Original Article

A hierarchical IMC data integration and measurement framework and its impact on CRM system quality and customer performance

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ABSTRACT Marketers and advertisers seek to get close to customers through data analytics procedures that allow for the measurement of personalized messages delivered across multiple communication touchpoints. This article tests a hierarchical integrated marketing communications data integration framework that utilizes customer information (transactional, demographic and psychographic) to develop personalized communication and communication campaigns distributed across multiple interactive customer touchpoints. Our model posits that by using basic customer data we can increase the priority for collecting other types of data needed to get close to customers. Our findings show that customer data needs are hierarchically ordered and that the sequential interaction between these variables impacts customer relationship management system quality and measurement of performance.
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Keywords: marketing analytics; customer data; integrated marketing communications (IMC); data quality; customer relationship management (CRM); marketing metrics

INTRODUCTION

Throughout the last few decades, marketers, advertisers, and even consumers, have held much hope for improving theory and best practice in integrated marketing communications (IMC) (Kerr *et al*, 2008; Kitchen *et al*, 2008). Recently, the merging of advanced marketing and advertising channels with more traditional communication media has altered the fabric of IMC (Sasser *et al*, 2007; Zigmond and Stipp, 2010), more specifically with regard to measuring ongoing and real-time 'interactive' buyer–seller relationships (Schultz and Patti, 2009; Hipperson, 2010; Acker *et al*, 2011). Interactive IMC has not only impacted the way marketers communicate with customers and prospects, but has also placed greater value on bringing together multiple data touchpoints, media and messages to deliver personalized marketing communications that maximize return on investment (Swain, 2004; Micu *et al*, 2011; Abdul-Muhmin, 2012). IMC has thus evolved from simply creating a consistent message to increasing the value of traditional and emerging media. To achieve maximum value, appropriate data analytics and smart marketing must construct synergies for enhancing customer loyalty and lifetime value (Assael, 2011; Stewart and Hess, 2011).

Developing personalized contact strategies places greater emphasis on amassing customer data from multiple sources (Zahay *et al*, forthcoming). As a proprietary resource, customer data offers marketers the opportunity to acquire competitive advantages by developing multi-channel initiatives designed to acquire and maintain close relationships with customers. In the last decade, because of the proliferation and adaptation of customer relationship management (CRM) systems and sophisticated marketing metrics, firms are increasingly focused on the value of customer analytics as a key organizational asset (Reimann *et al*, 2010; LaPointe, 2012). However, a CRM strategy based on quality data requires companies to organize and analyze every touchpoint so that the customer's value to the firm can be readily determined. Utilizing customer profiling, firms can then implement interactive IMC campaigns that maximize this value over time (Abdul-Muhmin, 2012). Through appropriate resource allocation and marketing mix optimization (Kumar and George, 2007), the anticipated outcomes of personalized, data-driven IMC programs include increased retention, share of wallet, customer lifetime value and profitability (Peltier *et al*, 2013).

Although marketing scholars are calling for research that increases the understanding of effective methods for collecting, storing, analyzing and utilizing different types of customer data (Precourt, 2011), measurement and data analytic problems abound. In many cases, technological advances have outpaced our ability to measure the effectiveness of IMC efforts in today's multi-channel, multi-touchpoint communication environment (Hallward, 2008; Precourt, 2009b; Wind and Sharp, 2009). As Wurtzel (2009, p. 263) noted 'it's the crisis in measurement. You can't sell what you can't measure, and, unfortunately, our measurement systems are not keeping up with either technology or consumer behavior'. Customer and prospect information can thus be misused or underutilized when marketers fail to have a data framework in place to maximize the power of interactive IMC initiatives. As a consequence, there is increasing evidence that many cross-platform IMC initiatives have not lived up to their potential (Kitchen *et al*, 2008; Kliatchko, 2008).

Given the inadequate state of IMC metrics (Wurtzel, 2009; Smit and Neijens, 2011) and mounting data integration concerns, research that develops mechanisms and methodologies for designing and measuring effective cross-media campaigns is warranted (Precourt, 2009a; Pettit, 2010). Despite this need, and although CRM has received increased coverage in both academic and popular press, few firms implement relational frameworks that provide a 360° view of their customers' transactional, attitudinal and psychographic profiles (Peltier *et al*, 2013). Moreover, most firms do not have a clear vision for how data collected from various touchpoints can be used singularly and in combination for launching personalized marketing strategies (O'Regan *et al*, 2011). Even fewer have metrics in place for measuring the impact that their interactive IMC programs have on customer retention and long-term profitability (Lee and Park, 2007). Now more than ever we have the ability to utilize real-time marketing analytics as a means of merging customer data from multiple customer touchpoints (Hipperson, 2010; Acker *et al*, 2011).

Owing to these concerns, the goal of our article is to develop and test an exploratory hierarchical IMC data integration and measurement framework that focuses on using customer information (transactional, demographic and psychographic) to develop personalized communication and marketing campaigns that can then be distributed via various interactive customer touchpoints. We extend recent work by Zahay *et al* (2012) and Peltier *et al* (2006) to propose an IMC data continuum. Our framework moves from data needed to profile customers, to data needed to develop personalized communications and offers, and finally to data needed to metricize how customers respond to marketing efforts across multiple contact points. Our model posits that the collection of basic customer data leads to placing higher priority on collecting other types of data needed to get close to customers and to nurture relationships.

