**
	Quarterly	**38.5**	**36.9**	28.2
	Yearly	19.0	14.9	11.3
Cost of customer acquisition (n = 159)	Not used	13.8	18.2	27.0
	Monthly	28.9	34.6	**33.3**
	Quarterly	**40.3**	**35.8**	30.2
	Yearly	17.0	11.3	9.4
Customer lifetime value (n = 124)	Not used	14.5	21.8	32.3
	Monthly	**27.4**	**29.8**	**26.6**
	Quarterly	**27.4**	27.4	**26.6**
	Yearly	30.6	21.0	14.5
Customer equity (n = 113)	Not used	10.6	23.9	30.1
	Monthly	33.6	30.1	**30.1**
	Quarterly	**39.8**	**39.8**	26.5
	Yearly	15.9	6.2	13.3

This table reports survey responses about the frequency of use of customer analytics in internal reporting (Q6) and for target setting (Q7) at three occupational levels (top management, middle management, and sales employees). Sample size varies per metric depending on the number of responses. In bold, we flag the highest percentage per metric for each occupation level.

maintaining customer data lies with either the A&F (24.3 percent) or marketing functions (26 percent). Our findings point at a limited involvement of the A&F function in the design and implementation of customer analytics (link *b*), confirming the critical issue of a possible lack of coordination between the accounting and marketing functions in deploying the most appropriate set of metrics (Gleaves, Burton, Kitshoff, Bates, and Whittington 2008; Matsuoka 2020).

TABLE 6

Position of Specialized Unit Collecting and Distributing Customer Analytics

	Unit in Staff of the Corporate			Unit in Line to Accounting and Finance (A&F) Function	
	Frequency	**Percent**		**Frequency**	**Percent**
Yes	106	93.0	Yes	99	86.8
No	8	7.0	No	15	13.2
Total	114	100.0	Total	114	100.0

This table reports responses to Q12b: What is the hierarchical position of the specialized unit in charge of customer analytics in your firm?

TABLE 7

Function Owner of Customer Analytics

Function	Frequency	Percent
Corporate management	147	49.0
Marketing	78	26.0
Accounting and Finance	73	24.3
Other	2	0.7

This table reports responses to Q13b: Which function is the owner of customer metrics in your firm?

TABLE 8

Assurance of Customer Analytics

	Specialized BI Unit		Chief Operating Officer		Chief Financial Officer		Internal Auditors		External Auditors	
	Frequency	**Percent**	**Frequency**	**Percent**	**Frequency**	**Percent**	**Frequency**	**Percent**	**Frequency**	**Percent**
No extent	5	1.7	6	2.0	6	2.0	5	1.7	8	2.7
Little extent	10	3.3	15	5.0	11	3.7	11	3.7	15	5.0
Some extent	62	20.7	50	16.7	56	18.7	55	18.3	50	16.7
Great extent	138	46.0	130	43.3	116	38.7	117	39.0	114	38.0
Very great extent	85	28.3	99	33.0	111	37.0	112	37.3	113	37.7

This table reports responses to Q13c: Which functions provide assurance as to the accuracy of customer metrics data in your firm?

With regards to accountability and verifiability of customer analytics, we were interested to learn more about the internal or external entities in charge of assuring this type of data. Table 8 shows that the role played by an assuror that verifies accuracy and consistency of customer metrics varies considerably in our sample. The Specialized BI Unit (74 percent of sampled firms answering great extent and very great extent) and the Chief Operating Officer (76 percent) are assigned greater responsibility in providing customer data assurance, and this signals an internal auditing role in the quality control of customer analytics. External auditors also seem to play a relevant role (75 percent of respondents), especially considering the growing demand for nonfinancial information in corporate disclosure (Srivastava and Rajgopal 2022). Notably, on this emergent trend, Interviewee F admitted that:

> Auditors always ask for customer metrics, though I am not sure how they use them.

Customer Analytics in Incentive Systems

Another objective of the survey is to elicit information on the integration of customer analytics in formal incentive systems (links *d* and *e* of the OA). We requested participants to indicate the percentage of monetary bonus assigned to each metric for the three occupational levels. The findings in Table 9 are categorized into five groups based on the relative percentage per metric, ranging from below 5 percent to over 50 percent. The lower response rate to this question, ranging from n = 87 for number of customers to n = 39 for CE, may be attributed to the lack of formal monetary incentive schemes in our sample. A first analysis shows that CLV and CE tend to be less represented in monetary bonus schemes compared with other metrics. Their inclusion is mostly in the category with a weight of less than 5 percent at all three occupational levels. Only a few responses (1.85 percent) indicate that CLV counts as a key indicator above 50 percent of top management compensation schemes, which overall signals a rather marginal role of these analytics in incentive systems. The interpretation regarding other metrics is less straightforward. Specifically, the number of customers metric scores higher percentages overall, particularly in the group ranging from 25 percent to 50 percent for sales employees. This is in line with expectations, given the direct link between sales personnel and customer base. A similar pattern is detectable for metrics such as gross and net customer additions. ARPU, churn, and cost of service belong mostly to the group below 5 percent to determine the bonus of all three occupational levels.

Our findings remain exploratory and highly dispersed; however, they reveal an interesting variation in the role that customer analytics play in compensation systems. This research area deserves attention to gain additional insights pertaining to the determinants and consequences of different incentive design choices (cf. Mintz and Currim 2013; Casas-Arce et al. 2017). Interviewee B provides an interesting example in the banking industry, in which the main analytics attached to managerial incentive schemes relate to customer retention:

> The retention activities, which are mainly based on a predictive algorithm but not only for churn, has set goals. So, each facility has retention goals in its commercial structure. Based on the achievement of retention targets, compensation adjustments are then carried out at the end of the year. It is not the only measure, but it is one of the key measures.

The interviews further reveal potential obstacles that firms encounter when using customer analytics in incentive systems; for example, they can experience difficulties in standardizing customer data (link *d*). On this critical issue, Interviewee C points out:

> Customer metrics change very rapidly. The problem is that the key performance indicators that are used also vary according to the results of the web and therefore the market. And then it can be defined maybe for a period of three months…in three months, strategies could change. For this reason, we prefer to stick to the usual financial results, such as revenues, EBITDA, etc.…It's not that these key performance indicators are different, in my opinion, in terms of logic; they are different in terms of intensity and frequency. Everything is magnified because it is based on data collected continuously, hour after hour, linked to millions of users who change behavior from one month to another, depending on cents in price variation.

Furthermore, Interviewee D emphasizes that exogenous, uncontrollable factors could impact customer analytics, which makes them problematic as metrics suitable for managerial incentive schemes:

> For example, the number of subscribers are all good as key performance indicators in a Management By Objectives system. However, standardizing the data is always a challenge because you can have a problem in a country, a carrier goes down, or a mobile operator changes policy. There are exogenous factors, such as regulatory problems; for instance, there are countries that now want double consent, and single consent is not enough to buy an app.

Customer Analytics for External Reporting, Investor Relations, and Valuation

Our results further reveal that the adoption of customer metrics for external reporting purposes scores relatively lower than it does for internal performance measurement systems. Although customer-level data are highly informative for capital markets (Gupta et al. 2004; McCarthy and Fader 2020; Kumar and Shah 2009; McCarthy and Pereda 2020), it might convey proprietary and strategic information that firms prefer not to disclose to competitors or regulators. The diffusion of CLV and CE in corporate external reporting is quite moderate; as shown in Table 10, Panel A, column (1), each is present in 24 percent of the surveyed organizations against, respectively, 40.7 percent and 37.7 percent in internal performance measurement systems (Table 4, column (1)). Size is a discriminant variable in explaining differences among firms (columns (3) and (4)); in this case, however, smaller firms have a higher propensity to disclose them. We can speculate that smaller firms have greater market demand for customer-related, forward-looking data; additionally, these firms

TABLE 9

Importance of Customer Analytics to Achieve a Monetary Bonus per Occupation Level

	Importance for Monetary Bonus	Number of Customers n = 87	Usage Traffic n = 68	Gross Customer Additions n = 61	Net Customer Additions n = 62	Average Revenue per User n = 71	Churn/ Retention Rate n = 56	Cost of Service n = 71	Cost of Customer Acquisition n = 63	Customer Lifetime Value n = 54	Customer Equity n = 39
Top management (%)	≤5	21.84	**36.76**	**31.15**	25.81	**32.39**	**46.43**	**36.62**	**42.86**	**40.74**	**41.03**
	≤10	**25.29**	23.53	27.87	**32.26**	28.17	26.79	23.94	22.22	31.48	30.77
	≤25	28.74	25.00	27.87	30.65	26.76	19.64	30.99	22.22	18.52	17.95
	≤50	18.39	13.24	13.11	11.29	8.45	7.14	8.45	12.70	7.41	10.26
	>50	5.75	1.47			4.23				1.85	
Middle management (%)	≤5	27.06	**31.34**	28.81	**31.15**	29.17	**47.27**	**43.66**	**39.68**	**50.00**	33.33
	≤10	17.65	**31.34**	**33.90**	27.87	**33.33**	23.64	22.54	26.98	28.85	**48.72**
	≤25	**31.76**	26.87	25.42	27.87	22.22	25.45	26.76	25.40	11.54	10.26
	≤50	22.35	10.45	10.17	13.11	11.11	3.64	7.04	7.94	9.62	7.69
	>50	1.18		1.69		4.17					
Sales employees (%)	≤5	27.59	**35.82**	27.42	28.57	**48.61**	**47.37**	**44.44**	**46.77**	**58.18**	**56.10**
	≤10	24.14	25.37	27.42	22.22	23.61	26.32	27.78	25.81	30.91	31.71
	≤25	13.79	26.87	**32.26**	**30.16**	19.44	15.79	22.22	22.58	7.27	9.76
	≤50	**28.74**	11.94	12.90	17.46	2.78	10.53	5.56	4.84	3.64	2.44
	>50	5.75			1.59	5.56					

This table reports responses to Q9: What is the percentage of a customer metric to assign a monetary bonus for each functional level? We clustered the responses in five categories (below 5 percent, between 5 percent and 10 percent, between 10 percent and 25 percent, between 25 percent and 50 percent, and above 50 percent). Sample size varies per metric depending on the number of responses. In bold, we flag the highest percentage per metric for each occupation level.