Responding to a call for research that links CRM initiatives to performance, we also assess the impact that these interactive IMC campaigns have on two marketing metrics: (i) the quality of the CRM database and (ii) customer performance. Our findings contribute to existing literature by offering a framework for how customer data can be used to design personalized and profitable communication strategies and tactics.

We begin with a brief review of the CRM and IMC literatures, then develop and test our IMC data integration framework, and close with a discussion of key strategic implications.

THEORETICAL BACKGROUND

CRM defined

Relevant to our IMC data integration framework, Payne and Frow (2005, p. 168) define CRM as a strategic process '... concerned with creating improved shareholder value through the development of appropriate relationships with key customers and customer segments … CRM provides enhanced opportunities to use data and information to both understand customers and co-create value with them'. This data-driven orientation requires the 'cross-functional integration of processes, people, operations and marketing capabilities that is enabled through information, technology and applications'. Following this logic, Even *et al* (2010) and Verhoef *et al* (2010) contend that the use of CRM as a tool for developing effective data-driven interactive marketing tactics requires an analytic-driven and holistic view of customers across multiple transactions, channels and customer touchpoints. Echoing this perspective, Boulding *et al* (2005, p. 157) advance the notion of CRM as a strategic mechanism for '... managing the dual-creation of value, the intelligent use of data and technology, the acquisition of customer knowledge and the diffusion of this knowledge', for the purpose of developing personalized relationships and enhanced customer value.

Interactive CRM data

Although CRM systems could logically contain an extensive array of IMC data types, we focus on those outlined by Zahay *et al* (2004, 2012) that are captured from

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interactive customer touchpoints (that is, Internet, email, telephone and personal service encounters), transactional data (that is, purchase history, credit history, payment history), psycho-demographics (that is, loyalty programs, satisfaction surveys) and customer lifetime value data (that is, retention, share of wallet). We adopt Peltier *et al*'s (2013) definition of high-quality customer data, which claims that information should be collected across multiple transactions, touchpoints and channels so that it accurately reflects the behavior and sentiments of customers, both collectively and individually. From this definition, it follows that a customer database becomes a means by which a firm can create a customer knowledgebase and make marketing decisions. As we focus on IMC data categories and interactive customer touchpoints, we omit mass media from our model.

CRM and IMC

The IMC literature places emphasis on two interrelated components of the IMC construct: (i) the use of multiple communication media and (ii) the consistency of messages achieved across these media. Specific to the former, effective IMC programs mandate a clear understanding of all sources of a brand's contact with consumers (Kitchen and Schultz, 2009). Regarding the latter, IMC requires clarity and consistency across multiple platforms, including a common message strategy, voice and look. More recently, IMC has been viewed as an opportunity for creating and sustaining consumer–marketer dialogue brought on by the use of sophisticated databases and CRM system applications (McGrath, 2010).
On the basis of the notion of interactive IMC (Peltier *et al*, 2006), this approach involves the development of communication strategies for delivering personalized messages and offers to prospects and customers over a range of dual-dialogue channels (Thomas and Sullivan, 2005). In this regard, IMC requires sound interactive marketing strategies driven by customer needs across the relationship lifecycle, beginning with the capture of new prospects and all the way through to customer valuation and retention strategies.

Data quality and customer analytics

Although the importance of having a quality CRM database is relatively undisputed, methods by which to measure data inputs across a diverse set of CRM systems needs is still unclear (Zahay *et al*, 2012). Despite this uncertainty, *access* to information collected and utilized across multiple transactions, channels and customer touchpoints is viewed as a minimum requisite for developing effective interactive IMC initiatives (Even *et al*, 2010; Verhoef *et al*, 2010).
As such, creating insightful data analytic initiatives necessitates a corporate-wide commitment to collecting customer information at all points of the relationship lifecycle, from the capture of new customers through to customer valuation and retention (Peltier *et al*, 2003). Along these lines, Zahay *et al* (2004) focus on analytic competencies across multiple sources including customer touchpoints, transaction data, loyalty/satisfaction data and customer lifetime value data. They find that having higher data quality relates to each type of data and ultimately is positively associated with customer and business performance, a finding corroborated by Zahay and Peltier (2008) and Zahay *et al* (2012).