TABLE 10

Use of Customer Analytics for External Reporting and Investor Relations

Panel A: Financial Reporting

	All		Size			Customer-Centric Strategy			Specialized Unit BI			Ownership Customer Data		
	(1) (%)	(2) Significantly Different	(3) <$1B Revenues (%)	(4) >$1B Revenues (%)	(5) Diff (3) − (4)[a]	(6) Low (%)	(7) High (%)	(8) Diff (6) − (7)[a]	(9) Not Present (%)	(10) Present (%)	(11) Diff (9) − (10)[a]	(12) Other than A&F (%)	(13) A&F (%)	(14) Diff (12) − (13)[a]
NuCust	65.0	2–10	72.2	62.7		56.9	71.8	0.007	60.2	72.8	0.026	64.0	68.0	
Usage	34.7	1, 9–10	43.1	32.0		27.7	40.5	0.021	31.7	39.5		34.7	34.7	
GCA	31.7	1, 5	44.4	27.6	0.008	27.0	35.6		26.9	39.5	0.023	29.3	38.7	
NCA	36.3	1, 6, 9–10	43.1	34.2		32.8	39.3		30.1	46.5	0.004	37.8	32.0	
ARPU	41.0	1, 3, 6, 8–10	58.3	35.5	0.001	29.9	50.3	0.000	32.3	55.3	0.000	38.7	48.0	
Churn	26.7	1, 4–5, 7	30.6	25.4		17.5	34.4	0.001	20.4	36.8	0.002	26.7	26.7	
CoS	36.3	1, 6, 9–10	47.2	32.9	0.028	32.8	39.3		30.6	45.6	0.009	33.3	45.3	
CoA	31.3	1, 5, 9–10	38.9	28.9		25.5	36.2	0.048	23.7	43.9	0.000	29.3	37.3	
CLV	24.0	1–2, 4–5, 7	34.7	20.6	0.015	20.4	27.0		18.8	32.5	0.007	19.6	37.3	0.002
CE	24.0	1–2, 4–5, 7	33.3	21.1	0.033	16.1	30.7	0.003	16.8	36.0	0.000	20.4	34.7	0.013

Column (1) exhibits the percentage of respondents (n = 300) among the ten metrics listed in each row. For example, for response 1, the recorded "65%" in the column signifies that 65 percent of the firms disclose the number of customers in external reporting. Column (2) shows the results of a t-statistic of the null hypothesis that the percentage for a given alternative is equal to the percentage of the other alternative responses. For example, for response 1, the recorded "2–10" in the column signifies that the percentage for the response in row 1 is significantly different from the percentages for the responses in rows 2–10. Columns (3) and (4) report the percentages for respondents employed in firms with revenues lower than $1B and higher than $1B, respectively. Column (5) reports the result of a test of the null hypothesis that the percentages in columns (3) and (4) are equal. Columns (6) and (7) report the percentages for respondents employed in firms with scores for customer-centric strategy above and below the mean, respectively. Column (8) reports the result of a test of the null hypothesis that the percentages in columns (6) and (7) are equal. Columns (9) and (10) report the percentages for respondents employed in firms without and with a Specialized Business Intelligence Unit, respectively. Column (11) reports the result of a test of the null hypothesis that the percentages in columns (9) and (10) are equal. Columns (12) and (13) report the percentages for respondents employed in firms where the ownership of customer data belongs to either a function other than Accounting and Finance (A&F) or to A&F, respectively. Column (14) reports the result of a test of the null hypothesis that the percentages in columns (12) and (13) are equal.

[a] We report only p-values lower than 0.05.

Variable Definitions:
NuCust = number of customers;
Usage = usage or traffic;
GCA = gross customer additions;
NCA = net customer additions;
ARPU = average revenue per user;
Churn = churn or retention rate;
CoS = cost of service;
CoA = cost of customer acquisition;
CLV = customer lifetime value; and
CE = customer equity.

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TABLE 10 (continued)