FRAMEWORK AND HYPOTHESES

Zahay *et al* (2012, 2004) argue that CRM data quality and customer performance may be explained through an examination of the hierarchical ordering of the value of different types of IMC data. Extending this work, our interactive IMC data integration and

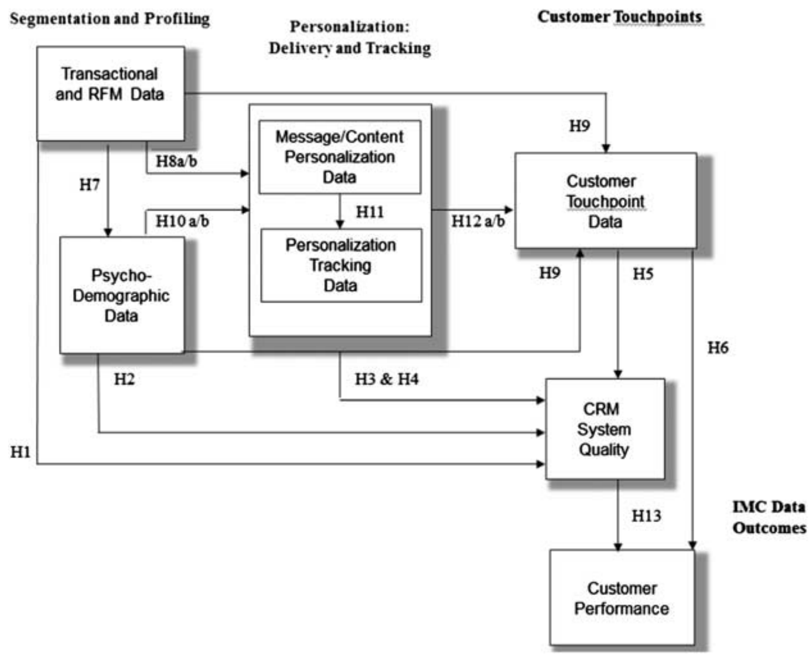

Figure 1: Interactive IMC data integration and measurement framework.

measurement framework is shown in Figure 1. We examine how the data collected from various acquisition points directly and indirectly impacts CRM data quality and customer performance. Building on previous research by Peltier *et al* (2006), Peltier *et al* (2003) and Zahay *et al* (forthcoming), these IMC data acquisition points are useful for creating personalized marketing offers and messages that are delivered via diverse interactive touchpoints. As given in Figure 1, we present the IMC data via a sequential ordering process: (i) transactional and psycho-demographic data are first used to create target segments and customer profiles; (ii) personalization data are then used to deliver and track the efficacy of messaging and offer tactics targeted to different segments; and lastly (iii) touchpoints represent target-specific data and outcomes collected from various interactive communication channels.

Our proposed interactive IMC data analytic framework brings together behavioral and psychographic data to develop target-specific and personalized messages and marketing offers delivered via interactive response channels. Although our framework includes a variety of direct effects, we are particularly interested in understanding the most effective ordering of these different types of data and determining how they indirectly impact CRM data quality and customer performance.

Transactional and RFM data – Direct effects

Understanding customers' past transactional history is a cornerstone metric driving successful CRM and IMC initiatives (Taylor, 2010) and is an important component of ARF's 360 human-centric advertising model (Romaniuk and Gugel, 2010). Transactional data are a key element for explaining why customer segments differ in their present contribution to the firm and are the dominant mechanism used by many interactive marketers to assess customer lifetime value and future potential (Homburg *et al*, 2008).

Advanced information technology innovation has increased the ability of firms to capture an expanding array of transactional data from diverse customer contact sources needed for generating important metrics such as customer lifetime value (CLV) and customer equity (Du *et al*, 2007). Most frequently, transactional data have been investigated in terms of the impact that RFM (Recency (last purchase), Frequency (number of transactions) and Monetary (value of transactions)) have on CLV. Despite an overwhelming consensus by direct and interactive marketers that RFM data have predictive power in determining CLV, little research examines how it impacts the quality of interactive CRM systems and the extent to which these data motivate the capture of other forms of customer information necessary for developing effective IMC initiatives (Zahay *et al*, 2012). Transactional and RFM data represent the base of our IMC model. We thus hypothesize that:

Hypothesis 1: Increased use of transactional data is positively related to CRM system quality.

Psycho-demographic data – Direct effects

Whereas transactional data measures customer behavior, psychographic-based data focuses on understanding customers in terms of their values, buying motivations, attitudes, beliefs and lifestyles. Psychographic data merged with common demographic data such as age, gender, income, marital status and family size allows marketers to appeal to the underlying motivations and lifestyles of different customer and prospect target audiences (Smith *et al*, 2010). Psycho-demographic data are most often generated internally from a customer satisfaction and needs survey, and externally from commercially acquired information about customers and prospects, which would then be appended to internal data files.

Although many studies have contributed to explaining consumer behavior, few have sought to utilize customers' psycho-demographics for segmenting customers using data mining techniques. The reason for this omission is that the psychographic data that are needed for data mining are stored in customers' minds, and not well integrated with demographic information, which is stored in a well-formed IMC database. In some ways, psycho-demographics are seen as static elements, yet when coupled with dynamic CRM data, such as transactional information, they can aid in the formation of a longitudinal view of the customer. Despite the logical connection between customer psycho-demographics and relational outcomes, scant research has empirically tested how their use impacts CRM data quality and customer performance. We posit:

Hypothesis 2: Increased use of psycho-demographic data is positively related to CRM system quality.