Panel B: Press Releases

	All		Size			Customer-Centric Strategy			Specialized Unit BI			Ownership Customer Data		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	(%)	Significantly Different	<$1B Revenues (%)	>$1B Revenues (%)	Diff (3) − (4)[a]	Low (%)	High (%)	Diff (6) − (7)[a]	Not Present (%)	Present (%)	Diff (9) − (10)[a]	Other than A&F (%)	A&F (%)	Diff (12) − (13)[a]
NuCust	27.0	6, 8–10	26.4	27.6		27.0	27.6		21.5	36.8	0.004	26.7	29.3	
Usage	25.7	6, 9–10	25.0	25.9		19.7	30.7	0.030	22.0	31.6	0.000	24.9	28.0	
GCA	25.3	6, 9–10	33.3	22.8		24.8	25.8		20.4	33.3	0.013	25.3	25.3	
NCA	30.3	3, 6–10	33.3	29.4		27.7	32.5		25.8	37.7	0.029	70.7	66.7	
ARPU	21.0	4, 10	22.2	20.6		20.4	21.5		18.8	24.6		21.3	20.0	
Churn	18.0	1–4	16.7	18.4		10.2	24.5	0.001	13.4	25.4	0.009	16.0	24.0	
CoS	23.7	4, 9–10	31.9	21.1		22.6	24.5		19.4	22.8		21.8	29.3	
CoA	20.7	1, 4, 9–10	20.8	20.6		19.7	21.5		20.4	29.8		82.2	70.7	0.032
CLV	16.3	1–4, 7	19.4	15.4		13.9	18.4		9.1	28.1	0.000	12.0	29.3	0.000
CE	13.7	1–5, 7–8, 10	18.1	12.3		11.7	15.3		11.8	31.6	0.026	12.0	18.7	

Column (1) exhibits the percentage of respondents (n = 300) among the ten metrics listed in each row. For example, for response 1, the recorded "27%" in the column signifies that 27 percent of the firms disclose the number of customers in press releases. Column (2) shows the results of a t-statistic of the null hypothesis that the percentage for a given alternative is equal to the percentage of the other alternative responses. For example, for response 1, the recorded "2–10" in the column signifies that the percentage for the response in row 1 is significantly different from the percentages for the responses in rows 2–10. Columns (3) and (4) report the percentages for respondents employed in firms with revenues lower than $1B and higher than $1B, respectively. Column (5) reports the result of a test of the null hypothesis that the percentages in columns (3) and (4) are equal. Columns (6) and (7) report the percentages for respondents employed in firms with scores for customer-centric strategy above and below the mean, respectively. Column (8) reports the result of a test of the null hypothesis that the percentages in columns (6) and (7) are equal. Columns (9) and (10) report the percentages for respondents employed in firms without and with a Specialized Business Intelligence Unit, respectively. Column (11) reports the result of a test of the null hypothesis that the percentages in columns (9) and (10) are equal. Columns (12) and (13) report the percentages for respondents employed in firms where the ownership of customer data belongs to either a function other than Accounting and Finance (A&F) or to A&F. Column (14) reports the result of a test of the null hypothesis that the percentages in columns (12) and (13) are equal.

[a] We report only p-values lower than 0.05.

Variable Definitions:
NuCust = number of customers;
Usage = usage or traffic;
GCA = gross customer additions;
NCA = net customer additions;
ARPU = average revenue per user;
Churn = churn or retention rate;
CoS = cost of service;
CoA = cost of customer acquisition;
CLV = customer lifetime value; and
CE = customer equity.

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TABLE 10 (continued)

Panel C: Conference Calls

	All		Size			Customer-Centric Strategy			Specialized Unit BI			Ownership Customer Data		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	(%)	Significantly Different	<$1B Revenues (%)	>$1B Revenues (%)	Diff (3) − (4)[a]	Low (%)	High (%)	Diff (6) − (7)[a]	Not Present (%)	Present (%)	Diff (9) − (10)[a]	Other than A&F (%)	A&F (%)	Diff (12) − (13)[a]
NuCust	37.0	3–4, 6, 8–10	40.3	36.0		30.7	42.3	0.037	30.1	48.2	0.002	35.1	42.7	
Usage	30.7	6, 8–10	34.7	29.4		27.0	33.7		23.1	43.0	0.000	29.3	34.7	
GCA	29.0	1, 9–10	36.1	26.8		22.6	34.4	0.026	20.4	43.0	0.000	28.4	30.7	
NCA	29.7	1, 6, 9–10	38.9	26.8	0.049	27.0	31.9		23.7	39.5	0.004	30.7	26.7	
ARPU	32.0	6, 8–10	47.2	27.2	0.001	26.3	36.8		26.9	40.4	0.015	32.0	32.0	
Churn	23.3	1–4, 7	30.6	21.1		16.1	29.4	0.006	19.4	29.8	0.009	23.6	22.7	
CoS	31.3	6, 8–10	41.7	28.1	0.030	21.2	39.9	0.001	25.8	40.4	0.008	29.8	36.0	
CoA	24.0	1–2, 5–6	20.8	20.6		17.5	29.4	0.016	19.4	22.8		23.1	26.7	
CLV	18.7	1–5, 7, 9	27.8	15.8	0.023	10.9	25.2	0.002	12.9	28.1	0.001	17.8	21.3	
CE	19.3	1–5, 7–8	26.4	17.1		10.9	26.4	0.001	11.8	31.6	0.000	17.8	24.0	