Personalization delivery and tracking data – Direct effects

Both marketing and advertising literature have long acknowledged that customers have diversified needs. These needs not only represent the product and service offers customers desire, but also the relevant messages that they receive and respond to (Zahay and Griffin, 2003; McCoy and Hargie, 2007). Broadly, personalization is the ability to individualize customer communications and marketing offers (Zahay *et al*, 2004). The creation and delivery of personalized marketing offers and communications move away from a one-size-fits-all strategy to the realization that customers are not faceless entities but rather are distinct individuals with different behavioral and psycho-demographic profiles (Chakraborty *et al*, 2003). Personalization is more than the mere identification and delivery of messages and offers; successful tracking of personalization efforts is also necessary in quality CRM systems

(Jackson, 2007). This tracking measures the extent to which customers receive the right offers and messages at the right time and place (Li *et al*, 2011).

Although there is scant research that examines the relationship between the amount of personalization data an organization collects and its performance, Zahay *et al* (2012) find that the data used to personalize buyer–seller relationships has the greatest impact on perceived data quality. Therefore, we hypothesize that:

Hypothesis 3: Increased use of offer and message personalization data is positively related to CRM system quality.

Hypothesis 4: Increased use of personalization tracking data is positively related to CRM system quality.

Customer touchpoint data – Direct effects

The success of an IMC campaign is contingent in part on how well advertising messages and offers are delivered across multiple interactive touchpoints (Hallward, 2008). Although there are varied definitions of customer touchpoints, most agree that they refer to a point of contact specific to the delivery and reception of communications and offers. In this regard, touchpoint planning is a comprehensive approach for designing, delivering, managing and measuring personalized customer relationships across communication channels (Jenkinson, 2007). *Interactive* customer touchpoints include information captured via the Internet, email clickthroughs, service encounters, telephone call centers and other channels offering dual-direction communication.

Research suggests that the development and management of highly valued customer relationships is impacted by the degree to which firms collect and integrate behavioral data at the point of information delivery (Davis, 2005). This value is expected to be higher when marketing communications work in tandem with other touchpoints to maximize customer connections. A core element of CRM systems is the ability to track where and how communications/offers are delivered, which in turn are assigned to individual customer files (Romaniuk and Gugel, 2010). Moreover, as a final link in our hierarchical IMC data process, we expect that using relevant customer touchpoints will positively impact the quality of CRM systems.

Hypothesis 5: Increased use of customer touchpoint data is positively related to CRM system quality.

Hypothesis 6: Increased use of customer touchpoint data is positively related to customer performance.

Indirect hypotheses

Zahay *et al* (2012) conceptualized a customer data pyramid relevant to understanding CRM system quality and customer performance. They contend that the value of a firm's customer data is tied to the ease by which it can be collected for use in CRM systems. The authors speculate that transactional history data would be at the bottom of the pyramid, followed by psycho-demographic data, personalization data and customer touchpoint data. Whereas they present no test of the ordering of these data categories and how they impact data categories higher in the pyramid, our IMC data framework posits the existence of an IMC data hierarchy, with data lower on the pyramid leading to increased collection of higher-order IMC data. Transactional and psycho-demographic data have been used extensively to develop customer segments. Zahay *et al* (2004) note that psycho-demographic data are more powerful than transactional data and are appended to transaction-based segments as a means of creating a picture of the profiles of target customers. Thus:

Hypothesis 7: Increased use of RFM/ transactional data is positively related to

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the collection of psycho-demographic data.

Targeted messaging and offer personalization uses data that are transformed by behavioral segmentation and profiling models (Peltier *et al*, 2003; Dutta-Bergman, 2006). The more basic data elements such as customer transactions and psycho-demographic data serve as inputs into the personalization process that requires a matching of what customers want and who they are with appropriate offers and brand messages (Jackson, 2007). In practice, effective database managers also append data collected from multiple touchpoints to a customer's behavioral and psycho-demographic profile as a means of providing a richer understanding of the relationship. Thus, we hypothesize that:

Hypothesis 8: Increased use of RFM/transactional data is positively related to the collection of (i) offer and message personalization data; and (ii) personalization tracking data.

Hypothesis 9: Increased use of transactional data is positively related to the collection of customer touchpoint data.

Hypothesis 10: Increased use of psycho-demographic data is positively related to collection of (i) offer and message personalization data; and (ii) personalization tracking data.

As provided in Figure 1, we alter the ordering of Zahay *et al*'s (2012) data pyramid by switching the sequencing of personalization data and touchpoint data. Specifically, because a firm's personalized messages and offers are distributed via selected touchpoints, touchpoint data logically holds the final position in the data hierarchy framework. This notion is in line with Jenkinson (2007), who proposes a model for distributing personalized customer communications and experiences across multiple touchpoints and media platforms.

Hypothesis 11: Increased use of offer and message personalization data is positively related to the collection of personalization tracking data.

Hypothesis 12: Increased use of (i) offer and message personalization data; and (ii) personalization tracking data is positively related to the collection of customer touchpoint data.

CRM data quality and customer performance

Closing the loop in our interactive IMC data framework, we assess the relationship between the quality of IMC data within a CRM system and customer performance. A growing stream of research shows that effective CRM implementation and use contributes to improved customer performance (for example, Homburg *et al*, 2008). Although evidence for the effect that CRM system data quality on customer performance is scant, we hypothesize that:

Hypothesis 13: The quality of IMC data in a CRM system is positively related to customer performance.