Column (1) exhibits the percentage of respondents (n = 300) among the ten metrics listed in each row. For example, for response 1, the recorded "37%" in the column signifies that 37 percent of the firms disclose the number of customers in conference calls. Column (2) shows the results of a t-statistic of the null hypothesis that the percentage for a given alternative is equal to the percentage of the other alternative responses. For example, for response 1, the recorded "2–10" in the column signifies that the percentage for the response in row 1 is significantly different from the percentages for the responses in rows 2–10. Columns (3) and (4) report the percentages for respondents employed in firms with revenues lower than $1B and higher than $1B, respectively. Column (5) reports the result of a test of the null hypothesis that the percentages in columns (3) and (4) are equal. Columns (6) and (7) report the percentages for respondents employed in firms with scores for customer-centric strategy above and below the mean, respectively. Column (8) reports the result of a test of the null hypothesis that the percentages in columns (6) and (7) are equal. Columns (9) and (10) report the percentages for respondents employed in firms without and with a Specialized Business Intelligence Unit, respectively. Column (11) reports the result of a test of the null hypothesis that the percentages in columns (9) and (10) are equal. Columns (12) and (13) report the percentages for respondents employed in firms where the ownership of customer data belongs to either a function other than Accounting and Finance (A&F) or to A&F, respectively. Column (14) reports the result of a test of the null hypothesis that the percentages in columns (12) and (13) are equal.

[a] We report only p-values lower than 0.05.

Variable Definitions:
NuCust = number of customers;
Usage = usage or traffic;
GCA = gross customer additions;
NCA = net customer additions;
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Churn = churn or retention rate;
CoS = cost of service;
CoA = cost of customer acquisition;
CLV = customer lifetime value; and
CE = customer equity.

experience less threat from industry competitors. The findings reveal that the disclosure of specific customer analytics, for instance, CE, is higher for customer-centric firms (as shown by significant coefficient in column (8)). Even more evident is the role played by Specialized BI Units in facilitating the disclosure of customer analytics in external reporting (as shown by significant coefficient in column (11)). There is a need to examine this issue related to link *a2* more thoroughly, particularly in response to the current debate on the shortcomings of traditional financial reporting methods that fail to accurately reflect the long-term value of businesses (Markey 2020; Damodaran, McCarthy, and Cohen 2022; Srivastava and Rajgopal 2022).

The voluntary disclosure of customer metrics in press releases and conference calls is lower compared with metrics available in the annual/quarter financial reporting. Table 10, Panel B and Table 10, Panel C, column (1) show that less than 20 percent of the respondents indicate the use of CLV and CE in press releases and conference calls. Moreover, for these external communication purposes, our survey findings suggest that the ownership of customer data by the A&F function plays no significant role (column (14)), except for CLV and CE in financial reporting (Table 10, Panel A, column (14)) and cost of customer acquisition (CoA) and CLV in press releases (Table 10, Panel B, column (14)). A deeper analysis of the dynamics that govern investor relations *vis-à-vis* these novel types of nonfinancial metrics seems warranted in future research. We can only speculate that firms that are more forward looking and transparent in their corporate communication tend to emphasize CLV and CE more in their financial disclosures as key drivers of future business value. This exploratory evidence aligns with the archival findings of Bonacchi et al. (2015), who found that conference calls and analyst reports do not reflect customer-related data beyond those available in firms' Securities and Exchange Commission filings (i.e., 10-Q/K). Finally, Table 11 exhibits survey findings regarding firms' use of customer analytics for internal valuation, valuation in the context of acquisition, and valuation required for impairment purposes. For internal valuation purposes (Table 11, Panel A, column (1)), the results show that CLV and CE are used less frequently than other metrics, with only 22 percent of respondents reporting their use. A similar pattern is observable regarding the use of these customer analytics in the context of an acquisition and an impairment test, with approximately 20 percent (Table 11, Panel B, column (1)) and 15 percent (Table 11, Panel C, column (1)) of respondents stating their use, respectively.

The Specialized Business Unit in charge of business intelligence plays a significant role, similarly to the findings exhibited in Table 10. Not surprisingly, in the presence of an A&F function that owns customer data, there are significantly higher levels of use of CLV and CE for internal valuation purposes (Table 11, Panel A, column (14)), thus revealing a greater emphasis on these two metrics in fundamental analyses of business value creation. Regarding the use of customer analytics for valuation purposes, Interviewee E interestingly states:

> Among the activities to support IPOs and M&As, we have been asked to value the customer base; we rely on both customer metrics provided by the company and our own assessment based on industry expertise.

This quote emphasizes the increasing demand for more complete disclosures on customer data that publicly listed firms currently face (links *a1* and *a2*), including churn/renewal rates, customer breakdown by cohort/age groups, and customer acquisition costs (cf. Damodaran et al. 2022; Srivastava and Rajgopal 2022).

V. CONCLUSIONS AND AGENDA FOR FUTURE RESEARCH

Our findings reveal that the use of customer analytics is still in its early stages and varies significantly across firms, with a higher level of penetration for traditional indicators than for more advanced metrics. We document for the first time a weak integration of CLV and CE in compensation and incentive systems and a relatively low ownership of customer analytics by the accounting function. Overall, the deployment of customer analytics in performance measurement and reporting systems appears to be contingent on the ability of a firm to fit its organizational architecture.

This study provides novel insights on the current diffusion and sophistication of customer analytics, although it is subject to several limitations. Given the current study's inherent exploratory design and the limited number of observations obtained from respondents in a single country, our results should be interpreted cautiously. Moreover, whereas the selection of survey participants based on a subscription-based model has certain advantages in terms of sampling convenience, a potential lack of external validity remains a caveat and requires replication of the questionnaire in other business model settings.

The descriptive analysis presented here should be considered and extended by future research. First, to better understand the availability and sophistication of customer analytics at the firm level of analysis, accounting scholars could exploit the extant body of knowledge built within the management accounting innovation literature (Ax and Bjørnenak 2007; Ax and Greve 2017). The OA framework leveraged in the current study could be exploited further to test interdependent relationships among the three organizational design features. Research is particularly needed to investigate the interactive effects that might dynamically unfold when customer analytics are simultaneously integrated in organizational structures, performance measurement, and incentive systems for various tasks and business functions

TABLE 11
Use of Customer Metrics in Valuation

Panel A: Internal Valuation of the Company

	All		Size			Customer-Centric Strategy			Specialized Unit BI			Ownership Customer Data		
	(1) (%)	(2) Significantly Different	(3) <$1B Revenues (%)	(4) >$1B Revenues (%)	(5) Diff (3) − (4)[a]	(6) Low (%)	(7) High (%)	(8) Diff (6) − (7)[a]	(9) Not Present (%)	(10) Present (%)	(11) Diff (9) − (10)[a]	(12) Other than A&F (%)	(13) A&F (%)	(14) Diff (12) − (13)[a]
NuCust	61.7	all	65.3	60.5		49.6	71.8	0.000	54.8	72.8	0.002	60.0	66.7	
Usage	35.7	1, 6, 9–10	40.3	34.2		30.7	39.9		30.6	43.9	0.020	36.0	34.7	
GCA	31.7	1, 9–10	38.9	29.4		27.7	35.0		26.9	39.5	0.023	30.7	34.7	
NCA	33.7	1, 6, 9–10	43.1	30.7		28.5	38.0		26.3	45.6	0.001	34.7	30.7	
ARPU	36.7	1, 6, 8–10	48.6	32.9	0.016	27.7	44.2	0.003	28.5	50.0	0.000	33.8	45.3	
Churn	26.3	1–2, 4–5, 7	29.2	25.4		18.2	33.1	0.004	21.0	35.1	0.007	25.3	29.3	
CoS	36.0	1, 6, 8–10	41.7	34.2		29.2	41.7	0.024	28.5	48.2	0.001	35.1	38.7	
CoA	30.0	1, 5, 7, 9–10	40.3	26.8	0.029	25.5	33.7		23.1	41.2	0.001	28.4	34.7	
CLV	22.0	1–5, 7–8	30.6	19.7		17.5	26.4		17.7	29.8	0.015	19.6	30.7	0.045
CE	22.3	1–5, 7–8	31.9	18.9	0.019	13.1	29.4	0.001	12.4	37.7	0.000	18.7	32.0	0.016

Column (1) exhibits the percentage of respondents (n = 300) among the ten metrics listed in each row. Column (2) shows the results of a t-statistic of the null hypothesis that the percentage for a given alternative is equal to the percentage of the other alternative responses. For example, for response 1, the recorded "2–10" in the column signifies that the percentage for the response in row 1 is significantly different from the percentages for the responses in rows 2–10. Columns (3) and (4) report the percentages for respondents employed in firms with revenues lower than $1B and higher than $1B, respectively. Column (5) reports the result of a test of the null hypothesis that the percentages in columns (3) and (4) are equal. Columns (6) and (7) report the percentages for respondents employed in firms with scores for customer-centric strategy above and below the mean, respectively. Column (8) reports the result of a test of the null hypothesis that the percentages in columns (6) and (7) are equal. Columns (9) and (10) report the percentages for respondents employed in firms without and with a Specialized Business Intelligence Unit, respectively. Column (11) reports the result of a test of the null hypothesis that the percentages in columns (9) and (10) are equal. Columns (12) and (13) report the percentages for respondents employed in firms where the ownership of customer data belongs to either a function other than Accounting and Finance (A&F) or to A&F, respectively. Column (14) reports the result of a test of the null hypothesis that the percentages in columns (12) and (13) are equal.

[a] We report only p-values lower than 0.05.

Variable Definitions:
NuCust = number of customers;
Usage = usage or traffic;
GCA = gross customer additions;
NCA = net customer additions;
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CoS = cost of service;
CoA = cost of customer acquisition;
CLV = customer lifetime value; and
CE = customer equity.