RESEARCH METHODOLOGY

Sample and data collection

A total of 525 executives in the financial services industry were selected from Hoover's database as the pool of potential respondents. Three data collection waves were conducted; two mail waves (including a US$2 bill as an incentive) and a follow-up telephone call. Respondents were given the option of mailing the questionnaire back or completing the questionnaire online via the attached URL. A second mailing was later sent to non-respondents (id codes were used to determine respondents) approximately 14 days after the mailing was delivered.

Table 1: Demographic profile of respondents

Percentage of sales	*Mean*
B2B sales percentage	45.2
B2C sales percentage	39.6
Retail sales percentage	50.2
Online sales percentage	10.3
External sales percentage	26.9
Sales/assets under management	*Per cent*
<50 million	13.0
51–250 million	18.7
250.1 million–1 billion	20.1
1.1–5 billion	29.5
>5 billion	18.7
Respondent age	*Per cent*
<35	9.1
35–44	27.9
45–54	38.2
55+	24.8

Finally, two graduate assistants called the remaining non-respondents, either speaking with them personally or leaving a voice mail message. In total, 170 questionnaires were returned. All but a few respondents used the online survey option, eliminating question non-response (responses were largely mandatory). Four respondents were removed in model development due to non-response, leaving a sample of 166. This resulted in an overall response rate of 32 per cent, which compares favorably with response rates typically received from business executives.

Table 1 contains the profile of respondents. Approximately 45 per cent of the businesses are B2B and about 40 per cent are B2C, with the remainder accounted for by other trade relationships. The respondents reported that 50 per cent of their business was conducted at retail or branch banking locations and relied on outside sales personnel for 27 per cent of their business. The majority of the respondents (63 per cent) were 45 years or older, suggesting that the sample had substantial industry experience. Online business was a little over 10 per cent of their sales, consistent with the industry average. Most of the firms (68.3 per cent) reported at least $250 million in sales/assets under management.

Possible biases of informants were controlled for by requiring informants to be: (i) knowledgeable in their area; (ii) have a great deal of business experience; and (iii) have a significant amount of background in their industry. In addition, a Harmon's one-factor test revealed that common method bias was not an issue in the data. In addition, *T*-tests comparing the responses of early responders to late responders did not provide any evidence of response bias.

Measures and validation

On the basis of prior work in the CRM and organizational learning literatures, scales were developed for the five independent variables in our model. Because our hypotheses posit that the increased use of these data types will lead to higher quality CRM systems, all variables were assessed using multi-item 5-point scales measuring the percentage of time that these data are collected for inclusion in their customer database (0 per cent, 25 per cent, 50 per cent, 75 per cent, 100 per cent). A summed average score was calculated for each.

Transactional/RFM Data ($\alpha = 0.83$) was measured by five items:
(i) Customers' last purchase date,
(ii) Revenue by product or product line,
(iii) Frequency of purchase,
(iv) Total revenue from customer and
(v) Length of time as customer.

Psycho-Demographic Data ($\alpha = 0.75$) was assessed by three items:
(i) Customer lifestyle data,
(ii) Customer psychographics and
(iii) Customer demographics.

Message/Offer Personalization Data ($\alpha = 0.82$) was measured by three items:
(i) Tailor marketing offers to customers,
(ii) Tailor communications to customers and
(iii) Tailor communications to prospects.

Personalization Tracking Data ($\alpha = 0.89$) was measured by three items:
(i) Tracking marketing offers/messages made to customers,
(ii) Tracking marketing offers/messages customers responded to and

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(iii) Tracking method of contact for marketing offers/messages.

Customer Touchpoint Data (α = 0.76) was assessed by three point of contact items:
(i) Email communications,
(ii) Personal service contacts and
(iii) Internet communications/sales.

The two dependent variables in the model are Overall CRM system quality and Customer Performance. In our model, Overall CRM system quality is an antecedent of Customer Performance.

Overall CRM System Quality (α = 0.76) was assessed by four items related to multi-touchpoint CRM system implementation:
(i) Overall Quality of Internet and Email Data,
(ii) Overall Quality of Loyalty/Retention Data,
(iii) Overall Quality of Contact Management Data and
(iv) Overall Quality of CRM Data Capabilities.

The scale ranged from 1 = poor to 5 = excellent.

Customer Performance (α = 0.76) was measured by three items that reflect elements of long-term customer profitability:
(i) Customer Retention on an annual basis,
(ii) Cross-Selling and
(iii) ROI on a customer basis.

Customer performance was stated as: 'To the best of your knowledge, please rate your business unit's performance in the past 2–3 years relative to the competition' on a 1 = lower to 5 = higher scale.

Items from the survey were subjected to an exploratory factor analysis, followed by an item to total correlation analysis. The method utilized was that suggested by McDonald (1999) where the CFA is guided and informed by the EFA results. Items with low item to total correlations were eliminated. Table 2 provides the reliability and factor loadings for the final independent variables. The coefficient α's range from 0.75 to 0.90, indicating satisfactory levels of reliability for the measures.