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TABLE 11 (continued)

Panel B: Valuation in the Context of an Acquisition

	All		Size			Customer-Centric Strategy			Specialized Unit BI			Ownership Customer Data		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	(%)	Significantly Different	<$1B Revenues (%)	>$1B Revenues (%)	Diff (3) − (4)[a]	Low (%)	High (%)	Diff (6) − (7)[a]	Not Present (%)	Present (%)	Diff (9) − (10)[a]	Other than A&F (%)	A&F (%)	Diff (12) − (13)[a]
NuCust	33.7	6, 9–10	27.8	35.5		29.2	37.4		30.1	39.5		33.8	33.3	
Usage	36.3	3–10	36.1	36.4		31.4	40.5		28.5	49.1	0.000	33.3	45.3	
GCA	28.3	2, 7, 10	37.5	25.4	0.048	24.1	31.9		23.7	36.0	0.022	27.6	30.7	
NCA	33.7	6, 9–10	38.9	32.0		23.4	42.3	0.001	25.8	46.5	0.000	36.0	26.7	
ARPU	29.0	2, 7, 10	31.9	28.1		26.3	31.3		24.7	36.0	0.037	28.9	29.3	
Churn	24.0	1–2, 4, 7	23.6	24.1		19.0	28.2		17.7	34.2	0.001	23.1	26.7	
CoS	36.3	3, 5–6, 8–10	34.7	36.8		36.5	36.2		33.9	40.4	0.001	36.0	37.3	
CoA	29.3	2, 7, 9–10	34.7	27.6		27.7	30.7		23.1	39.5	0.003	27.1	36.0	
CLV	19.7	1–2, 4, 7–8	25.0	22.8		19.0	27.0		14.5	37.7	0.000	18.2	38.7	0.000
CE	23.3	1–5, 7–8	19.4	19.7		17.5	21.5		14.0	28.9	0.002	18.2	24.0	

Column (1) exhibits the percentage of respondents (n = 300) among the ten metrics listed in each row. Column (2) shows the results of a t-statistic of the null hypothesis that the percentage for a given alternative is equal to the percentage of the other alternative responses. For example, for response 1, the recorded "2–10" in the column signifies that the percentage for the response in row 1 is significantly different from the percentages for the responses in rows 2–10. Columns (3) and (4) report the percentages for respondents employed in firms with revenues lower than $1B and higher than $1B, respectively. Column (5) reports the result of a test of the null hypothesis that the percentages in columns (3) and (4) are equal. Columns (6) and (7) report the percentages for respondents employed in firms with scores for customer-centric strategy above and below the mean, respectively. Column (8) reports the result of a test of the null hypothesis that the percentages in columns (6) and (7) are equal. Columns (9) and (10) report the percentages for respondents employed in firms without and with a Specialized Business Intelligence Unit, respectively. Column (11) reports the result of a test of the null hypothesis that the percentages in columns (9) and (10) are equal. Columns (12) and (13) report the percentages for respondents employed in firms where the ownership of customer data belongs to either a function other than Accounting and Finance (A&F) or to A&F, respectively. Column (14) reports the result of a test of the null hypothesis that the percentages in columns (12) and (13) are equal.

[a] We report only p-values lower than 0.05.

Variable Definitions:
NuCust = number of customers;
Usage = usage or traffic;
GCA = gross customer additions;
NCA = net customer additions;
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CoS = cost of service;
CoA = cost of customer acquisition;
CLV = customer lifetime value; and
CE = customer equity.

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TABLE 11 (continued)

Panel C: Valuation Required for the Impairment Test of Goodwill/Customer List

	All		Size			Customer-Centric Strategy			Specialized Unit BI			Ownership Customer Data		
	(1) (%)	(2) Significantly Different	(3) <$1B Revenues (%)	(4) >$1B Revenues (%)	(5) Diff (3) − (4)a	(6) Low (%)	(7) High (%)	(8) Diff (6) − (7)a	(9) Not Present (%)	(10) Present (%)	(11) Diff (9) − (10)a	(12) Other than A&F (%)	(13) A&F (%)	(14) Diff (12) − (13)a
NuCust	30.7	4–6, 8–10	26.4	27.6		28.5	32.5		28.0	35.1		30.7	30.7	
Usage	25.0	6, 9–10	25.0	25.9		18.2	30.7	0.013	17.2	37.7	0.000	26.2	21.3	
GCA	25.0	6, 9–10	33.3	22.8		16.8	31.9	0.003	16.7	38.6	0.000	21.3	36.0	0.011
NCA	24.3	1, 6, 9–10	33.3	29.4		22.6	25.8		19.9	31.6	0.022	24.9	22.7	
ARPU	24.0	1, 9–10	22.2	20.6		24.1	23.9		20.4	29.8		24.0	24.0	
Churn	18.3	1–4, 7	16.7	18.4		12.4	23.3	0.015	14.0	25.4	0.013	19.6	14.7	
CoS	27.3	6, 9–10	31.9	21.1		25.5	28.8		24.2	32.5		25.3	33.3	
CoA	22.7	1, 9–10	20.8	20.6		19.0	25.8		22.0	23.7		21.3	26.7	
CLV	15.3	1–5, 7–8	18.1	12.3		8.0	22.1	0.001	9.1	26.3	0.000	15.1	17.3	
CE	15.7	1–5, 7–8	19.4	15.4		8.8	20.9	0.004	9.1	25.4	0.000	14.7	17.3	