Table 2: Reliability and factor loadings for independent variables

	Factor loading
Transactional/RFM data (α = 0.83)	
Customers' last purchase date	0.81
Frequency of purchase	0.76
Total revenue from customer	0.67
Revenue by product or product line	0.65
Psycho-demographic data (α = 0.75)	
Customer lifestyle data	0.90
Customer psychographics/personality	0.86
Customer demographics	0.67
Message/offer personalization data (α = 0.82)	
Tailor communications to customers	0.92
Tailor marketing offers to customers	0.92
Tailor marketing offers to prospects	0.84
Personalization tracking data (α = 0.9)	
Tracking marketing messages/offers made to customers	0.84
Tracking marketing messages/offers customers responded to	0.79
Tracking method of contact for marketing offer	0.70
Customer touchpoint data (α = 0.76)	
Email communications	0.88
Service contacts	0.77
Internet communications/sales	0.77

We next conducted a confirmatory factor analysis. A global CFA for discriminant validity was not conducted because the data did not meet the five observations per indicator variable threshold (Hair *et al*, 2010). Because of the small sample size, the dependent and independent variables were analyzed separately. However, using AMOS, separate CFAs were conducted on the independent and dependent variables. Fornell and Larcker's (1981) criterion is that evidence of discriminant validity is shown if the average variance extracted (AVE) is greater than the square of the construct's correlations with the other factors, squared inter-item correlation (SIC). The results of an AVE analysis demonstrate that the AVE of the items in the scale are greater than the SIC, providing evidence of discriminate validity in the constructs.

The fit indices of the dependent variable CFA indicate a good fit, especially for the

Table 3: Item correlations and reliabilities

Variables	*PSYCH*	*RFM*	*TOUCH*	*MESSAGE*	*PERS*	*CRM*	*PERF*
Psycho-Demographic	1	—	—	—	—	—	—
RFM/Transactional	0.419**	1	—	—	—	—	—
Customer Touchpoints	0.154*	0.255**	1	—	—	—	—
Message/Offer Personalization	0.275**	0.204**	0.107	1	—	—	—
Personalization Tracking	0.410**	0.326**	0.231**	0.540**	1	—	—
CRM System Quality	0.456**	0.357**	0.270**	0.484**	0.476**	1	—
Customer Performance	0.129	0.111	0.334**	0.082	0.1	0.241**	1
Mean	2.68	3.63	3.67	3.64	3.17	2.99	3.33
Standard Deviation	1.15	1.17	1.11	1.1	1.17	0.77	0.75

* and ** indicate significance at 0.05 and 0.01, respectively; $N = 166$.

relatively small sample size, with χ^2 50.45 (DF = 10), normed fit index (NFI) = 0.935, incremental fit index (IFI) = 0.958, comparative fit index (CFI) = 0.958, the Tucker-Lewis index (TLI) = 0.938 and the root mean square error of approximation (RMSEA) = 0.10. The fit indices of the independent variable CFA also indicated a reasonable fit, again especially for the small sample size, with χ^2 181.21 (DF = 94), NFI = 0.872, IFI = 0.934, CFI = 0.933, the TLI = 0.914 and the RMSEA = 0.075. Having conducted these tests for discriminate validity, the final scales were created as summed mean scores of the individual items. The correlation matrix along with the means and standard deviations of our summed dimensions are reported in Table 3. Whereas the correlation matrix demonstrates some of the primary relationships such as the strong relationship between both customer touchpoints, CRM data quality and performance, the SEM as fit demonstrates the complex relationships of the variables.

Analysis and results

The hypothesized direct and indirect relationships were tested in a combined SEM model using AMOS 19. Both the Goodness of Fit Index (GFI 0.995) and Adjusted Goodness of Fit Index (AGFI = 0.982), which measure the fit of the combined measurement and structural model to data ($\chi^2 = 2.64$) were greater than 0.90 (Baumgartner and Homburg, 1996). The Root Mean Residual, which assesses the correlations between the residual variance of the model items, and should be less than 0.05 for a close fit, is 0.027 (Bagozzi and Yi, 1988). The Steiger-Lind RMSEA, a non-centrality measure of the square root of an estimate of the population discrepancy divided by the degrees of freedom that should be as close to 0 as possible, is 0.001. CFI, a normed comparative fit index that should be as close to 1 as possible, was 0.95 (Bentler, 1990).

The results of the hypotheses testing based on the model are summarized in Table 4. Alternate models were tested that eliminated variables and/or paths and that reversed the hypothesized directional relationships. None of these alternate models fit better than the model reported in Figure 1, nor had as much explanatory power. Because the one-tailed test is most appropriate for these data (being that negative responses were not allowed or appropriate), all paths except RFM/transactional data to offer/message personalization data and psycho-demographic data to customer touchpoints were significant at $P < 0.05$. The path from RFM/Transactional data to CRM system quality was significant at $P < 0.055$.

Mediation tests

As CRM system quality is the key construct in this research, several mediation tests were conducted using the approach advocated by Zhao *et al* (2010) via an SPSS script file

Table 4: Results and hypothesis testing structural equation model

				Standard coefficient	t-value
H1	RFM/Transactional	→	CRM System Quality	0.110†	1.60
H2	Psycho-Demographic	→	CRM System Quality	0.248***	3.50
H3	Offer/Message Personalization	→	CRM System Quality	0.144*	1.87
H4	Personalization Tracking	→	CRM System Quality	0.303***	4.22
H5	Customer Touchpoints	→	CRM System Quality	0.139*	2.20
H6	Customer Touchpoints	→	Customer Performance	0.293***	3.96
H7	RFM/Transactional	→	Psycho-Demographic	0.419***	5.93
H8a	RFM/Transactional	→	Offer/Message Personalization	0.140*	2.06
H8b	RFM/Transactional	→	Personalization Tracking	n.s.	n.s.
H9	RFM/Transactional	→	Customer Touchpoints	0.201**	2.60
H10a	Psycho-Demographic	→	Offer/Message Personalization	0.275***	3.67
H10b	Psycho-Demographic	→	Personalization Tracking	0.230***	3.29
H11	Psycho-Demographic	→	Customer Touchpoints	n.s.	n.s.
H12	Offer/Message Personalization	→	Personalization Tracking	0.452***	7.06
H13	Personalization Tracking	→	Customer Touchpoints	0.165*	2.12
H14	CRM System Quality	→	Customer Performance	0.211***	3.96

$^{\dagger}P$ *0.10*, $^{*}P<0.05$, $^{**}P<0.01$, $^{***}P<0.001$ (one-tailed tests).
Notes: Model fit: χ^2 (166) = 2.64, GFI = 0.995, AGFI = 0.982, CFI = 0.95, RMSEA = 0.001.

Table 5: Results mediation tests

Independent variable	*Dependent variable*	*Mediator*	*Direct effect (standard regression coefficients (significance level)*	*Indirect effect (standard regression coefficients (significance level)*	*Result*
RFM/ Transactional	Customer Performance	CRM system quality	0.1129 (0.0028)**	0.2361 (0.0124)*	Partial Mediation
Psycho-demographic	Customer Performance	CRM system quality	0.0830 (0.1008) ns	0.3068 (0.0046)**	Mediation
Customer Touchpoints	Customer Performance	CRM system quality	0.1879 (0.0431)*	0.2384 (0.000)**	Partial Mediation
Personalization Tracking	Customer Performance	CRM system quality	0.0705 (0.1819) ns	0.3355 (0.0028)**	Mediation
Offer/Message Personalization	Customer Performance	CRM system quality	0.0546 (0.2724) ns	0.3193 (0.0019)**	Mediation

* and ** indicate significance at $P<0.01$ and $P<0.05$; ns: non-significant.
All tests are two tailed.

developed by Hayes (Preacher and Hayes, 2008). We examined the relationships in the model to determine if CRM system quality mediated the relationship between the antecedent variables and the dependent performance variable, Customer Performance. We anticipated the finding that CRM system quality would be critical to the model, and reinforced by these tests.

Indeed, the mediation tests in Table 5 show that CRM system quality mediates the effect of the collection of, Psycho-demographic, Personalization/ Tracking, Offer/Message Personalization on performance. In the cases of these types of data – Psycho-demographic, Personalization/ Tracking, Offer/Message Personalization – the indirect effects are larger than the direct effect and the direct effect becomes insignificant when the mediator is included in the equation, consistent with direct mediation. In other words, the organization's business and customer performance is not achieved directly from data collection but through paying attention to CRM system quality.

Table 5 also shows that CRM system quality partially mediates (complementary mediation in the language of Zhao *et al*, 2010) the impact of the collection of RFM/

Transactional data and Customer Touchpoint data on Customer Business Performance. The indirect paths from Organizational Culture to performance are stronger than the direct, consistent with mediation, but both the indirect and direct effects are significant. These results indicate that CRM system quality does mediate the path from collection of RFM/Transactional data and Customer Touchpoint data to Performance. Again, the organization's business and customer performance is not achieved directly from data collection but through using the information gained from data collection to improve CRM system quality. However, because the relationship is not reflective of full mediation, there might be another factor to consider in future analyses. As both RFM/ Transactional data and Customer Touchpoint data are complex concepts, it is not surprising that these constructs might need to be expanded to increase understanding of the mediation effects.

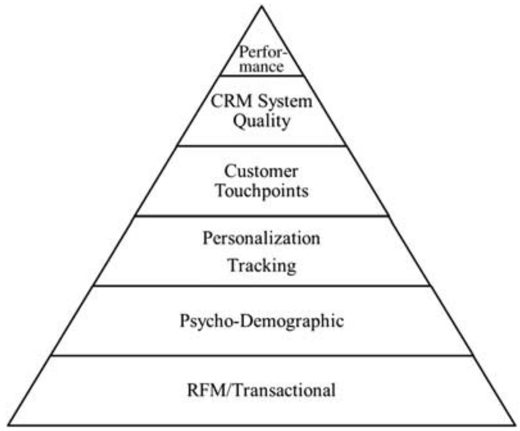

Figure 2: Data pyramid.

DISCUSSION

This model extends and focuses previous work and shows the importance of several types of customer information and their ultimate impact not only on personalized communications, but of equal value, on CRM system quality and customer performance. Our model empirically demonstrates the fact that CRM System Quality leads to enhanced customer performance, showing that a strategic data system is not only important for personalized communications and customer touchpoints, but can eventually yield higher returns and loyalty from customers. As shown in Figure 2, our findings highlight the fact that easier-to-collect customer data impacts the extent to which other higher-level customer data are collected and utilized for getting close to customers.