Column (1) exhibits the percentage of respondents (n = 300) among the ten metrics listed in each row. Column (2) shows the results of a t-statistic of the null hypothesis that the percentage for a given alternative is equal to the percentage of the other alternative responses. For example, for response 1, the recorded "2–10" in the column signifies that the percentage for the response in row 1 is significantly different from the percentages for the responses in rows 2–10. Columns (3) and (4) report the percentages for respondents employed in firms with revenues lower than $1B and higher than $1B, respectively. Column (5) reports the result of a test of the null hypothesis that the percentages in columns (3) and (4) are equal. Columns (6) and (7) report the percentages for respondents employed in firms with scores for customer-centric strategy above and below the mean, respectively. Column (8) reports the result of a test of the null hypothesis that the percentages in columns (6) and (7) are equal. Columns (9) and (10) report the percentages for respondents employed in firms without and with a Specialized Business Intelligence Unit, respectively. Column (11) reports the result of a test of the null hypothesis that the percentages in columns (9) and (10) are equal. Columns (12) and (13) report the percentages for respondents employed in firms where the ownership of customer data belongs to either a function other than Accounting and Finance (A&F) or to A&F, respectively. Column (14) reports the result of a test of the null hypothesis that the percentages in columns (12) and (13) are equal.

[a] We report only p-values lower than 0.05.

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NuCust = number of customers;
Usage = usage or traffic;
GCA = gross customer additions;
NCA = net customer additions;
ARPU = average revenue per user;
Churn = churn or retention rate;
CoS = cost of service;
CoA = cost of customer acquisition;
CLV = customer lifetime value; and
CE = customer equity.

(Widener et al. 2008). Such a focus is largely absent in extant research and would contribute to the stream of studies on complementarities in management control (Chapman, Grabner, and Moers 2020). Action research and field experiments in selected companies willing to expand the availability of customer analytics and link them with their managerial incentive systems would help establish the causal effects of metrics like CLV in executive compensation schemes. Additionally, there is a surprising lack of research on the allocation of decision rights, especially on how Chief Financial Officers and Chief Marketing Officers interact and coordinate (Phillips and Halliday 2008), in contrast with the body of literature that examines the linkages between management accounting and other corporate functions (Gleaves et al. 2008; Kraus et al. 2015). Whereas marketing managers typically have decision rights on how to measure and model customer behavior, they face the challenge of cascading these decisions into other firm areas (Kumar and Rajan 2009a, 2009b). Chief Financial Officers and management accountants are in turn expected to coordinate with marketing colleagues to measure marketing cost structure more accurately (Aguilar and Ittner 2019; Labro 2019) and exploit the predictive ability of customer analytics (IMA 2014; McCarthy and Fader 2020). We suggest exploring whether, why, and how the distinct motivations of marketing or accounting functions influence the extent of implementation, for example, depending on opportunity framing and the motivation to achieve both economic and social gains (Ax and Greve 2017). Such a line of inquiry would contribute to theories of innovation diffusion that have moved beyond neoinstitutionalist or contingency-based approaches to include the interplay between economic and cultural considerations of an adoption trajectory.

Second, it would be fruitful to focus on customer analytics as an emergent family of nonfinancial, forward-looking indicators of future financial performance. At the individual level of analysis, we call for research on how users cognitively process such novel information for decision making and decision control. This line of investigation could draw on and contribute to the body of experimental studies on mental models of strategy maps (e.g., Lipe and Salterio 2002; Libby, Salterio, and Webb 2004; Humphreys, Gary, and Trotman 2016) and preferably involve controllers or marketing managers with established experience. In addition, future research should gather empirical evidence concerning the real effects of using predictive analytics at the firm level (e.g., Huelsbeck, Merchant, and Sandino 2011; Labro, Lang, and Omartian 2023) in both contractual and noncontractual settings. The diffusion of analytics poses the challenge of documenting under which specific circumstances they will deliver the expected effects. We thus encourage both qualitative and quantitative data collection in field studies that investigate the implementation of best-practice customer analytics, similar to previous marketing case studies (e.g., Kumar, Venkatesan, Bohling, and Beckmann 2008).

Third, we believe further attention should be focused on the interplay between the internal reporting of customer analytics and their (lack of) disclosure in corporate financial statements (Srivastava and Rajgopal 2022). Contributions that draw upon developments in recent valuation research in marketing (McCarthy et al. 2017; McCarthy and Fader 2018, 2020) are especially timely. Recent marketing studies provide normative models in both contractual and noncontractual settings (see McCarthy and Pereda 2020 for a review), and such work should be complemented and validated by empirical evidence from accounting scholars. This line of investigation would be extremely valuable in generating practical recommendations for marketing managers as well as for financial analysts interested in how to value firms for portfolio selection purposes or in mergers and acquisitions (e.g., Damodaran et al. 2022).

In conclusion, our findings open opportunities for future research on the rapidly changing trends in customer analytics. Chief Marketing Officers struggle to justify their rising investments in a turbulent marketplace where customers are increasingly moving to digital channels. Our assertion is that Chief Financial Officers need to support Chief Marketing Officers in adapting an OA with an appropriate customer analytics sophistication and use. We believe that accounting and marketing scholars can join forces and fruitfully contribute to these developments by engaging in a shared research agenda that focuses on the impact of customer analytics on value creation.

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