Our hierarchical IMC model provides guidance in a world where managers are grappling to understand 'big data' and how to manage and integrate disparate customer databases across an exploding number of media channels. In this context, targeted media campaigns that span multiple media types, especially in light of the dynamic nature of technology such as the social media digital space, need to be tightly integrated (Wakolbinger *et al*, 2009) in order to make them advantageous for firms. Such cross-media campaigns can only be developed with clean segmentation and profiling data in combination with personalized tracking information. In recent years, the channels of sales have grown, allowing for the ability to reach customers not only through bricks-and-mortar and e-commerce, virtually via v-commerce (Krishen *et al*, forthcoming), and also through mobile environments or kiosks (Bui *et al*, 2012). In combination with multiple media formats, these channels not only allow for truly integrated communications, but also present an even more pressing challenge for firms as they struggle to optimize and organize their customer information.

With such opportunities in digital advertising, e-marketing, viral marketing and social media marketing, there is an even more pressing need for firms to remain vigilant in tracking transactional and psycho-demographic data now than ever before; as the model here shows, this data can

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be used to personalize delivery and track it and improve customer touchpoints. The model clearly suggests that firms pay a performance price for not collecting critical types of information and not using it for personalized communications. In fact, it is primarily through the collection of Psycho-Demographic data and both Message/Content Personalization and Personalization Tracking Data and the increase in CRM system quality that results that performance is achieved in this context. Substantiating this finding, current research in the area of digital television advertising indicates that firms now have even greater opportunities to personalize message qcontent in interactive platforms (Lekakos, 2009). In spite of the increased capability for personalization, the connection of personalization with performance remains under-researched. This study extends the research of Zahay and Griffin (2004) in which a link from message personalization to performance was established, by focusing more sharply on the role of CRM data quality in creating firm performance.

This model also suggests that increased personalization message and content data delivery and tracking leads to increased customer touchpoint data. In other words, customers are more likely to follow up and return contact to a firm when the materials they receive are personalized and the content is delivered in a timely manner. Our findings also support the idea that firms will pay a performance price without a data collection process at customer touchpoints that is both efficient and effective. In fact, in line with this notion, Lautman and Pauwels (2009) find that advertising and promotion awareness can be termed a ‘metric that matters’ and can lead to not only base sales, but incremental sales of a product as well. Moreover, the longevity factor of the customer relationship cycle is of utmost importance; making an initial impression on a customer can drive a spike in sales, but without an ongoing and personalized communication plan, the customer can eventually switch to another product or firm.

With updated data banks, firms can accurately profile customers and target their personalized communications to those with high wallet share through proper touchpoint data. As our model shows, this touchpoint data eventually leads to CRM System Quality and ultimately to CRM performance, hence completing the feedback loop. To further validate this cycle, Baldinger *et al* (2002) conduct a longitudinal study and suggest that continued loyalty to a brand leads to increased market share and that customer retention is essential to grow in a competitive market. Hence, the role of CRM System Quality and how it leads to improved customer performance is essential for firms to eventually increase market penetration and performance.

LIMITATIONS AND FUTURE RESEARCH

As with all research, there are limitations. Given the exploratory nature of this study, more work needs to be done on larger sample sizes in diverse industries and to understand how CRM quality can lead to customer performance. As firms are increasingly globalizing, future research should test our model from a cross-cultural perspective and identify ways in which it is impacted by self-construal. For example, research spanning multiple cultures shows that knowledge management, when combined with a customer focus, can create a very effective model for the deployment of CRM (called KCRM) efforts (Lin *et al*, 2006). In essence, their framework suggests that customer information must be managed through efforts that include knowledge identification, capture, selection, storage, sharing, application, creation and selling.

The impact of different types of data we identified in our model on KCRM, then, is also a fruitful area of future research. To that end, one aspect of knowledge management, customer knowledge orientation, requires that companies keep marketing databases up-to-date, utilize internal database marketing information, monitor the accuracy of information in marketing databases and utilize performance-based reward systems (Stein and Smith, 2009). Stein and Smith (2009) find that customer knowledge orientation leads directly to more use of CRM, which then enhances firm performance. Thus, accurate customer knowledge ultimately leads to better firm performance. Our model also finds this important linkage.

Finally, even though our model does not measure loyalty outcomes, opportunity exists to further this type of research along those lines. The ability to contact appropriate customers based on accurate profiling over time is a necessity to guarantee an ongoing relationship. Research indicates that customer retention is enhanced when customers are satisfied and their complaints are handled in an efficient and appropriate manner; to mitigate such complaints and handle customer communications effectively, firms must have a quality CRM system and strategy in place (Zineldin, 2006). The link to customer loyalty that firms can make when they have high CRM System Quality enables them to continue relationships with customers, thus creating a feedback loop for our IMC model. In essence, by retaining customers, firms are able to update transactional, psycho-demographic and personalization tracking data on an ongoing basis.

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